Reduced Latency and Market Quality on the Tokyo Stock Exchange

Abstract

The introduction of Arrowhead by the Tokyo Stock Exchange, the world's second largest exchange, substantially reduced latency resulting in an increase in high-frequency trading (HFT) from zero to 36% of volume in 2011. We find that Arrowhead affects market quality by improving limit order book (LOB) liquidity as measured by the cost of immediacy (COI) and LOB slope. Arrowhead also reduced return volatility and the average trade size, increased autocorrelation and cross correlation in order flow, fleeting orders, trading volume, and quotes to trade ratio,. Finally, Arrowhead increased the ability of COI to explain trade prices, fleeting orders, trading speed, and the quotes to trade ratio.

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The heart of modern trading is the electronic limit order book (LOB), which displays aggregate liquidity supply and is now the primary way of trading equities worldwide.[1] Trade automation and increased speed of trading have improved market quality in terms of reduced transactions costs, increased risk-sharing, consumption smoothing and enhanced market quality (Chordia, Roll, and Subrahmanyam, 2008; Boehmer and Kelley, 2009; Hendershott, Jones and Menkveld, 2011), but has also increased the cost of immediacy (Hendershott and Moulton, 2011). The introduction of the Arrowhead high speed trading system on the Tokyo Stock Exchange (TSE) in January of 2010 reduced latency from 6 seconds to 3 milliseconds. Since that time High Frequency Trading's (HFT) market share of all trading in TSE equities has soared from about 0% to as much as 36% by April 2011 and dark pool activity has started in its nascent stages.[2] And 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). Moreover, NYSE Euronext and TSE have signed a master agreement to allow their customers to access each exchange's markets through a linked network.[3]The unprecedented growth of HFT in the US has led SEC to approve a new rule (163) requiring consolidated audit trail (CAT) to monitor and analyze the trading activity across the US markets.[4] Given the importance of HFT in globally integrated financial markets, we use the TSE's introduction of Arrowhead as a natural experiment to ascertain how the spectacular growth of HFT has affected market quality–both the evolution of price discovery and LOB liquidity measures.

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[1] For example, Jain (2005) documents that 85 of the 100 leading exchanges in the world employed electronic trading in the year 2000.
[2] Tokyo stock Exchange Annual Report, 2011
[3] http://www.tse.or.jp/english/news/48/111207_a.html and http://www.advancedtrading.com/exchanges/229300020
[4] http://www.sec.gov/news/press/2012/2012-134.htm

In addition, we analyze the role liquidity provision of a pure LOB in explaining the evolution of key market quality parameters. There is a rich literature on the relation between traditional liquidity measures based on quotes at the top of a LOB and various dimensions of market quality such as trade price location (Parlour, 1998; Kaniel and Liu, 2005), speed of trading (Biais, Hillion, and Spatt, 1995; Hendershott and Moulton, 2011), quotes to trade ratio or cancellation to trade ratio (Menkveld, 2012), return volatility (Foucault, Moinas, and Theissen, 2007), autocorrelation (Parlour, 1998; Barclay and Warner, 1993) and return cross correlation (Caballe and Krishnan, 1994).

However, the importance of liquidity away from the best bid and ask in high-frequency markets is highlighted by Aitken, Almeida, Harris, and McInish (2007) who document that traders provide liquidity simultaneously at multiple prices as well as Goettler, Parlour, and Rajan (2005) and Rosu (2009) who model this behavior. Therefore, in addition to the traditional liquidity measures, we also examine several new measures that quantify the state of the LOB beyond the best quotes that we believe are important for HFT in any LOB. Biais, Hillion and Spatt (1995) and Naes and Skjeltorp (2006) formally define a comprehensive LOB slope measure as the weighted average of the change in quantity supplied in the LOB per unit change in the price, which is particularly important in fast-paced markets where orders frequently climb up or down the book. The change in LOB Slope measures the resiliency of the full LOB from a liquidity supply perspective.

To better understand the interaction between liquidity demanders and liquidity suppliers in high-frequency markets, we use a cost of immediacy (COI) measure. [5] The COI measure captures the fact that liquidity demanders incur progressively higher cumulative costs as the

[5] 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.

available depth at the top of the LOB in fast markets becomes insufficient to fully execute the order (Irvine, Benston, and Kandel, 2000; and Kang and Yeo, 2008; Boehmer, Saar, and Yu, 2005 pp. 808). An important incremental aspect of the COI measure is that it takes into consideration order size or execution quantity, and, hence, accounts for the tightness and the depth of the LOB. By incorporating the elasticity of liquidity supply and the cost of immediately executing large orders, respectively, these two comprehensive LOB liquidity measures—LOB Slope and COI—represent the vital statistics of the modern HFT trading systems.

We find that Arrowhead increased trading volume, reduced the average trade size and improved liquidity as reflected by a steeper LOB Slope and a lower COI. We also find that Arrowhead reduced return volatility, increased autocorrelation and cross correlation in order flow, and increased the quotes to trade ratio. The effects of Arrowhead are more pronounced for the large-cap stocks. Finally we show that Arrowhead increased the ability of COI in explaining the trade prices, the quotes to trade ratio, fleeting orders, and the speed of trading. In contrast, Arrowhead has no influence on the ability of COI in explaining the evolution of volatility, autocorrelation, and cross correlation.

Our results can be useful in understanding market quality on a fully-electronic order-driven market, and particularly the effects of low latency systems such as Arrowhead. In addition, our findings suggest that comprehensive liquidity measures are particularly informative for HFT over very short time horizons.

I. Arrowhead, New LOB Liquidity Measures, and Hypothesis Development

A. Arrowhead low latency trading system

On January 4, 2010, the TSE launched a new, high-tech trading platform called "Arrowhead," that cost about $142 million. A number of studies focusing on multimarket trading, expected returns, minimum trading unit, price limits and liquidity for Japanese stocks were published before the introduction Arrowhead when the Tokyo Stock Exchange (TSE) used to have a provision for warning quotes and delayed trading (Hamao, Masulis and Ng, 1990; Chan, Hamao and Lakonishok, 1991; Lehmann and Modest, 1994; Bremer, Hiraki, and Sweeney, 1997). Ahn, Hamao and Ho (2002) analyze liquidity dynamics after the removal of warning quote system on August 24, 1998 on TSE and decompose the components of bid-ask spreads only at the top of the LOB. Hamao and Hasbrouck (1995) advance the literature further by analyzing trade executions beyond the best bid and offer and concluding that non-execution risk is very low on the TSE despite the absence of market makers and reliance on public limit orders to supply liquidity.

With the new low latency Arrowhead trading platform, the Tokyo Stock Exchange has eliminated the matching cycle delay, executes orders immediately, and instantaneously updates the limit order book, rendering computerized trading strategies more powerful (Uno and Shibata, 2011). Now the TSE can process trades in two milliseconds (time elapsed between order placement and order execution), which is 1,500 times faster than the three to six seconds it used to take under their previous trading system; the new speed is roughly the same as that of NYSE and LSE according to the TSE factbook.[6] The new system was introduced to attract investors who depend on sophisticated software to make split-second trades. The new trading platform

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

also helps the TSE stay ahead of the growing number of rival proprietary trading systems (PTSs), such as Kabu.com and SBI Japannext.[7] One of the goals of our paper is to understand the liquidity dynamics and market quality in the modern trading era induced by the Arrowhead trading system and other changes on TSE described above.

Gomber and Gsell (2006, p.541) define high frequency trading as a technology that "emulates a broker's core competence of slicing a big order into a multiplicity of smaller orders and of timing these orders to minimize market impact via electronic means." Hence, not only speed of execution, but also the availability of real-time market data and minimum latency has become key success factors as milliseconds can make a difference in the quality of execution. Hasbrouck and Saar (2011) finds that traders chase market prices or search for latent liquidity. The authors argue that these dynamic trading strategies have arisen from a combination of factors that includes improved technology, an active trading culture, and an increasing utilization of latent liquidity. It is evident that the speed of trading influences the relationship between the liquidity and the key market quality parameters. TSE's launch of Arrowhead provides a natural experiment to test the effect of high frequency trading on market quality and to analyze its impact on the evolution of future trade price, speed of trading, quotes to trade ratio, price volatility, autocorrelation, and cross correlation.

B. LOB liquidity measures

Kyle (1985) 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

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

resiliency,'' (p. 1316). We capture these notions with two new comprehensive LOB liquidity measures that characterize the entire supply schedule in HFT environment: LOB Slope and COI. LOB Slope can predict resiliency of the full limit order book and COI relates to the tightness and depth of the limit order book that is relevant to traders desiring to immediately execute large quantities.

B1. LOB Slope

LOB Slope captures the elasticity of liquidity supply in a LOB and hence, changes in LOB Slope 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:

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

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 with a limit price p_τ. These 2 slope measures are calculated at the end of each minute. LOB Slope is calculated as the average of *BIDSLOPE* and *ASKSLOPE.* The steeper LOB Slope indicates liquid markets because large quantities can be traded with very little price impact.

B2. Cost of Immediacy or COI: A comprehensive measure of LOB liquidity

Apart from the resiliency of liquidity supply, the other main dimensions of LOB liquidity that affect the cost of immediacy are LOB's tightness and depth. COI reflects these concepts and captures the round trip cost of trading 1% of daily volume by walking up or down the LOB, as necessary. The further the market orders walk, the larger the difference between the execution price and the mid-quote, and, therefore, the higher the COI (Irvine, Benston, and Kandel, 2000).

We estimate the COI separately on the buy and the sell sides of the LOB for each stock at the end of each minute as follows. Let *T* be the total number of shares to be bought or sold. We denote the j^{th} best bid (ask) price as P_j^{Sell} (P_j^{Buy}) and the j^{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 to be bought at each price point *k* and I_k^{Sell} is defined analogously.

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

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

where *K* is the number of price steps, I_k^{Buy} (I_k^{Sell}) is the volume executed at the k^{th} price step with limit price p_k.

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

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

Note that following Kang and Yeo (2008), the COI measures shown above are scaled by the stock's mid-quote to enable cross-sectional and panel data comparisons. COI, that measures round trip trading cost, is calculated as the sum of *ASKCOI* and *BIDCOI.* 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 merely to the second step. Hence, the COI is higher for stock L as compared to stock H. A deep LOB can absorb a sudden surge in the demand for liquidity with minimal price impact. Hence, lower COI represents a more liquid market.[8] Also, higher LOB Slope represents a more liquid market.

For simplicity, the hypotheses for various market quality parameters in the remainder of this section are stated with respect to COI. We note that the predictions for the relation of the market quality parameters with respect to LOB Slope have the opposite signs because COI has an inverse relation with liquidity supply whereas LOB Slope has a direct relation with liquidity supply.

C. Impact of Arrowhead on LOB liquidity in terms of COI and Slope

Theoretical models on the liquidity provisions of a limit order book offer ambiguous predictions regarding the impact of increased speed of trading. Foucault, Röell, and Sandås's (2003) theoretical model show 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

[8] Trades matched and executed within each minute are not part of the LOB, but 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 average trade size (ATS) and number of trades (NTRD) 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.

(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, Baruch (2005) and Boehmer, Saar and Yu (2005) suggest that the increased transparency and 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. Further, Foucault, Kadan and Kandel (2005) show that the faster order arrival rates reduce the expected waiting time for the orders in the LOB, and, hence, the liquidity suppliers require less compensation per unit of time for supplying liquidity in faster markets which should result in lower spreads. Most of the existing literature compares speed across market structures (Battalio, Hatch, and Jennings, 2003; Boehmer, 2005). However, it is difficult to control for all differences across markets. The effect of changing speed within a market is an important and understudied area (Hendershott and Moulton, 2011). Introduction of Arrowhead provides a natural experiment to test the predictions of the theoretical models of high frequency trading for LOB liquidity in terms of COI and SLOPE. Using Stoll's (2000) model, we test the following hypothesis:

Hypothesis 1. Arrowhead reduces COI and increases SLOPE.

D. Liquidity and future trade price location: Informativeness of the LOB Slope and COI before and after Arrowhead

In the traditional price discovery literature, limit orders are generally viewed as passive orders that supply liquidity whereas market orders are viewed as aggressive informed orders that demand liquidity (Glosten and Milgrom, 1985; Glosten, 1994; Seppi, 1997, Parlour, 1998). However, a strategic analysis of order submission choices has led many researchers such as Kaniel and Liu (2006) and Bloomfield, O'Hara, and Saar (2005) to develop theoretical models and laboratory experiments that predict the use of limit orders by informed traders possessing long-lived information. Harris and Hasbrouck (1996) limit orders placed at the top of the book or inside the NBBO quotes have better returns compared to market orders. Biais, Hillion, and Spatt (1995), Ellul, Holdings, Jain and Jennings (2007), and Chakravarty, Jain, Upson, and Wood (2012) indicate that aggressive liquidity demanders react to the dynamics of informed liquidity supply and hammer the shallower side of the book to sweep the available liquidity ahead of other market participants. Such follow-on order strategies arise more frequently in high-frequency markets from order splitting, herding or imitating behavior, and commonality in analysis of news and information. These strategies imply that higher liquidity on the ask side or lower *ASKCOI* (meaning a high density of sell orders in LOB) attracts further selling, much of which could be in form of aggressive market sell orders.[9] Such orders increase the proportion of sell trades that are executed at bid prices. Conversely, higher *ASKCOI* reduce the proportion of trades' occurring at the bid. Extending the argument to the opposite side of the book, higher *BIDCOI* increases the proportion of trades' occurring at the bid. In Figure 1, Stock L has higher *BIDCOI* than *ASKCOI* while Stock H has lower *BIDCOI* than *ASKCOI*, which suggests that Stock L will have higher proportions of trades executed at the bid price due to follow-on strategies while Stock H will have lower proportions of trades executed at the bid price.

The use of follow-on strategies is further facilitated through high frequency trading systems. Baruch (2005), Foucault, Kadan and Kandel (2005), and Boehmer, Saar and Yu (2005) suggest that the increased transparency and higher speed of trading can increase the competition among traders and lower the trading spreads. Thus, we expect that the traders become even more responsive to LOB's shape with high frequency trading:

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[9] The use of a market sell order in this example increase the probability of order execution. When there are already a large number of limit sell orders in the LOB, a new limit sell order would have to stand behind the queue with a lower execution probability.

Hypothesis 2. Lower *ASKCOI* or higher *BIDCOI* leads to a larger proportion of trades executed at the bid price with high frequency trading systems like Arrowhead.

A natural experiment to test this hypothesis occurred on January 4, 2010, when the TSE launched a new, high-tech trading platform called "Arrowhead." The TSE can process trades in two milliseconds, 1,500 times faster than their previous trading system and roughly the same speed as the NYSE. We create a dummy variable for Arrowhead, *ARROW*, and interact it with the *ASKCOI* and *BIDCOI* measures to assess their effect on proportion of trades occurring at the bid in the high frequency trading environment.

An immediate implication of the Hypothesis 1 is that repeated executions and liquidity depletion on a given side of LOB changes the shape of the LOB and gives rise to imbalances. Prices must then change to restore a balanced LOB equilibrium. Several studies have shown that bid and ask prices and LOB imbalances at the top of the book contain relevant information about future trade locations and price changes (Huang and Stoll, 1994; Engle and Patton, 2004; Kalay and Wohl, 2002; Harris and Panchapagesan, 2005; Frino, Jarnecic, and McInish, 2005; Cao, Hansch, and Wang, 2009).[10] However, the top of the LOB is just the tip of the iceberg (Aitken, Almeida, Harris and McInish, 2007) in HFT environment. We test the theoretical predictions by Rosu (2009) that higher liquidity or lower *ASKCOI* (*BIDCOI*) motivates sellers (buyers) to submit more aggressive orders (fleeting orders) on that side of the market, resulting in a decrease (increase) in trade prices. In Figure 1, Stock L has higher *BIDCOI* and lower ASKCOI which suggests that Stock L will attract more aggressive sell orders resulting in price decline. While

[10]Cao, Hansch, and Wang, (2009) consider the quotes beyond the best bid-ask quotes, but their analysis is based on the asymmetry between the total quantity supplied irrespective of the price steps and their scope is limited to price prediction unlike our comprehensive analysis of the evolution of the entire LOB including several measures of price discovery. We also consider a richer characterization of the LOB by looking at the interaction between the quantity and the price of the liquidity supplied.

Stock H has higher *ASKCOI* and lower BIDCOI which will attract more aggressive buy orders, resulting in price increase. Specifically, we test the following hypothesis:

Hypothesis 3. Lower *ASKCOI* leads to lower future trade prices in HFT systems. Lower *BIDCOI* leads to higher future trade prices.

Our newer comprehensive LOB liquidity measures allow us to capture the entire liquidity supply schedule on each side of the market (bid and ask). Also, TSE's order level dataset enables us to accurately classify trade initiator's direction as buy versus sell without having to rely on any inference mechanisms. This feature is essential to correctly test the existence of follow-on strategies that are hard to detect in conventional datasets like TAQ.

E. Liquidity-volatility relation before and after Arrowhead

Aggressive liquidity provision by HFT on both sides of the market dampens the short-term price volatility, at least under normal market conditions.[11] Hence, increased HFT after the introduction of Arrowhead should reduce COI and thereby, reduce short-term volatility. Understanding lower COI as the main conduit for volatility reduction is important to resolve the debate about the volatility increasing versus volatility dampening effects of HFT. For e.g. Hendershott, Jones, and Menkveld (2011) and Hendershott and Moulton (2011) find that HFT increases COI and, thereby, leads to a significant increase in volatility whereas Brogaard (2010) and Hasbrouck and Saar (2011) argue that HFT enables aggressively competitive electronic liquidity provision at a much lower cost than that of traditional market makers and, therefore dampens short-term volatility.

[11]The HFTs are not subject to the affirmative obligations that bound formally designated market makers. As a result, during extremely rare episodes, HFTs can simply step away from the market, leaving the markets extremely volatile as was observed during the "flash crash" of May, 2011 (Cartea and Penalva, 2011; Jarrow and Protter, 2011).

Foucault, Moinas, and Theissen (2007) develop a theoretical model for a LOB market where traders differ in terms of their private information about future return volatility. According to the model, the LOB is a conduit for volatility information because of the option-like features of limit orders.[12] As the value of options depends on volatility, traders should incorporate volatility information in their limit order submissions. In particular, Foucault, Moinas, and Theissen (2007) document that it is optimal for informed liquidity providers with private information about volatility to trade less aggressively if volatility is expected to increase. Hence, this future higher volatility information is expected to create gaps in LOB resulting in gentler slope and higher COI for liquidity demanders in periods preceding increased volatility. Hasbrouck (1999), Rahman, Lee and Ang (2002), Ahn, Bae and Chan (2001) and Naes and Skjeltorp (2006) find a positive relation between transaction cost at the top of the book and short-term volatility in the US, Hong Kong and Norway markets, respectively. Also, most of the above studies have drawn their conclusions by studying hybrid markets where the specialist or designated market maker are obligated to lower short-term volatility by acting as a counterparty. However, no one has tested this relation for Japanese markets which is a pure LOB and where the introduction of Arrowhead HFT system lowers transactions cost by giving liquidity providers an opportunity to balance their inventory more quickly.

Lower *COI* leads to lower future return volatility as shown in figure 1. Stock H has lower *COI* as compared to Stock L. Hence, Stock H can accommodate increased liquidity demand without significantly affecting the prices, resulting in price smoothing and lower volatility. Since, Arrowhead lowers COI, it is associated with lower short-term volatility:

Hypothesis 4. Arrowhead reduces COI and. thereby, dampens stock return volatility.

[12] Placing a limit buy (sell) order can be viewed as writing a free out-of-money put (call) option (Copeland and Galai, 1983).

F. Liquidity and correlation in order flow before and after Arrowhead

F.1. Autocorrelation

Autocorrelation and cross correlation in order flow are important measures of the market efficiency (McKenzie and Faff, 2003; Chen, Su and Huang, 2008). 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; Hasbrouck and Saar (2011) suggest that HFT strengthens this pattern creating negative serial correlation in order flow. In contrast, Biais, Hillion and Spatt (1995) suggest that traders may herd or might split large orders or traders 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. HFT can also strengthen this pattern by facilitating automated order splitting and copycat strategies as well as by lowering COI. Going back to figure 1, Stock H has lower *COI* and can accommodate the order slicing activity of the informed investors, resulting in higher autocorrelation.

Hypothesis 5. Arrowhead lowers *COI* or improves liquidity leading to higher autocorrelation in the order flow.

F.2. Fleeting orders

In general, impatient traders submit market orders, while patient traders submit limit orders except when the limit order book is “full.” When the LOB is not full, new limit orders are mostly placed inside the bid-ask spread. Rosu (2009) proposes that when the LOB is full, traders play a “game of attrition.” During these times some patient trader either places a market order, or submits a quick (fleeting) limit order, which some trader from the other side of the book immediately accepts. Simply stated, the bottom seller places a limit order at a lower price than the prevailing best ask price, and the top buyer immediately accepts the offer by placing a market order. Faster markets should facilitate these fleeting orders. We present the first test of Rosu's theory of attrition by analyzing the following hypothesis:

Hypothesis 6. Arrowhead lowers *COI* or improves liquidity, leading to increase in fleeting orders.

F.3. Cross correlation

On the one hand, for informationally-unrelated stocks, Baker and Wurgler (2006) argue that sentiments drive investors' propensity to speculate and that when markets are liquid this propensity to speculate in individual stocks is very high. Hence, if investors' private signal about a stock does not contain a market-wide component, stocks' cross correlations in general with the overall market will be lower with rapid trading. On the other hand, high COI based illiquid environment will discourage idiosyncratic information production and stocks will tend to move in tandem with the broad market. Furthermore, literature also documents the existence of commonality or positive correlation in returns and liquidity of informationally-related securities (Chordia, Roll, and Subrahmanyam, 2000; Hasbrouck and Seppi, 2001; Caballe and Krishnan, 1994). Arrowhead facilitated high frequency program trading increases the cross-correlation among securities by making it easier to rapidly trade baskets of securities. Using the order level data from TSE, we test these competing effects:

Hypothesis 7. Arrowhead lowers *COI*, which can increase cross-correlation due to program trading

G. Liquidity supply and frequency of trading

Empirical studies have delivered opposing views on the relation between liquidity supply and frequency of trading, which captures liquidity demand. Biais, Hillion, and Spatt (1995), Griffiths, Smith, Turnbull, and White (2000), Ranaldo (2004), Boehmer (2005), and Ellul, Holdings, Jain and Jennings (2007) find an inverse relationship between execution speed and top of the book bid-ask spreads whereas Hendershott and Moulton (2011) find a positive relation between high frequency trading and cost of immediacy. This confusion could result from a failure to consider liquidity beyond the best quotes (Aitken, Almeida, Harris, and McInish, 2007). Furthermore, there is a bi-directional relation between cost of trading and trading frequency. We not only examine the impact of *COI* on trade frequency and quotes to trade ratio but also test the impact of high frequency trading on *COI* in the context of Arrowhead, an exogenous event. Rosu (2009) argues that when the markets are liquid, the traders on both sides (ask and bid) play a game of attrition. In his theoretical model he shows that the bottom seller places a limit order at some lower price (below the existing best quote), and the top buyer immediately accepts the offer by placing a market order. Rosu (2009) calls these orders as fleeting orders and predicts that when the LOB is deep, traders may submit quick, or fleeting, limit orders. When the LOB is deep, the cost of walking down/up the LOB is lower. Thus, we expect faster trading to follow a deeper book. HFT should exacerbate this game of attrition leading to higher quotes to trade ratio and greater speed of trading. Figure 1 show that Stock H has lower *COI* as compared to Stock L, reflecting the lower cost of walking up or down the LOB. Hence, Stock H should attract more aggressive limit orders increasing the frequency or speed of trading. Also, as suggested by Rosu (2009) and Hasbrouck and Saar (2011), an increase in HFT activity should increase the quote revisions and cancellations frequencies resulting in higher quotes to trade ratio. Understanding this aspect of trading is critical, especially due to increasing popularity of algorithmic trading (Hendershot, Jones and Menkveld, 2011). Using the available liquidity supply schedule of the entire LOB, we test the following hypotheses:

Hypothesis 8 Lower *COI* leads to higher speed of trading and higher quotes to trade ratio. HFT further increases speed of trading and generate higher quotes to trade ratio.

II. Data sources and Sample Formation

Our sample includes the data on the intra-day price and the number of shares for every trade and the five best bid and ask quotes along with the associated depth for all the TOPIX index companies listed on the first section of the TSE.[13] Our main sample period includes 3 full calendar months: the pre-financial-crisis period of June 2008, the post-financial-crisis period of January 2009, and the post-Arrowhead period of January 2011.[14] We obtain these data from the Nikkei Digital Media Inc.'s Nikkei Economic Electronic Database Systems (NEEDS) database. 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 a minimum trading unit that depends on the stock's price. To smooth the price movements, TSE also sets price limits that vary with stock prices.[15] Historically, TSE had provisions for warning quotes, which are automated non-tradable indicative quotes placed by the exchange to smooth the price movements. These frequent warning quotes were abandoned on August 24, 1998. TSE also has provisions for Special quotes which arise in situations similar to those that trigger a

[13]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).

[14] 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.

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

warning quote but with multiple orders on the active side of the LOB.[16] To account for these special quotes we calculate COI and LOB Slope with and without these special quotes and test our results. We incorporate these special features of TSE in our main analysis as well as conduct several robustness tests to ensure that our results can be generalized beyond the TSE. Since, there are no hidden orders on the TSE, trades can only occur at the bid or ask, which allows for cleaner predictions.[17] The dataset also includes data from the pre-trading and post-trading periods outside the regular business hours; we remove those observations from our final sample. We eliminate less than 1% of the observation in our sample to eliminate potential data errors such as trades with zero prices or zero volume, quotes with bid greater than ask, and limit orders with zero limit price. We separately analyze the stocks in the three market capitalization and liquidity based TOPIX sub-indices. The largest 100 stocks are in the TOPIX 100 Index, the next 400 medium capitalization stocks are in the TOPIX Mid 400 Index, and the remaining 1,068 small capitalization stocks belonging to the first-section of TSE are in the TOPIX Small Index.

Keeping in mind the different 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 Naes and Skejltorp (2006) to compute the proportion of stocks for which the coefficients are significant and also follow Ellul, Holden, Jain, Jennings (2007) to use a test of proportions to access the statistical significance of the averaged coefficients. 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. We also eliminate firms

[16] See Hamao and Hasbrouck (1995) for details about the warning quotes and special quotes.
[17] 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).

whose price changed sufficiently to move from one tick size category to another. Then we select 150 stocks, top 50 from each TOPIX 100 Index, TOPIX MID 400 Index, and TOPIX Small Index, for the post-crisis and post-Arrowhead analyses.

III. Results

A. Descriptive statistics from the benchmark period before the crisis and Arrowhead

Table 1 provides summary statistics for our sample of 1,557 stocks for June 2008, the normal period before the recent financial crisis. We use these statistics as a benchmark to assess any changes in January 2009 resulting from the crisis and in January 2011due to the reduction in latency after the introduction of Arrowhead.[18] We present the results for the whole sample and also for large-, mid- and small-cap stocks separately. *MKTCAP*, the average market capitalization in billion JPY, is 223.37 for the entire sample, 33.18 for the small-cap firms and 2,179 for the large-cap firms. The *MONTHLY VOLUME* for large-cap firms is 143.72 million shares per stock, which is about 3 times the *MONTHLY VOLUME* for the medium-cap firms and almost 16 times the *MONTHLY VOLUME* for the small-cap firms. The minute by minute stock *RETURN*, as measured by the log change in the quote midpoints, is -0.0005%. We find that the proportion of orders executed at the bid price, *BIDPROP*, is about 50%, with the other 50% of the trades executed at the ask price, implying almost an overall symmetric distribution between buy and sell trades. Nonetheless, we later find that the proportion varies significantly depending on COI and the overall shape of the LOB. For each firm, at the end of each minute of trading, we calculate volatility (*VOLATILITY)*, defined as the absolute value of return residual from the equation shown in the header for Table 1. Mean *VOLATILITY* for the sample stocks is 0.13% per minute. Small firms are, on average, more volatile than large or medium firms.

[18] 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.

Minute-by-minute autocorrelation, *AUTO CORR*, is on average, positive 0.07 and decreases with size. *CROSS CORR*, measures how the order flow on a stock co-varies with the order flow on the other stocks in the overall stock market during each minute of trading, where the order flow of the other stocks is proxied by the order flow of TOPIX exchange traded fund[19]. We find that *CROSS CORR* is on average, positive 0.02 for the stocks under investigation.

The mean $ASKCOI_{i,t}$ and $BIDCOI_{i,t}$ are 34.47 and 34.03 basis points respectively. $COI_{i,t}$ is the sum of $ASKCOI_{i,t}$ and $BIDCOI_{i,t}$ and can be viewed as the round trip cost of immediacy for trading 1% of the average daily volume. The mean *COI* of 68.50 basis points indicates that it costs market-order traders (impatient traders) 0.69% more to buy and sell 1% of the stock's average daily trading volume than the cost of trading the same amount at the quote midpoint. The *COI* is highest for small-cap stocks, and, hence, we conclude that these stocks are less liquid.

The mean $ASKSLOPE_{i,t}$ and $BIDSLOPE_{i,t}$ are 12.37 and 12.39, respectively. Unlike COIs, SLOPEs on bid and ask side are not additive. The mean LOB $\mathrm{Slope}_{i,t}$, which is the average of $ASKSLOPE_{i,t}$ and $BIDSLOPE_{i,t}$, of 12.38 indicates that 12.38% more volume is supplied for every change in the price step of the LOB. The steeper the *SLOPE*, the higher is the liquidity. The mean LOB Slope of 25.57 for large-cap stocks is more than two times the mean LOB Slope of 8.89 for the small-cap stocks.

The bid-ask spread is lower for large-cap stocks and increases as the firm size decreases, while the depth at the best quotes is highest for large-cap stocks and declines with the firm size. The proportionate spread, *SPREAD*, is 0.56% for the overall sample and ranges from 0.19% for large stocks to 0.69% for small stocks. Note that a trader executing a large order equal to 1% of daily volume in a large cap stock has to actually pay 0.41% COI which is more than twice the

[19] The TOPIX exchange traded fund (Local code: 1306) is managed by Nomura Asset Management.

0.19% spread at the top of the book. The average depth at the best quotes, *DEPTH*, is 22,320 stocks.

Number of trades per minute, *NTRDS*, on the TSE is 2.91 in this benchmark period before Arrowhead. Large-cap stocks trade 5.09 times each minute while mid- and small-cap stocks trade 3.08 and 2.26 times each minute, respectively, before the launch of Arrowhead. The maximum and 95th percentile for large-cap stocks and the maximum and 99th percentile for mid-cap stocks is 18 trades per minute, whereas the older trading system took more than 3 seconds to processing orders from submission to execution according to TSE. This distribution indicates that the desire of traders for an even higher trade frequency for large- and mid-cap stocks could be truncated by the limits of the older system. Hence, the speed limit of older trading system could be more binding for large- and mid-cap stocks. This low order processing speed limited the ability of sophisticated traders to slice their larger orders into multiple smaller orders and implement other trade execution strategies for better quality of execution. Average trade size (*ATS*) is 2,583 shares per trade.[20] *ATS* is higher for large firms than for medium or small firms. Since there are no hidden orders on the TSE, we can precisely observe the number of times the quotes are updated during each minute and, hence, accurately measure the *QUOTES TO TRADE RATIO*. We find that the *QUOTES TO TRADE RATIO* is on average 4.78 per minute for the full sample suggesting that the number of quote revisions is about 5 times the number of executed trades. *QUOTES TO TRADE RATIO*$_i$ is much lower for smaller firms as compared to large- and mid-cap stocks.[21] .

[20] The mean ATS seemed to be larger for TSE as compared to the US markets. A further analysis reveal that this is due to the presence of minimum trading units on TSE, which results in a round lot of 1,000 shares for a majority trades on TSE. We find that median ATS is 1,000 while the 95th percentile, 99th percentile and the maximum for ATS are 9000, 26667, and 5821000, respectively.

[21] We find that the frequency of quote updates is much higher for large-cap firms (28.10 times per minute) than small-cap firms (9.04 times per minute) which suggests that the 3 second latency for the older trading system was a

B. Liquidity effects of the Arrowhead low latency trading platform

Table 2 reports the descriptive statistics for the post crisis and the post Arrowhead periods. Consistent with Hendershott, Jones, and Menkveld (2011), we find that Arrowhead increased trading volume (*MONTHLY VOLUME*) by 6% from 93 million shares per stock per month to 99 million shares for the entire sample. The increase is much higher compared to the benchmark volume of 25 million shares in Table 1, which suggest that crisis also induced an increase in trading volume. The *MONTHLY VOLUME* for large-cap firms increased dramatically; after Arrowhead it is almost 13% higher relative to the period preceding Arrowhead in Table 2 and over 65% higher relative to the pre-crisis benchmark period in Table 1. However, the *MONTHLY VOLUME* for mid- and small-cap firms declined after Arrowhead relative to the benchmark volume before Arrowhead in Table 2 or Table 1. The opposite results of a volume increase for large cap stocks and a volume decrease for small cap stocks once again suggests that the Arrowhead system relaxed the speed limit that was binding mainly for the large capitalization stocks.

We also find that volatility declined significantly to 0.06% for all firms relative to the pre-crisis and pre-Arrowhead benchmarks of 0.14% and 0.13%, respectively. Volatility declined from 0.13% to 0.02% for the large-cap stocks. Hence, as shown by Baruch (2005) and Boehmer, Saar, and Yu (2005), higher speed of trading and greater transparency result in higher competition among liquidity suppliers at various price points that, in turn, results in price smoothing or a decline in volatility.

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binding constraint for large cap stocks. Thus, Arrowhead should have a meaningful impact on the trading in large cap stocks.

The mean autocorrelation (*AUTO CORR)* and cross correlation (*CROSS CORR*) in order flow has increased for a majority of the sample firms during the post-Arrowhead period. However, the effect of Arrowhead in more pronounced for the large- and mid-cap stocks.

We find that *COI* declined for more than 50% for all the sample firms during the post-Arrowhead period, which supports Rosu's (2009) and Foucault, Kadan, and Kandel's (2005) predictions that faster arrival rates reduce the expected waiting time for orders in the queue so that limit orders require lower compensation for waiting. Lower COI reflects this reduction in costs of supplying liquidity. We also find that the LOB Slope (*SLOPE*) has increased significantly in 2009-2011 compared its level in 2008, for the large- and mid-cap firms. These results indicate an overall increase in liquidity supplied by the LOB during the post Arrowhead period.

The average number of trades (*NTRDS*) in the one-minute period increased by more than 50% from 7.34 trades per minute to 11.15 trades per minute during the post-Arrowhead period. The results from Table 1 we find that *NTRDS* increased by almost 5 times from the pre-crisis period. We also find that the average trade size (*ATS*) declined substantially, which is why the total volume did not rise as dramatically. These results suggest a significant increase in the sophisticated order slicing on the TSE post Arrowhead supporting the findings in Hendershott, Jones, and Menkveld (2011, figure 4). We also find that *QUOTES TO TRADE RATIO* and *TRADESPEED* (inverse of the average time between trades per minute of trading) has increased significantly during the post-Arrowhead period. This increase in trading speed is much more pronounced in the large-cap stocks.

Thus, the Arrowhead system has a significant impact on liquidity, especially for large-cap stocks. The reduction in COI is particularly notable and beneficial to investors. In the following sections, we examine how COI and LOB Slope are related to market quality before and after Arrowhead.

C. Impact of Arrowhead on COI and SLOPE

Figure 2, Panels A and B, plots five-minute averages for minute-by-minute COI and SLOPE. We observe the standard U-shape pattern for intraday COI and SLOPE. We also find that Arrowhead has significantly improved the LOB liquidity by reducing the COI and increasing the SLOPE. 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 $COI_{i,t}$ is the sum of $ASKCOI_{i,t}$ and $BIDCOI_{i,t}$ and can be viewed as the round trip cost of immediacy for trading 1% of the average daily volume. $SLOPE_{i,t}$ is the average of slope for the five best bids and five best asks. *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 end of minute trading price, $LOG\ NTRDS_{i,t}$ 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, $LOG\ VOLUME_{i,t}$ 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 3 summarizes the results from the estimation of stock-by-stock regressions using high frequency, minute-by-minute data. *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. Panel B shows that SLOPE has significantly increased during the post-Arrowhead period. Overall, our results support the theoretical predictions of Foucault, Kadan and Kandel (2005) and Boehmer, Saar and Yu (2005) and are consistent with our Hypothesis 1. HFT increases competition among traders resulting in tightening of the LOB. This reduces COI and increases SLOPE.

D. Predicting the future trade price location

Figure 3, Panel A, shows a negative relationship between LOB liquidity imbalance (*ASKCOI* minus *BIDCOI*) and the future proportion of sell trades executed at bid prices. We formally test the relation between various LOB liquidity measures and future trade price by estimating the following regression model:

$$\%BID_{i,t+1} = \alpha_i + \beta_{1i} ASKCOI_{it-j} + \beta_{2i}\, BIDCOI_{it-j} + \beta_{3i}\, MONDAY_{t+1} + \beta_{4i}\, SPREAD_{i,t-j} + \beta_{5i}\, DEPTH_{i,t-j} + \beta_{6i}\, VOLATILITY_{i,t-j} + \beta_{7i}\, VOLUME_{i,t-j} + \beta_{8i}\, MKTRET_{i,t-j} + \mu_{i,t} \quad (6a)$$

where $\%BID_{i,t+1}$ is the proportion of orders executed at the bid price. $ASKCOI_{i,t}$ is the cost that liquidity demanders incur to buy 1% of the daily average trading volume. $BIDCOI_{i,t}$ is the cost that liquidity demanders incur to sell 1% of the daily average trading volume. We also define bid and ask liquidity using elasticity based measures that are calculated in terms of *BIDSLOPE* (*ASKSLOPE*), which is the slope for the five best bids (asks). Several control variables are included to capture potential information accumulation or differences in opinion (Harris and Raviv, 1993) and relative pessimism in market sentiment (wider spreads, lower depth, higher volatility or volume, and negative market return) that could result in a greater proportion of sells occurring at the bid prices. $MONDAY_{t+1}$ is a dummy variable that equals 1 for Mondays to capture information accumulation over the weekend (French, 1980; Foster and Viswanathan, 1990), and 0 otherwise. $SPREAD_{i,t}$ is the proportionate spread and $DEPTH_{i,t}$ is the average depth at the best bid and best ask quotes (Hasbrouck, 1999). $VOLATILITY_{i,t}$ is the absolute value of the return, conditional on its own 12 lags and day-of-week dummies. $VOLUME_{i,t}$ is the average trading volume each minute. $MKTRET_{\mathrm{i,t}}$ is the return on the market as measured by return on the TSE exchange traded fund. α and β are parameters to be estimated and $\mu_{i,t+1}$ 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.

We also estimate an alternative regression specification where the dependent variable is the signed change in the future trade price, ΔPRI:

$$\Delta PRI_{\,i,t+1} = \alpha_i + \beta_{1i} ASKCOI_{it\text{-}j} + \beta_{2i}\, BIDCOI_{it\text{-}j} + \beta_{3i}\, MONDAY_{t+1} + \beta_{4i}\, SPREAD_{i,t\text{-}j} + \beta_{5i}\, DEPTH_{i,t\text{-}j} + \beta_{6i}\, VOLATILITY_{i,t\text{-}j} + \beta_{7i}\, VOLUME_{i,t\text{-}j} + \beta_{8i}\, MKTRET_{i,t\text{-}j} + \mu_{i,t} \qquad (6b)$$

Table 4, Panels A and C, summarize the results using the cost-based COI measures and Table 4, Panel B and D, present similar results for the elasticity-based SLOPE measures. In

Table 4, Panel A, we find a statistically significantly negative (positive) relationship between *ASKCOI* (*BIDCOI*) and the future proportion of sell trades executed at bid prices. As the *ASKCOI* increases, reflecting lower liquidity on the ask side of LOB, the proportion of additional sell orders executed at the bid prices goes down significantly in the standalone COI regression model in column (1) as well as the full model including all control variables in column (2). The standardized coefficient of -2.89 is the average for all stock-by-stock regressions, with 96% of the coefficients being significant and 85% of those having a negative sign as shown in column (3). Conversely, higher liquidity on the bid side or lower *BIDCOI* reduces the proportion of sell trades. However, the predictive power of COI is short lived for one minute and is not significant for longer time intervals. Results shown in Table 4, Panel A, column (4) for the 2nd minute are insignificant and the numbers for the following 30 minutes, not reported, are also insignificant. The results are consistent across different size based portfolios (Table 4, Panel A, columns (5) through (7)). The inverse relation between *ASKCOI* and the proportion of trades executed at the bid is evidence supporting our Hypothesis 1. Our results reject Parlour's (1998) liquidity replenishment predictions in the shorter time period. Instead, the results are consistent with the findings in Biais, Hillion and Spatt (1995) and Ellul, Holdings, Jain and Jennings (2007) that deep LOB or lower *COI* on ask- (bid-) side of LOB is followed by sell (buy) market orders, increasing (decreasing) the proportion of trades executed at the bid prices.

As a follow up analysis, we analyze the impact of changes in *COI* on future trade price movements. Results are summarized in Table 4, Panel A, columns (8) though (11). We find that the lower *ASKCOI* (*BIDCOI*) or higher liquidity on ask- (bid-) side leads to decrease (increase) in future trade prices at the end of the next 1 and 2 trading minutes. These results are consistent across different size based portfolios (Table 4, Panel A, columns (12) through (14)). Hence, lower *ASKCOI* increases the proportion of trades executed at the bid (or increases sell market orders), which induces a downward pressure on prices, resulting in a decrease in the future trade prices. Higher (lower) *ASKCOI* attracts buy (sell) market orders as traders become more aggressive to get their orders executed, resulting in a price increase (decline). The positive relation between *ASKCOI* and future trade price supports our Hypothesis 2 and is consistent with the finding in Cao, Hanch, and Wang (2009).

Results for *SLOPE*, reported in Table 4, Panel C, are qualitatively similar for large and medium capitalization stocks. The coefficients in Panel A are opposite in sign to those in Panel C because *COI* is an inverse measure of liquidity whereas *SLOPE* is a direct measure of liquidity. The *SLOPE* does not significantly predict the future trade location and price movements for the small-cap firms. Hence, the *COI* do a better job of explaining the future trade price location than the *SLOPE* for all three categories of stocks.

Table 4, Panels B and D summarize the results of the stock-by-stock regression analysis at the 1-minute frequency for the effect of Arrowhead on trade price location. The additional variables added to the model described by equation (6) are the dummy for Arrowhead, which takes the value of 1 for the post Arrowhead period and 0, otherwise, and the interaction terms between *ASKCOI*, *BIDCOI* and the Arrowhead dummy, and the interaction terms between *ASKSLOPE, BIDSLOPE* and the Arrowhead dummy.

Table 4, Panel B, reports a statistically significant negative (positive) coefficient of -4.32 (5.53) for *ASKCOI* (*BIDCOI*). These results are consistent with pre-crisis period findings reported in Table 4, Panel A. Lower *ASKCOI* (*BIDCOI*) attracts sell (buy) market orders as traders become more aggressive resulting in higher (lower) proportions of trades executed at the bid price. These results support our Hypotheses 1 for both, the post-crisis and the post-

Arrowhead periods and are consistent with the findings in Biais, Hillion, and Spatt (1995), and Ellul, Holdings, Jain and Jennings (2007).We also find a statistically significant and negative (positive) coefficient of -4.26 (3.59) for *ARROW*ASKCOI* (*ARROW*BIDCOI*) that suggests that Arrowhead has significantly improved the informativeness of *COI* for the future trade price location for a majority of sample stocks. A further analysis using the 3 size based portfolios shows that the effect of Arrowhead on the relation between *COI* and future trade price location is more pronounced for the large- and mid-cap firms.

Table 4, Panel D, reports results for a similar analysis using LOB SLOPE measures. We find a statistically significant positive (negative) coefficient of 3.90 (-4.01) for *ASKSLOPE* (*BIDSLOPE*). These results are consistent with pre-crisis period findings reported in Table 4, Panel C. Steeper *ASKSLOPE* (*BIDSLOPE*) attracts sell (buy) market orders as traders become more aggressive resulting in higher (lower) proportions of trades executed at the bid price. We find a statistically significant coefficient for *ASKSLOPE* (*BIDSLOPE*) for 92% (91%) of the sample stocks. Comparing these results with the ones for the benchmark period summarized in Table 4, Panel C, we find that informativeness of the LOB Slope measures significant improved during the post-crisis and the post-Arrowhead periods. During the benchmark period the coefficient for *ASKSLOPE* (*BIDSLOPE*) is statistically significant for 62% (60%) of the sample stocks. We also find a statistically significant and positive (negative) coefficient of 2.25 (2.12) for *ARROW* ASKSLOPE* (*ARROW* BIDSLOPE*) which suggests that Arrowhead has significantly improved the informativeness of LOB Slope for the future trade price location for a majority of sample stocks. A further analysis using the 3 size based portfolio reveals that the effect of Arrowhead on the relation between LOB Slope and future trade price location is consistent across the different size categories.

Table 4, Panel B, also reports the results for informativeness of *COI* for future trade price movements (columns 9 through 16). We find a statistically significant positive (negative) coefficient of 4.57 (-4.19) for *ASKCOI* (*BIDCOI*). These results are again consistent with pre-crisis period findings reported in Table 4, Panel A, supporting our Hypothesis 2, which states that lower *ASKCOI* (*BIDCOI*) attracts sell (buy) market orders as traders become more aggressive to get their orders executed first, exerting downward (upward) pressure on prices. We also find a statistically significant and positive (negative) coefficient of 2.23 (-3.05) for *ARROW*ASKCOI* (*ARROW*BIDCOI*) for large-cap firms that suggest that Arrowhead has significantly increased the sensitivity of future trade price movements to *COI* for a majority of the large-cap stocks. This result highlights the fact that high speed not only increases competition among liquidity providers in normal times, but also makes it easier for the liquidity suppliers to exit the market. Thus, after the introduction of Arrowhead, we have faster price increases (decreases) in lower (higher) *ASKCOI* environments. Table 4, Panel D, reports similar results for informativeness of LOB Slope for future trade price movements, which are qualitative similar to the COI results described above.

E. Liquidity-volatility relation: before and after Arrowhead

Figure 2, Panel B, shows that the *VOLATILITY* has declined during the post-Arrowhead period. We also observe the existence of well-established U-shape patterns (McInish and Wood, 1993) in VOLATILITY during both pre- and post-Arrowhead periods. Figure 3, Panel B, shows a positive relation between *COI* and future volatility. We test the relative informativeness of COI, LOB Slope, and other traditional liquidity measures in explaining future return volatility by estimating the following regression equation:

$$|\varepsilon_{i,t+1}| = \alpha_i + \beta_{1i} DISDT_{i,t} + \beta_{2i} SLOPE_{it} + \beta_{3i} COI_{i,t} + \beta_{4,m} MONDAY_{t+1} + \beta_{5i} NTRDS_{i,t} + \beta_{6i} ATS_{i,t} + \beta_{7i} SPREAD_{i,t} + \beta_{8i} DEPTH_{i,t} + \beta_{9i} HIGHSPEED_{i,t} + \beta_{10i} LOWSPEED_{i,t} + \beta_{11i} MKTRET_{i,t} + \sum_{j=0}^{11} \delta_{i,j} |\varepsilon_{i,t-j}| + \mu_{i,t+1} \quad (7)$$

where $|\varepsilon_{i,t+1}|$ is the future return volatility measured by absolute value of the return residual, conditional on its own 12 lags and day-of-week dummies following Schwertz (1989). $COI_{i,t}$ is the sum of $ASKCOI_{i,t}$ and $BIDCOI_{i,t}$ and can be viewed as the round trip cost of immediacy for trading 1% of the average daily volume. $SLOPE_{i,t}$ is the average of slope for the five best bids and five best asks. $DISDT_{i,t}$ is a measure dispersion of limit orders proposed by Kang and Yeo (2008) and describes the shape of the LOB in terms of how tightly clustered (liquid) or dispersed (illiquid) limit orders are in the LOB. During a liquid market, limit order traders compete with each other to gain price priority leading to a smaller *DISDT* measure. $NTRDS_{i,t}$ is the number of transactions, $ATS_{i,t}$ is the average trade size (Jones, Kaul and Lipson, 1994).We create two dummy variable to capture the effect of speed of trading on return volatility (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 75^{th} 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 25^{th} percentile value. Other control variables are defined in the previous sub-section.

Table 5, Panel A, summarizes the results from the estimation of stock-by-stock regressions using high frequency, minute-by-minute data. *COI's* positive coefficients of 6.55 in the standalone model (1) and 2.48 in the full regression model (4) indicate that higher COI is followed by higher future volatility and lower *COI* is followed by lower volatility. Steeper *SLOPE* also leads to lower future volatility. Column (5) summarizes the distribution of statistical significance in the stock by stock estimations. The coefficient of COI is significant for 78% of the sample stocks and 84% of the coefficients are positive.

Table 5, Panel A, column 6, reports the results from an alternative analysis using the GARCH(1,1) specification (summarized in the footnote 22) for return volatility and they are consistent with the results derived using the two stage OLS regressions.[22] Higher *COI* leads to higher future return volatility and lower *COI* is followed by lower future volatility. These results are consistent across the different size portfolios (Table 5, Panel B). The LOB Slope (measure of dispersion) is informative for future return volatility for about 60% (47%) of the sample stocks. Also, neither of these latter two measures is consistent across the different firm size portfolios (Table 5, Panel B). In general, measure of dispersion is a better predictor of future return volatility for small-cap stocks while *SLOPE* significantly predicts future return volatility for a majority of large- and mid-cap firms. Overall, the relation between *COI* and future volatility is the strongest of the three comprehensive LOB liquidity measures. Our results support Naes and Skjeltorp's (2006) findings for Norwegian stocks. Our results are consistent with our Hypothesis 3 (a) and the theoretical predictions of Foucault, Moinas, and Theissen (2007) that lower *COI* lowers future return volatility.

Table 5, Panel C, summarize the results for the effect of Arrowhead on return volatility and the relationship between *COI* and *SLOPE* and return volatility. A statistically significant and positive (negative) coefficient of 5.94 (-2.06) for *COI* (*SLOPE*) suggests that lower (steeper) *COI* (*SLOPE*), implying higher LOB liquidity, leads to lower future return volatility, which is consistent with the pre-crisis period results summarized in Table 5, Panel A, and with Hypothesis

[22]We have also used the following GARCH(1,1) specification for return volatility:

$$R_t = \sum_{k=1}^{5} \alpha_k D_k + \sum_{j=1}^{12} \beta_j R_{t-j} + \varepsilon_t$$

$$\sigma_t^2 = \alpha_0 + \beta_{1i} DISDT_{i,t} + \beta_{2i} SLOPE_{it} + \beta_{3i} COI_{i,t} + \beta_{4,m} M_{t+1} + \beta_{5i} NTRDS_{i,t} + \beta_{6i} ATS_{i,t} + \beta_{7i} SPREAD_{i,t} + \beta_{8i} DEPTH_{i,t} + \beta_{9i} HIGH\ SPEED_{i,t} + \beta_{10i} LOW\ SPEED_{i,t} + \beta_{11i} MKTRET_{i,t} + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \gamma \sigma_{t-1}^2$$

4. We find a statistically significant and negative coefficient of -0.47 for the dummy variable *ARROW* in the full sample, which shows that Arrowhead has reduced return volatility for a majority of the sample stocks. We note that the coefficients regarding the reduction in volatility due to Arrowhead are significant only for large- and mid-cap stocks. More importantly, based on the statistically insignificant coefficient for the interaction variable *ARROW*COI* (*ARROW*SLOPE*), we conclude that Arrowhead does not significantly impact the inverse relation between *COI* (*SLOPE*) and future return volatility.

F. Autocorrelation, Fleeting orders, and liquidity

Figure 3, Panel C, shows a negative relation between COI and future autocorrelation. We formally analyze this relation by estimating the following regression model:

$$AUTOCORR_{i,t+1} = \alpha_i + \beta_{1i}COI_{i,t} + \beta_{2i}SLOPE_{i,t} + \beta_{3i}\,NTRDS_{i,t} + \beta_{4i}\,ATS_{i,t} + \beta_{5i}\,SPREAD_{i,t} + \beta_{6i}\,DEPTH_{i,t}+\beta_{7i}\,HIGHSPEED_{i,t} +\beta_{8i}\,LOWSPEED_{i,t}+\beta_{9i}VOLATILITY_{i,t}+\beta_{10i}RETURN_{i,t} + \mu_{i,t+1} \quad (8)$$

where $AUTOCORR_{i,t+1}$ is the future trade-by-trade autocorrelation for stock *i* and minute *t+1*.[23] The remaining variables are as defined previously.

Based on the results summarized in Table 6, Panel A, we find that *COI* has a statistically significant negative coefficient of -0.44 in the future trade-by-trade autocorrelation (*AUTOCORR*) (Column (1)). Hence, the lower the *COI*, the higher is the stock's *AUTOCORR*. These results are consistent for a majority of large- and mid-cap stocks. We also find that the LOB Slope significantly positively predicts *AUTOCORR* for large-cap stocks. Thus both COI and slope regressions suggest a positive relation between LOB liquidity and *AUTOCORR*. Our results provide supportive evidence for our Hypothesis 5 and are consistent with the models of

[23] We also analyze order-by-order autocorrelation and get qualitatively similar results as those for trade-by-trade autocorrelation.

strategic trading that suggest that rational informed investors spread their trading over time to conceal information (see Kyle, 1985, and Barclay and Warner, 1993). Such stealth trading will lead to positive autocorrelation in highly liquid markets.

Table 6, Panel B, summarizes the results for the effect of Arrowhead on *AUTOCORR* and on the relationship between *COI* and *SLOPE* and *AUTOCORR*. We find a statistically significant and negative (positive) coefficient of -0.56 (0.31) for *COI* (*SLOPE*), which suggests that lower (steeper) *COI* (*SLOPE*) leads to high future *AUTOCORR*. These results are consistent with the pre-crisis period results summarized in Table 6, Panel A, and with Hypothesis 5. We also find that Arrowhead significantly increased *AUTOCORR* for a majority of large- and mid-cap stocks, as reflected by the positive and statistically significant coefficient of 1.12 for the *ARROWHEAD* dummy. Further, the statistically insignificant interaction term (ARROW*COI) suggests that Arrowhead has not altered the inverse relationship between *COI* and *AUTOCORR*. Hence, HFT facilitates automated order splitting and herding strategies resulting in higher autocorrelation.

Next, we test the “fleeting order” theory proposed by Rosu (2009) by analyzing the regression equation (8), where *AUTOCORR* is defined as the correlation between improvement in bid (or ask) quotes and location of next trade (at the bid or the ask). Table 6, Panel C summarizes the results from this analysis. We find a negative (positive) and statistically significant coefficient of -1.01 (1.76) for COI (SLOPE). This suggests that during highly liquid markets, when a trader improves the best bid (ask), the top trader on the ask (bid) side of the market quickly accepts the updated order by placing a market order to buy (sell). Hence, higher liquidity makes traders impatient resulting in higher fleeting orders. Further, we find a positive and statistically significant coefficient for ARROWHEAD suggesting that Arrowhead has increased such attrition behavior of LOB. We also find that Arrowhead has significantly improved the informativeness of COI (SLOPE) for fleeting orders as reflected by negative (positive) and statistically significant coefficient for ARROW*COI (ARROW*SLOPE). These results are consistent with our Hypothesis 6.

G. Cross-correlation and liquidity

Figure 3, Panel D, shows a positive relation between *COI* and future cross-correlation. We formally test the informativeness of the various liquidity measures for predicting the future return cross-correlation using the following regression model:

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

where $CROSSCORR_{i,t+1}$ measures how the order flow on stock *i* co-varies with the order flow for the market as measured by the trading activity for TOPIX exchange traded fund for minute *t+1*. The remaining variables are as defined previously.

Based on the results summarized in Table 7, Panel A, we find a, statistically significant and positive coefficient for *COI* for 69% of the sample stocks. A further analysis based on the three size based portfolios reveals that the predictive power of *COI* is consistent across different firm sizes. Hence, lower *COI*, reflecting higher liquidity, results in lower future *CROSSCORR*, which supports Kyle's (1985) and Barclay and Warner's (1993) argument that if informed investors' private signal about a stock does not contain a market wide component, then stocks cross correlation with the market will be negative in highly liquid markets.[24] Overall, our findings suggest that liquid markets increase information production resulting in higher trading

[24]Baker and Wurgler (2006) argue that sentiments drive the investors' propensity to speculate and during the liquid markets this propensity to speculate is very high.

in individual stocks. These findings reject our Hypothesis 7. We also find that *SLOPE* significantly predicts *CROSSCORR* for a majority of large-cap firms.

Table 7, Panel B, summarizes the results for the effect of Arrowhead on *CROSSCORR* and the relationship between *COI* and *SLOPE* and *CROSSCORR*. We find a positive and statistically significant coefficient, 0.41, for *COI* that suggests higher *COI* leads to higher *CROSSCORR*. Coefficient for *SLOPE* is statistically significant and negative for a majority of the large cap stocks. Our results are consistent with the pre-crisis period results summarized in Table 7, Panel A, and support Hypothesis 7. We also find a positive and statistically significant coefficient of 0.91 for ARROWHEAD dummy. Hence, Arrowhead increases cross-correlation due to increase in program trading. We do not find any significant effect of Arrowhead on the level of *CROSSCORR* or on the informativeness of *COI* (or *SLOPE*) for *CROSSCORR*.

H. Speed of trading and liquidity

Figure 2, Panels E and F, show that the number of trades and quotes to trade ratio has significantly increased during the post-Arrowhead period. We also observe the existence of well-established U-shape patterns (McInish and Wood, 1993) for these variables during both pre- and post-Arrowhead periods. Figure 3, Panels E and F, show a negative relation between COI and the future speed of trading and $QUOTES\ TO\ TRADE\ RATIO_i$. We formally test the relation by analyzing the following regression model separately for quote arrival and trade arrival:

$$TRADESPEED_{i,t+1} \text{ or } QUOTES\ TO\ TRADE\ RATIO_{i,t+1} = \alpha_i + \beta_{1i} SLOPE_{i,t} + \beta_{2i} COI_{i,t} + \beta_{3i} MONDAY_{t+1} + \beta_{4i} NTRDS_{i,t} + \beta_{5i} ATS_{i,t} + \beta_{6i} SPREAD_{i,t} + \beta_{7i} DEPTH_{i,t} + \beta_{8i} VOLATILITY_{i,t} + \beta_{9i} MKTRET_{i,t} + \mu_{i,t+1}$$

where *$TRADESPEED_{i,t+1}$* is the future number of trades per minute (Table 8, Panels A) and *QUOTES TO TRADE $RATIO_{i,t+1}$* is the ratio of future number of quote updates to the number of trader per minute (Table 8, Panel C). The remaining variables are as defined previously.

Table 8, Panel A, shows that *COI* significantly negatively predicts the future speed of trading as measured by the number of trades per minute of trading. Hence, the higher the *COI*, the lower is the speed of trading. These results are consistent across different size-based portfolios. Our results further documents that SLOPE is informative for the future number of trades per minute for a majority of large- and mid-cap stocks. Higher liquidity supply in the LOB increases the frequency of matched trades. We also find that the lagged average trade size and lagged number of trades also significantly positively predicts the future number of trades, supporting the positive autocorrelation in order type prediction of Biais, Hillion and Spatt (1995). Additionally, we find that the depth at the best quotes and volatility are significantly positively related to the future number of trades for majority of large- and mid-cap stocks. Our results on the negative association between *COI* and speed of trading provide supportive evidence for Hypothesis 8 and the theoretical predictions of Rosu (2009) that during liquid markets with lower *COI*, traders submit quick orders.

Table 8, Panel C, shows that *COI* (*SLOPE*) significantly negatively (positively) predicts the future *QUOTES TO TRADE RATIO*. These results are consistent across different size-based portfolios. Hence, the higher the *COI*, the lower is the *QUOTES TO TRADE RATIO*. Higher liquidity supply in the LOB increases the frequency of quote revisions, increasing the quotes to trade ratio. We also find that the lagged number of trades and depth at the best quotes significantly predicts the future quotes to trade ratio for a majority of large- and mid-cap stocks.

Table 8, Panels B and D, summarize the results for the effect of Arrowhead on the speed of trading (as measured by the inverse of time between trades, *TRADE* SPEED) and *QUOTES TO TRADE RATIO*, and the relation between these variables and *COI* (or *SLOPE*). Table 8, Panel B, reports a statistically significant and negative (positive) coefficient of -1.24 (1.19) for *COI* (*SLOPE*), suggesting that higher *COI* (gentler *SLOPE*) leads to lower *TRADESPEED*, which is consistent with the benchmark period results summarized in Panel A. We also find a positive coefficient for the *ARROWHEAD* dummy for large- and mid-cap stocks suggesting that Arrowhead significantly increased *TRADESPEED* for a majority of large- and mid-cap firms.. Further, we find a statistically significant and negative coefficient of -1.14 for *ARROW*COI*, which suggests that Arrowhead significantly strengthened the impact that *COI* have on the future *TRADESPEED* for a majority of sample stocks. We also find Arrowhead has significantly increased the informativeness of *SLOPE* for future TRADESPEED for a majority of large-cap stocks as reflected by a positively significant coefficient of 1.92 for *ARROW*SLOPE*.

Table 8, Panel D, summarizes similar results for *QUOTES TO TRADE RATIO*. We find a statistically significant and negative (positive) coefficient of -1.31 (2.03) for *COI* (*SLOPE*), suggesting that higher *COI* (gentler *SLOPE*) leads to lower *QUOTES TO TRADE RATIO*, which is consistent with the pre-crisis period results summarized in Panel C. We also find a positive and statistically significant coefficient of 2.59 for the *ARROWHEAD* dummy suggesting that Arrowhead has significantly increased the *QUOTES TO TRADE RATIO* for a majority of sample stocks. Finally, we find that Arrowhead significantly increased the informativeness of *COI* (*SLOPE*) for the future *QUOTES TO TRADE RATIO* for a majority of the sample firms as reflected by the significantly negative (positive) coefficient for *ARROW*COI* (*ARROW*SLOPE*).

Hence, the results summarized in Table 8, Panels B and D, support Hypothesis 8. Arrowhead significantly increased the speed of trading for a majority of large- and mid-cap stocks. In addition, lower *COI* and steeper *SLOPE* increase the speed of trading for the post-crisis and the post-Arrowhead periods.

H. Comparative analysis of comprehensive and traditional liquidity measures

COI and *SLOPE* may be redundant if they are highly correlated with traditional liquidity measures or with one another. We find the following correlations: *COI* and *SPREAD*, 0.15; *COI* and *DEPTH*, -0.24; *SLOPE* and *SPREAD*, -0.36; and *SLOPE* and *DEPTH*, 0.04. All of these correlations are low enough to suggest that *COI* and *SLOPE* contain significantly different information than either of the traditional liquidity measures. We also find that correlation between *SLOPE* and *COI* is -0.39. Based on the results summarized in Tables 2 through 7, we find that *SPREAD* and *DEPTH* do not have any significant predictive power for the majority of key parameters for market quality while *COI* and *SLOPE* consistently and significantly predicts the key market quality parameters. *DEPTH* is a significant predictor of future speed of trading (Table 8). Hence, higher top of the book *DEPTH* leads to a faster speed of trading. This result supports the attrition theory of Rosu (2009) who shows that in liquid markets traders play a game of attrition, i.e., the bottom seller places a limit order at some lower price (below the existing best quote), and the top buyer immediately accepts the offer by placing a market order. Hence, in this case, the top of the LOB should be more informative as compared to a more comprehensive *COI* measure as the patient traders do not participate in the attrition game. But overall, the *COI* measure dominates the traditional liquidity variables in explaining the evolution of the state of the limit order book with respect to proportion of trades executed at the bid and the ask prices, trade price movement, future volatility, autocorrelation, cross-correlation, and speed of trade arrivals.

IV. Robustness tests

We perform additional robustness tests to confirm the results presented above. Due to computational burdens of working with high frequency data, we limit the robustness analysis to Tables 2, 3, and 4 when the coefficients are nearly identical in robustness tests.

Since, our sample has an unequal numbers of stocks in each of the three size categories, we re-analyze the results by selecting the top 40 firms based on capitalization for each of the three size portfolios. By conducting this further analysis, we find results that are consistent with the ones presented in the reported tables in terms of statistical significance of *COI* and *SLOPE* coefficients for a greater proportion of stocks.

The TSE has a provision of special quotes, which are automated non-tradable indicative quotes placed by the exchange to smooth the price movements by encouraging investors to place balancing orders on the other side (to avoid the sudden jumps in prices). 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 in Table 4, Panel A, for ASKCOI variable changes minimally from -2.86 with special quotes to -2.91 without them.

TSE has a variable minimum trading unit (MTU) with each firm selecting its MTU. Differences in the MTU 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. The sample size drops from 1,557 stocks to 917 stocks by imposing this filter. Our results from this reduced sample are consistent with the ones presented earlier for Tables 2 and 3. This is not surprising because firms with a high (low) share price typically choose a small (large) MTU.

V. Conclusion

Using Tokyo Stock Exchange (TSE) data, we analyze the effect of high frequency trading (HFT) and cost of immediacy on market quality in terms of liquidity, volatility, autocorrelation, number of trades, and quotes to trade ratio. We examine the informativeness of two LOB liquidity measures–the cost of immediacy for trading 1% of average daily volume (*COI*) (Irvine, Benston, and Kandel, 2000), and a measure of the elasticity of depth over the price steps, LOB (*SLOPE*) (Biais, Hillion and Spatt, 1995)–to understand the evolution of market quality .

We find that the introduction of Arrowhead trading system, which significantly reduced latency on the TSE, reduced volatility and improved the limit order book (LOB) liquidity as reflected by reduced COI and increased LOB slope, for a majority of the sample stocks. The average number of trades for each minute of trading increased by more than 50% while the average trade size declined substantially, generating an increase of only 6% in the total trading volume. Further, Arrowhead significantly increased autocorrelation and cross correlation in the order flow and the quotes to trade ratio.

Analyzing all the stocks included in the TOPIX index, we find that the *COI* is the dominant liquidity measure that significantly and consistently predicts future trade price.
We find a significantly negative (positive) relationship between ask-side (bid-side) *COI* and the future proportion of sell (buy) trades executed at bid prices. These results are consistent across

large-, medium- and small-cap stocks. We also find that steeper (gentler) *ASKSLOPE* (*BIDSLOPE*) leads to higher proportions of sell trades executed at the bid prices for a majority of the large- and mid-cap firms.

As a follow up analysis we show that lower *COI* on the ask- (bid-) side of the LOB leads to lower (higher) future trade prices. The results are consistent across large-, mid- and small-capitalization stocks. We also find that steeper (gentler) *ASKSLOPE* (*BIDSLOPE*) leads to decrease (increase) in future trade prices for a majority of the large- and mid-cap firms. Higher ask- (bid-) side liquidity motivates sellers (buyers) to submit more aggressive orders (fleeting orders) on that side of the market, resulting in a decrease (increase) in trade prices.

Next, we show that the *COI* significantly and consistently predicts future return volatility. The lower the *COI* the lower is the future return volatility. Lower *COI* reflects a highly liquid market that can easily accommodate large buy or sell volumes without affecting prices significantly, resulting in low return volatility. We also find that the LOB Slope (*SLOPE*) is informative in explaining future return volatility for the majority of large- and mid-cap stocks.

Next, we show that lower *COI* lowers the autocorrelation in the order flow for a majority of the large- and mid-cap firms. Liquidity facilitates order splitting to conceal information, leading to higher autocorrelation. We also find that higher *COI* leads to positive cross correlation and these results are also consistent across different size-based portfolios. Liquid markets increase information production and motivates trading in individual stocks, resulting in lower cross correlation. We document that steeper *SLOPE* leads to lower autocorrelation and cross correlation for a majority of large-cap stocks.

We find that *COI* is significantly inversely related to the future speed of trading. These results are consistent across different size-based portfolios. *COI* have stronger predictive power than the *SLOPE* for predicting the future number of trades, while LOB Slope consistently and significantly positively predicts the future quotes to trade ratio.

Finally, we document that Arrowhead has significantly improved the informativeness of *COI* and *SLOPE* for future trade price location, speed of trading and quotes to trade ratio for a majority of large-cap stocks.

Overall, Arrowhead significantly improved price discovery and market quality in terms of better liquidity, reduced volatility, and greater speed of trading on the TSE. Our results from the examination of the introduction of Arrowhead indicate that future researchers need to consider an additional aspect of liquidity that has not previously received much attention–the speed of trading. The results from this study have potential applications in academic models and for optimizing the order submission strategies.

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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

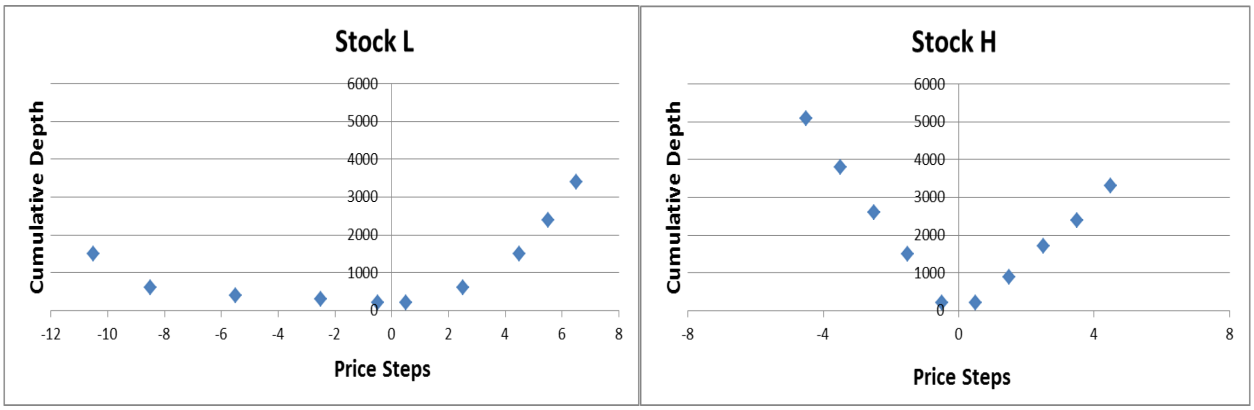
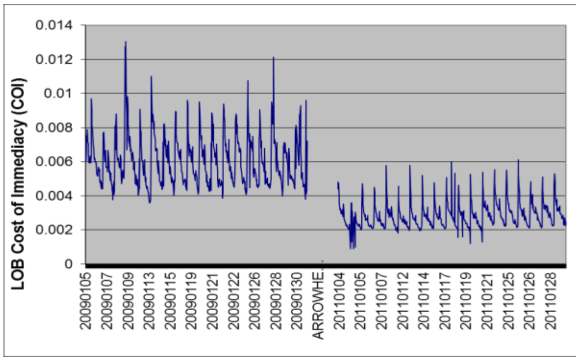
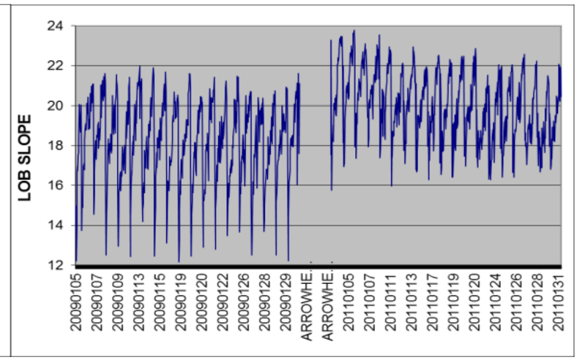


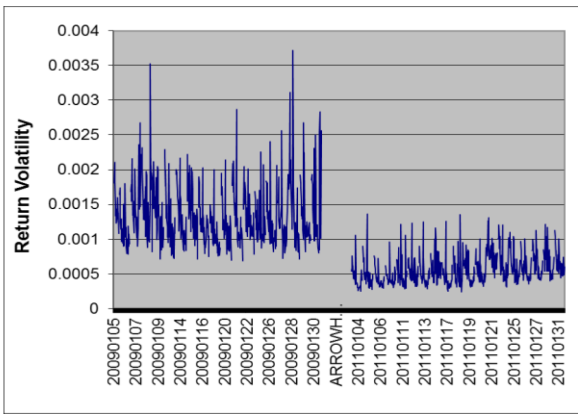
Figure 1. Hypothetical limit order book (LOB) for 2 stocks
In the graphs, 1 and -1 represent the best ask and best bid, respectively, which are presented in the first row of the table. For each firm we show the depth and price for the first five steps on each side of the LOB. The graphs illustrate the volume elasticity for the two stocks. The vertical axis shows the cumulative order volume that can be executed as investors walk up or down the LOB. The negative (positive) numbers on the horizontal axis represent the price steps on the bid-side (ask-side) of 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.

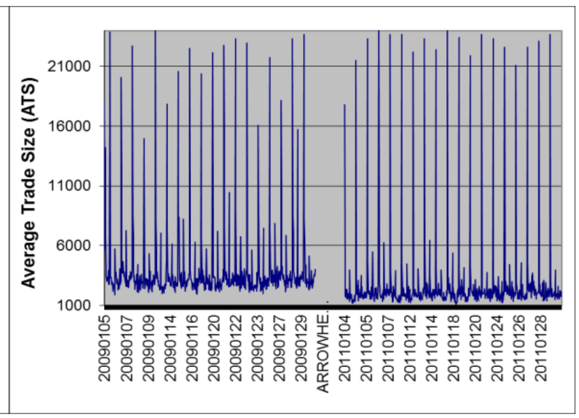




Panel A: Minute-by-Minute COI

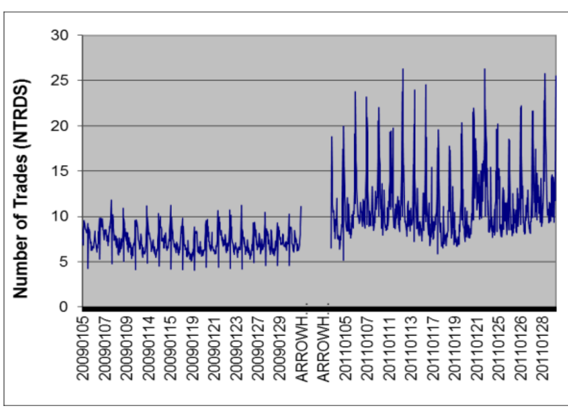
Panel B: Minute-by-Minute LOB SLOPE

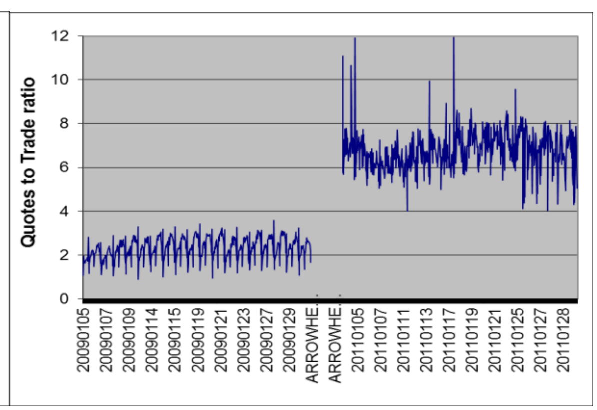




Panel C: Minute-by-Minute Volatility

Panel D: Minute-by-Minute ATS

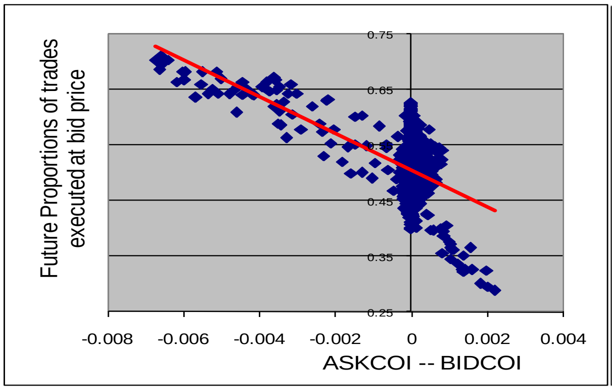


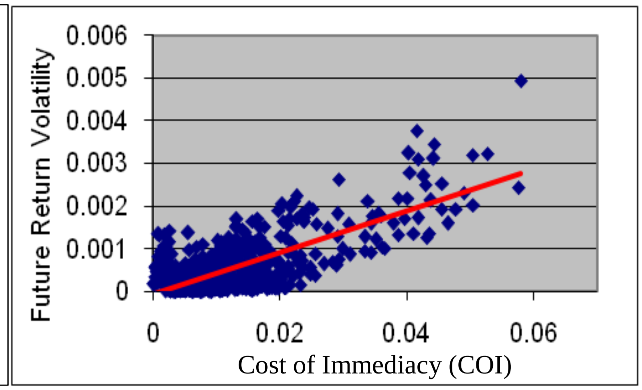


Panel E: Minute-by-Minute NTRDS

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

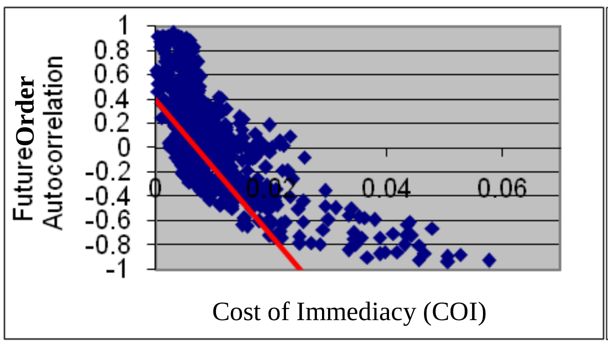
Figure 2. Impact of Arrowhead on Key market quality parameters.

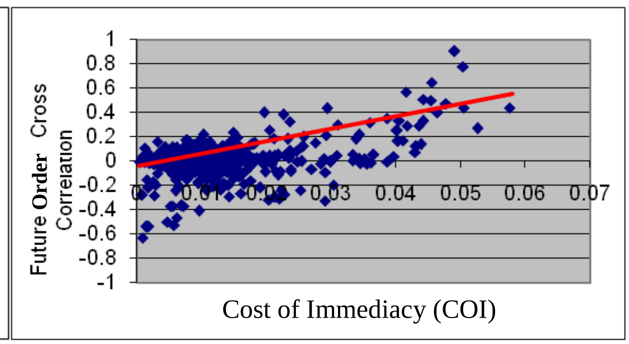




Panel A: COI and future trade placements

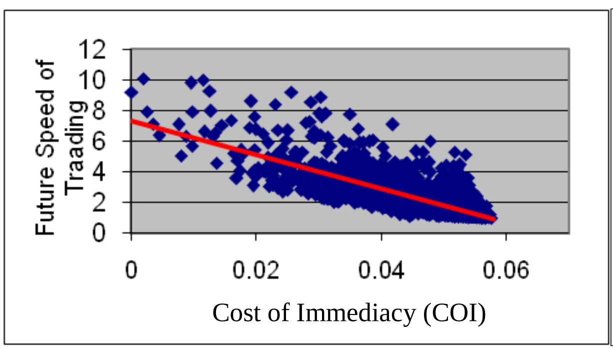
Panel B: COI and future return volatility

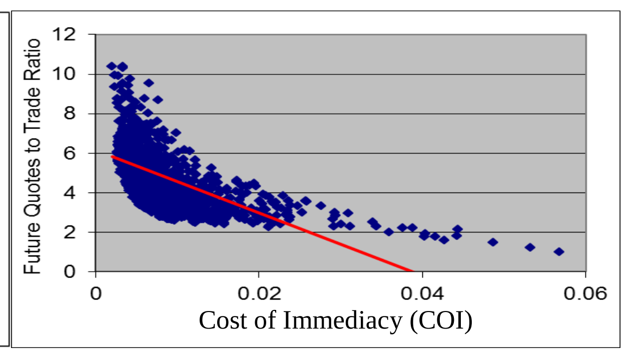




Panel C: COI and future autocorrelation

Panel D: COI and future cross correlation





Panel E: COI and future number of trades

Panel F: COI and future quotes to trade ratio

Figure 3. Graphical representations of the key results

*We draw the best fitting line only when the correlation coefficient among the variables is greater than 0.50

Table 1
Descriptive statistics for the benchmark period

We present summary statistics from 1 June 2008 to 30 June 2008 for all Tokyo Stock Exchange (TSE) first section firms. In Panel A we report the average market capitalization (*MKTCAP*) and monthly volume (*MONTHLY VOLUME*). *RETURN* is the return on security *i* as measured by the log change in the bid-ask quote midpoint. *BIDPROP* is the proportion of orders executed at the bid price. We measure minute-by-minute return volatility (*VOLATILITY)* by estimating the following regression for each security *i*: $RETURN_{i,t} = \sum_{k=1}^{5} \propto_k D_k + \sum_{j=1}^{12} \beta_j RETURN_{i,t-j} + \varepsilon_{i,t}$ where D_k is a day-of-the-week dummy for day *k* and the 12 lagged returns estimate the short-term conditional expected returns. Volatility is defined as the absolute value of the residual *VOLATILITY*= $|\varepsilon_{i,t}|$

AUTO CORR is the return autocorrelation. *CROSS CORR* measures how the order flow on stock *i* co-vary with the order flow on the market as proxied by the order flow on the TOPIX exchange traded fund. In Panel B we report data for liquidity measures. 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. *COI* (=*ASKCOI*+ *BIDCOI*) measures the cost that liquidity demanders have to bear above the intrinsic value due to a sudden surge in the demand for 1% of the daily average trading volume. *SPREAD* is the proportionate spread over each minute of trading. *DEPTH* is the average depth at the best bid and best ask. *NTRDS* is the number of trades for each minute and *ATS* is the average trade size for each minute. We also compute the ratio of number of quotes to trades during each minute (*QUOTES TO TRADE RATIO*). The large, medium, and small classifications are based on the TOPIX 100 Large-Sized Stocks Index, the TOPIX Mid400 Index, and the TOPIX Small Index, respectively.

	All firms (n = 1,557)	Large (n = 100)	Medium (n = 389)	Small (n = 1,068)
Panel A: Firm and market characteristic averages				
MKTCAP (billion.JPY)	223.37	2,179	294.96	33.18
MONTHLY VOLUME (million shares)	25.26	143.22	46.73	7.91
RETURN	-0.0005%	0.0000%	-0.0000%	-0.0007%
BIDPROP	50.02%	50.01%	49.98%	50.05%
VOLATILITY	0.13%	0.04%	0.10%	0.19%
AUTO CORR	0.07	0.02	0.07	0.09
CROSS CORR	0.02	0.01	0.03	0.02
Panel B: Liquidity measures				
COI (basis pts)	68.50	40.99	45.51	84.35
ASKCOI (basis pts)	34.47	20.61	22.78	42.47
BIDCOI (basis pts)	34.03	20.38	22.72	41.88
SLOPE	12.38	25.57	19.38	8.89
ASKSLOPE	12.37	25.52	19.33	8.92
BIDSLOPE	12.39	25.61	19.43	8.85
SPREAD	0.56%	0.19%	0.27%	0.69%
DEPTH	22.32	37.79	27.73	19.16
NTRDS	2.91	5.09	3.08	2.26
ATS	2,583	5,281	3,089	1,557
QUOTES TO TRADE RATIO	4.78	5.99	5.76	4.28

Table 2
Liquidity changes around Arrowhead reduction in latency

We present summary statistics for a stratified sample of 150 firms listed on the first section of TSE formed by selecting the firms with the highest market capitalization in the large, medium, and small firm groups. Before and after columns represent the pre and post launch periods of the new Arrowhead HFT platform. The treatment period for our natural TSE system overhaul experiment comprises of data for January 2011 and the control period comprises data for January 2009. Variable definitions and classifications are the same as described in Table 1.

	All firms (n = 150)		Large (n = 50)		Medium (n = 50)		Small (n = 50)	
	Before	After	Before	After	Before	After	Before	After
Panel A: Firm and market characteristics								
MONTHLY VOLUME (million shares)	93.74	99.19	237.77	267.60	36.13	35.86	5.02	4.18
BIDPROP (%)	49.26	50.01	49.50	50.02	49.01	49.98	49.29	50.01
VOLATILITY (%)	0.14	0.06	0.13	0.02	0.14	0.06	0.16	0.08
AUTO CORR	0.06	0.12	0.13	0.20	0.09	0.15	-0.01	0.01
CROSS CORR	-0.03	0.04	0.03	0.10	-0.02	0.04	-0.05	-0.02
Panel B: Liquidity measures								
COI (basis pts)	59.52	28.38	57.24	26.29	57.39	27.85	66.03	33.26
ASKCOI(basis pts)	29.87	14.41	28.79	13.21	28.95	13.96	32.82	17.81
BIDCOI (basis pts)	29.66	13.97	28.45	13.08	28.44	13.88	33.21	15.46
SLOPE	20.39	20.68	23.35	25.81	20.98	21.47	14.95	12.17
ASKSLOPE	20.34	20.73	23.30	25.73	20.92	21.40	14.91	12.15
BIDSLOPE	20.44	20.61	23.40	25.90	21.05	21.54	14.99	12.18
SPREAD	0.23%	0.16%	0.21%	0.14%	0.20%	0.15%	0.31%	0.23%
DEPTH (‘000)	44.90	257.71	84.72	545.93	30.72	67.98	2.35	39.47
NTRDS	7.34	11.15	10.75	18.14	6.10	7.11	3.71	3.42
ATS	3,800	3,732	7,047	6,665	2,262	2,025	822	744
QUOTES TO TRADE RATIO	4.89	5.69	6.41	7.17	5.94	6.37	4.32	4.47
TRADE SPEED	0.08	0.12	0.11	0.19	0.06	0.08	0.04	0.06

Table 3.
Liquidity changes around Arrowhead reduction in latency

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

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

where *ARROWHEAD* is a dummy variable that equals 1 for the post Arrowhead low latency trading system (January 2011) and 0 otherwise (January 2009). The remaining variables are as defined earlier. 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 in parentheses). The remaining columns present the standardized parameter estimates averaged across all individual security regression equations. The large, medium, and small classifications are based on the TOPIX 100 Large-Sized Stocks Index, the TOPIX Mid 400 Medium-Sized Stocks Index, and the TOPIX Small-Sized Stocks Index, respectively.

Panel A. Impact of Arrowhead on COI

	(1)	(2)	(3)	(4)	(5)
Variables	All Firms	%t (%sign)	Large-cap	Mid-cap	Small-cap
ARROWHEAD	-3.55*	98 (95)	-4.53*	-2.89*	-1.92*
LOGVOL	-2.04*	84 (74)	-5.07*	-1.54*	-1.96*
LOGNTRDS	1.84*	80 (71)	3.83*	2.06*	0.91*
HIGH SPEED	-0.21	75 (53)	-1.06*	-0.12	0.78*
LOW SPEED	1.17	42 (74)	2.07*	1.17	-0.33
VOLATILITY	4.30*	100 (99)	4.64*	4.23*	3.89*
LOGPRICE	-2.44*	95 (89)	-2.86*	-2.29*	-2.35*
MKTRET	-0.14	46 (60)	-0.21	-0.18	-0.01
ADJ R^2	0.148		0.114	0.121	0.174

Panel B. Impact of Arrowhead on LOB SLOPE

	(1)	(2)	(3)	(4)	(5)
Variables	All Firms	%t (%sign)	Large-cap	Mid-cap	Small-cap
ARROWHEAD	2.31*	93 (97)	3.39*	2.22*	1.84*
LOGVOL	2.14*	76 (86)	4.04*	1.82*	0.44
LOGNTRDS	-0.41	40 (68)	-0.58	-0.44	-0.16
HIGH SPEED	-0.01	55 (52)	0.27	0.18	-0.47
LOW SPEED	-0.19	18 (64)	-0.44*	-0.32	0.22
VOLATILITY	-2.93*	100 (99)	-5.38*	-3.92*	-2.32*
LOGPRICE	2.31*	89 (93)	3.07*	2.34*	1.71*
MKTRET	0.08	13 (51)	0.12	0.06	0.07
ADJ R^2	0.139		0.167	0.126	0.112

* significant at the .05 level of significance using the 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. The test statistic is a z-score (z) defined by the following equation: $z = \frac{(P-p)}{\sigma}$, where P is the hypothesized value of population proportion in the null hypothesis (0.60 in our setting), p is the sample proportion, and σ is the standard deviation of the sampling distribution which is given by: $\sigma = sqrt\left[\frac{P*(1-P)}{n}\right]$, where n is the sample size.

Table 4
Trade price location

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

$$\Delta PRI_{i,t+1} = \alpha_i + \beta_{1i} ASKCOI_{it-j} + \beta_{2i} BIDCOI_{it-j} + \beta_{3i} MONDAY_{t+1} + \beta_{4i} SPREAD_{i,t-j} + \beta_{5i} DEPTH_{i,t-j} + \beta_{6i} VOLATILITY_{i,t-j} + \beta_{7i} VOLUME_{i,t-j} + \beta_{8i} MKTRET_{i,t-j} + \mu_{i,t+1}$$

where $\Delta PRI_{i,t+1}$ is the percentage of trades executed at the bid during the next minute of trading (columns 1 through 4) and change in trade prices for columns (8) through (11), in turn. For Panels A and B, we use cost based liquidity measures: $ASKCOI_{i,t}$ is the cost that liquidity demanders bear to buy 1% of the daily average trading volume and $BIDCOI_{i,t}$ cost that liquidity demanders bear to sell 1% of the daily average trading volume. For Panels C and D, we define ask and bid liquidity using elasticity based measures that are calculated in terms of *ASKSLOPE* and *BIDSLOPE* using Equations 2 and 3, in turn, for each firm, for every change in the LOB. $MONDAY_{t+1}$ is a dummy variable that equals 1 for Mondays and 0 otherwise. $SPREAD_{i,t}$ is the proportionate spread and $DEPTH_{i,t}$ is the average depth at the best bid and best ask quotes. $VOLATILITY_{i,t}$ is the absolute value of the return, conditional on its own 12 lags and day-of-week dummies, $VOLUME_{i,t}$ is the trading volume, $MKTRET_{i,t}$ is the return on the market as measured by the return on TSE exchange traded fund, α and β are parameters to be estimated, and $\mu_{i,t+1}$ is a random error term. The subscripts *i* and *t* indicate firm *i* and minute *t*, respectively. We present the results based on calendar time forecasting by predicting the trade price location changes based on the previous minute's and 2 minutes lagged LOB information for our benchmark period of June 2008 in Panels A and C. Panels B and D summarizes the results for impact of Arrowhead for the post financial crisis period using the following model:

$$\Delta PRI_{i,t+1} = \alpha_i + \beta_{1i} BIDCOI_{it} + \beta_{2i} ASKCOI_{it} + \beta_{3i} MONDAY_{t+1} + \beta_{4i} SPREAD_{i,t} + \beta_{5i} DEPTH_{i,t} + \beta_{6i} VOLATILITY_{i,t} + \beta_{7i} VOLUME_{i,t} + \beta_{8i} MKTRET_{i,t} + \beta_{9i} ARROWHEAD_{i,t} + \beta_{10i} ARROWHEAD_{i,t} * BIDCOI_{it} + \beta_{11i} ARROWHEAD_{i,t} * ASKCOI_{it} + \mu_{i,t+1}$$

where *ARROWHEAD* is a dummy variable that equals 1 for the post Arrowhead low latency trading system (January 2011) and 0 otherwise (January 2009). The remaining variables are as defined earlier. 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 in parentheses). The remaining columns present the standardized parameter estimates averaged across all individual security regression equations. The large, medium, and small classifications are based on the TOPIX 100 Large-Sized Stocks Index, the TOPIX Mid 400 Medium-Sized Stocks Index, and the TOPIX Small-Sized Stocks Index, respectively.

Panel A. Predicting the trade price location ($\Delta PRI_{i,t+1}$) with COI measures for the benchmark period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
					Large	Mid	Small					Large	Mid	Small
Dep. Var.	% trades executed at bid during the following minutes							Change in trade price in the following minutes						
Variable	$bid_{i,t+1min}$	$bid_{i,t+1min}$	%t(%sign)	$bid_{i,t+2min}$	$bid_{i,t+1min}$			$\Delta PRI_{i,t+1min}$	$\Delta PRI_{i,t+1min}$	%t(%sign)	$\Delta PRI_{i,t+2min}$	$\Delta PRI_{i,t+1min}$		
ASKCOI	-2.86*	-2.89*	96(85)	-0.36	-3.06*	-3.04*	-2.76*	3.29*	4.04*	81(97)	2.60*	3.54*	4.45*	3.91*
BIDCOI	2.07*	2.18*	97(91)	0.89	2.67*	2.33*	1.41*	-2.23 *	-3.88 *	79(86)	-2.17*	-4.28*	-5.25*	-3.38*
MONDAY		-0.60*	53(70)	-0.52*	-0.06	-0.67*	-0.62*		0.33	6(82)	0.48	0.47	0.46	0.27
SPREAD		-0.29	22(53)	-0.06	-0.64	-0.24	-0.15		-0.34	57(56)	-0.03	-0.29	-0.17	-0.25
DEPTH		0.28	27(60)	0.23	0.13	0.06	0.38		0.19	13(55)	0.11	0.02	0.17	0.27
VOLATILITY		0.64	4(67)	0.09	0.82	0.90	-0.39		0.51	38(62)	0.32	0.17	0.50	0.54
VOLUME		-0.05	7(53)	-0.14	-0.02	-0.01	-0.06		0.14	39(53)	0.17	0.10	0.17	0.14
MKTRET		-1.60*	57(100)	-0.96	-2.34*	-2.86*	-1.11*		3.30*	65(96)	3.01*	9.15*	7.02*	1.30*
ADJ R^2	0.006	0.028		0.010	0.029	0.028	0.027	0.015	0.045		0.039	0.054	0.046	0.038

Table 4-continued

Panel B. Predicting the trade price location ($\Delta PRI_{i,t+1}$) with COI measures post financial crisis and post Arrowhead

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	% of following trades executed at bid								Change in following trade price							
Variables	All Firms	%t (%sign)	Large-cap	%t (%sign)	Mid-cap	%t (%sign)	Small-cap	%t (%sign)	All Firms	%t (%sign)	Large-cap	%t (%sign)	Mid-cap	%t (%sign)	Small-cap	%t (%sign)
ASKCOI	-4.52*	87(98)	-7.54*	98(98)	-4.85*	94(100)	-1.52*	73(93)	4.57*	89(99)	4.79*	93(100)	4.93*	82(100)	4.00*	89(96)
BIDCOI	5.53*	91(99)	9.87*	100(100)	5.08*	96(100)	2.23*	76(94)	-4.19*	87(99)	-4.26*	92(100)	-4.35*	80(95)	-3.98*	88(100)
ARROW	1.23	52(60)	1.25	54(58)	1.46	52(56)	0.98	50(69)	0.12	12(78)	0.31	20(40)	0.22	11(80)	-0.16	4(100)
ARROW* ASKCOI	-4.26*	78(90)	-7.50*	94(90)	-3.56*	85(98)	-1.12	52(79)	1.54	32(80)	2.23*	60(100)	0.93	31(70)	0.80	10(60)
ARROW* BIDCOI	3.59*	74(86)	7.87*	84(95)	2.59*	83(90)	1.94	56(68)	-2.65	37(76)	-3.05*	66(79)	-3.02	39(71)	-1.45	8(78)
ADJ R^2	0.044		0.053		0.041		0.021		0.041		0.056		0.045		0.019	

Panel C. Predicting the trade price location ($\Delta PRI_{i,t+1}$) with LOB Slope measures for the benchmark period

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
					Large	Mid	Small					Large	Mid	Small
Dep. Var.	% trades executed at bid during the following minutes							Change in trade price in the following minutes						
Variable	$bid_{i,t+1min}$	$bid_{i,t+1min}$	%t(%sign)	$bid_{i,t+2min}$		$bid_{i,t+1min}$		$\Delta PRI_{i,t+1min}$	$\Delta PRI_{i,t+1min}$	%t(%sign)	$\Delta PRI_{i,t+2min}$		$\Delta PRI_{i,t+1min}$	
ASKSLOPE	1.63*	1.52*	62(90)	0.95	3.49*	2.36*	0.06	-1.97*	-2.02*	53(100)	-1.12	-2.62*	-2.58*	-1.77
BIDSLOPE	-1.72*	-1.49*	60(89)	-0.96	-3.07*	-2.56*	-0.05	2.05*	1.99*	53(99)	1.10	2.65*	2.81*	1.67
MONDAY		-0.79*	51(71)	-0.62*	-0.13	-0.85*	-0.82*		0.27	4(79)	0.44	0.38	0.38	0.22
SPREAD		-0.09	20(55)	-0.07	-1.31	-0.29	0.35		-0.08	57(56)	-0.02	-0.09	-0.03	-0.11
DEPTH		0.44	25(69)	0.34	0.69	0.39	0.41		0.13	12(60)	0.18	0.04	0.13	0.18
VOLATILITY		0.11	5(61)	0.08	0.27	0.19	-0.25		0.53	38(61)	0.29	0.13	0.47	0.58
VOLUME		-0.10	6(63)	-0.16	-0.13	-0.04	-0.12		0.12	37(51)	0.19	0.36	-0.34	0.09
MKTRET		-1.60*	56(100)	-1.06	-2.30*	-2.86*	-1.10*		3.21*	65(96)	3.00*	9.09*	7.01*	1.31*
ADJ R^2	0.004	0.014		0.012	0.016	0.015	0.012	0.003	0.029		0.032	0.042	0.031	0.027

Table 4-continued

Panel D. Predicting the trade price location ($\Delta PRI_{i,t+1}$) with LOB Slope measures post crisis and post Arrowhead

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	% of following trades executed at bid								Change in following trade price							
Variables	All Firms	%t (%sign)	Large-cap	%t (%sign)	Mid-cap	%t (%sign)	Small-cap	%t (%sign)	All Firms	%t (%sign)	Large-cap	%t (%sign)	Mid-cap	%t (%sign)	Small-cap	%t (%sign)
ASKSLOPE	3.90*	92(99)	6.11*	99(100)	3.33*	98(100)	-1.86*	79(97)	-2.99	49(97)	-4.55*	62(96)	-2.70	38(94)	-1.72	22(100)
BIDSLOPE	-4.01*	91(99)	-6.31*	98(100)	-3.98*	98(100)	-1.83*	76(94)	2.91	41(87)	4.56*	60(80)	2.40	40(89)	1.76	24(100)
ARROW	0.61	48(55)	0.96	58(59)	0.86	54(51)	0.04	32(56)	0.42	36(60)	0.57*	66(61)	0.82	35(71)	-0.18	6(100)
ARROW* ASKSLOPE	2.25*	79(71)	3.81*	96(71)	1.76*	81(72)	0.62	58(69)	-1.74	29(93)	-3.10*	62(92)	-1.83	27(100)	-0.29	8(75)
ARROW* BIDSLOPE	-2.12*	78(69)	-4.05*	90(71)	-1.47*	83(70)	-0.68*	62(65)	0.88	37(76)	1.73*	62(75)	0.53	34(76)	0.35	24(67)
ADJ R^2	0.027		0.039		0.024		0.017		0.016		0.027		0.010		0.012	

* significant at the .05 level of significance using the 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. The test statistic is a z-score (z) defined by the following equation: $z = \frac{(P-p)}{\sigma}$, where P is the hypothesized value of population proportion in the null hypothesis (0.60 in our setting), p is the sample proportion, and σ is the standard deviation of the sampling distribution which is given by: $\sigma = sqrt\left[\frac{P*(1-P)}{n}\right]$, where n is the sample size.

Table 5

A liquidity–volatility regression model

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

$$|\varepsilon_{i,t+1}| = \alpha_i + \beta_{1i} COI_{i,t} + \beta_{2i} SLOPE_{it} + \beta_{3i} DISDT_{i,t} + \beta_{4,m} MONDAY_{t+1} + \beta_{5i} NTRDS_{i,t} + \beta_{6i} ATS_{i,t} + \beta_{7i} SPREAD_{i,t}$$

$$+\beta_{8i} DEPTH_{i,t} + \beta_{9i} HIGHSPEED_{i,t} + \beta_{10i} LOWSPEED_{i,t} + \beta_{11i} MKTRET_{i,t} + \sum_{j=0}^{11} \delta_{i,j} |\varepsilon_{i,t-j}| + \mu_{i,t+1}$$

where $|\varepsilon_{i,t+1}|$ is the future return volatility measured as defined in Table 1, $COI_{i,t}$ is the cost that liquidity demanders have to bear to trade 1% of the daily average trading volume, $SLOPE_{i,t}$ is the average of the slope for the five best bids and five best asks, $DISDT_{i,t}$ is the dispersion of limit orders, $MONDAY_{t+1}$ is a dummy variable that equals 1 for Mondays and 0 otherwise, $NTRDS_{i,t}$ is the number of trades, $ATS_{i,t}$ is the average trade size, $SPREAD_{i,t}$ is the proportionate spread, $DEPTH_{i,t}$ is the sum of depth at the best bid and best ask quotes, $HIGH\ SPEED_{i,t}$ is a dummy variable that takes a value 1 if the speed of quote updates is greater than its 75th percentile value and $LOW\ SPEED_{i,t}$ is a dummy variable that takes a value 1 if the speed of quote updates is less than its 25th percentile value. $MKTRET_{i,t}$ is the return on the market as measured by the return on the TSE exchange traded fund. α, β, and δ are parameters to be estimated, and $\mu_{i,t+1}$ is a random error term. The subscripts i and t indicate firm i and minute t. $\delta_{i,j}$ captures the persistence in volatility. We present the results based on calendar time forecasting by predicting the return volatility for the full sample and for three size based portfolios based on the previous minute's lagged LOB information for our benchmark period of June 2008 in Panels A and B. Panel C summarizes the results for the impact of Arrowhead for the post financial crisis period using the following model:

$$|\varepsilon_{i,t+1}| = \alpha_i + \beta_{1i} COI_{i,t} + \beta_{2i} SLOPE_{it} + \beta_{3i} DISDT_{i,t} + \beta_{4,m} M_{t+1} + \beta_{5i} NTRDS_{i,t} + \beta_{6i} ATS_{i,t} + \beta_{7i} SPREAD_{i,t} + \beta_{8i} DEPTH_{i,t} + \beta_{9i} TRADING\ SPEED_{i,t} + \beta_{10i} ARROWHEAD_{i,t} + \beta_{11i} MKTRET_{i,t} + \beta_{12i} ARROWHEAD_{i,t}{*}COI_{i,t} + \beta_{13i} ARROWHEAD_{i,t}{*}SLOPE_{it} + \beta_{14i} ARROWHEAD_{i,t}{*}DISDT_{i,t} + \sum_{j=0}^{11} \delta_{i,j} |\varepsilon_{i,t-j}| + \mu_{i,t+1}$$

where *ARROWHEAD* is the dummy variable that equals 1 for the post Arrowhead period (January 2011) and 0 otherwise (January 2009). The remaining variables are as defined earlier. 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 in parentheses). Column (6) in Panel A reports the results from stock by stock GARCH(1,1) analysis. The remaining columns present the standardized parameter estimates averaged across all individual security regression equations. The large, medium, and small classifications are based on the TOPIX 100 Large-Sized Stocks Index, the TOPIX Mid 400 Medium-Sized Stocks Index, and the TOPIX Small-Sized Stocks Index, respectively.

Panel A. Predicting future return volatility for the benchmark period

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	B_1	B_2	B_3	All Firms	%t (%sign)	GARCH(1,1) estimation
COI	6.55*			2.48*	78 (84)	2.54*
SLOPE		-3.25*		-0.36*	60 (62)	-0.41*
DISDT			5.33*	1.01	47 (79)	0.97
MONDAY				0.04	28 (52)	0.04
NTRDS				1.74	31 (81)	1.79
ATS				2.12*	57 (84)	2.22*
SPREAD				0.85	50 (54)	0.65
DEPTH				-0.26	30 (55)	-0.30
HIGH SPEED				-0.18	27 (72)	-0.21
LOW SPEED				0.65	10 (98)	0.74
MKTRET				0.52	35 (62)	0.59
ADJ R^2	0.039	0.035	0.036	0.051		0.055

Table 5 continued

Panel B. Predicting future return volatility across different firm sizes for the benchmark period

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Large-cap	%t (%sign)	Mid-cap	%t (%sign)	Small-cap	%t (%sign)
COI	2.97*	81 (100)	3.52*	76 (98)	2.08*	77 (78)
SLOPE	-0.40*	73 (74)	-0.26*	64 (66)	0.05	46 (49)
DISDT	-0.26	24 (54)	0.77	35 (68)	1.20*	55 (83)
MONDAY	0.05	5 (40)	0.06	6 (57)	0.03	38 (52)
NTRDS	3.16	36 (100)	2.33	28 (98)	1.41	32 (74)
ATS	4.33*	64 (100)	3.79*	56 (99)	1.36*	51 (76)
SPREAD	0.98	21 (72)	0.87	30 (51)	0.84	60 (54)
DEPTH	-0.58	19 (53)	-0.57	20 (54)	-0.12	35 (58)
HIGH SPEED	-0.06	4 (50)	-0.16	6 (55)	-0.20	37 (83)
LOW SPEED	0.61	5 (100)	0.53	6 (100)	0.73	11 (97)
MKTRET	0.65	18 (72)	0.47	25 (68)	0.53	41 (60)
ADJ R^2	0.024		0.039		0.057	

Panel C. Predicting future return volatility post crisis and post Arrowhead

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	All Firms	%t (%sign)	Large-cap	%t (%sign)	Mid-cap	%t (%sign)	Small-cap	%t (%sign)
COI	5.94*	89 (99)	4.89*	92 (96)	6.04*	87 (100)	6.92*	88 (100)
SLOPE	-2.06*	64 (69)	-2.53*	79 (81)	-1.98*	74 (71)	-0.71	39 (52)
ARROW	-0.47*	61 (89)	-0.36*	90 (89)	-0.70*	64 (72)	-0.36	31 (100)
ARROW*COI	0.25	8 (73)	0.14	2 (0)	0.43	14 (67)	0.18	9 (100)
ARROW*SLOPE	-0.15	10 (57)	-0.18	14 (71)	-0.13	9 (75)	-0.03	6 (31)
ADJ R^2	0.162		0.162		0.159		0.165	

* significant at the .05 level of significance using the 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. The test statistic is a z-score (z) defined by the following equation: $z = \frac{(P-p)}{\sigma}$, where P is the hypothesized value of population proportion in the null hypothesis (0.60 in our setting), p is the sample proportion, and σ is the standard deviation of the sampling distribution which is given by: $\sigma = sqrt\left[\frac{P*(1-P)}{n}\right]$, where n is the sample size.

Table 6

Return autocorrelation and liquidity

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

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

where $AUTOCORR_{i,t+1}$ is the trade-by-trade autocorrelation for stock i and minute $t+1$. The remaining variables are as defined in Table 3. We present the results based on calendar time forecasting by predicting the return autocorrelation for the full sample and for three size based portfolios based on the previous minute's lagged LOB information for our benchmark period of June 2008 in Panel A. Panel B summarizes the results for the impact of Arrowhead for the post financial crisis period using the following model:

$AUTOCORR_{i,t+1} = \alpha_i + \beta_{1i}COI_{i,t} + \beta_{2i}SLOPE_{i,t} + \beta_{3i}NTRDS_{i,t} + \beta_{4i}ATS_{i,t} + \beta_{5i}SPREAD_{i,t} + \beta_{6i}DEPTH_{i,t} +\beta_{7i}\,TRADING\ SPEED_{i,t} +\beta_{8i}VOLATILITY_{i,t} +\beta_{9i}RETURN_{i,t} +\beta_{10i}ARROWHEAD_{i,t} +\beta_{11i}MKTRET_{i,t} +\beta_{12i} ARROWHEAD_{i,t}*COI_{i,t} +\beta_{13i}ARROWHEAD_{i,t}*SLOPE_{it} +\mu_{i,t+1}$

The variables are as defined previously. For Panel C, AUTOCORR is defined as the correlation between improvement in bid (or ask) quotes and location of next trade (at the bid or the ask). 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 in parentheses). The remaining columns present the standardized parameter estimates averaged across all individual security regressions. The large, medium, and small classifications are based on the TOPIX 100 Large-Sized Stocks Index, the TOPIX Mid 400 Medium-Sized Stocks Index, and the TOPIX Small-Sized Stocks Index, respectively.

Panel A. Predicting future autocorrelation for the benchmark period

	(1)	(2)	(3)	(4)	(5)
Variables	All Firms	%t (%sign)	Large-cap	Mid-cap	Small-cap
COI	-0.38*	68(77)	-0.88*	-0.48*	-0.15
SLOPE	0.25	40(71)	0.42*	0.31	0.21
NTRDS	0.97*	78(93)	1.23*	0.98*	0.87
ATS	-0.29	43(75)	-0.77*	-0.22	-0.28
SPREAD	-0.07	39(89)	-0.61*	-0.06	-0.01
DEPTH	0.16	37(82)	1.04*	0.32	0.01
VOLATILITY	-0.99*	82(95)	-1.66*	-1.53*	-0.75
RETURN	0.13	10(57)	0.12	0.18	0.11
HIGH SPEED	0.84	37(61)	0.50	0.72	0.94*
LOW SPEED	-0.31	7(82)	-0.24	-0.44	-0.27
ADJ R^2	0.034		0.033	0.042	0.032

Panel B. Predicting future autocorrelation post crisis and post Arrowhead

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	All Firms	%t (%sign)	Large-cap	%t (%sign)	Mid-cap	%t (%sign)	Small-cap	%t (%sign)
COI	-0.56*	72(84)	-0.84*	88(90)	-0.52*	92(80)	-0.26	36(74)
SLOPE	0.31*	52(62)	0.82*	76(82)	0.07	48(54)	0.04	32(48)
ARROW	1.12*	74(84)	1.55*	84(92)	1.10*	88(96)	0.79	48(64)
ARROW*COI	-0.07	22(78)	-0.12	28(82)	-0.06	32(88)	-0.01	6 (64)
ARROW*SLOPE	0.11	28(75)	0.15	34(76)	0.11	32(78)	0.06	16(70)
ADJ R^2	0.049		0.043		0.050		0.055	

Panel C. Predicting fleeting orders pre and post Arrowhead

	(1)	(2)	(3)	(4)	(5)
Variables	All Firms	%t (%sign)	Large-cap	Mid-cap	Small-cap
ARROWHEAD	1.81*	84(96)	2.21*	1.95*	1.23*
COI	-1.01*	76(88)	-1.52*	-1.07*	-0.54
SLOPE	1.76*	91(89)	1.75*	2.06*	1.58*
ARROW*COI	-0.71*	67(65)	-0.88*	-0.83*	-0.48
ARROW*SLOPE	0.86*	75(71)	0.94*	0.99*	0.65*
NTRDS	0.81*	88(86)	0.91*	0.78*	0.79*
ATS	-0.28	68(55)	-0.88*	-0.21	0.25
SPREAD	-1.43*	81(96)	-1.32*	-1.80*	-1.19*
DEPTH	0.96*	79(72)	0.93*	0.82*	1.17*
VOLATILITY	0.39	29(65)	-0.13	0.38	0.72
RETURN	1.39*	76(98)	2.01*	1.13*	0.99*
ADJ R^2	0.109		0.119	0.107	0.100

* significant at the 0.05 level of significance using the 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. The test statistic is a z-score (z) defined by the following equation: $z = \frac{(P-p)}{\sigma}$, where P is the hypothesized value of population proportion in the null hypothesis (0.60 in our setting), p is the sample proportion, and σ is the standard deviation of the sampling distribution which is given by: $\sigma = sqrt\left[\frac{P*(1-P)}{n}\right]$, where n is the sample size.

Table 7

Cross-correlation and liquidity

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

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

where $CROSSCORR_{i,t+1}$ measures how the order flow on stock *i* co-varies with the order flow on the market as proxied by the order flow on the TSE exchange traded fund for minute *t*. The remaining variables are as defined in Table 3. We present the results based on calendar time forecasting by predicting the return cross correlation for the full sample and for three size based portfolios based on the previous minute's lagged LOB information for our benchmark period of June 2008 in Panel A. Panel B summarizes the results for the impact of Arrowhead for the post-financial-crisis period using the following model:

$AUTOCORR_{i,t+1} = \alpha_i + \beta_{1i}COI_{i,t} + \beta_{2i}SLOPE_{i,t} + \beta_{3i}NTRDS_{i,t} + \beta_{4i}ATS_{i,t} + \beta_{5i}SPREAD_{i,t} + \beta_{6i}DEPTH_{i,t} + \beta_{7i}TRADING\ SPEED_{i,t} + \beta_{8i}VOLATILITY_{i,t} + \beta_{9i}RETURN_{i,t} + \beta_{10i}ARROWHEAD_{i,t} + \beta_{11i}MKTRET_{i,t} + \beta_{12i}ARROWHEAD_{i,t}{*}COI_{i,t} + \beta_{13i}ARROWHEAD_{i,t}{*}SLOPE_{it} + \mu_{i,t+1}$

The variables are as defined previously. 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 in parentheses). The remaining columns present the standardized parameter estimates averaged across all individual security regressions. The large, medium, and small classifications are based on the TOPIX 100 Large-Sized Stocks Index, the TOPIX Mid 400 Medium-Sized Stocks Index, and the TOPIX Small-Sized Stocks Index, respectively.

Panel A. Predicting future return cross correlation for the benchmark period

	(1)	(2)	(3)	(4)	(5)
Variables	All Firms	%t (%sign)	Large-cap	Mid-cap	Small-cap
COI	0.72*	69(78)	1.04*	0.71*	0.52*
SLOPE	-0.28*	51(69)	-0.46*	-0.18	-0.15
NTRDS	-0.14	25(59)	-0.52	-0.09	-0.01
ATS	-0.21	51(55)	-0.56*	-0.17	-0.13
SPREAD	0.13	49(69)	0.46	0.25	0.03*
DEPTH	-0.08	34(50)	-0.63	-0.05	-0.05
VOLATILITY	0.50	62(55)	2.15*	0.98*	0.19
RETURN	0.01	1(54)	0.08	0.05	-0.01
HIGH SPEED	0.06	26(93)	0.07	0.05	0.06
LOW SPEED	-0.07	5(53)	-0.14	-0.08	-0.01
ADJ R^2	0.087		0.072	0.088	0.102

Panel B. Predicting future return cross correlation post crisis and post Arrowhead

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	All Firms	%t (%sign)	Large-cap	%t (%sign)	Mid-cap	%t (%sign)	Small-cap	%t (%sign)
COI	0.41*	72 (65)	0.68*	84 (72)	0.38*	78 (64)	0.06	54 (48)
SLOPE	-0.22*	50 (62)	-0.43*	76 (65)	-0.23	47 (57)	-0.04	10 (46)
ARROW	0.91*	64 (79)	1.17*	84 (77)	0.95*	76 (85)	0.02	32 (70)
ARROW*COI	0.38	18 (71)	0.53	22 (75)	0.31	17(68)	0.30	13 (69)
ARROW*SLOPE	-0.14	28 (66)	-0.30	42 (76)	-0.18	22 (61)	-0.01	15 (60)
ADJ R^2	0.078		0.082		0.073		0.079	

* significant at the 0.05 level of significance using the 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. The test statistic is a z-score (z) defined by the following equation: $z = \frac{(P-p)}{\sigma}$, where P is the hypothesized value of population proportion in the null hypothesis (0.60 in our setting), p is the sample proportion, and σ is the standard deviation of the sampling distribution which is given by: $\sigma = sqrt\left[\frac{P*(1-P)}{n}\right]$, where n is the sample size.

Table 8

Predicting trade speed and quotes to trade ratio using SLOPE and COI measures, before and after Arrowhead

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

$TRADESPEED_{i,t+1}$ *or* $QUOTES\ TO\ TRADE\ RATIO_{i,t+1} = \alpha_i + \beta_{1i}\,COI_{i,t} + \beta_{2i}\,SLOPE_{i,t} + \beta_{3i}\,MONDAY_{t+1} + \beta_{4i}\,NTRDS_{i,t} + \beta_{5i}\,ATS_{i,t} + \beta_{6i}\ SPREAD_{i,t} + \beta_{7i}\,DEPTH_{i,t} + \beta_{8i}VOLATILITY_{i,t} + \beta_{9i}\ MKTRET_{i,t} + \mu_{i,t+1}$

where $TRADESPEED_{i,t+1}$ *or* $QUOTES\ TO\ TRADE\ RATIO_{i,t+1}$ is the future number of trades per minute for Panels A and B, and the future number of quotes to number of trades ratio for Panels C and D. The remaining variables are as defined in Table 3. We present the results based on calendar time forecasting by predicting the speed of trading, for the full sample and for three size based portfolios, based on the previous minute's lagged LOB information for our benchmark period of June 2008 in Panels A and C. Panels B and D summarizes the results for impact of Arrowhead for the post financial crisis period using the following model:

$TRADESPEED_{\ i,t+1}$ *or* $QUOTES\ TO\ TRADE\ RATIO_{i,t+1} = \alpha_i + \beta_{1i}\,COI_{i,t} + \beta_{2i}\,SLOPE_{i,t} + \beta_{3i}\,MONDAY_{t+1} + \beta_{4i}\,NTRDS_{i,t} + \beta_{5i}\,ATS_{i,t} + \beta_{6i}\,SPREAD_{i,t} + \beta_{7i}\,DEPTH_{i,t} + \beta_{8i}VOLATILITY_{i,t} + \beta_{9i}MKTRET_{i,t} + \beta_{10i}ARROWHEAD_{i,t} + \beta_{11i}ARROWHEAD_{i,t}{*}COI_{i,t} + \beta_{12i}ARROWHEAD_{i,t}{*}SLOPE_{it} + \mu_{i,t+1}$

where *TRADESPEED* is inverse of the time between trades. The remaining variables are as defined previously. 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 in parentheses). The remaining columns present the standardized parameter estimates averaged across all individual security regression equations. The large, medium, and small classifications are based on the TOPIX 100 Large-Sized Stocks Index, the TOPIX Mid 400 Medium-Sized Stocks Index, and the TOPIX Small-Sized Stocks Index, respectively.

Panel A: Predicting the future number of trades for the benchmark period

	(1)	(2)	(3)	(4)	(5)
Variables	All Firms	%t (%sign)	Large-cap	Mid-cap	Small-cap
COI	-2.95*	88 (95)	-4.31*	-2.96*	-1.72*
SLOPE	2.05*	66 (88)	3.00*	2.95*	1.36
MONDAY	-0.01	23 (46)	0.10	-0.03	-0.01
SPREAD	-0.48	40 (83)	-0.22	-0.18	-0.64
DEPTH	1.23*	51 (74)	6.02*	2.41*	0.41
ATS	3.82*	77 (89)	7.74*	5.69*	2.84*
NTRDS	3.98*	85 (99)	7.66*	5.01*	3.22*
VOLATILITY	1.66	42 (99)	2.90*	2.88*	1.14
MKTRET	-0.09	10 (52)	-0.08	-0.01	-0.11
ADJ R^2	0.101		0.133	0.090	0.102

Panel B: Predicting the future speed of trading post crisis and post Arrowhead

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	All Firms	%t (%sign)	Large-cap	%t (%sign)	Mid-cap	%t (%sign)	Small-cap	%t (%sign)
COI	-1.24*	65 (73)	-1.33*	76 (75)	-1.75*	69 (79)	-0.38	35 (65)
SLOPE	1.19*	60 (69)	1.37*	79 (79)	1.21*	61 (67)	0.96	41 (61)
ARROW	1.02*	88 (68)	3.70*	100 (80)	1.08*	100 (62)	-1.06	48 (64)
ARROW*COI	-1.14*	67 (71)	-3.06*	82 (70)	-2.25*	76 (71)	1.45	44 (76)
ARROW*SLOPE	0.97	48 (59)	1.92*	91 (75)	0.71	39 (55)	0.15	11 (50)
ADJ R^2	0.044		0.068		0.044		0.020	

Table 8-continued

Panel C: Predicting the future quotes to trade ratio for the benchmark period

	(1)	(2)	(3)	(4)	(5)
Variables	All Firms	%t (%sign)	Large-cap	Mid-cap	Small-cap
COI	-0.84*	62 (63)	-2.69*	-1.71*	-0.25
SLOPE	1.15*	75 (89)	1.23*	1.52*	0.65*
MONDAY	0.19	23 (64)	0.51	0.56	0.06
SPREAD	-0.49	49 (78)	-0.14	-0.47	-0.59*
DEPTH	0.34	47 (79)	1.03*	0.61*	0.18
VOLATILITY	0.14	16 (51)	0.83	0.13	0.08
ATS	-0.47	35 (61)	-0.91*	-0.40	-0.03
NTRDS	-0.77	46 (62)	-2.01*	-0.72*	-0.22
MKTRET	0.04	4 (52)	0.02	0.03	0.05
ADJ R^2	0.091		0.114	0.082	0.090

Panel D: Predicting the future quotes to trade ratio post crisis and post Arrowhead

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	All Firms	%t (%sign)	Large-cap	%t (%sign)	Mid-cap	%t (%sign)	Small-cap	%t (%sign)
COI	-1.31*	64 (72)	-2.91*	71 (87)	-2.23*	69 (81)	-0.67	46 (60)
SLOPE	2.03*	79 (92)	2.38*	86 (97)	2.85*	88 (99)	1.57*	65 (74)
ARROW	2.59*	88 (97)	3.51*	98 (100)	3.06*	91 (99)	1.09*	78 (92)
ARROW*COI	-1.54*	81 (88)	-3.04*	96 (99)	-2.77*	92 (100)	-0.68*	73 (79)
ARROW*SLOPE	2.33*	83 (96)	3.42*	99 (100)	3.11*	95 (100)	1.82*	68 (85)
ADJ R^2	0.193		0.216		0.168		0.188	

* significant at the 0.05 level of significance using the 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. The test statistic is a z-score (z) defined by the following equation: $z = \frac{(P-p)}{\sigma}$, where P is the hypothesized value of population proportion in the null hypothesis (0.60 in our setting), p is the sample proportion, and σ is the standard deviation of the sampling distribution which is given by: $\sigma = sqrt\left[\frac{P*(1-P)}{n}\right]$, where n is the sample size.