Systemic Microstructure Risks of High Speed Trading

I. Introduction

High speed trading has become a global phenomenon and following a number of market mishaps has caught the attention of regulators.[1] HFT's market share on the NYSE is as much as 73% (Hendershott, Jones, and Menkveld, 2011; Easley, Lopez de Prado, and O'Hara, 2011).[2] The introduction of the Arrowhead high-speed-trading platform by the Tokyo Stock Exchange (TSE) in January of 2010 reduced latency from 6 seconds to 2 milliseconds. By April of 2011 co-located, high frequency trading's (HFT) market share soared from about 0% to as much as 36%.

Despite its growing popularity, the empirical evidence on the risks of high speed trading has so far been limited and inconclusive. On the one hand, HFT has enhanced market quality by reducing quoted spreads, increased risk-sharing, consumption smoothing, and price efficiency (Chordia, Roll, and Subrahmanyam, 2008; Boehmer and Kelley, 2009; Hendershott, Jones and Menkveld, 2011; Hendershott and Riordan, 2011; Hasbrouck and Saar, 2013; Foucault, Hombert, and Rosu, 2012; Carrion, 2013; Martinez and Rosu, 2013). On the other hand, HFT has also increased volatility (Boehmer, Fong, and Wu, 2013; Zhang, 2010; Brogaard, 2010), effective spreads, adverse section costs (Hendershott and Moulton, 2011), cost of trading (Moallemi, and Sağlam, 2010), the severity of losses from episodic illiquidity as observed during the Flash Crash of May 2010 (Easley, Lopez de Prado, and O'Hara, 2011; Cartea and Penalva,

[1] Germany is set to advance a bill requiring traders to register with Germany's Federal Financial Supervisory Authority and collect fees from those who use high-speed trading platforms. (http://online.wsj.com/article/SB10000872396390444813104578018292059338944.html). On August 1, 2012, France introduced a high-frequency trading tax. More recently, in the US, Securities and Exchange Commission (SEC) has adopted a rule requiring exchanges and FINRA to file a plan to build a Consolidated Audit Trail (CAT) in part to monitor HFT (http://www.sec.gov/news/press/2012/2012-134.htm).

[2] Moreover, there is still room for growth as is evident from the fact that HFT's market share on the NYSE is as much as 73% (Hendershott, Jones, and Menkveld, 2011; Easley, Lopez de Prado, and O'Hara, 2011). Baron, Brogaard, and Kirilenko (2012) conjecture that firm concentration in HFT is increasing over time.

2011; Jarrow and Protter, 2011), and the frequency of technology glitches such as the Knight Capital Group software breakdown in August 2012 and the problems with the beginning of trading for the Facebook and BATS IPOs.[3]

We use the TSE's introduction of Arrowhead as a natural experiment to ascertain how the reduced latency of Arrowhead has affected liquidity supply on the Limit Order Book (LOB), systematic microstructure trading risks such as, shock propagation risk, quote stuffing risk, and tail risk.[4] Clearly identifiable latency shock and milder regulatory environment in Japan are distinct characteristics of our analysis that help isolate the effects of low latency relative to other studies focusing on US and Europe.[5]

There is a rich theoretical literature on the relation between traditional liquidity measures based on quotes at the top of a LOB and various dimensions of market quality (Biais, Hillion, and Spatt, 1995; Hendershott and Moulton, 2011; Foucault, Moinas, and Theissen, 2007). The measures of systemic risks, such as CoVaR (Adrian and Brunnermeier, 2011), quote stuffing risks, such as the quotes-to-trade ratio (Menkveld, 2012; Hagströmer and Nordén, 2013), and shock propagation risks, such as autocorrelation (Chaboud, Chiquoine, Hjalmarsson, and Vega, 2013; Parlour, 1998; Barclay and Warner, 1993) and cross correlation in order flow (Ben-David, Franzoni, and Moussawi, 2012; Chordia, Roll, and Subrahmanyam, 2000), are also discussed in the existing literature. However, most of these studies analyze these key market microstructure

[3] See Jones (2013) for a recent survey of the burgeoning market microstructure literature on HFT.

[4] TSE role in the world markets is highlighted by the master agreement it has signed with NYSE Euronext to allow both of their customers to access each exchange's markets through a linked network. http://www.tse.or.jp/english/news/48/111207_a.html and http://www.advancedtrading.com/exchanges/229300020

[5] For example, US regulations include the SEC market access rule 15c3-5 (http://www.sec.gov/rules/final/2011/34-64748fr.pdf) and limit up limit down rule (https://www.nasdaqtrader.com/content/MarketRegulation/LULD_FAQ.pdf). In Europe a number of countries have adopted or proposed rules that seek to curb HFT activity. France for instance implemented an HFT tax and a transaction tax in August 2012 (Colliard and Hoffmann, 2013). Italy followed suit with an HFT tax in September 2013. There is a broader financial transaction tax being considered by eleven Eurozone countries (http://marketsmedia.com/hft-makes-last-stand-in-europe-as-ftt-and-mifid-ii-edge-closer/).

parameters in pre-HFT markets and do not consider liquidity supplied by traders simultaneously at multiple price levels away from the best bid and ask in high-frequency markets, the importance of which is highlighted empirically by Aitken, Almeida, Harris, and McInish (2007), and theoretically by Goettler, Parlour, and Rajan (2005), and Rosu (2009).

To address this deficiency, in addition to the traditional liquidity measures such as spreads, we also examine several newer measures that quantify the state of the LOB beyond the best quotes. These measures are LOB slope and cost of immediacy (COI) for orders larger than the top of the book depth.[6] These LOB measures are particularly relevant in fast-paced markets where orders frequently walk up or down away from the best quotes in the limit order book in the previous instant. More importantly, these LOB measures have not been analyzed in the literature in the context of HFT risks.[7] The change in the LOB Slope (ΔSLOPE) i.e., the rate at which the LOB refills measures the resiliency of the full LOB from a liquidity supply perspective while COI comprehensively measures both the inside tightness and outside depth of the LOB (Jain and Jiang, 2014). By incorporating the elasticity of liquidity supply and the cost of immediately executing large orders, respectively, these two comprehensive LOB liquidity measures represent the vital statistics of the modern low latency trading platforms. We also develop additional measures of systemic microstructure risks based on correlation, order flow, and CoVaR.

We find that Arrowhead improves market quality and price discovery by increasing trading volume, LOB liquidity, and the number of trades. We extend the literature in newer

[6] For a description of these measures see Biais, Hillion and Spatt (1995), Naes and Skjeltorp (2006) for LOB slope and Irvine, Benston, and Kandel (2000), Kang and Yeo (2008), and Boehmer, Saar, and Yu (2005, pp. 808) for COI.
[7] Our LOB slope measure is defined as the weighted average of the change in quantity supplied in the LOB per unit change in the price while The COI measure captures the fact that liquidity demanders incur progressively higher cumulative costs as the available depth at the top of the LOB in fast markets becomes insufficient to fully execute the order. For COI transaction cost measure, weighted average LOB information for executions at multiple price points resulting from walking up or down the book is used instead of stopping merely at the top of the LOB bid-ask spreads. COI formulae are provided in the next section.

directions by showing that Arrowhead amplifies systemic microstructure risks by increasing return and order-flow CoVaR, the order flow autocorrelations and cross correlations, and quotes-to-trade ratio. Arrowhead increased the speed of trading for only the stocks listed on TSE. Using the stocks listed on Osaka stock exchange as a control sample, we document that the amplification of systemic microstructure risk is a result of Arrowhead using a t-test and difference-in-differences regression analyses. Moderation of extraordinary market wide volatility in large groups of stocks such as the one that occurred in the Flash crash in May 6, 2010 in the US is of significant regulatory interest.[8] We find that Arrowhead increases the exposure to these types of systemic microstructure risks even more during tail risk events, which could potentially lead to a highly destabilizing market situation, such as Flash Crash, indicating that low latency markets may benefit from safety features such as kill switches, circuit breakers, and rigorous software testing. The effects of Arrowhead are more pronounced for the large-cap stocks. Finally, we show that Arrowhead's effect on market quality and systemic risk varies positively with the liquidity supply of the LOB.[9] We show that our results are robust after controlling for intraday seasonality and TSE's unique market features, such as special quotes, minimum trading units, and tick sizes.

II. Low latency trading, LOB liquidity, and systemic risk measures

A. Arrowhead low latency trading platform

On January 4, 2010, the TSE launched a new, high-tech trading platform called "Arrowhead," that cost about $142 million.[10] A number of studies focusing on different aspects

[8] See for example, the discussion on http://www.sec.gov/news/press/2011/2011-84.htm about the development of more sophisticated mechanisms such as the limit up limit down (LULD) pilot rule.
[9] Carrion (2013) and Hendershott and Riordan (2013), using the top of the LOB information, find that algorithmic traders actively monitor market liquidity and submit orders depending on the size of the best bid-ask quote.
[10] TSE, with more than 95% of domestic equity market share, is the largest stock exchange in Asia (TSE Annual Report, 2011). The recent approval of its merger with Osaka Stock Exchange, may make the merged exchange a

of the TSE market were published before the introduction of Arrowhead (Hamao, Masulis and Ng, 1990; Chan, Hamao and Lakonishok, 1991; Lehmann and Modest, 1994; Hamao and Hasbrouck, 1995; Bremer, Hiraki, and Sweeney, 1997).[11] However, the results from these previous studies may not apply to the TSE after the major reduction in latency. Arrowhead can process trades in two milliseconds (time elapsed between order placement and order execution), which is at least 1,500 times faster than the TSE's previous trading platform; the new speed is roughly the same as that of the NYSE and LSE according to the TSE Factbook.[12] The new platform was introduced to attract investors who depend on sophisticated software to make split-second trades.[13] The new trading platform also helps the TSE stay ahead of the growing number of rival proprietary trading systems (PTSs), such as Kabu.com and SBI Japannext.[14] The goal of our paper is to understand the changes in LOB liquidity and systemic microstructure risks associated with high frequency trading induced by the Arrowhead trading platform.

The TSE started offering co-location services during November, 2008. The fees have mostly remained the same (Fixed basic charges + Power and cooling fees + Electricity usage fee) since that time. The one fee that changed post-Arrowhead is the Arrownet connection fee, which is a fixed amount charged for bandwidth subscribed.

B. Data sources and sample formation

Our data includes the price and the number of shares for every trade and for the five best

monopoly for trading equities in Japan (http://www.bloomberg.com/news/2012-06-07/tse-s-osaka-merger-gets-90-odds-as-first-deal-since-10.html).

[11] On August 24, 1998 TSE removed warning quote system, Ahn, Hamao and Ho (2002) analyze liquidity dynamics after this change and decompose the components of bid-ask spreads only at the top of the LOB.

[12] TSE Fact book 2011 retrieved from http://www.tse.or.jp/english/market/data/factbook/index.html

[13] TSE started offering co-location services during November, 2008. The fees have mostly remained the same (Fixed basic charges + Power and cooling fees + Electricity usage fee) since that time. The one fee that changed post-Arrowhead is the Arrownet connection fee, which is a fixed amount charged for bandwidth subscribed.

[14] The best execution rule in Japan is to select the exchange with best liquidity (and not best price as is the case with the US exchanges) which suppresses the competition among exchanges as an order is always routed to an exchange with highest trading volume (http://www.nri.co.jp/english/opinion/lakyara/2012/pdf/lkr2012150.pdf). The two largest stocks listed on TSE, Sony Corp and Honda Motors, are not traded at all on any proprietary trading system (PTS) during pre- and post-Arrowhead periods. Almost all of the trading happened on TSE.

bid and ask quotes and depths at every instant for all the TOPIX index constituent companies listed on the first section of the TSE.[15] Our sample period includes the pre-financial-crisis month of June 2008, the post-financial-crisis month of January 2009, and the post-Arrowhead month of January 2011.[16] We

obtain these data from the Nikkei Digital Media Inc.'s Nikkei Economic Electronic Database Systems (NEEDS) database.

The TSE, with more than 95% of domestic Japanese equity market share, is the largest stock exchange in Asia.[17] The TSE is a pure order driven market with no market makers. TSE trading takes place in two different trading sessions. The morning session begins at 9:00 a.m. and ends at 11:00 a.m., while the afternoon session begins at 12:30 p.m. and ends at 3 p.m. Both limit and market orders are permitted. The TSE has tiered minimum tick sizes and minimum trading units that depend on the stock's price. To smooth the price movements, the TSE also sets price limits that vary with stock prices.[18] The TSE also has provisions for special quotes which are automated non-tradable indicative quotes placed by the exchange to reduce price volatility.[19] Additionally, there are no hidden orders on the TSE, trades can only occur at the bid or ask,

[15]The TSE, with a total market capitalization of about $3 trillion, is the second largest stock exchange in the world, the largest being the NYSE Euronext (TSE annual report, 2009). TSE has 2 main sections and a Mothers section. The First Section comprises the largest and the most liquid companies which are part of the Tokyo Stock Price Index (TOPIX).

[16] We test our results for two additional pre-crisis months- September 2007 and January 2008- and the results are qualitatively similar to the ones presented here. We analyze one month of data due to computational limitations. Each month of data is about 125 GB; simple sorting and estimation of cross-correlation takes over 2 weeks.

[17] Van Kervel (2012) suggests that HFTs submits duplicate limit orders on several trading venues, which might cause a strong overestimation of liquidity aggregated across trading venues. Madhavan (2012) find market fragmentation in the US led to the Flash Crash of May 6, 2010. But unlike the US markets, Japanese stock market is not fragmented, which helps us make cleaner predictions. Any given stock can only be traded on one exchange. So, we don't believe our results are driven by inflated liquidity estimations. TSE is close to monopolistic stock exchange in the theoretical model of Pagnotta and Philippon (2012).

[18] See http://www.tse.or.jp/english/market/index.html for the institutional details of TSE and its history

[19] In our sample period, special quotes occur less than 1% of the time. See Hamao and Hasbrouck (1995) for details about the warning quotes and special quotes.

which allows for cleaner predictions.[20] We incorporate these special features of the TSE in our main analysis as well as conduct several robustness tests to ensure that our results can be generalized beyond the TSE.

We remove trades outside of regular trading hours and trades with zero prices or zero volume, quotes with bid greater than ask, and limit orders with zero limit price.[21] We separately analyze the TSE first-section stocks in the three market capitalization and liquidity based TOPIX sub-indices comprising the largest TOPIX 100 Index stock, 389 TOPIX Mid 400 Index medium capitalization stocks, and the remaining 1,068 small capitalization stocks belonging to the first-section of TSE in the TOPIX Small Index.

Along with the introduction of Arrowhead, the TSE also reduced tick sizes for certain stocks. Since the focus of our study is analyzing the impact of changes in the speed of trading, we eliminate firms for which the tick size changes and select 150 stocks, the top 50 each from the remaining TOPIX 100, the TOPIX MID 400, and the TOPIX Small indices. Keeping in mind the different minimum trading units and tick sizes for stocks with different price levels, we estimate time-series regressions separately for each security and then the parameter estimates are averaged across the cross-section of sample securities. We follow Brockman, Chung, and Pérignon (2009), Naes and Skjeltorp (2006) to compute the proportion of stocks for which the coefficients are significant and also follow Ellul, Holden, Jain, and Jennings (2007) to use a test of proportions to access the statistical significance of the averaged coefficients.

C. LOB liquidity measures

[20] Dark pools operated in Japan by Bank of America Corp., BNP Paribas SA, Citigroup Inc., Credit Suisse Group AG (CS), Daiwa, Goldman Sachs Group Inc., Instinet Group Inc., Liquidnet Holdings Inc., Morgan Stanley, Nomura Holdings Inc., and UBS AG, account for less than 2% of trading volume (http://mobile.bloomberg.com/news/2011-10-07/barclays-planning-tokyo-dark-pool-daiwa-sees-expansion-in-asia).
[21] These filters remove less than 0.38% of the total number of observations.

Kyle (1985, p. 1316) notes that ‘‘liquidity is a slippery and elusive concept, in part because it encompasses a number of transactional properties of markets, these include tightness, depth, and resiliency.’’ We capture these notions with two comprehensive LOB liquidity measures that characterize the entire supply schedule in low latency environment: LOB Slope and COI.

C1. LOB Slope: A resiliency measure of LOB liquidity

LOB Slope (*SLOPE*) captures the elasticity of liquidity supply in a LOB, and, hence, changes in *SLOPE* (ΔSLOPE) measure the resiliency of the full LOB. The measure originally proposed by Biais, Hillion and Spatt (1995) and formally defined by Naes and Skjeltorp (2006), captures the change in quantity supplied in the LOB per unit change in the price:

$$BIDSLOPE_{i,t} = \frac{1}{N_B}\left\{\frac{v_1^B}{|p_1^B/p_0-1|} + \sum_{\tau=1}^{N_B-1}\frac{v_{\tau+1}^B/v_\tau^B-1}{|p_{\tau+1}^B/p_\tau^B-1|}\right\};\ ASKSLOPE_{i,t} = \frac{1}{N_A}\left\{\frac{v_1^A}{|p_1^A/p_0-1|} + \sum_{\tau=1}^{N_A-1}\frac{v_{\tau+1}^A/v_\tau^A-1}{|p_{\tau+1}^A/p_\tau^A-1|}\right\} \qquad (1)$$

where N_B and N_A are the total number of bid and ask prices (tick levels), respectively, τ denotes number of price steps, with $\tau = 0$ representing the best bid-ask mid-point, p_τ is the price of τ^{th} price step, v_τ is the natural logarithm of accumulated total share volume at the price level τ. *SLOPE* is calculated as the average of *BIDSLOPE* and *ASKSLOPE.* Steeper *SLOPE* indicates more liquid markets because large quantities can be traded with very little price impact.

C2. Cost of Immediacy (COI): A measure of LOB's depth and tightness

Apart from the resiliency of liquidity supply, the other main dimensions of LOB liquidity are the LOB's tightness and depth. Traditionally bid-ask spreads are used to measure tightness but COI improves upon that measure to reflect both tightness and depth at levels beyond the best bid and ask. COI captures the round trip cost of trading 1% of daily volume by walking up or down the LOB, as necessary (Irvine, Benston, and Kandel, 2000).

We estimate the instantaneous COI separately on the buy and the sell sides of the LOB for each stock. Let *T* be the total number of shares to be bought or sold by the liquidity demander. We denote the liquidity supplier's k^{th} best bid (ask) price as the liquidity demander's p_k^{Sell} (p_k^{Buy}) and the k^{th} best bid (ask) size as Q_j^{Sell} (Q_j^{Buy}). We define two indicator variables, I_k^{Buy} and I_k^{Sell}. I_k^{Buy} refers to number of shares that liquidity suppliers are willing to buy at each price point *k* and I_k^{Sell} is defined analogously.

$$I_k^{Buy} = \begin{cases} Q_j^{Buy} & if\ T > \sum_{j=1}^{k} Q_j^{Buy} \\ \left(T - \sum_{j=1}^{k-1} Q_j^{Buy}\right) & if\ T > \sum_{j=1}^{k-1} Q_j^{Buy}\ and\ T < \sum_{j=1}^{k} Q_j^{Buy} \\ 0 & otherwise \end{cases} \tag{2}$$

where *K* is the total number of price steps in a LOB,

Then, we compute *ASKCOI* and *BIDCOI* for stock *i* as follows:

$$ASKCOI_i = \frac{\sum_{k=1}^{K} I_k^{Buy}\left(p_k^{Buy} - Midquote\right)}{T \times Midquote};\ BIDCOI_i = \frac{\sum_{k=1}^{K} I_k^{Sell}\left(Midquote - p_k^{Sell}\right)}{T \times Midquote} \tag{3}$$

Following Kang and Yeo (2008), the COI measures are scaled by the stock's mid-quote to enable cross-sectional and panel data comparisons. *COI* is calculated as the sum of *ASKCOI* and *BIDCOI*. Lower *COI* represents a more liquid market.[22] To illustrate the interpretation of *COI*, Figure 1 presents a snapshot of the LOB for two hypothetical firms. If we compare the best quotes (top of the LOB) for the two stocks, we conclude that both stocks are equally liquid. To understand the LOB dynamics, consider a market order to sell 1,000 shares. For stock L, the market order will have to walk up all 5 steps to completely fill the order while for stock H, the market sell order only needs to walk up to the second step. Based on equation (3), stock L has a higher *COI* of 47.32 basis points compared to 13.17 basis points for stock H, so stock L is less liquid than stock H. *COI* has an inverse relation with liquidity supply whereas *SLOPE* has a direct relation with liquidity supply.

[22] Trades matched and executed instantly are not part of the LOB snapshot at any instance, but they are reflected in our measures by a decrease in cumulative depth of the LOB. Thus, both liquidity suppliers and demanders from the recent past determine *COI* at any given instant. *COI* is the remuneration required by the current suppliers from the next liquidity demander. In order to account for the effect of liquidity demanding market orders in the recent past, we also include lagged average trade size (LAGATS) and number of trades (LAGNTRD) per minute of trading as control variables in subsequent analysis. Order cancellations and revisions are immediately reflected in LOB and, hence, our measures account for the cancelled and revised limit orders.

D. CoVaR and CoVaQ: new approaches to measuring systemic microstructure risk

Measuring systemic risk is challenging. The most common traditional measure of risk is value at risk (VaR), which focuses on the risk of an individual institution in isolation. However, Adrian and Brunnermeier (2011) argue that the VaR risk measure does not necessarily reflect systemic risk. Brunnermeier, Crocket, Goodhart, Persaud, and Shin (2009) support the idea that a systemic risk measure should identify the risk on the entire market by individual stocks. Adrian and Brunnermeier (2011) propose a new measure for systemic risk, CoVaR, which captures a stock's marginal contribution to systemic return risk, where the R at the end stands for return. CoVaR captures the VaR of one portfolio conditional on the VaR of another portfolio. Hence, the CoVaR examines the spillover effect from one stock's selling pressure to another stock or the whole stock market. However, the approach can be generalized to reflect any type of risk measure.

We estimate the time-varying COVAX and VAX conditional on a vector of lagged state variable, S_{t-1}, where the "X" stands for either the microstructure risks related to trade prices or liquidity risks related to quotes. We aggregate the high frequency individual trades and quotes data to form minute by minute observations and then run the following 3 regressions:

$$X_{i,t} = \alpha_i + \beta_i S_{t-1} + \varepsilon_{i,t}$$

$$X_{MKT,t} = \alpha_{MKT} + \beta_{MKT} S_{t-1} + \varepsilon_{MKT,t}$$

$$X_{MKT,t} = \alpha_{MKT|i} + \beta_{MKT|i} S_{t-1} + \gamma_{MKT|i} X_{i,t} + \varepsilon_{MKT|i,t}$$

where $X_{i,t}$ is either return or quotes to trade ratio aggregated for every minute of trading for stock *i*, S_{t-1} are lagged state variables that include liquidity, number of trades, average trade size, speed of trading, and volatility, and $X_{MKT,t}$ is the a generic variable measured for every minute of trading for the market index.[23] We then generate the predicted values from the above regressions to obtain:

$$VAX_{i,t} = \alpha_i \; + \; \beta_i S_{t-1}$$

$$VAX_{MKT,t} = \alpha_{MKT} \; + \; \beta_{MKT} S_{t-1}$$

$$COVAX_{i,t} = \alpha_{MKT|i} \; + \; \beta_{MKT|i} S_{t-1} \; + \; \gamma_{MKT|i} VAX_{i,t}$$

$$\Delta COVAX_{i,t} = COVAX_{i,t} - VAR_{MKT,t}$$

where $\Delta COVAX_{i,t}$ denotes the difference between the *VAX* of the stock market conditional on the illiquidity risk of a particular stock *i*, $COVAX_i$, and the unconditional *VAX* of the stock market, i.e., $VaR_{MKT,t}$ (Adrian and Brunnermeier, 2011). Hence, $\Delta CoVaX_{i,t}$ serves as a measure of how much a stock adds to overall systemic risk. We estimate two measures of CoVaX: *CoVaR* using the minute-to-minute trade price risk and *CoVaQ* using our minute-to-minute measure of quote based risk.

III. Hypothesis development

A. Impact of Arrowhead and LOB liquidity risk

Theoretical models on the liquidity provisions of a LOB offer ambiguous predictions regarding the impact of increased speed of trading. Foucault, Röell, and Sandås's (2003) theoretical model shows that faster markets can raise adverse selection costs because informed liquidity demanders can more closely monitor the market for any temporary mispricing or stale quotes. Focusing only on the top of the book bid-ask spreads, Hendershott and Moulton (2011) show that this higher adverse selection cost increases the compensation required by liquidity suppliers, which, in turn, increases the cost of immediacy for liquidity demanders. However,

[23] We also calculate the systemic risk measure for returns and systemic risk caused by increase in superficial order flow, autocorrelation and cross correlation in order flow by replacing *X* by *Return*, *Quotes-to-trade ratio, autocorrelation,* and *cross correlation,* respectively, in equations 1,2, and 3.

Foucault, Kadan and Kandel (2005), Baruch (2005), and Boehmer, Saar and Yu (2005) indicate that the higher speed of trading can increase the competition among liquidity suppliers at various price points that, in turn, should reduce the cost of immediacy for liquidity demanders. Much of the previous literature on HFT analyzes the top of the LOB. The introduction of Arrowhead provides a natural experiment to test the predictions of the theoretical models on the effect of low latency trading on full LOB liquidity. Using Stoll's (2000) friction model and control variables as applicable in the LOB context, we test the following hypothesis:

Hypothesis 1. Arrowhead reduces *COI* and increases *SLOPE*.

B. Impact of Arrowhead on shock propagation risk: Autocorrelation and Cross correlations

The more significant contribution of our study is the analysis of risks of high speed trading. Following Parlour (1998) and Chordia, Roll, and Subrahmanyam (2000), we measure shock propagation risk in terms of autocorrelation and cross correlation in order flow. Biais and Woolley (2011) suggest that high frequency trades are highly correlated as they rely on similar strategies, and, hence, might contribute to destabilizing markets.[24] Ben-David, Franzoni, and Moussawi (2012) and Chaboud, Hjalmarsson, Vega, and Chiquoine (2013) analyze algorithmic trading in the foreign exchange markets and show that the algorithmic strategies used in the market are not as diverse as those used by non-algorithmic traders. The authors further assert that HFT has the potential to rapidly propagate liquidity shocks across securities leading to a system-wide crash. Hence, autocorrelation and cross correlation in order flow can serve as important measures of shock propagation risk. We are among the first to test the effect of HFT on shock propagation risk in a pure LOB market. Additionally, we show that COI serves as a channel

[24] The August 2007 mini crash offers a good illustration of how correlated strategies can generate systemic risk: At that time, many algorithms were using similar strategies. Thus, they were simultaneously hit by a shock, and reacted similarly, which generated a downward spiral in the market.

through which HFT affects systemic microstructure risk.[25] We test the following hypotheses that include the mechanisms of risk propagation:

Hypothesis 2. Arrowhead facilitates order splitting and leads to higher autocorrelation in order flow.

Hypothesis 3. Arrowhead increases cross correlation by facilitating program trading of baskets of securities.

C. Quote stuffing risk: Quotes-to-trade ratio

Another risk created by HFT is the significant increase in superficial order flow (Egginton, Van Ness, and Van Ness, 2012; Baruch and Glosten, 2013). The speed with which the quotes are posted and cancelled has been criticized by market participants because it creates a false sense of deep liquidity supply for a stock (Golub, Keane, and Poon, 2012; Gai, Yao, and Ye, 2012). According to the Security and Exchange Commission (SEC) 2010 Concept Release on Equity Market Structure "the submission of numerous orders that are cancelled shortly after submission" is one of the characteristics of HFT. Biais and Woolley (2011) define quote stuffing as a trading strategy which involves submitting an unwieldy number of orders to the market to generate congestion. Such stuffing activity is classified as a type of market manipulation.[26] However, the number of quotes can increase for price efficiency reasons such as speedier

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[25] Literature thus far, provides contradictory predictions on the effect of LOB liquidity provision on systemic risk. *Autocorrelation*: Parlour (1998) predicts that an order increasing the LOB's depth is more likely to follow an order decreasing depth on that side of the market creating negative serial correlation in order flow. In contrast, Biais, Hillion and Spatt (1995) suggest that traders might herd or might split large orders or trades over time to conceal information (see Kyle (1985); Barclay and Warner (1993)). Such herding or stealth trading leads to positive autocorrelation in highly liquid markets.
Cross Correlation: Baker and Wurgler (2006) argue that if investors' private signals about a stock do not contain a market-wide component, stocks' cross correlations with the overall market will be lower with rapid trading as sentiments drive investors' propensity to speculate and when markets are liquid this propensity to speculate in individual stocks is very high. On the other hand, Chordia, Roll, and Subrahmanyam (2000) and Hasbrouck and Seppi (2001) document the existence of commonality or positive cross correlation in liquidity of informationally-related securities.

[26] Dodd-Frank Act, Section 747 classifies quote stuffing activities as disruptive practices and prohibits "bidding or offering with the intent to cancel the bid and offer before execution."

incorporation of fundamental information into prices through aggressive quote revisions and trading around the news events. In this case, low latency trading not only increases the number of quotes placed by liquidity suppliers but it also increases the number of trades.[27] Hence, to truly understand the dynamics of liquidity suppliers and demanders in a pure LOB market, we calculate the quotes-to-trade ratio. Quote stuffing creates a false sense of the actual supply for a stock, and hence, adversely affects the market quality (Egginton, Van Ness, and Van Ness, 2012). In particular, the excessive quotes posted for non-executions can affect price discovery. Such activity might also increase the trading risk due to increase in market congestion. Additionally, liquidity dry-ups following a quote-stuffing event may spill over and result in system-wide failure. We expect an increase in the quotes-to-trade ratio, or quote stuffing risk during the post Arrowhead period. Using the available liquidity supply schedule of the entire LOB, we test the following hypothesis:

Hypothesis 4. Low latency generates a higher quotes-to-trade ratio resulting in a greater quote stuffing risk.

D. Impact of Arrowhead on advanced measures of systemic microstructure risk: CoVaR and CoVaQ

Iati (2009) documents that HFT trading firms represent approximately 2% of the nearly 20,000 trading firms operating in the U.S. markets, but account for over 73% of all U.S. equity trading volume. Many of these high frequency firms are in the business of liquidity provision, and act as market makers (Kirilenko, Kyle, Samadi, and Tuzun, 2010). Providing liquidity in a high frequency environment introduces new risks for market makers and if HFT traders believe that the losses from trading are too high, they will liquidate their positions and leave the market,

[27] Hagströmer and Nordén (2013) suggest that most common and robust metric for quoting intensity is the quotes-to-trade ratio.

adding to the imbalance in trade and potentially leading to a crash (Easley, Lopez de Prado, and O'Hara, 2011). This ability of HFT to vanish quickly from the market can result in episodes of sudden illiquidity. At such times, losses tend to spread across financial institutions, threatening the financial system as a whole. Such increase in co-movement gives rise to systemic risk (Adrian and Brunnermeier, 2011). Using *CoVaR* systemic risk measure, proposed by Adrian and Brunnermeier (2011), we are among the first to test the risk of high speed trading::

Hypothesis 5. Arrowhead increases the high speed basket trading ability of HFTs leading to an increase in shock propagation risk and systemic illiquidity risk.

IV. Results

A. Descriptive statistics and effects of the Arrowhead low latency trading platform

Table 1, Panel A, reports the descriptive statistics for the pre-crisis, post-crisis, and the post-Arrowhead periods.[28] Columns (1) through (5) present the impact of Arrowhead on the entire sample of firms, while the last 3 columns document the differential effects of Arrowhead on large-cap firms compared to small-cap firms. We find that the shock propagation risk as measured by autocorrelation (*AUTO CORR*) and cross correlation (*CROSS CORR*) in order flow, increased significantly during the post-Arrowhead period. In particular, co-movement of order flow measured by cross-correlation changed from a diversified portfolio's risk mitigating negative values to risk enhancing positive values. *QUOTE STUFFING RISK*, as proxied by the quotes-to-trade ratio, also significantly increased during the post-Arrowhead period as compared to both the pre-Arrowhead and pre-crisis periods. Our finding of an increase in the number of quotes relative to the number of trades suggests a more congested market.

[28] Uno and Shibata (2011) provide an excellent description of Arrowhead and its impact on the trading frequency and top of the book spreads. We analyze the effect of Arrowhead on evolution of LOB.

Table 1 further documents that systemic microstructure risks, as proxied by ΔCOVAR and ΔCOVAQ, have increased significantly during the post-Arrowhead period. In other words, the intensity of the price change spillovers from one stock to another has increased after the introduction of Arrowhead. The increased intensity of order flow co-movement is a potential mechanism of the price change co-movement. These increasing co-movements signify heightened systemic risks posed by high speed trading. These results indicate that the reduction in latency has increased the probability of a highly destabilizing market situation on the TSE similar to the Flash Crash, in the U.S. Results presented in column (8) of Table 1, Panel A, document that the differences in *AUTOCORR, CROSS CORR, QUOTE STUFFING RISK, ΔCOVAR and ΔCOVAQ,* between the large- and small-cap stocks increased significantly post-Arrowhead, indicating that the increase in systemic risk is much larger for the large-cap firms relative to small-cap firms. The market quality measures shown in Table 1, Panel A, confirm that liquidity improved after the introduction of low-latency trading, pointing to the similarity in basic patterns in data for Japanese and US markets. Thus, the new systemic microstructure risk results presented in our paper may be generalizable to other major markets.

The traditional top of the LOB liquidity measures such as *SPREAD* and *DEPTH* and the new comprehensive LOB liquidity measures such as *COI* and *SLOPE,* all demonstrate that the liquidity improved for all the sample firms post-Arrowhead.[29] The finding of liquidity improvement supports Rosu's (2009) and Foucault, Kadan, and Kandel's (2005) theoretical prediction that faster arrival rates reduce the expected waiting time for orders in the queue so that limit orders require lower compensation for waiting.

Consistent with Hendershott, Jones, and Menkveld (2011), we find that Arrowhead increased *MONTHLY VOLUME* by 17% from 94 million shares per stock per month pre-

[29] Note that spreads and COI are inverse measures of liquidity and their reduction implies improved liquidity.

Arrowhead to 110 million shares for the entire sample. We also document that while, historically, the large-cap firms had higher *MONTHLY VOLUME* as compared to small-cap firms, this difference has widened significantly after the introduction of Arrowhead. These results may indicate that Arrowhead relaxed the speed limit that was binding mainly for the large-cap stocks or that high-frequency traders tend to focus on large cap stocks. The number of trades (*NTRDS*) increased by more than 50% from 7.34 trades per minute to 11.15 trades per minute, post Arrowhead, but the average trade size (ATS) declined significantly, which is why the total volume did not rise as dramatically post-Arrowhead. These results suggest a significant increase in sophisticated order slicing on the TSE due to increase in HFT. Finally, we find that the *TRADESPEED* (inverse of the average time between trades per minute of trading) increased significantly by 50% from 0.08 pre-Arrowhead to 0.12 post-Arrowhead.[30] The increase in *NTRDS* and *TRADESPEED* and the decline in ATS are more prominent for the large-cap firms.

To make sure that our findings are indeed related to low latency and do not simply reflect a time trend, we report the key market quality parameters during the pre- and post-Arrowhead periods for the stocks listed on the Osaka Stock Exchange (OSE), which did not experience any reduction in latency during our sample period and can therefore serve as a control sample. If our results represent time trends or are driven by some macro-level factors, we expect to observe similar changes in liquidity and trading risk factors for stocks listed on the OSE and the stocks listed on TSE. Table 1, Panel B, reports our findings. The last 3 columns in this panel are copied from Table 1, Panel A, for comparison purposes. Columns (1) and (2) report the means for the various liquidity and risk measures for the pre- and post-Arrowhead periods while column (3) reports the differences in the means reported in the first 2 columns. We do not find any

[30] Hendershott, Jones, and Menkveld (2011) find that autoquote increased the number of messages by 6%. Menkveld (2012) finds that cancellation-to-trade ratio for a European market (CHI-X) is 5.

significant differences in the OSE systemic risk measures before and after the launch of TSE Arrowhead for the stocks listed on the OSE. Also, with the exception of *COI*, which has a statistically significant reduction at the 10% level of Post Arrowhead, we fail to find any significant differences in the OSE liquidity measures before and after the launch of Arrowhead for the stocks listed on the OSE. Therefore, we conclude that the systemic risk changes for the stocks listed on TSE are associated with TSE's decline in latency after the launch of Arrowhead and not general market conditions in Japan.[31]

B. Impact of Arrowhead on LOB liquidity

Figures 2 and 3, Panels A and B plot intraday averages for *COI* and *SLOPE* in five minute buckets throughout each trading day. We observe the standard U-shape and inverted U-shape patterns for intraday *COI* and *SLOPE*, respectively (see McInish and Wood, 1992). We observe that Arrowhead improved the LOB liquidity by reducing the *COI* and increasing the *SLOPE* supporting the descriptive results presented in Table 1. We formally test this relation by estimating the following regression model based on Stoll (2000) specifications:

$$COI_{i,t} \text{ or } SLOPE_{i,t} = \alpha_i + \beta_{1i}\, ARROWHEAD_{it} + \beta_{2i}\, LOG\ PRICE_{it} + \beta_{3i}\, LOG\ NTRDS_{i,t}$$
$$+ \beta_{4i}\, VOLATILITY_{i,t} + \beta_{5i}\, LOG\ VOLUME_{i,t} + \beta_{6i}\, MKTRET_{i,t} + \beta_{9i}\, HIGHSPEED_{i,t}$$
$$+ \beta_{10i}\, LOWSPEED_{i,t} + \mu_{i,t}$$

where *ARROWHEAD* is the dummy variable that equals 1 for the post Arrowhead period (January 2011) and 0 otherwise (January 2009), $LOG\ PRICE_{i,t}$ is the natural log of the trading price at the end of minute, $LOG\ NTRDS_{i,t}$ is the natural log of number of trades per minute of trading, $VOLATILITY_{i,t}$ is the absolute value of the return, conditional on its own 12 lags and day-of-week dummies (Schwertz, 1989; Jones, Kaul, and Lipson, 1994; Naes and Skjeltorp,

[31] In the next section we provide the regression results for the stocks listed on TSE. We test the robustness by analyzing the same regression models for the Osaka stocks and show that the coefficient on ARROWHEAD is not significant.

2006), $LOG\ VOLUME_{i,t}$ is the natural log of the average trading volume each minute, $MKTRET_{i,t}$ is the return on the market as measured by return on the TSE exchange traded fund. We create two dummy variable to capture the effect of speed of trading on liquidity (Hendershott and Moulton, 2011): $HIGHSPEED_{i,t}$ is a dummy variable that takes a value 1 if the speed of quote updates is greater than its 75th percentile value and $LOWSPEED_{i,t}$ is a dummy variable that takes a value 1 if the speed of quote updates is less than its 25th percentile value. α and β are parameters to be estimated and $\mu_{i,t}$ is a random error term. The subscripts i and t indicate firm i and minute t, respectively. The regressions are estimated for each security and then the parameter estimates are averaged across securities.

Table 2 summarizes the results from the estimation of stock-by-stock regressions using the high frequency quotes and trades data aggregated at one minute interval. *ARROWHEAD's* negative coefficient of -3.55 in Panel A indicates that Arrowhead has significantly reduced the *COI* for a majority of the sample stocks. Column (2) summarizes the distribution of statistical significance in the stock by stock estimations. The coefficient of *ARROWHEAD* is significant for 98% of the sample stocks and 95% of the coefficients are negative. We also find that, consistent with the prior literature (Stoll, 2000), *COI* is positively related to *NTRDS* and *VOLATILITY* while negatively related to *VOLUME* and *PRICE*. Table 2, Panel B, shows that *SLOPE* has significantly increased post Arrowhead. Overall, our results support the theoretical predictions of Foucault, Kadan and Kandel (2005) and Boehmer, Saar and Yu (2005) and are consistent with Hypothesis 1. Higher speed of trading due to introduction of Arrowhead increases competition among traders resulting in tightening of the LOB, resulting in an increase in liquidity and a decline in the transactions costs. The coefficients are opposite in sign because *COI* is an inverse measure of liquidity whereas *SLOPE* is a direct measure of liquidity.

C. Impact of Arrowhead on shock propagation risks: Autocorrelation and Cross Correlation

This section analyzes the impact of Arrowhead on 2 measures of shock propagation risks suggested by Chaboud, Hjalmarsson, Vega, and Chiquoine (2013) and Chordia, Roll, and Subrahmanyam (2000)—autocorrelation and cross correlation in order flow.

Figures 2 and 3, Panel C, and Table 1 show a significant increase in *AUTOCORR* post-Arrowhead.[32] We formally analyze this relation by estimating a regression model with *AUTOCORR* as the dependent variable. Based on the results summarized in Table 3, Panel A, we find that Arrowhead significantly increases *AUTOCORR* for a majority of sample stocks, as reflected by the positive and statistically significant coefficient of 1.12 for *ARROWHEAD*. These results are consistent with Hypothesis 2 and indicate that lower latency of Arrowhead facilitates automated order splitting and herding strategies resulting in higher autocorrelation in order flow. The increase in *AUTOCORR* during the post-Arrowhead period is not significant for the small-cap firms, documenting the differential effect of low latency trading across the stocks with different market capitalizations.

We also find that *COI* (*SLOPE*) has a statistically significant and negative (positive) coefficient of -0.56 (0.31). Hence, the higher LOB liquidity the higher is *AUTOCORR*. These results are consistent for a majority of large-cap stocks. Our results are consistent with the models of strategic trading that support the idea that rational informed investors spread their trading over time to conceal information (see Kyle, 1985, and Barclay and Warner, 1993). Such stealth trading leads to positive autocorrelation in highly liquid markets characterized by lower COI.

Table 3, Panel B, summarizes the results for the effect of Arrowhead on *CROSSCORR*.

[32] We also analyze trade-by-trade autocorrelation and obtain qualitatively similar results as those for order flow autocorrelation.

We find a positive and statistically significant coefficient of 1.15 for *ARROWHEAD*. Hence, Arrowhead increases cross correlation in order flow potentially due to increase in program trading. This finding is consistent with Hypothesis 3 and the theoretical prediction of Biais and Woolley (2011) and Chaboud, Hjalmarsson, Vega, and Chiquoine (2013) who deomnstrate that high frequency trades are highly correlated and hence, might contribute to destabilizing markets. The results further document that the increase in *CROSSCORR* is not statistically significant for the small-cap stocks. Hence, Arrowhead has increased the shock propagation risk for mainly large-cap stocks.

We also find a statistically significant and positive (negative) coefficient of 0.68 (-0.43) for *COI* (*SLOPE*) for a majority of large-cap stocks.[33] The lower cross correlation in a more liquid market indicates that stock-specific idiosyncratic information dominates the systemic components and informed investors private information is incorporated in prices at a more intense rate (Kyle, 1985), Barclay and Warner, 1993).

D. Impact of Arrowhead on quote stuffing risk as measured by the quotes-to-trade ratio

Figures 2 and 3, Panel D, and Table 1 show that the quotes-to-trade ratio significantly increased during the post-Arrowhead period, suggesting that Arrowhead has increased *QUOTE STUFFING RISK*. We also observe the existence of well-established inverse U-shape patterns (McInish and Wood, 1992) for each of the trading sessions across all sample trading days, during both pre- and post-Arrowhead periods across the two trading sessions. We formally test the impact of Arrowhead by analyzing the regression model described in Table 4. We find a positive and statistically significant coefficient of 2.44 for the *ARROWHEAD* dummy, which documents that Arrowhead has significantly increased the *QUOTE STUFFING RISK* for a majority of

[33] The average Variance Inflation Factors (VIF) for all the variables are less than 5, hence, we do not have any multicollinearity issues when analyzing the proposed regression model. For each independent variable, VIF is calculated as: $VIF_i = 1/(1-R_i^2)$ (see Greene (2000) for more details).

sample stocks, supporting our Hypothesis 4. Thus, traders cancel their orders with a higher intensity in low latency environments, resulting in an increase in the unexecuted quotes.

The results further report a significantly negative (positive) coefficient for *COI* (*SLOPE*) suggesting that the *QUOTE STUFFING RISK* is higher during the liquid markets. Finally, we find that Arrowhead significantly increased the intensity of *QUOTE STUFFING RISK* during the liquid markets as reflected by the significantly negative (positive) coefficient for *ARROWHEAD**COI* (*ARROWHEAD**SLOPE*) for a majority of the sample firms.

E. Impact of Arrowhead on advanced systemic microstructure risk measures: CoVaR and CoVaQ

The earlier results document that the shock propagation risk has increased Post Arrowhead due to an increase in the co-movement in order flow. Such increases of co-movement give rise to systemic risk. Using an improved measure of systemic risk proposed by Adrian and Brunnermeier (2011), $\Delta CoVaR_{i,t}$, we test the impact of Arrowhead on the overall systemic microstructure risk.

Figures 2 and 3, Panels E and F, and Table 1 show an increase in the systemic risk, as proxied by ΔCoVaR and ΔCoVaQ, during the post-Arrowhead period. In Table 5 we formally test this finding using the regression framework. We find a positive and statistically significant coefficient of 0.49 for *ARROWHEAD* in Panel A and 1.21 in Panel B, suggesting that Arrowhead has increased systemic microstructure risk potentially due to an increase in program trading. This result provides evidence for supports our Hypothesis 5 and is consistent with the theoretical prediction of Biais and Woolley (2011), who support the idea that high frequency trades are highly correlated and hence, might contribute to destabilizing markets.

We also document that higher LOB liquidity decreases the systemic microstructure risk for 87% of the large-cap stocks. This finding documents that liquid markets increase stock-specific information production which reduces the probability of systemic risk. Finally, we find that Arrowhead significantly increases the intensity of *SYSTEMIC RISK* during liquid markets as reflected by the significantly positive (negative) coefficient for *ARROWHEAD*COI* (*ARROWHEAD*SLOPE*) for a majority of the sample firms. Table 5, Panel B, reports the findings for quotes-to-trade ratio, ΔCoVaQ, which are consistent with the ones presented earlier.[34]

F. Difference in differences regression analysis: TSE vs Osaka

To test whether our findings are related to low latency or merely reflect a time trend, we conduct difference in differences regression analyses for the various liquidity and risk measures. Stocks listed on the Osaka Stock Exchange (OSE), which did not experience any reduction in latency during our sample period, serves as a control sample. Table 6 reports the difference in differences estimates, which indicate the impact of Arrowhead on TSE firms as compared to that on OSE firms. We find significant difference-in-differences effects with respect to various liquidity and risk measures documenting the significant increase in systemic risk and liquidity for TSE stocks. Overall, the results of the estimation of our difference-in-differences research design are consistent with the ones presented in the earlier sections.

G. Tail risk

Biais, Foucault, Moinas (2012) demonstrate that HFTs can process information on stock values faster than other traders. Thus, they increase the intensity of adverse selection particularly during systemic risk events, such as the May 6th 2010 Flash Crash. To test the changes in tail

[34] We also find consistent results for cross correlation and autocorrelation in order flow ΔCoVaR (probability of a sell order followed by a sell order in the market portfolio and the same stock, respectively).

risks introduced by Arrowhead, we identify the trading minutes when the market return is extremely negative (5th percentile) and analyze the effect of low latency on various parameters of market quality and systemic risk. Table 7 and Figure 4 summarize the results from this analysis. In Panel A, we define tail risk events as the minutes during which the return on market index is in bottom 5th percentile (5% extreme negative market return minutes). But the tail itself can be different before and after Arrowhead. In Panel B, we control for this by matching the tail risk events by the actual extreme negative return values. In Panel B tail risk events, during either period, are defined as minutes for which the market return lies between -0.42% (minimum for post-Arrowhead) and -0.11% (5th percentile for post-Arrowhead). In both Panels, we find that Arrowhead has significantly increased the various systemic microstructure risks, such as shock propagation risk (*AUTOCORR* and *CROSS CORR*), quote stuffing risk (*QUOTES-TO-TRADE* ratio), and *ΔCOVAR* and *ΔCOVAQ* during tail risk events.

We formally test the above descriptive results using regression analyses and the results are summarized in Table 7, Panel C. In addition to the control variables used in the previous regression models, we include a dummy variable, *TAILMIN*, that takes the value of 1 for the trading minutes during which the return on the market index is in the bottom 5th percentile (5% extreme negative market return minutes), and zero otherwise. To understand the effect of Arrowhead, we also add the interaction between *ARROWHEAD* and *TAILMIN*. We find that *TAILMIN* is significantly positively related to our various systemic microstructure risk measures such as shock propagation risk (*AUTOCORR* and *CROSS CORR*), quote stuffing risk (*QTR*), and *ΔCOVAR* and *ΔCOVAQ*, which document a significant increase in trading risk during extreme negative market conditions. We also find a significant and positive coefficient for *ARROWHEAD*TAILMIN* for all the regressions, which indicates that post-Arrowhead trading risks has significantly increased during extreme market conditions as compared to the pre-Arrowhead period. Our results document that HFT has the potential to quickly propagate liquidity shocks across the markets and HFT's shock propagation ability increases during the extreme market conditions, which could potentially lead to a highly destabilizing market situation, such as the Flash Crash.

V. Robustness tests

We perform additional robustness tests to confirm the results presented above. First we, account for the effect of intraday seasonality. Figure 3 documents that our systemic microstructure risk measures vary across the trading day. We also observe differences in patterns across the two trading sessions. Hence, to control for intraday seasonality we include a dummy variable that takes a value of 1 for the first half hour (9:00 AM-9:30 AM) and last half an hour (2:30 PM- 3:00 PM) of trading and is zero otherwise. A second dummy variable takes the value of 1 for the last half hour (10:30 AM-11:00 AM) of trading right before the recess and first half an hour (12:30 PM- 1:00 PM) of trading right after the recess and is zero otherwise. We find that the coefficients of these two dummy variables is statistically significant at the 0.01 level, indicating that intraday seasonality is important for the LOB liquidity and various trading risk factors. But our results for the effect of Arrowhead are qualitatively similar to the ones presented earlier in terms of direction and level of significance.

The TSE has a provision of special quotes, which are automated non-tradable indicative quotes placed by the exchange to advertise potential jumps in price and to encourage investors to place balancing orders on the other side. Our data identifies these types of special quotes. We delete these special quotes and re-analyze our results. We find that less than 1% of the quotes in our sample are "special quotes." Our results are robust to this alternate data specification as the direction and statistical coefficients are identical to those reported in the paper for all the tables. For example, the coefficient for *ARROWHEAD* in Table 2 changes minimally from -3.55 with special quotes to -3.78 without them.

The TSE has a variable minimum trading unit (MTU) and tick sizes which varies with stock prices. Differences in the MTU and tick sizes across stocks can potentially impact some of our predictions (Amihud, Mendelson, and Uno, 1999). To investigate, we analyze the stocks with MTU of 1,000 because a majority of stocks on the TSE have a MTU of 1,000. Our results from this reduced sample are consistent with the ones presented earlier. This is not surprising because our approach of averaging stock-by-stock regression coefficients controls for various differences across firms including varying MTU and tick sizes.

VI. Conclusion

The introduction of the Arrowhead high-speed trading platform by the Tokyo Stock Exchange (TSE) reduced TSE latency from 6 seconds to 2 milliseconds. Using this event as a natural experiment, we analyze the impact of this significant reduction in latency on Limit Order Book (LOB) liquidity and systemic microstructure risks, as measured by CoVaR, CoVaQ, autocorrelation, cross correlation, quotes-to-trade ratio, and tail risk.

We find that the introduction of the Arrowhead trading platform improved LOB liquidity as reflected by reduced COI and increased LOB slope for a majority of the sample stocks. These newer measures of aggregated liquidity in LOB are essential tools for any trader in high speed markets. The average number of trades for each minute of trading also increased by more than 50% while the average trade size declined substantially, generating an increase of only 17% in total trading volume.

Arrowhead significantly increased the shock propagation risk by increasing both autocorrelation and cross correlation in the order flow, quote-stuffing risk by increasing the quotes-to-trade ratio, and systemic trading risk by increasing the CoVaR and CoVaQ. Furthermore, Arrowhead increased the exposure to these systemic microstructure risks even more during tail risk events. These contrasting effects of Arrowhead are analogous to the increased speed and fatality risk associated with automobiles relative to pedestrian traffic. Thus, our results inform the discussion about low latency markets, particularly the need for safety features such as kill switches and circuit breakers, analogous to airbags and seatbelts needed for high speed driving..

References

Adrian, Tobias, and Markus K. Brunnermeier, 2011, CoVaR. No. w17454. *National Bureau of Economic Research*, Boston.

Aitken, Michael, Niall Almeida, Frederick Harris, and Thomas McInish, 2006, Liquidity supply in electronic markets, *Journal of Financial Markets* 10, 144-168.

Ahn, Hee-Joon, Jun Cai, Yasushi Hamao, and Richard Y. K. Ho, 2002, The components of the bid-ask spreads in a limit-order market: Evidence from the Tokyo Stock Exchange, *Journal of Empirical Finance* 9, 399-430.

Amihud, Yakov, Haim Mendelson, and Jun Uno, 1999, Number of shareholders and stock prices: Evidence from Japan, *Journal of Finance* 54, 1169–1184.

Baker, Malcolm, and Jeffrey Wurgler, 2006, Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645-1680.

Barclay, Michael J., and Jerold B. Warner, 1993, Stealth trading and volatility: Which trades move prices? *Journal of Financial Economics* 34, 281-306.

Baron, Matthew, Jonathan Brogaard, and Andrei Kirilenko, 2012, The trading profits of high frequency traders, *Working paper*, University of Washington.

Baruch, Shmuel, 2005, Who benefits from an open limit-order book? *Journal of Business* 78, 1267–1306.

Baruch, Shmuel, and Lawrence R. Glosten, 2013, Flickering quotes, *Working paper*, Columbia University.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2012, Hedge fund stock trading in the financial crisis of 2007-2009, *Review of Financial Studies*, 25, 1-54.

Biais, Bruno, Pierre Hillion, and Chester Spatt, 1995, An empirical analysis of the limit order book and the order flow in the Paris Bourse, *Journal of Finance* 50, 1655–1689.

Biais, Bruno, Thierry Foucault, and Sophie Moinas, 2012, Equilibrium algorithmic trading, *Working paper*, IDEI Toulouse.

Biais, Bruno, and Paul Woolley, 2011, High frequency trading, *Working Paper*, Toulouse University, IDEI.

Boehmer, Ekkehart, Gideon Saar, and Lei Yu, 2005, Lifting the veil: An analysis of pre-trade transparency at the NYSE, *Journal of Finance* 60, 783–815.

Boehmer, Ekkehart, and Eric K. Kelley, 2009, Institutional investors and the informational efficiency of prices, *Review of Financial Studies* 22, 3563–3594.

Boehmer, Ekkehart, Kingsley Fong, and Julie Wu, 2013, International evidence on algorithmic trading, *Working paper*, EDHEC Business School.

Bremer, Marc, Takato Hiraki, and Richard J. Sweeney, 1997, Predictable patterns after large stock price changes on the Tokyo Stock Exchange, *Journal of Financial and Quantitative Analysis* 32, 345-365.

Brockman, Paul, Dennis Y. Chung, and Christophe Pérignon, 2009, Commonality in liquidity: A global perspective, *Journal of Financial and Quantitative Analysis* 44, 851-882.

Brogaard, Jonathan A., 2010, High frequency trading and its impact on market quality, *Working paper*, University of Washington.

Brunnermeier, Marcus, Andrew Crocket, Charles Goodhart, Avinash D. Persaud, and Hyun Shin, 2011, The Fundamental Principles of Financial Regulation: 11th Geneva Report on the World Economy, Centre for Economic Policy Research (CEPR).

Cartea, Alvaro, and Jose Penalva, 2011, Where is the value in high frequency trading? *Working paper*, Universidad Carlos III de Madrid.

Carrion, Allen, 2013, Very fast money: High-frequency trading on the NASDAQ, *Journal of Financial Markets*, forthcoming.

Chaboud, Alain, Benjamin Chiquoine, Erik Hjalmarsson, and Clara Vega, 2013, Rise of the machines: Algorithmic trading in the foreign exchange markets, *Journal of Finance,*forthcoming.

Chan, Louis K.C., Yasushi Hamao, and Josef Lakonishok, 1991, Fundamentals and stock returns in Japan, *Journal of Finance* 46, 1739–1764.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2000, Commonality in liquidity, *Journal of Financial Economics* 56, 3-28.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2008, Liquidity and market efficiency, *Journal of Financial Economics* 87, 249–268.

Colliard, Jean-Edouard, and Peter Hoffmann, 2013, Sand in the Chips? Evidence on Taxing Transactions in Modern Markets." Social Science Research Network Working Paper Series.

Easley, David A., Marcos Lopez de Prado, and Maureen O'Hara, 2011, The microstructure of the “Flash Crash”: Flow toxicity, liquidity crashes, and the probability of informed trading, *Journal of Portfolio Management* 37, 118-128

Egginton, Jared, Bonnie F. Van Ness, and Robert A. Van Ness, 2012, Quote stuffing, *Working paper*, University of Mississippi.

Ellul, Andrew, Craig W. Holden, Pankaj K. Jain, and Robert H. Jennings, 2007, Order dynamics: Recent evidence from the NYSE, *Journal of Empirical Finance*, 14, 636-661.

Foucault, Thierry, Ailsa Röell, and Patrick Sandås, 2003, Market making with costly monitoring: An analysis of the SOES controversy, *Review of Financial Studies* 16, 345–384.

Foucault, Thierry, Johan Hombert, and Ioanid Rosu, 2012, News trading and speed. Available at SSRN 2188822.

Foucault, Thierry, Sophie Moinas, and Erik Theissen, 2007, Does anonymity matter in electronic limit order markets? *Review of Financial Studies* 20, 1707-1747.

Foucault, Thierry, Ohad Kadan, and Eugene Kandel, 2005, Limit order book as a market for liquidity, *Review of Financial Studies* 18, 1171-1217.

Gai, Jiading, Chen Yao, and Mao Ye, 2012, The externalities of high-frequency trading, *Working paper*, University of Illinois at Urbana-Champaign.

Goettler, Ronald L., Christine A. Parlour, and Uday Rajan, 2005, Equilibrium in a dynamic limit order market, *Journal of Finance* 60, 2149–2192.

Golub, Anton, John Keane, and Ser-Huang Poon, 2012, High frequency trading and mini flash crashes, *Working paper,* Available at SSRN 2182097.

Greene, William H., 2000, Econometric Analysis, 4th ed., Prentice Hall, Englewood Cliffs.

Hagströmer, Björn, and Lars Nordén, 2013, The diversity of high-frequency traders, *Journal of Financial Markets* 16, 741-770.

Hamao, Yasushi, Ronald W. Masulis, and Victor K. Ng, 1990, Correlations in price changes and volatility across international stock markets, *Review of Financial Studies* 3, 281-307.

Hamao, Yasushi and Joel Hasbrouck, 1995, Securities trading in the absence of dealers: Trades and quotes in the Tokyo Stock Exchange, *Review of Financial Studies* 8, 849-878.

Hasbrouck, Joel, and Duane Seppi, 2001, Common factors in prices, order flows and liquidity, *Journal of Financial Economics* 59, 383–411.

Hasbrouck, Joel, and Gideon Saar, 2013, Low-latency trading, *Journal of Financial Markets*, forthcoming.

Hendershott, Terrence, Charles M. Jones, and Albert J. Menkveld, 2011, Does algorithmic trading improve liquidity? *Journal of Finance* 66, 1-33.

Hendershott, Terrence, and Pamela C. Moulton, 2011, Automation, speed, and stock market quality: The NYSE's hybrid, *Journal of Financial Markets* 14, 568-604.

Hendershott, Terrance, and Ryan Riordan, 2011, High frequency trading and price discovery. *Working paper*, University of California, Berkeley.

Hendershott, Terrance, and Ryan Riordan, 2013, Algorithmic trading and the market for liquidity, *Journal of Financial and Quantitative Analysis*, forthcoming.

Iati, Robert, 2009, High-Frequency Trading Technology, TABB Group.

Irvine, Paul, George J. Benston, and Eugene Kandel, 2000, Liquidity beyond the inside spread: Measuring and using information in the limit order book, *Working paper*, Emory University.

Jain, Pawan and Christine X. Jiang, 2014, Predicting future price volatility: Empirical evidence from an emerging limit order market, Pacific-Basin Finance Journal, forthcoming.

Jarrow, Robert and Philip Protter, 2011, A dysfunctional role of high frequency trading in electronic markets, *Working paper*, Johnson School Research Paper Series No. 08-2011.

Jones, Charles, 2013, What do we know about high-frequency trading? *Working Paper*, Columbia University.

Jones, Charles M., Gautam Kaul, and Marc L. Lipson, 1994, Information, trading, and volatility, *Journal of Financial Economics* 36, 127–154.

Kang, Wenjin, and Wee Yong Yeo, 2008. Liquidity beyond the best quote: A study of the NYSE limit order book. *Working Paper*, National University of Singapore.

Kirilenko, Andrei, Albert S. Kyle, Mehrdad Samadi, and Tugkan Tuzun, 2012, The flash crash: The impact of high frequency trading on an electronic market, *Working paper*, CFTC and the University of Maryland.

Kyle, Albert, 1985, Continuous auctions and insider trading, *Econometrica* 53, 1315-1335.

Lehmann, Bruce N., and David M. Modest, 1994, Liquidity on the Tokyo Stock Exchange: A bird's eye view, *Journal of Finance* 49, 183-214.

Madhavan, Ananth, 2012, Exchange-traded funds, market structure, and the flash crash, *Financial Analysts Journal* 68, 20-35.

Martinez, Victor, and Ioanid Rosu, 2013, High frequency traders, news and volatility, *Working paper*, Baruch College.

McInish, Thomas and Robert Wood, 1992, An analysis of intraday patterns in bid/ask spreads for NYSE stocks, *Journal of Finance* 47, 753-764.

Menkveld, Albert J., 2012, High frequency trading and the new-market makers. EFA 2011; AFA, http://ssrn.com/abstract=1722924

Moallemi, Ciamac C., and Mehmet Sağlam, 2010, The cost of latency, *Working paper*, Columbia University.

Naes, Randi, and Johannes A. Skjeltorp, 2006, Order book characteristics and the volume-volatility relation: Empirical evidence from a limit order market, *Journal of Financial Markets* 9, 408-432.

Pagnotta, Emiliano and Thomas Philippon, 2012, Competing on speed, *Working paper*, New York University.

Parlour, Christine A., 1998, Price dynamics in limit order markets, *Review of Financial Studies* 11, 789–816.

Rosu, Ioanid, 2009, A dynamic model of the limit order book, *Review of Financial Studies* 22, 4601–4641.

Schwertz, William, G., 1989, Why does stock market volatility change over time? *Journal of Finance* 44, 1115-1153.

Stoll, Hans, R., 2000, Friction. *Journal of Finance* 55, 1479–1514.

TSE Annual Report, 2009. Retrieved on November 27, 2009 from: http://www.tse.or.jp/english/about/ir/financials/annual/annual_2009.pdf

TSE Annual Report, 2011. Retrieved on April 4, 2012 from: http://www.jpx.co.jp/en/investor-relations/ir-library/annual-reports/pdf/annual_2011.pdf

TSE Fact book 2011 retrieved on March 10, 2012 from: http://www.tse.or.jp/english/market/data/factbook/index.html

Uno, Jun, and Mai Shibata, 2011, Speed of trade and liquidity, *Working paper*. Available at SSRN: http://ssrn.com/abstract=1910200

Van Kervel, Vincent, 2012, Liquidity: What you see is what you get? *Working paper*, Available at SSRN 2021988.

Zhang, Frank, 2010, High-frequency trading, stock volatility, and price discovery. *Working Paper*, Yale University.

Snapshot of the LOB

Stock L				Stock H			
Bid Side		Ask Side		Bid Side		Ask Side	
Depth	Price	Depth	Price	Depth	Price	Depth	Price
200	20	200	21	200	20	200	21
100	18	400	23	1,300	19	700	22
100	15	900	25	1,100	18	800	23
200	12	900	26	1,200	17	700	24
900	10	1,000	27	1,300	16	900	25

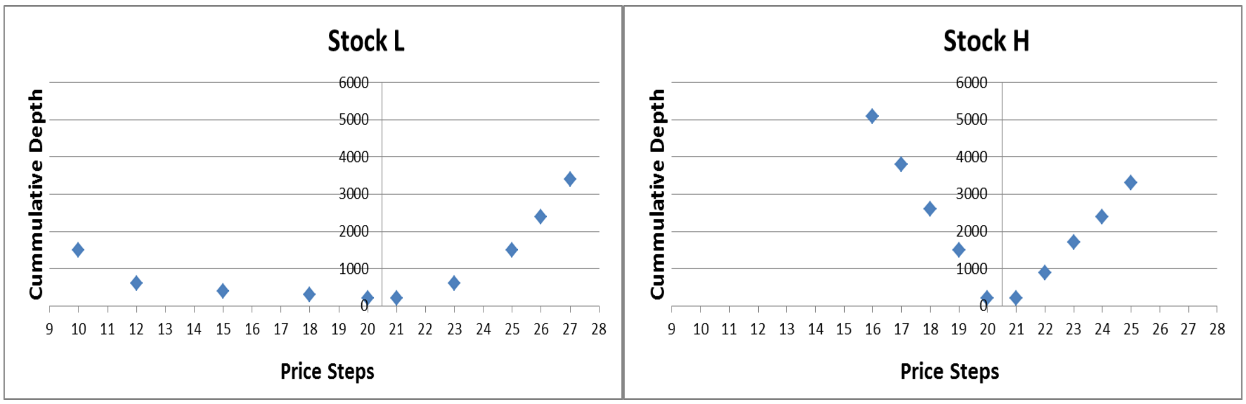
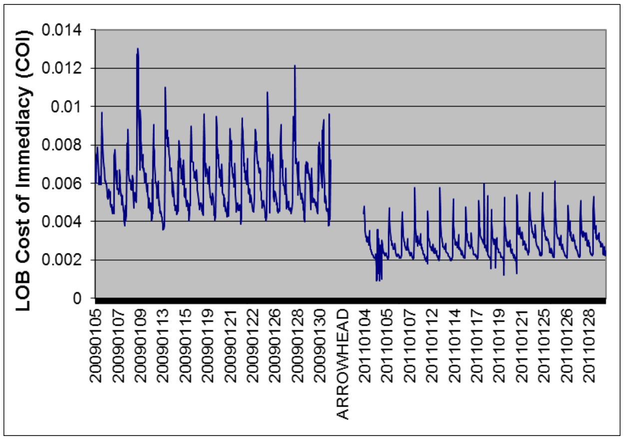
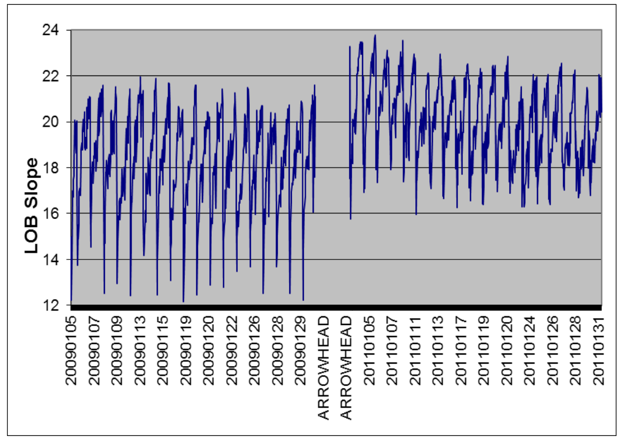


Figure 1. Hypothetical limit order book (LOB) for 2 stocks

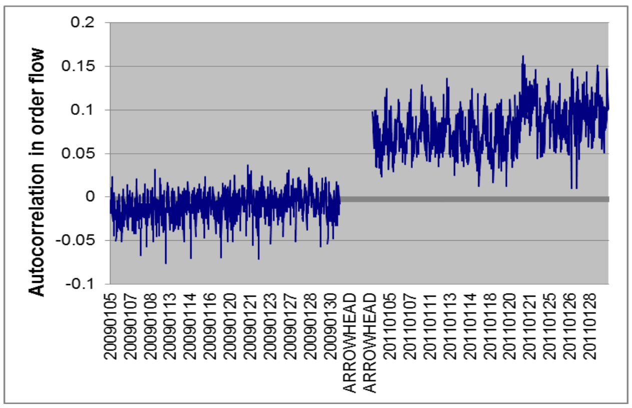
We illustrate the volume elasticity for two hypothetical stocks. In the table for each stock we show the depth and price for the best five asks (steps) and best five bids. For each stock we present a graph that shows the price and cumulative depth for the best five asks and bids. The vertical axis shows the cumulative order volume that can be executed as investors walk up or down the LOB. The slope of the curve is one of our comprehensive measures of LOB liquidity. The steeper the slope, the higher is the liquidity. The prices are in units of a hypothetical currency.



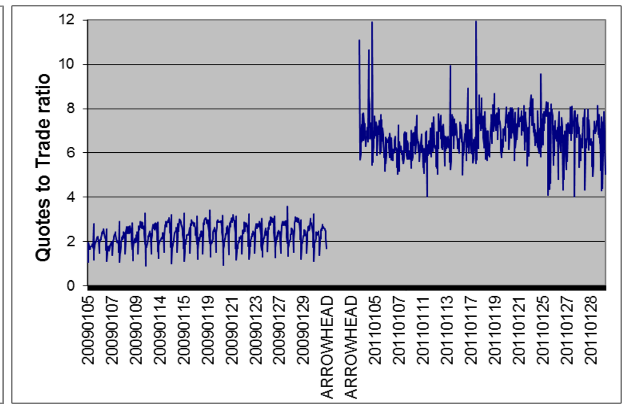
Panel A: Minute-by-Minute COI



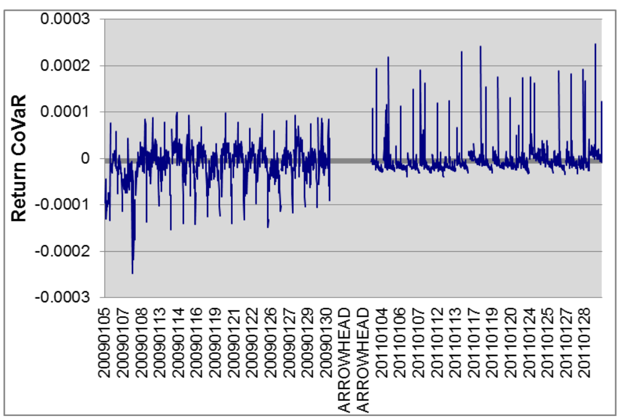
Panel B: Minute-by-Minute LOB SLOPE



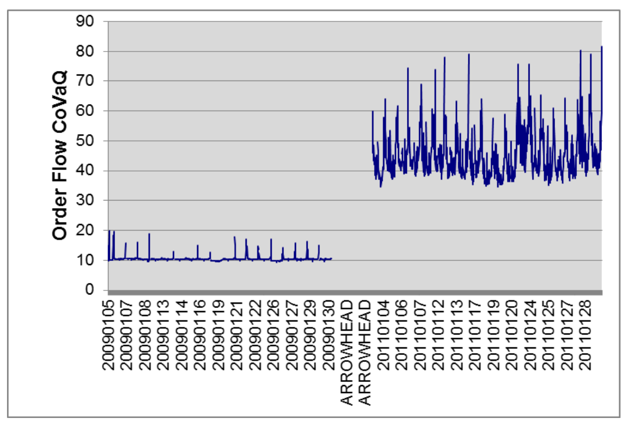
Panel C: Minute-by-Minute Autocorrelation



Panel D: Minute-by-Minute Quotes-to-trade ratio



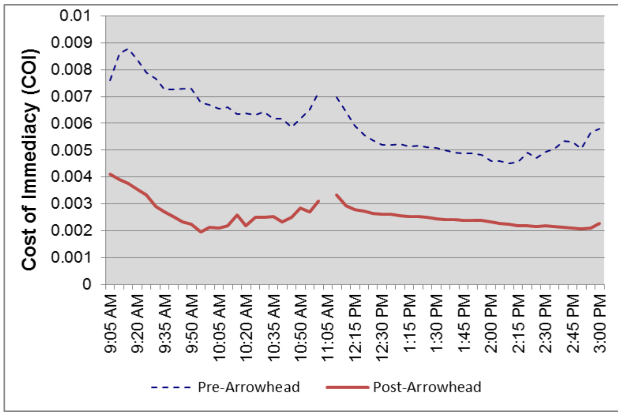
Panel E: Minute-by-minute CoVaR

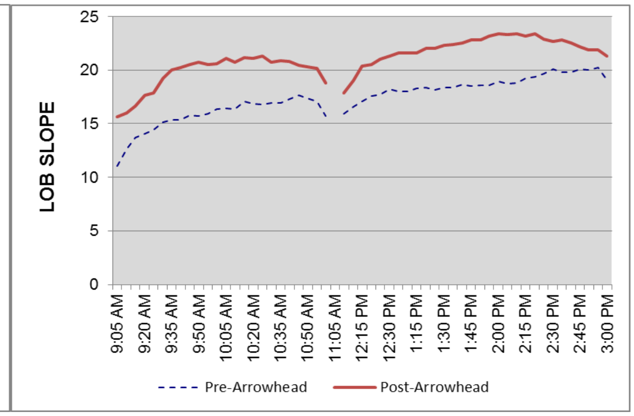


Panel F: Minute-by-Minute CoVaQ

Figure 2. Impact of Arrowhead on LOB liquidity and various trading risks

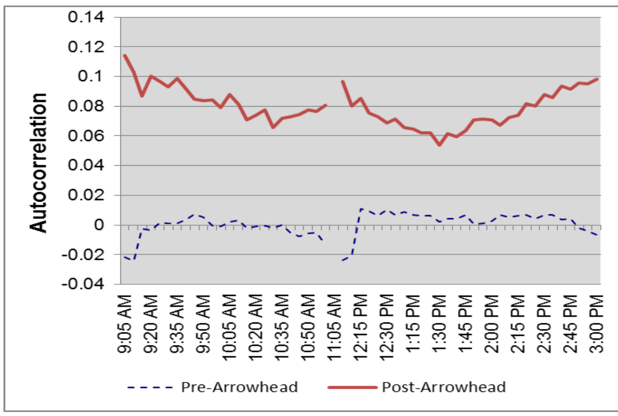
These graphs illustrate the effect of Arrowhead on LOB liquidity as measured by COI, LOB Slope, autocorrelation in order flow, quote stuffing risk (quotes-to-trade ratio), and systemic trading risk (minute-by-minute CoVaR and CoVaQ). The graphs include the pre-Arrowhead sample period of January, 2009 and the post-Arrowhead sample period of January, 2011. All variables are calculated for every stock for every minute of trading and then averaged across stocks and five minutes of trading.

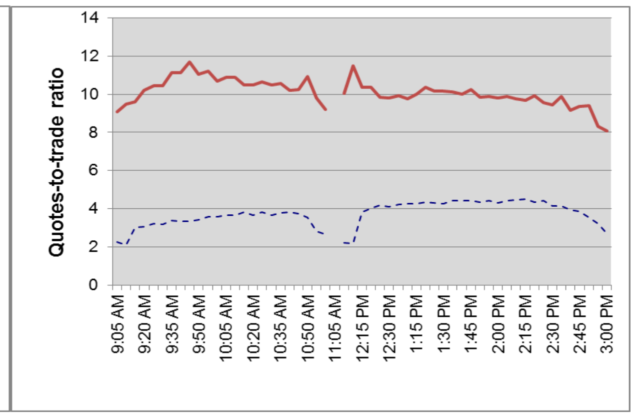




Panel A: Minute-by-Minute COI

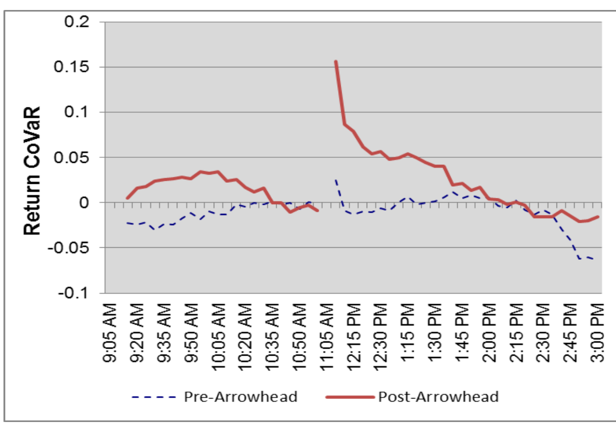
Panel B: Minute-by-Minute LOB SLOPE

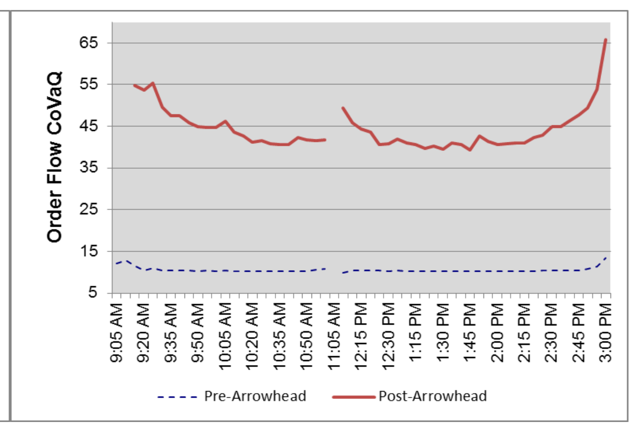




Panel C: Minute-by-Minute Autocorrelation

Panel D: Minute-by-Minute Quotes-to-trade ratio



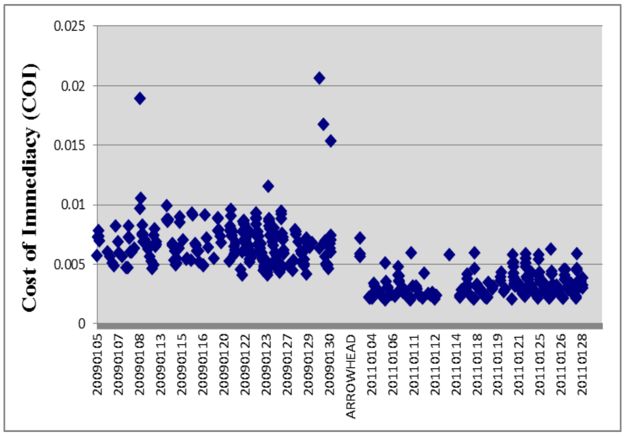


Panel E: Minute-by-minute CoVaR

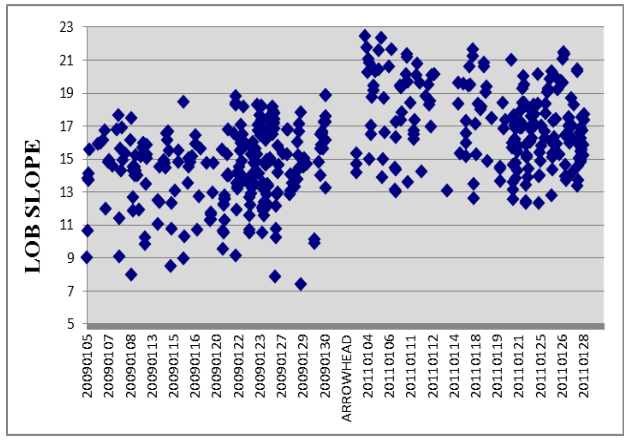
Panel F: Minute-by-Minute CoVaQ

Figure 3. Impact of Arrowhead on intraday patterns for LOB liquidity and various trading risks

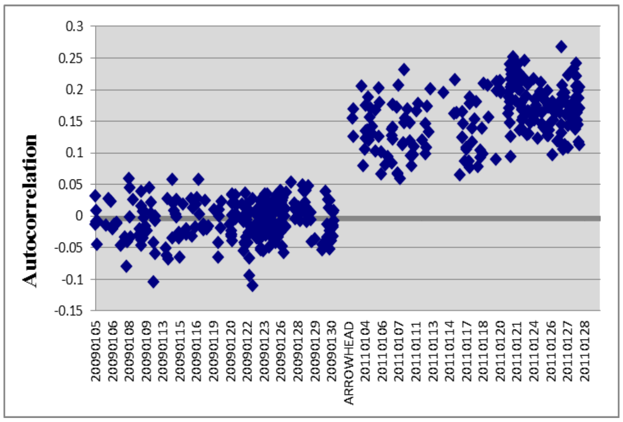
These graphs illustrate the effect of Arrowhead on intraday patterns for LOB liquidity as measured by COI, LOB Slope, autocorrelation in order flow, quote stuffing risk (quotes-to-trade ratio), and systemic trading risk (minute-by-minute CoVaR and CoVaQ). All variables are calculated for every stock for every minute of trading and then averaged across stocks and five minutes of trading. The graphs present the five minute averages for the pre-Arrowhead sample period of January, 2009 and the post-Arrowhead sample period of January, 2011.



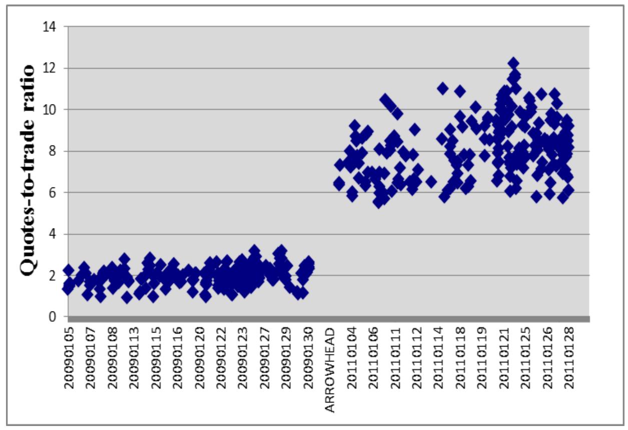
Panel A: Cost of Immediacy (COI)



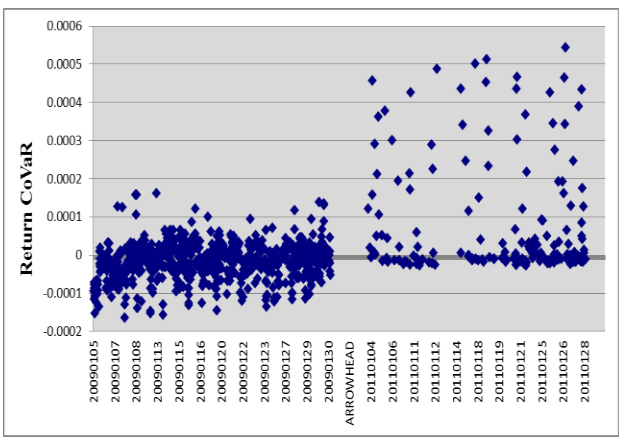
Panel B: LOB Slope



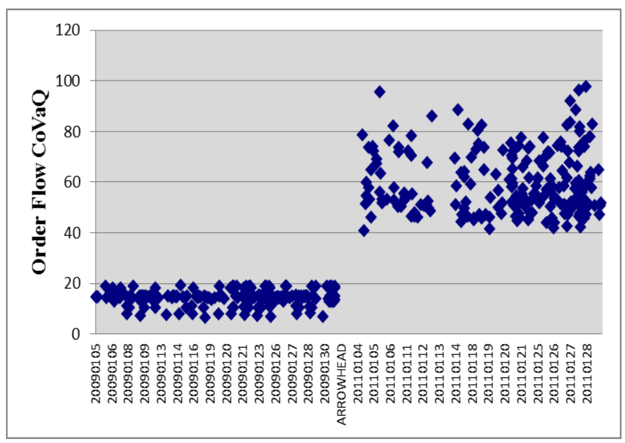
Panel D: Autocorrelation



Panel E: Quotes-to-trade ratio



Panel F: Return CoVaR



Panel G: Order Flow CoVaQ

Figure 4. Tail risk

These graphs illustrate the effect of Arrowhead on LOB liquidity as measured by COI and LOB Slope, Shock propagation risk (autocorrelation in order flow, quote stuffing risk (quotes-to-trade ratio), and systemic trading risk (Return CoVaR and Order Flow CoVaQ) during the tail risk events. Tail risk events are defined as the trading minutes for which the market return is in the lowest 5th percentile during the pre-Arrowhead month of Jan 09 or the post-Arrowhead month of Jan 2011.

Table 1. Liquidity changes around Arrowhead reduction in latency

We divide the stocks on the TSE into large, medium, and small categories based on market capitalization and present statistics for the 50 largest firms from each category (n = 150). In Panel A, we examine the effect of the reduction in latency due to the introduction of Arrowhead in January 2010 using data for three periods: Pre Arrowhead (January 2009), Post Arrowhead (January 2011), and Pre Crisis (June 2008), while in Panel B, we report the time series differences for various market quality measures for a sample of 150 Osaka stocks, pre and post the launch of Arrowhead on TSE. *AUTOCORR* is the first order autocorrelation of daily returns and *CROSSCORR* is the mean of the correlation of each stock, in turn, with the market index. *QUOTE STUFFING RISK* (*QSR)* is the ratio of the number of quotes to trades during each minute. *ΔCOVAR* (multiplied by 1000) and *ΔCOVAQ* are measures of systemic risk due to returns and quote stuffing risk, respectively. We also report means across firms for various liquidity measures. *COI* (=*ASKCOI* + *BIDCOI*) measures the cost that liquidity demanders have to bear due to a demand for 1% of the daily average trading volume. LOB Slope for the five best asks (*ASKSLOPE*) and five best bids (*BIDSLOPE*) is calculated using Equations 2 and 3, respectively. *SLOPE* is (*BIDSLOPE* + *ASKSLOPE*)/2. *SPREAD* is the proportional spread over each minute of trading. *DEPTH* is the average depth at the best bid and best ask in thousands. *VOLUME* is the monthly volume in millions of shares. *NTRDS* is the mean number of trades for each minute and *SIZE* is the mean trade size for each minute. *TRADESPEED* is the inverse of the average time between trades per minute of trading. All measures are time weighted for a given stock and then averaged across stocks. Columns (1), (2), and (3) report the means and Columns (4) and (5) report the difference in means between the Post-Arrowhead period and the Pre-Crisis and Pre-Arrowhead periods, in turn. Columns (6) and (7) report the difference in means between large- and small-cap stocks during the Pre- and Post-Arrowhead periods, respectively, while column (8) reports the effect of Arrowhead on the differences between large-and small-cap stocks.

Panel A. Sample TSE firms

	All Firms					Large-cap minus small-cap		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pre-Crisis	Arrowhead				Arrowhead		
		Pre	Post	(3) – (2)	(3) – (1)	Pre	Post	(7) – (6)
Trading Risk Measures								
AUTOCORR	0.03	0.02	0.11	0.09**	0.08**	0.05	0.16	0.11**
CROSSCORR	0.02	-0.03	0.04	0.07**	0.02	0.08	0.12	0.04*
QSR	2.74	2.89	6.69	3.80**	0.95**	2.09	3.70	1.61*
ΔCOVAR	-0.10	-0.07	0.10	0.17**	0.22**	0.02	0.05	0.03*
ΔCOVAQ	9.57	10.3	44.2	33.9**	34.6**	9.04	39.4	30.3**
Market Quality Measures								
COI (basis pts)	51.2	59.5	28.4	-31.1**	-22.9**	-8.79	-6.97	1.82*
SLOPE	19.6	20.4	20.7	0.29**	1.12*	8.40	13.64	5.24**
SPREAD (%)	0.22	0.23	0.16	-0.07*	-0.06*	-0.10	-0.09	0.01
DEPTH (‘000)	32.8	44.9	258	213**	225**	82.4	506	424**
VOLUME	95.0	93.7	109.9	16.1**	14.9**	233	283	50.7**
NTRDS	4.08	7.34	11.2	3.81**	7.07**	7.04	14.7	7.68**
SIZE	4,185	3,800	3,132	-668**	-1,05**	6,225	5,921	-304**
TRADESPEED	0.07	0.08	0.12	0.04**	0.05**	0.07	0.13	0.06**

Panel B. Osaka vs. TSE

	Osaka Stocks			TSE Stocks		
	(1)	(2)	(3)	(4)	(5)	(6)
	Pre-Arrowhead	Post-Arrowhead	Difference	Pre-Arrowhead	Post-Arrowhead	Difference
AUTO CORR	0.073	0.082	0.009	0.02	0.11	0.09**
CROSS CORR	0.041	0.048	0.007	-0.03	0.04	0.07**
QSR	5.17	5.23	0.06	4.89	5.69	0.80**
ΔCOVAR	0.076	0.093	0.017	-0.08	0.12	0.20**
ΔCOVAQ	26.64	28.11	1.47	10.3	44.2	33.9**
COI (basis pts)	61.12	54.93	-6.19†	59.5	28.4	-31.1**
SLOPE	17.88	18.14	0.26	20.4	20.7	0.29**

†, *, and ** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 2. Liquidity changes around introduction of Arrowhead

For each firm in our sample, we estimate the following equations:

$$X_{i,t} = \alpha_i + \beta_{1i}\, ARROWHEAD_{it} + \beta_{2i}\, LOG\ PRICE_{it} + \beta_{3i}\, LOG\ NTRDS_{i,t} + \beta_{4i}\, VOLATILITY_{i,t} + \beta_{5i}\, LOG\ VOL_{i,t} + \beta_{6i}\, MKTRET_{i,t} + \beta_{9i}\, HIGHSPEED_{i,t} + \beta_{10i}\, LOWSPEED_{i,t} + \mu_{i,t}$$

where X represents *COI or SLOPE*, in turn, as defined in Table 1, and μ is a random error. In this legend the subscripts refer to firm i in minute t. *ARROWHEAD* is a dummy variable that equals 1 for the post Arrowhead period of January 2011 and 0 for the pre Arrowhead period of January 2009. *LOG PRICE* is the natural log of the trading price at the end of each minute, *LOG NTRDS* is the natural log of the number of trades per minute of trading. *VOLATILITY* is the absolute value of the residuals from:

$$R_{i,t} = \sum_{k=1}^{5} \propto_{i,k} D_k + \sum_{j=1}^{12} \beta_{i,j} R_{i,t-j} + \varepsilon_{i,t}$$

where D is a day-of-the-week dummy and R is the return on the market, the subscript j allows for 12 lagged returns, α and β are coefficients to be estimated, and ε is a random error term. *LOG VOL* is the natural log of the trading volume each minute. *MKTRET* is the minute-by-minute return on the market. We calculate the number of quote updates as the sum of new quotes + revisions + cancellations for each minute of trading. *HIGHSPEED* is a dummy variable that takes a value of 1 if the speed of quote updates is greater than its 75th percentile value and *LOWSPEED* is a dummy variable that takes a value 1 if the speed of quote updates is less than its 25th percentile value. Columns with heading %t (%sign) report the percentage of t-statistics that are significant (the percentage of parameter estimates that have the same sign as the reported average estimates). Columns 3-5 present the standardized parameter estimates averaged across all individual security regressions.

	(1)	(2)	(3)	(4)	(5)
Panel A. Impact of Arrowhead on *COI*					
Variables	All firms	%t (%sign)	Large cap	Mid cap	Small cap
ARROWHEAD	-3.55*	98 (95)	-4.53*	-2.89*	-1.92*
LOG PRICE	-2.44*	95 (89)	-2.86*	-2.29*	-2.35*
LOG NTRDS	1.84*	80 (71)	3.83*	2.06*	0.91*
VOLATILITY	4.30*	100 (99)	4.64*	4.23*	3.89*
LOG VOL	-2.04*	84 (74)	-5.07*	-1.54*	-1.96*
MKTRET	-0.14	46 (60)	-0.21	-0.18	-0.01
HIGHSPEED	-0.21	75 (53)	-1.06*	-0.12	0.78*
LOWSPEED	1.17	42 (74)	2.07*	1.17	-0.33
ADJ R^2	0.148		0.114	0.121	0.174
Panel B. Impact of Arrowhead on *SLOPE*					
ARROWHEAD	2.31*	93 (97)	3.39*	2.22*	1.84*
LOG PRICE	2.31*	89 (93)	3.07*	2.34*	1.71*
LOG NTRDS	-0.41	40 (68)	-0.58	-0.44	-0.16
VOLATILITY	-2.93*	100 (99)	-5.38*	-3.92*	-2.32*
LOG VOL	2.14*	76 (86)	4.04*	1.82*	0.44
MKTRET	0.08	13 (51)	0.12	0.06	0.07
HIGHSPEED	-0.01	55 (52)	0.27	0.18	-0.47
LOWSPEED	-0.19	18 (64)	-0.44*	-0.32	0.22
ADJ R^2	0.139		0.167	0.126	0.112

* significant at the .05 level using a test of proportions, which tests the null hypothesis that significantly more than 60% of the individual coefficient estimates have the same sign as the mean.

Table 3. Shock propagation risk: Autocorrelation and cross correlation in order flow

We present the results for the impact of Arrowhead on autocorrelation in order flow (*AUTOCORR*) and *CROSSCORR,* measures of systemic risk for the full sample and for two size-based portfolios using the following equations:

$$X_{i,t+1} = \alpha_i + \beta_{0i}\, ARROWHEAD_{i,t} + \beta_{1i}\, COI_{i,t} + \beta_{2i}\, SLOPE_{i,t} + \beta_{3i}\, NTRDS_{i,t} + \beta_{4i}\, ATS_{i,t} + \beta_{5i}\, SPREAD_{i,t} + \beta_{6i}\, DEPTH_{i,t} + \beta_{7i}\, VOLATILITY_{i,t} + \beta_{8i}\, RETURN_{i,t} + \beta_{9i}\, HIGHSPEED_{i,t} + \beta_{10i}\, LOWSPEED_{i,t} + \beta_{11i}\, ARROWHEAD_{i,t}{*}COI_{i,t} + \beta_{12i}\, ARROWHEAD_{i,t}{*}SLOPE_{it} + \mu_{i,t+1}$$

where X represents $AUTOCORR_{i,t+1}$ and $CROSSCORR_{i,t+1}$, in turn, and μ is a random error. In this legend the subscripts refer to firm ***i*** in minute *t*. *ARROWHEAD*COI* and *ARROWHEAD*SLOPE* are multiplicative variables that are the product of the two variables indicated. All the remaining variables are defined in Tables 1 and 2. Columns 1, 3, 5 and 7 present the standardized parameter estimates averaged across all individual security regressions. Columns 2, 4, 6, and 8 report the percentage of t-statistics that are significant, and, in parentheses, the percentage of parameter estimates that have the same sign as the reported average estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Impact of Arrowhead on autocorrelation (dependent variable) in order flow								
	Full Sample				Large cap		Small cap	
Variables	Coef	%t (%sign)	Coef	%t (%sign)	Coef	%t (%sign)	Coef	%t (%sign)
ARROWHEAD	0.96*	78(82)	1.12*	74(84)	1.55*	84(92)	0.79	48(64)
COI	-0.61*	68(77)	-0.56*	72(84)	-0.74*	88(90)	-0.26	36(74)
SLOPE	0.35	47(71)	0.31*	52(62)	0.42*	76(82)	0.04	32(48)
NTRDS	0.91*	78(93)	0.97*	79(86)	1.06*	85(94)	0.87	79(86)
ATS	-0.17	43(75)	-0.29*	51(78)	-0.42*	64(88)	-0.28	51(78)
SPREAD	-0.04	39(89)	-0.08	32(84)	-0.15	39(86)	-0.01	32(84)
DEPTH	0.19	37(82)	0.17	41(75)	0.38*	58(81)	0.01	41(75)
VOLATILITY	-0.87*	82(95)	-0.92*	86(91)	-1.24*	92(96)	-0.75	86(91)
RETURN	0.12	10(57)	0.14	13(53)	0.12	21(59)	0.11	13(53)
HIGHSPEED	0.93*	57(65)	0.98*	61(74)	0.96*	79(82)	0.94*	61(74)
LOWSPEED	-0.29	7(82)	-0.23	9(90)	-0.24	13(96)	-0.27	9(90)
ARROWHEAD*COI			-0.07	22(78)	-0.12	28(82)	-0.01	6 (64)
ARROWHEAD*SLOPE			0.11	28(75)	0.15	34(76)	0.06	16(70)
ADJ R^2	0.046		0.049		0.043		0.055	

Panel B: Impact of Arrowhead on cross correlation (Dependent variable) in order flow

	Full Sample				Large Cap		Small Cap	
Variables	Coef	%t (%sign)	Coef	%t (%sign)	Coef	%t (%sign)	Coef	%t (%sign)
ARROWHEAD	1.15*	69(80)	0.91*	64(79)	1.17*	84(77)	0.02	32 (70)
COI	0.47*	75(72)	0.41*	72(65)	0.68*	84(75)	0.06	54 (48)
SLOPE	-0.28*	51(69)	-0.32*	50(62)	-0.43*	79(74)	-0.04	10 (46)
NTRDS	-0.17	21(60)	-0.15	25(54)	-0.52	31(56)	-0.01	16(47)
ATS	-0.28	48(55)	-0.21	51(58)	-0.56*	62(65)	-0.13	46(52)
SPREAD	0.08	34(65)	0.11	49(64)	0.34	45(70)	0.03*	52(60)
DEPTH	-0.12	39(50)	-0.17	34(56)	-0.27	38(60)	-0.05	30(50)
VOLATILITY	0.53	60(58)	0.61*	62(65)	0.81*	74(75)	0.19	43(55)
RETURN	0.01	1(50)	0.01	2(60)	0.04	3(68)	-0.01	1(54)
HIGHSPEED	0.05	29(83)	0.02	25(90)	0.07	32(58)	0.06	17(93)
LOWSPEED	-0.08	2(60)	-0.04	1(75)	-0.14	4(80)	-0.01	1(60)
ARROWHEAD*COI			0.38	18(71)	0.53	22 (75)	0.30	13 (69)
ARROWHEAD*SLOPE			-0.14	28(66)	-0.30	42 (76)	-0.01	15 (60)
ADJ R^2	0.076		0.078		0.082		0.079	

* significant at the 0.05 level using a test of proportions, which tests the null hypothesis that significantly more than 60% of the individual coefficient estimates have the same sign as the mean.

Table 4. Message traffic: Quote stuffing risk

For the full sample and for two size based portfolios, we present the results of our estimation of the following equation:

$$QSR_{i,t+1} = \alpha_i + \beta_{0i}\,ARROWHEAD_{i,t} + \beta_{1i}\,COI_{i,t} + \beta_{2i}\,SLOPE_{i,t} + \beta_{3i}\,NTRDS_{i,t} + \beta_{4i}\,ATS_{i,t}$$
$$+ \beta_{5i}\,SPREAD_{i,t} + \beta_{6i}\,DEPTH_{i,t} + \beta_{7i}\,VOLATILITY_{i,t} + \beta_{8i}\,RETURN_{i,t} + \beta_{9i}\,HIGHSPEED_{i,t}$$
$$+ \beta_{10i}\,LOWSPEED_{i,t} + \beta_{11i}\,ARROWHEAD_{i,t}{*}COI_{i,t} + \beta_{12i}\,ARROWHEAD_{i,t}{*}SLOPE_{it} + \mu_{i,t+1}$$

The variables are as defined in the previous tables. Columns 1, 3, 5 and 7 present the standardized parameter estimates averaged across all individual security regressions. Columns 2, 4, 6, and 8 report the percentage of t-statistics that are significant, and, in parentheses, the percentage of parameter estimates that have the same sign as the reported average estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample				Large-cap		Small-cap	
Variables	Coef	%t (%sign)	Coef	%t (%sign)	Coef	%t (%sign)	Coef	%t (%sign)
ARROWHEAD	2.24*	91(95)	2.59*	88(97)	3.51*	98(100)	1.09*	78(92)
COI	-0.98*	60(74)	-1.31*	64(72)	-2.91*	71(87)	-0.67	46(60)
SLOPE	2.15*	77(89)	2.03*	79(92)	2.38*	86(97)	1.57*	65(74)
NTRDS	-0.55	43(62)	-0.77	48(60)	-0.94*	56(72)	-0.22	31(52)
ATS	-0.42	32(61)	-0.47	35(67)	-0.54	44(75)	-0.45	26(53)
SPREAD	-0.56	44(73)	-0.49	38(71)	-0.14	28(67)	-0.59*	51(78)
DEPTH	0.39	48(80)	0.34	43(79)	0.63*	57(78)	0.18	33(75)
VOLATILITY	0.11	19(58)	0.14	21(51)	0.23	26(69)	0.08	16(42)
RETURN	0.02	3 (50)	0.03	4 (52)	0.02	5 (60)	0.05	1 (46)
HIGHSPEED	0.86*	64(78)	0.92*	69(84)	1.21*	73(92)	0.06	43(62)
LOWSPEED	-0.13	5 (60)	-0.10	4 (65)	-0.14	6 (75)	-0.05	2 (53)
ARROWHEAD *COI			-1.54*	81(88)	-3.04*	96(99)	-0.68*	73(79)
ARROWHEAD *SLOPE			2.33*	83(96)	3.42*	99(100)	1.82*	68(85)
ADJ R^2	0.177		0.193		0.216		0.188	

* significant at the 0.05 level using a test of proportions, which tests the null hypothesis that significantly more than 60% of the individual coefficient estimates have the same sign as the mean.

Table 5. Investigating the effect of latency on systemic trading risk

Using the introduction of Arrowhead as a natural experiment, we investigate the effect of latency on systemic risk by estimating the following equations:

$X_{i,t+1} = \alpha_i + \beta_{0i}\, ARROWHEAD_{i,t} + \beta_{1i} COI_{i,t} + \beta_{2i} SLOPE_{i,t} + \beta_{3i}\, NTRDS_{i,t} + \beta_{4i}\, ATS_{i,t} + \beta_{5i}\, SPREAD_{i,t} + \beta_{6i}\, DEPTH_{i,t} + \beta_{7i} VOLATILITY_{i,t} + \beta_{8i} RETURN_{i,t} + \beta_{9i}\, HIGHSPEED_{i,t} + \beta_{10i}\, LOWSPEED_{i,t} + \beta_{11i}\, ARROWHEAD_{i,t}{*}COI_{i,t} + \beta_{12i}\, ARROWHEAD_{i,t}{*}SLOPE_{it} + \mu_{i,t+1}$

where X represents $\Delta COVAR_{i,t+1}$ and $\Delta COVAQ_{i,t+1}$, in turn, and μ is a random error. In this legend the subscripts refer to firm i in minute t. Panel A reports the results based on $\Delta COVAR$ and Panel B report the results based on $\Delta COVAQ$. The variables are as defined in the previous tables. Columns 1, 3, 5 and 7 present the standardized parameter estimates averaged across all individual security regressions. Columns 2, 4, 6, and 8 report the percentage of t-statistics that are significant, and, in parentheses, the percentage of parameter estimates that have the same sign as the reported average estimates.

Panel A. Effect of Arrowhead on systemic price changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample				Large-cap		Small-cap	
Variables	Coef	%t (%sign)	Coef	%t (%sign)	Coef	%t (%sign)	Coef	%t (%sign)
ARROWHEAD	0.52*	76(84)	0.49*	71(79)	1.01*	87(92)	0.01	49(35)
COI	0.48*	75(91)	0.56*	72(84)	0.84*	88(90)	0.26	36(74)
SLOPE	-0.37*	56(67)	-0.31*	52(62)	-0.82*	76(82)	-0.04	32(48)
NTRDS	0.71*	89(95)	0.54*	74(87)	1.02*	86(91)	-0.38	41(56)
ATS	0.13*	55(76)	0.11	48(69)	0.69*	55(63)	0.58*	53(62)
SPREAD	0.11	48(81)	0.19	49(77)	0.17	44(57)	0.04	38(73)
DEPTH	-0.14*	51(84)	-0.21*	53(85)	-0.19*	59(78)	-0.17	36(88)
VOLATILITY	0.61*	76(84)	0.51*	72(88)	0.21*	54(91)	0.04	41(91)
RETURN	0.66*	80(99)	0.58*	83(99)	0.73*	89(99)	0.34	45(98)
HIGHSPEED	-0.42*	51(84)	-0.48*	54(89)	0.32*	52(97)	-0.67*	69(94)
LOWSPEED	-0.18	29(82)	-0.27	23(76)	-0.36*	57(60)	-0.02	15(79)
ARROWHEAD *COI			1.11*	64(86)	1.39*	68(92)	0.91*	58(70)
ARROWHEAD *SLOPE			-0.17	41(56)	-0.41*	69(85)	-0.01	19(27)
ADJ R^2	0.138		0.153		0.197		0.135	

Panel B. Effect of Arrowhead on systemic quote stuffing risk

	Full Sample				Large Cap		Small Cap	
Variables	Coef	%t (%sign)	Coef	%t (%sign)	Coef	%t (%sign)	Coef	%t (%sign)
ARROWHEAD	0.99*	76(84)	1.21*	77(88)	1.80*	97(99)	0.38	39(75)
COI	0.95*	76(96)	1.08*	85(81)	1.47*	95(94)	0.54*	68(70)
SLOPE	-0.41	39(67)	-0.36	48(71)	-0.89*	78(89)	-0.01	24(64)
NTRDS	0.59*	71(87)	0.64*	62(80)	1.01*	71(91)	0.09	44(68)
ATS	-0.44*	58(69)	-0.39*	62(64)	-0.54*	69(77)	-0.15	18(65)
SPREAD	0.37*	55(76)	0.36	52(58)	0.39	48(44)	-0.28	59(48)
DEPTH	-0.55*	71(95)	-0.51*	75(92)	-0.77*	86(98)	-0.37	43(90)
VOLATILITY	0.14	36(82)	0.16	34(88)	0.19	39(93)	0.09	31(82)
RETURN	0.13	25(78)	0.12	27(71)	0.15	21(78)	0.10	12(75)
HIGHSPEED	0.78*	73(67)	0.83*	70(68)	0.97*	84(91)	0.22	42(58)
LOWSPEED	-0.14	19(58)	-0.12	18(60)	-0.21	17(64)	-0.04	17(64)
ARROWHEAD *COI			1.96*	82(88)	2.31*	89(100)	1.52*	78(75)
ARROWHEAD *SLOPE			-1.18*	66(78)	-1.72*	81(88)	-0.07	53(50)
ADJ R^2	0.041		0.043		0.054		0.039	

* significant at the 0.05 level using a test of proportions, which tests the null hypothesis that significantly more than 60% of the individual coefficient estimates have the same sign as the mean.

Table 6. TSE Vs. Osaka: Difference in Difference regression analyses

We present the results for the differential impact of Arrowhead on various systemic risk and liquidity measures for the stocks listed on the TSE and Osaka stock exchanges. TSE difference is defined as the average value of the variable after the introduction of Arrowhead minus the average value before Arrowhead. Osaka difference is defined analogously using the TSE arrowhead introduction date as the pseudo-event even though Osaka stock exchange did not experience any latency reduction. We present the test statistics for the full sample and for three size-based portfolios. The variables are defined in Tables 1 and 2. We report the parameter estimates (coefficient) and standard error in parentheses.

	Full Sample (TSE difference-Osaka difference)	**Large Cap**	**Medium Cap**	**Small Cap**
Variable	Coefficient (Std Err)	Coefficient (Std Err)	Coefficient (Std Err)	Coefficient (Std Err)
AUTO CORR	0.56** (0.12)	1.23** (0.15)	0.61** (0.11)	0.21 (0.24)
CROSS CORR	0.29* (0.11)	0.47** (0.12)	0.28* (0.09)	0.19† (0.10)
QSR	0.68** (0.16)	0.87** (0.14)	0.54* (0.19)	0.57* (0.19)
ΔCOVAR	0.76** (0.18)	1.23** (0.15)	0.61** (0.11)	0.21 (0.24)
ΔCOVAQ	1.43** (0.34)	2.21** (0.54)	1.28** (0.32)	0.95* (0.31)
COI (basis pts)	-0.21* (0.10)	-0.50** (0.11)	-0.29* (0.12)	-0.06 (0.08)
SLOPE	0.11 (0.08)	0.18* (0.09)	0.10 (0.09)	0.04 (0.06)

†, *, and ** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 7. Tail risk: Pre and post Arrowhead

We analyze the behavior of the key market quality and systemic risk parameters during extreme negative market movements. The variables are as defined previously. Columns (1) and (2) report the means for the key variables during the pre- and post-Arrowhead period, respectively. Column (3) reports the difference in means (post-Arrowhead minus pre-Arrowhead). For Panel A we create a subsample of trading minutes for which the market returns are in 5th percentile (5% extreme negative returns), while for Panel B, we create a subsample of trading minutes for which the market returns are between -0.42% (minimum for post-Arrowhead) and -0.11% (5th percentile for post-Arrowhead). We present the results from following regression model in Panel C:

$$X_{i,t+1} = \alpha_i + \beta_{0i}\, ARROWHEAD_{i,t} + \beta_{1i}\, TAILMIN_{i,t} + \beta_{2i}\, ARROWHEAD_{i,t}{*}TAILMIN_{i,t} + \beta_{3i}\, COI_{i,t} + \beta_{4i}\, SLOPE_{i,t} + \beta_{5i}\, NTRDS_{i,t} + \beta_{6i}\, ATS_{i,t} + \beta_{7i}\, SPREAD_{i,t} + \beta_{8i}\, DEPTH_{i,t} + \beta_{9i} RETURN_{i,t} + \beta_{10i}\, HIGHSPEED_{i,t} + \beta_{11i}\, LOWSPEED_{i,t} + \mu_{i,t+1}$$

where *TAILMIN* ia a dummy variable that takes the value of 1 for the trading minutes during which the return on market index is in bottom 5th percentile (5% extreme negative market return minutes), zero otherwise and *ARROWHEAD*TAILMIN* is a interaction variable that is the product of the two variables indicated. The remaining variables are as defined in the previous tables. Columns 1, 3, 5, 7, and 9 present the standardized parameter estimates averaged across all individual security regressions. Columns 2, 4, 6, 8, and 10 report the percentage of t-statistics that are significant, and, in parentheses, the percentage of parameter estimates that have the same sign as the reported average estimates.

Panel A. Effect of Arrowhead on tail risk, as defined by trading minutes when the market return is in the 5th percentile or less

	(1)	(2)	(3)
Varibles	Pre Arrowhead	Post Arrowhead	(1) – (2)
AUTOCORR	-0.01	0.16	0.17**
CROSSCORR	0.04	0.10	0.06**
QSR	2.00	8.18	6.18**
ΔCOVAR (basis pts)	0.05	0.24	0.19**
ΔCOVAQ	16.32	74.21	57.89**

Panel B. Effect of Arrowhead on tail risk in the post period, as defined by trading minutes when the market return is between its minimum (-0.42%) and the cutoff for the **5th** percentile (-0.11%)

	(1)	(2)	(3)
Varibles	Pre Arrowhead	Post Arrowhead	(1) – (2)
AUTOCORR	-0.02	0.16	0.18**
CROSSCORR	0.04	0.10	0.06**
QSR	2.06	8.18	6.12**
ΔCOVAR (basis pts)	0.53	1.02	0.49**
ΔCOVAQ	18.05	74.21	56.16**

**significant at the 0.01 level using the two sample t-test.

Panel C. Effect of Arrowhead on Tail Risk: Regression analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables	AUTO CORR	%t (%sign)	CROSS CORR	%t (%sign)	QTR	%t (%sign)	COVAR	%t (%sign)	COVAQ	%t (%sign)
ARROWHEAD	0.76*	69(74)	0.99*	72(85)	2.11*	88(96)	0.63*	77(86)	1.03*	72(85)
TAILMIN	0.63*	55(60)	0.91*	79(92)	1.84*	85(99)	0.82*	81(90)	0.91*	66(85)
ARROWHEAD *TAILMIN	1.03*	84(96)	1.12*	82(84)	2.26 *	94(99)	0.93*	85(92)	1.01*	78(90)
COI	-0.56*	72(70)	0.51*	79(80)	-0.81*	62(78)	0.52*	70(86)	0.87*	68(92)
SLOPE	0.38	43(75)	-0.41*	58(75)	1.84*	79(91)	-0.35*	54(70)	-0.32	42(67)
NTRDS	0.81*	77(90)	-0.12	15(67)	-0.41	37(60)	0.64*	75(90)	0.63*	65(84)
ATS	-0.23	40(68)	-0.29	50(54)	-0.49	25(67)	0.17	49(70)	-0.47*	53(70)
SPREAD	-0.07	39(89)	0.08	30(65)	-0.62	48(69)	0.05	42(87)	0.45*	61(72)
DEPTH	0.14	37(82)	-0.19	35(52)	0.23	39(84)	-0.11	39(73)	-0.64*	76(91)
RETURN	0.09	5(66)	0.01	1(50)	0.01	2 (67)	0.74*	82(99)	0.11	19(76)
HIGHSPEED	0.72*	61(67)	0.09	25(90)	0.93*	69(80)	-0.39	47(78)	0.65*	69(65)
LOWSPEED	-0.20	8(80)	-0.11	3(67)	-0.10	7 (75)	-0.17	22(78)	-0.18	25(63)
ADJ R^2	0.049		0.113		0.204		0.161		0.062	

* significant at the 0.05 level using a test of proportions, which tests the null hypothesis that significantly more than 60% of the individual coefficient estimates have the same sign as the mean.