# High-Frequency Trading and Long-Term Investors: A View from the Buy-Side

**Abstract**: With the proliferation of high-frequency trading (HFT), understanding the effects of HFT on market quality and the opportunities that HFT creates for long-term (LT) investors is important in building an efficient regulatory framework. This paper demonstrates an approach that allows us to estimate the effects of HFT on market quality using information on daily aggregate volumes of HFT and of LT investors provided by a bulge-bracket broker in two trading environments that are different in terms of electronic liquidity, the evolving Tokyo equity market and the mature London equity market. Our results suggest that HFT is mostly involved in opportunistic liquidity provisioning rather than engaging in predatory strategies, at least for liquid stocks. While HFT market making activity increases short-term intraday volatility and therefore adversely affects transaction costs, this effect is more than offset by the significant compression of bid-ask spreads leading to a net reduction of trading costs for LT investors.

Keywords: High-Frequency Trading, Liquidity, Trading Costs
JEL Classifications: G12, G15

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## INTRODUCTION

The ongoing technological revolution and a host of regulatory changes over the last decade have brought significant changes to the microstructure of markets across the globe. The decentralization of market centers has produced a rich and highly fragmented liquidity landscape. The complexity and fluidity of the modern marketplace has helped create new types of arbitrage opportunities. These opportunities, combined with relatively inexpensive technology and low costs of entry, explain the rapid proliferation of so-called high-frequency trading (HFT), which describes the trading activities of a loosely defined category of market participants that include electronic market makers and statistical arbitrageurs. While a broadly accepted definition of HFT has yet to emerge, this category of market participants is often portrayed as a low-risk, technology-fueled activity that takes advantage of short-term opportunities. The efficiency of the new marketplace in terms of price discovery and trading costs for traditional retail and institutional investors has recently become the focus of public and regulatory scrutiny. Much of this attention has brought the ethics and fairness of HFT, as well as its effects on the quality of markets, into question.

Thus far, evidence related to the effects of HFT on the quality of the market remains inconclusive. Its proponents claim that HFT helps reduce intraday volatility, bid-ask spreads and the overall level of transaction costs for retail and institutional investors because high-frequency traders are primarily involved in market making and statistical arbitrage, activities that mostly provide liquidity to other market participants. These arguments are supported by recent works on the U.S. stock market by Brogaard (2010), Jovanovic and Menkveld (2012) and Hendershott and Riordan (2009). Critics of HFT accuse the HFT firms of front-running large institutional orders. They also argue that the liquidity provided by HFT is fictitious; although such liquidity is plentiful during "normal" market conditions, it disappears at the first sign of trouble because market makers liquidate their positions and exacerbate adverse price movement. Speaking metaphorically, trading institutional-sized orders is like walking on thin ice, which feels deceptively safe until it breaks. Such hypersensitive market liquidity hurts the confidence of the slow-to-react long-term investors who ultimately determine a stock's valuation, impairing the price discovery process.

In his recent paper, Zhang (2010) argues that HFT is positively correlated with stock volatility after controlling for other exogenous determinants of volatility. He finds that HFT generates harmful effects for the U.S. market by introducing price swings and increasing short-term volatility. Investors also note that the proliferation of HFT has increasingly shifted market liquidity toward a smaller subset of the investable universe and that less liquid stocks remain expensive to trade. This shift became a self-fulfilling prophecy because liquidity begets liquidity and, when institutional investors shy away from hard-to-trade securities, market makers have even more reason to focus on a handful of liquid instruments. Ultimately, this type of liquidity landscape limits investment opportunities and contributes to higher short-term correlations across the entire market.

Although these arguments may sound mutually exclusive, there are elements of truth in all of them. The low cost of entry, low capital requirements and the loss of specialist-era market making privileges led to fierce competition among marker makers, razor-thin profits and no appetite for overnight risk. As a result, a market maker has little or no economic incentive and sufficient financing to stabilize a stock price even at the cost of losing a measure of retail and institutional flow. Facing diminishing profits, market makers are more concerned with controlling losses and, for them, that means being able to re-price their quotes fast enough to avoid being adversely selected. Thus, cutting-edge technology becomes a pre-requisite to preserving an edge in the existing market environment.

Market participants who are unable or unwilling to make similar investments in trading technology find themselves at a disadvantage. Very few asset managers generate enough trading revenues or explicitly track the contribution of trading to a firm's investment process to justify maintaining a high-performance trading infrastructure so they rely on sell-side brokers to execute their orders. A sell-side trading infrastructure is significantly more complex than an infrastructure executing narrowly focused HFT strategies and is therefore less nimble and more expensive to upgrade. As a result, brokers generally prefer to invest in the development of dark pools instead of directly competing with HFT firms on exchanges and ECNs because they have more control over their client's trading flow and may be able to offer lower execution costs and a greater degree of anonymity.

Given the magnitude of recent changes and the complexity of the current marketplace, it is essential for an investor to understand how this new environment affects the cost of trading, liquidity risk and the choice of the investable universe. This study aims to shed more light on HFT activity and its interaction with the order flow of long-term (LT) investors.

While most of the existing literature on HFT focuses on the U.S. stock market, this study analyses HFT activity in UK and Japan. The UK market is not dissimilar to the

U.S. market in terms of the maturity of electronic offerings, its fragmentation and its HFT populace. By contrast, the Tokyo Stock Exchange (TSE) is a recent entrant to the arena of high-speed trading; the Arrowhead initiative is only 2 years old and the HFT share has soared from a measly 10% in 2009 to nearly 40% in 2012.

We use AllianceBernstein's trading data and the data on aggregate HFT and LT investor daily volumes routed through a single bulge-bracket broker to answer the following questions:

a. What are the characteristics of stocks that are traded by HFT?
b. How do HFT daily volumes in the most- and least-traded stocks correlate with market dynamics and LT investor volumes?
c. What is the intraday liquidity interaction between HFT and LT investor?
d. What are the factors that can explain the changes in daily volumes for HFT firms?
e. How does HFT affect trading costs for a traditional buy-side investor?

Our results confirm the conventional view that HFT trades in liquid stocks. Compared to LT investors, HFT is more two-sided, implying dominant market making (liquidity rebate) strategies that are tied to managing market risks.

We argue that HFT accentuates intraday volatility that negatively affects the cost of trading, but this effect is more than offset by compressed bid-ask spreads. While front running could not be fully ruled out in certain scenarios, HFT firms were net liquidity suppliers over the lifetime of our orders. We analysed the trading costs incurred by our trades and found that HFT activity helped reduce them in the aggregate. The last conclusion is clearly affected by the choice of the tradable universe, order sizing, and trading style, so we do not suggest generalizing this conclusion to all LT investors. Instead, we present a framework that can be used to evaluate individual cases.

This paper is organized as follows. Section 2 gives an overview of characteristics of the most- and least-traded stocks by HFTs in the London and Tokyo markets. We also discuss daily cross-correlations between HFT and LT investor volumes. Section 3 focuses on the intraday effects of HFT in Japanese market. In Section 4, we concentrate on the effect of HFT on short-term volatility in the London market. Section 5 analyses major triggers of order flow for traditional institutional investors and HFT firms. Section 6 presents analysis of HFT's effect on trading costs incurred by trading AllianceBernstein's buy-side orders. Section 7 concludes the paper.

## SECTION 2: HIGH-FREQUENCY TRADING: WHAT DO THEY TRADE?

### 2.1. Sample Description

The dataset provides aggregate daily volumes routed by HFT and LT investors in the stocks from the Bloomberg European 500 Index (BE500) and Nikkei 225 via a bulge-bracket broker with a significant presence in both markets. In this paper, we take advantage of the data with a clear distinction between HFT firms and other traders who use algorithms. Specifically, in these data, HFT firms are defined by the broker as users of ultra-low latency infrastructure. Such users employ trading platforms that enable them to make trading decisions within microseconds. Achieving such low latency requires an optimized end-to-end trading infrastructure. The faster a trading application responds to market signals, the higher the chances of getting the order filled or cancelled before it gets adversely selected. These high-speed orders are generated within the co-located servers of proprietary trading desks and hedge funds and are sent via binary protocols to the exchange's matching engine. By contrast, the data define LT investors as users of traditional DMA/DSA (direct market/strategy access), SORs (smart order routers) and dark pools. While ultra-low latency infrastructures are available to some LT investors in the U.S. now, these tools were not an option for LT investors in the Japanese and London markets in 2010.

The data cover the time period from January 1 to June 30, 2010. For Europe, it contains the date, symbol and daily USD notional value for each stock in the Bloomberg European 500 Index (BE500), separately reported for HFT and LT investors. For the Japanese market, we have HFT and LT investor sided intraday trading volumes (shares and ¥ notional) bucketed into 6 intervals, including the first and last 30 minutes of each trading session and the time in between for each stock in the Nikkei 225. The Tokyo market has 2 sessions. In 2010, it operated from 9:00 AM to 11:00 AM and from 12:30 PM to 3:00 PM. Since November 21, 2011, the TSE extended its morning session by 30 minutes.

Reported absolute levels of HFT and LT investor volumes suggest the prominent role of the broker in providing low latency and traditional DMA/DSA infrastructure in Japan and the UK. Specifically, in the first half of 2010, the broker retains a broad client base with a market share of 29% in the TOPIX. This number splits into 18% and 11% between LT investor and HFT clients, respectively. This split does not reflect the 80/20 ratio between LT and HFT reported by TSE for the first half of 2010, suggesting a leading position of the broker as a provider of low latency infrastructure in Tokyo. In the UK, the broker's market share comprises 10% of the FTSE 350, which represents approximately 90% of the UK equity market by capitalization. The broker's market share is equally split between HFT and LT investor clients, which is consistent with a 45% HFT market share that was reported for the UK in 2010 by various sell-side publications.

We set the stage by creating two groups of stocks per market, the stocks that are most and least traded by HFT based on the total notional turnover over the period. In addition, we take into account the consistency of trading activity for each stock. We label the first group "*HiVLM*" and the second group "*LoVLM*". For each market, "*HiVLM*" represents stocks in the top tertiles of notional value that are traded every day. "*LoVLM*" represents stocks that are in the bottom tertiles of notional value. We discuss the differences in stock characteristics between these two groups below.

**2.2. UK Market**

Our data sample covers the first two quarters of 2010 and includes periods of up-trending and downtrending markets associated with lower- or higher-implied volatilities. It also includes the flash crash date. Figure 1 shows cumulative close-to-close returns for the market and the implied volatility index. In Europe, implied volatility jumped at the end of April 2010, while the market continued to downtrend after several months of price rebounding. This period coincides with the onset of the European debt crisis.

There are 140 UK stocks in the daily volume data obtained from the broker. We create *HiVLM* and *LoVLM* groups in the UK out of roughly 50 stocks. Table 1 shows stock characteristics such as beta, bid-ask spread, median daily volume (MDV) and daily high-to-low (HL) volatility, which is calculated as the log of the ratio of the maximum to the minimum price. Though all stocks in the analysis are liquid, the *HiVLM* group is clearly associated with higher liquidity and a lower bid-ask spreads class compared to the

*LoVLM* group. The difference in daily volatility is insignificant between the two groups; we will discuss this point later.

We have also noticed that *HiVLM* belong to major equity indexes that are likely to be traded by HFT to hedge their exposures. For example, all *HiVLM* in the UK are in the FTSE 100. Of the *LoVLM* group, less than 30% of the stocks belong to this index. Moreover, the *HiVLM* occupy the top of the index constituents list by market capitalization. Specifically, approximately 70% of UK *HiVLM* are in the top 30% of stocks in the FTSE 100. It is not surprising then that *HiVLM* and *LoVLM* differ significantly in share float; the average number of floating shares for *HiVLM* is 5 bn, whereas for *LoVLM* this number is only 0.5 bn shares.

Correlations of HFT and LT investor daily volumes are much higher for *HiVLM*; the correlations of both HFT and LT investor daily volumes to overall market volume are also higher for *HiVLM* (Table 2). This observation is also hardly surprising given that *HiVLM* are traded every day. It underscores the opportunistic nature of trading in less liquid instruments because, for both stocks traded by HFT and by LT investors, the distribution of daily volumes as % MDV in *LoVLM* group is much more heavily skewed compared to the distribution for the *HiVLM* group. This suggests that the daily volumes routed through an individual broker in *LoVLM* are significantly less stable and driven by stock-specific events or available liquidity.

**2.3. Japanese Market**

The Japanese market shows both uptrend and downtrend periods over the first 6 months of 2010. Figure 2 shows the cumulative close-to-close return for the Nikkei 225 and Japan volatility index, the VXJ. Table 3 shows the average bid-ask spreads, the MDV and daily HL volatilities for the 75 stocks in *HiVLM* and 75 stocks in *LoVLM* from the Nikkei 225. For the Japanese market, 95% of the *HiVLM* are in the top 15% of TOPIX, whereas 80% of the *LoVLM* fall in the top 15-30% of TOPIX stocks by market capitalization weight. The conclusion is similar to that in the UK market with *HiVLM* group showing lower bid-ask spreads and higher daily volume. Likewise, the cross-correlations of HFT, LT and market volumes are much higher for the *HiVLM* group (Table 4).

Japanese data provides sided daily volumes for both HFT and LT investors, which allows us to establish whether trading is predominantly conducted on one or both sides of the market. Table 5 shows correlation patterns for HFT and LT investors' sided volumes (in shares). *HiVLM* show higher correlations between buy and sell volumes for both HFT and LT investors, implying more two-sided market activity compared to *LoVLM*. This is further confirmed by absolute daily order imbalances, |Buy-Sell|/(Buy+Sell) which are significantly higher for *LoVLM* (Table 6). Comparing the correlations between buy- and sell-volumes for HFT and LT investors, the data in Tables 5 and 6 clearly suggest that HFT is on both sides of the market and that LT investors mostly trade on one side, particularly in *LoVLM*.

These results imply that HFT is predominantly involved in market making in liquid stocks. This activity reinforces market two-sidedness, which we observe in *HiVLM*, by providing two-sided quotes and profiting by earning the bid-ask spread and liquidity rebates. In *LoVLM*, HFT firms show high enough absolute daily order imbalances to suggest a combination of market making and perhaps intraday statistical arbitrage strategies. For LT investors, trading *LoVLM* indicates exacerbated liquidity, information leakage and higher overall transaction costs.

Sarkar and Schwartz (2009) show that market sidedness is related to the following three aspects of liquidity: immediacy, the bid-ask spread and the depth. A two-sided market offers a high level of immediacy because traders on either side of the market have little difficulty in finding a counterparty to execute a trade. Bid-ask spreads are typically compressed because competition between buyers and sellers leads to tighter quotes and more depth. By contrast, a one-sided market is associated with reduced liquidity in all three dimensions: less immediacy, lower depth and wider bid-ask spreads. Here we must note that the typical assumption about two-sided markets is heterogeneity of trading motives for the market participants. Conversely, if high-frequency traders are the dominant market force and act largely on the identical set of signals, quoting only within a narrow window of market conditions that they consider "normal", the benefits of two-sided markets for other participants will only be realized within this window of normalcy and will deteriorate quickly outside of it. For this reason, the quoted bid-ask spread and the depth of the book may not adequately describe the quality of the market; instead, it is important to look at realized spreads and actual liquidity provided by market makers.

## SECTION 3: INTRADAY ACTIVITY OF HFT AND LT INVESTORS IN THE JAPANESE MARKET

The Japanese market went through great change in 2010 because of the significant reform of its market structure. The Tokyo Stock Exchange (TSE) launched Arrowhead in January 2010, which is its next-generation high-speed trading platform. Rival proprietary trading systems started clearing trades in July 2010. In tandem with Arrowhead, the TSE reduced the tick size for several stock categories; the tick size is the smallest increment by which a stock price can move. These changes were introduced to accommodate electronic liquidity providers in Japan to meet the needs of investors for faster order and execution processing.

While turmoil in the U.S. and European financial markets in 2010-2011 depressed equity transaction volumes across the globe, HFT liquidity has played an increasingly important role in Japanese markets, contributing to the strength of market volumes. According to the TSE, only 10% of traded volume came from global financial firms with HFT business at the end of 2009. The same report quotes traded volume submitted through co-located facilities to reach 20% during the first half of 2010 and 33% during the first half of 2011.

The Japanese market and its growing HFT activity is an interesting natural experiment to study HFT effects on market quality. In this section, we attempt to answer the question of how HFT has affected the Japanese market. Specifically, the HFT contribution to the overall quality of the market is discussed here in the context of the provision of intraday liquidity and short-term stock volatility and quoted bid-ask spreads.

### 3.1. Intraday Liquidity Provisioning

The previous section established that HFT is primarily involved in liquidity provisioning in a select group of highly liquid stocks. It is logical to assume that this liquidity is primarily provided to net liquidity takers such as LT and retail investors. The availability of intraday sided volumes traded in Japanese market via the broker allows us to analyze how HFT liquidity is distributed over specific intraday periods, ie, morning, midday and evening, and how HFT liquidity interacts with LT investor flows.

As discussed above, the relative levels of market share between HFT and LT investors do not reflect the 20/80 ratio reported by the TSE for the first half of 2010. We decided to scale broker's LT investor volumes to bring the proportion of HFT to LT investor volumes in line with TSE figures. After rescaling, HFT and LT investor market shares comprise 20% and 80% of the total volume traded in the TOPIX and 28% and 72% in the Nikkei 225, respectively. Figure 3 exhibits the average HFT and LT investors' traded volumes per stock as a percentage of daily volume per 30 minutes in each intraday period. HFT and rescaled LT investor broker's volumes comprise the market daily volume in each time interval.

While LT investor volumes are strongly U-shaped with a heavy volume at market close, HFT volume distribution is significantly flatter throughout the trading day, with only moderate increase during day's opening and closing sessions. There is almost no difference in intraday HFT volume profiles between *HiVLM* and *LoVLM* in spite of the fact that LT investor volume is significantly more U-shaped in the *LoVLM* group. We also find a higher proportion of HFT volume in *HiVLM* vs. *LoVLM*, which validates the difference in HFT activity in the two groups of stocks. We explain the low ratio of HFT volumes during the two opening sessions by HFT's risk aversion of trading with asymmetrically informed market participants. Both sessions are periods of price discovery when new information is being absorbed by the market based on overnight news and the news arriving from Europe during the TSE lunch break. The standard asymmetric information models in the market microstructure literature predict that bid-ask spreads increase and that trading volume decreases as information asymmetry increases (eg, Easley and O'Hara 1987; Admati and Pfleiderer 1988). As for imbalance between HFT executable liquidity and net executed LT investor trading volume at market close, it is dictated by the avoidance of carrying significant positions to the next trading day.

To assess HFT's role in intraday liquidity, Figure 4 and 5 show the average order imbalances per stock as a percentage of daily volume for *HiVLM* and *LoVLM*. Taken together, the data on both volume charts provides evidence that the positions taken by HFT firms are essentially flat throughout the day, suggesting the short-term nature of their trading strategies and tight inventory management.

In *HiVLM*, HFT consists of net liquidity providers during the trading day except for the open, where HFT and LT investors are competitors, ie, they tend to trade on the same side of market. This is the intraday period in which front running by HFT firms remains plausible and inflates transaction costs for institutional investors. Although the difference between the means of HFT and LT investors' order imbalances for *HiVLM* is statistically insignificant at the 5% confidence level in the morning, HFT firms remain net liquidity suppliers in the afternoon, finishing the day net-positive (Fig. 5) as opposed to net-negative LT investors, which indicates significant liquidity provisioning by electronic market makers and potentially overall lower transaction costs for LT investors. Daily risk exposures may be managed by spreading equities against futures and ETFs. Negative daily imbalances for LT investors may be explained by the predominantly down-trending market of the first half of 2010 and sizeable fund redemptions.

By contrast, positive morning imbalances in *LoVLM* are statistically significant at the 5% level for both HFT and LT investors. In the afternoon, HFTs and LT investors are net-negative, efficiently closing their daily positions via futures and ETFs to hedge directional price risk.  While hedging risk exposure with ETFs and futures in liquid stocks is cost efficient on average, it is likely to be less efficient for less-liquid instruments. We therefore conclude that the possibility of front running during the day is more pronounced in the *LoVLM* universe.

Finally, our findings regarding HFT liquidity provisioning is the net of broker's bias, although we notice some specifics in the distribution of LT investor intraday ordering in the broker's data. This is the result of contrasting results between *HiVLM* and *LoVLM* with the same endogeneity in the LT investor order flow.

### 3.2. HFT Activity Effect on Short-Term Volatility and Bid-Ask Spreads

Other important aspects of HFT activity include its effects on short-term volatility and quoted spreads. While there is consensus that HFT's market making tightens the quoted spread via liquidity provisioning, existing evidence of HFT's effect on intraday volatility is mixed. Several studies argue that HFT's liquidity provisioning dampens short-term volatility (Hasbrouck and Saar 2011; Bogaard 2010). Others link HFT with heightened volatility levels (Lehalle and Burgot 2009). One of the possible explanations for these different conclusions is the absence of a universally accepted definition of HFT. Among the defining characteristics of HFT is algorithmic trading that is also employed by traditional buy-side investors. The absence of consensus in the definition of HFT leads to analyses of data that may be predominantly buy-side in nature. In this study, HFT firms are strictly referred to as the users of co-location services that the TSE only began offering at the beginning of 2010 and that are still utilized predominantly by HFT firms.

Because HFTs do not establish long-term positions and end the day flat, we do not expect them to affect daily price volatility. Short-term volatility, measured over a duration commensurate with the HFT holding period, may be a different matter. We replicated the list of stocks traded by HFT firms for 2011 using the information about the distribution of market capitalization and floating shares in the broker's data for 2010. We utilize the available list of stocks traded by HFT in the first half of 2011 along with 2010 data to assess the effect of the growing HFT presence on short-term stock volatility and quoted spreads. Specifically, we construct 5-, 10- and 30-minute high-low (HL) volatilities. Each measure of short-term volatility is a log of the ratio of the maximum to the minimum price in an interval. For daily volatility, we choose two range-based standard metrics, daily HL volatility and open-to-close (CO) volatility, which is measured as absolute value of close-to-open returns for the day. We compute the average short-term and daily stock volatility for *HiVLM* and *LoVLM* for the first half of 2010 and 2011.

We use average 5-minute quoted spreads as a measure for the daily spread. As discussed above, the TSE changed the minimum tick size rules in early 2010; the revision affected 6 price categories of stocks. Appendix A describes the implemented tick size change. Our sample of *HiVLM* is dominated by stocks with a price below 2000 ¥, which is the group in which tick size did not change. This group comprises 60% of the data. The price category above 2000 ¥ and below 5000 ¥ comprises 30% of the sample and presents a group with the most pronounced tick size changes. Specifically, for a price category between 2000 ¥ and 3000 ¥, the minimum price variation decreased from 5 ¥ to 1 ¥, whereas for stocks between 3000 ¥ and 5000 ¥ the tick size dropped from 10 ¥ to 5 ¥. In comparison, the *LoVLM* data set is dominated by stocks that are below 2000 ¥ and that belong to the price category that was not affected by the new tick size regulation.

Table 7 shows the spreads and volatility measures separately for each intraday time interval and price category. We removed bargain stocks with prices below 300 ¥ from the data sample. Additionally, we calculated the minimum bid-ask spread, ie, the spread based on the minimum price variation. The results suggest a slower market for *LoVLM*, where bid-ask bouncing is the main driver behind 5-minute HL stock volatility. By contrast, 5-minute HL stock volatility is approximately 2 times higher than the bid-ask spread for the faster market of *HiVLM*.

We use the difference-in-differences method (DID) proposed by Ashenfeletr and Card (1985) to estimate the effect of increased HFT liquidity on short-term price volatility and spreads. This econometrics method has been widely used in the social sciences to estimate the effects of policy or an event. Jovanovic and Menkveld (2012) use a DID analysis to assess the treatment effect of HFT entry on market quality in terms of liquidity and price efficiency around the introduction of a new HFT-friendly trading venue, the Chi-X.

The simplest framework permits outcomes to be observed for two groups in two time periods. One of the groups (treatment) is exposed to the treatment in the second period. The other group (control) is not exposed to the treatment in either period. The DID estimator estimates the time difference for the treated and untreated group and then takes the difference in the time differences. In other words, the average gain in the control group is subtracted from the average gain in the treatment group. This approach allows two major biases to be removed, which are the permanent differences between the groups in the second period, on the one hand, and the bias associated with comparison across time in the treatment group because of trends, on the other. More detail on the DID analysis along with an analysis of its estimates can be found in Appendix B.

Following Jovanovic and Menkveld (2012), we define the growing HFT liquidity from 2010 to 2011 in the Japanese market as the treatment effect. The treatment group is *HiVLM* and the control group is *LoVLM*. There is a significant overlap in the stocks between 2010 and 2011 in each group. Specifically, approximately 80% of stocks in *HiVLM* were traded both in 2010 and 2011. There is an overlap of approximately 75% in the stocks of the control group between these years.

Table 8 exhibits the DID estimates of the percentage changes from the first half of 2010 to the first half of 2011 in volatilities and quoted spreads because of the increased HFT presence in the Japanese market. Additionally, we calculate the percentage change in bid-ask spread improvement over tick size, eg, the difference between the quoted spread and the minimum tick size price movement. First, we show that intraday volatility rose in stocks in which HFT activity is high. In other words, HFT adds a volatility layer over and above pre-existing fundamental volatility. Specifically, the growing HFT presence caused the rise in 5- and 10-minute HL stock volatility by 10% and 2%, respectively, for *HiVLM* in the price category below 2000 ¥. These numbers match 8% and 1%, respectively, for *HiVLM* that were subject to tick size reduction. We also find that the influence of HFT on stock volatility is limited to short intraday time intervals only, ie, 5 and 10 minutes. These results show the absence of statistically significant effects of the increased market share of HFT on daily volatility measures such as HL, CO and 30 minute intraday volatility, which validates the short-term nature of HFT strategies.

Second, increased liquidity provisioning by HFT leads to tighter quoted spreads. In our analysis, we find significantly more compressed quoted spreads in the stocks in which tick size was reduced. On average, the spread decreased only 3% for the price category up to 2000 ¥, improving (getting tighter) to minimum tick size by 26%. Stocks in the 3000 - 5000 ¥ price range show quoted spread reductions of approximately 12% and 28% spread improvement over minimum tick size. There have been debates that the benefits in terms of spread and liquidity are far less significant in markets in which the tick sizes were not changed. Our analysis provides supporting evidence that reducing tick sizes in liquid stocks helps to attract liquidity and to enable increased capability in the market place to facilitate tighter spreads. Significant spread improvement over minimum price variation indicates that it becomes rare to observe wide quoted spread in a faster market because of quote stickiness.

Not surprisingly, smaller ticks intensify competition among market makers and natural liquidity providers, and therefore attract more liquidity and tighten the bid-ask spread. More tick granularity increases the efficiency with which statistical arbitrageurs can locate liquidity from one asset to a related one, resulting in more liquid market. By contrast, larger tick sizes increase incentives for investors to find price improvement via non-display trading venues and contribute to liquidity fragmentation.

The DID method does not address causality concerns, but the explanation of increased short-term volatility and decreased spreads by a selection bias (where HFT firms chose to trade stocks with growing short-term volatility and decreasing spreads), is unlikely. First, taking into account that HFT firms traded predominantly the same stocks in 2010-2011, it is difficult to explain a mechanism that allows HFT firms to select stocks that would exhibit an increase in short-term (5 minute) volatility, but the same daily volatility. Second, if HFT firms had picked stocks with decreasing spreads, it would signal a profit-minimizing strategy that is counter-intuitive. Additionally, we checked how the 5-minute HL volatility changed for two groups of stocks in 2009, ie, in the pre-HFT era in Tokyo (see Appendix B). We find no statistically significant difference in 5-minute HL volatility at the 5% level of confidence, suggesting a parallel volatility shift in time between the groups in the absence of treatment.

Our result of increased short-term volatility because of the presence of HFT confirms finding in the recent empirical studies (Lehalle and Burgot 2009). One of the possible mechanisms that explain accentuated volatility in the presence of HFT is that trading in large volumes observed for *HiVLM* induces volatility. Dichev et al. (2011) show a reliable and economically substantial positive relation between volume of trading and stock volatility. In other words, stock trading produces a volatility beyond the one based on fundamentals. While we find that mean and median daily volumes per name increased from 2010 to 2011 for *HiVLM* with a price below 2000 ¥, they remain intact in a price category between 2000 ¥ and 5000 ¥. Therefore, a rise in short-term volatility cannot be fully attributable to increased trading volume.

Other possible explanation for an observed increase in short-term volatility is that tighter bid-ask spreads come at the expense of available liquidity, eg, decline in quoted depth. Interestingly, we find that the effect of decreased spread and increased short-term volatility is greatest in low-priced, high-volume stocks. This argument is supported by empirical studies of other markets (eg, Chan and Hwang 2001) that find the greatest effect of spread compression along with declining quoted depth on low-priced, high-volume stocks. Notably, however, quoted depth may differ from actual depth because of hidden liquidity and flickering quotes from HFT.

### 3.3. HFT and LT Trading Volume Sensitivity to Intraday Volatility

To provide additional evidence that HFT is low-risk activity, we focus on size positioning of HFT and traditional LT investors in the most volatile intraday period – the opening of the morning session. We examine the sensitivity of HFT and LT investor executed sizes after market opening, ie, in the first 30 minutes of the trading day, to the risk of price movement measured as the 30-minute HL stock volatility. Figure 6 shows the "isothermal" density plots of executed sizes as a percentage of market volume traded in the first 30 minutes against the volatility level. The HFT volume distribution in *HiVLM* is centered near 20% of the morning volume and 30-45 bps HL volatility range. This indicates that HFT firms trade the entire universe of *HiVLM* every day, maintaining a certain level of market participation within a "comfortable" range of volatility, ie, controlling for market risks by limiting net positions and avoiding trades with asymmetrically informed market participants near market opening.

LT investors' volume distribution shows a significantly more opportunistic trading pattern. There is always trading activity at the 5% participation level because of rebalances and cash flows. The distribution, however, is significantly more heavy-tailed with respect to volatility, indicating the occurrence of news-driven trading. LT investor volumes also reveal the arrival of large orders in a relatively calm market. Apparently, HFT and LT investor volume distributions are a poor match for one another, and HFT cannot meet a demand for liquidity from large or high-volatility institutional orders because the activities of electronic liquidity providers are governed by risk management considerations. This observation supports the arguments of the opponents of HFT that when the market needs liquidity the most, electronic liquidity suppliers may not be willing to provide it.

It is not surprising that LT investors reduce the size of their trades with the increase in volatility in *HiVLM*. Table 9 reports the regression results of executed volumes against 30-minute volatility that confirm the higher risk aversion of LT investors to short-term volatility and signal no sensitivity of HFT volumes to volatility risk in stocks with high HFT activity. By contrast, the opposite is true for *LoVLM*. HFT executed volumes indicate risk aversion whereas LT investor volumes show no sensitivity to short-term volatility in the morning. This result may be explained by unstable liquidity patterns in *LoVLM* stocks with LT investors willing to pay higher transaction costs because future liquidity is uncertain. By contrast, LT investors are less willing to pay the premium in liquid *HiVLM* because they can reliably find liquidity over the rest of the day. When HFT supplies liquidity to less-liquid stocks in the morning, it presents a significant risk of being adversely selected by large institutional orders, which makes HFT significantly more risk averse. In this environment, LT investors predominantly trade with themselves.

## SECTION 4: HFT ACTIVITY AND SHORT-TERM VOLATILITY, UK

For the UK market, we contrast short-term volatility and quoted spread profiles between *HiVLM* and *LoVLM* in the first half of 2010. There were no changes in tick size rules in London market in this period. Figure 9 exhibits 5-minute HL stock volatility and quoted spread. We remove 1% of outliers where 5-minute HL volatility is larger than 200 bps. The volatility profile shows a U-shaped pattern that indicates accentuated volatility around market opening and reveals no difference between *HiVLM* and *LoVLM* in the first 30 minutes of the trading day. Accentuated open volatility observed in the first 30 minutes of trading for *HiVLM* is partially attributable to the complexities of price discovery with a leading role of more liquid stocks in discovering equilibrium values. This effect was documented in the pre-HFT era in U.S. and European markets (Pagano et al. 2008).

The data suggest that, on average, the 5-minute HL volatility in *HiVLM* exceeds the short-term volatility level in *LoVLM*, although the quoted spread is 90% higher for *LoVLM* compared to *HiVLM*. Specifically, short-term volatility is 30% higher in the stocks in which HFT is active. This evidence for the London market supports our finding in Section 3 that HFT amplifies short-term stock volatility. We must clarify that the 30% change reflects level change in short-term volatility in the UK market, whereas the 10% change in the Tokyo market indicates the volatility slope, ie, the volatility growth rate. Having received earlier exposure to electronic liquidity, the UK market may be the predictive scenario for the forthcoming rise in the short-term volatility level in Tokyo.

**SECTION 5: TRIGGERS OF HFT DAILY VOLUMES**

This section attempts to detect the main factors that drive HFT and LT investor daily volumes. The SEC has described LT investors as market participants who provide capital investments and are willing to accept the risk of ownership in listed securities for an extended period of time. LT investors conduct research to reveal opportunities for long-term investment strategies and are concerned about the long-term prospects of companies. By contrast, HFT firms do not aim to establish and hold long-term positions. Instead, they enter into short-term positions and typically finish the trading day “flat”, ie, without carrying any significant position overnight. For this reason, HFT firms should have different motives for trading a security in a given instance.

Brogaard (2010) tests the effect of Quarterly Earnings Announcements and broad market volatility captured by the VIX index on HFT activity in the U.S. market. The author shows that Quarterly Earnings Announcements have an insignificant effect on HFT volumes, while higher implied volatility tends to increase HFT activity, and this relationship is statistically significant. We use identical factors to test their effects on both HFT and LT investor’s activity in the UK and Japanese markets. The information on Quarterly Earnings Announcements and implied volatility indices is available on Bloomberg. As we noted in Section 2, liquidity begets liquidity and larger demand for liquidity from LT investors tends to generate higher liquidity supply from market makers in a select group of liquid stocks. Likewise, a large amount of available liquidity may trigger LT investors to enter into larger trades. We will use simultaneous equations to detect the factors affecting trading activity in the market.

**5.1. UK Market**

Table 10 shows the regression results for the UK Market, which indicates a bi-directional causality between HFT and LT investors’ volumes and implies that liquidity does in fact beget liquidity and that illiquidity begets illiquidity. HFT activity has positive and statistically significant relation with implied volatility. By contrast, traditional investors reduce trading volume in the periods of great uncertainty in the market (Figure

6). This suggests that short-term traders, whose profits are limited by how much a stock can move in a given amount of time, generally seek more volatile markets, whereas LT investors tend to reduce their trading when risk is heightened. This result is in line with the previous findings of Brogaard (2010). We must stress that HFT firms' appetite for more volatile markets is subject to managing overall market risks. HFT firms will benefit from increased broad market volatility by earning higher spreads while controlling for risk by hedging their market exposures. As we have shown in Section 3.3, HFT firms are much more cautious in trading with asymmetrically informed market participants (for instance by avoiding highly volatile opening sessions) because it is generally more difficult to hedge this type of risk.

While LT investor activity is positively correlated with Quarterly Earnings Announcements, the effect of these events on HFT activity is small. This finding is consistent with differences in motives for trade initiation between two groups of market participants. The sizable market microstructure literature confirms increasing volumes of traditional institutional investors in response to Quarterly Earnings Announcements.

**5.2. Japanese Market**

The results of the regression for the Japanese market are shown in Table 11. We observe similar implications for HFT and LT investors' volumes as those obtained in the analysis of the UK market. Specifically, the presence of LT investors tends to attract HFT liquidity and vice versa. In accordance with the long-term investment prospective, Quarterly Earnings Announcements have a positive effect on the trading activity of LT investors and little effect on HFT firms. Highly volatile markets have adverse effects on the activities of LT investors and positive effects on the volumes traded by HFT firms.

## SECTION 6: IMPACT OF HFT ON TRADING COSTS OF LT INVESTORS

HFT remains controversial with regulators because of concerns that some HFT strategies may be taking advantage of LT investor flow. In this section, we first examine whether we find any evidence of front running by HFT firms. Second, we focus on trade implementation costs incurred by a LT investor in *HiVLM* and *LoVLM*.

### 6.1. Do HFTs Front Run LT Investors?

While we cannot rule out the possibility that some HFT strategies are predatory, proving this requires a thorough analysis of the tick data and exchange or broker data for reliable identification of market participants. In this section, we attempt to answer the following much simpler question: Can aggregated HFT activity be characterized as predatory? To answer this question, we analyse the order imbalances for the trades executed by AllianceBernstein's buy-side desk in *LoVLM* and *HiVLM* for the UK and Japanese markets. The purpose is to look for indications of front running – a predatory strategy that detects large orders and enters the same side position early to unwind it at more favorable price and profit from the market impact created by the large order. Within *HiVLM* and *LoVLM* sets, we select more potentially detectible trades with a duration longer than 5 minutes and a participation rate higher than 5%. The resulting subsets of trades are dominated by market orders that represent approximately 90% of the trades in both samples. The rest are aggressive limit orders.

We calculate 5-minute order imbalances obtained from the tick data using the Lee and Ready (1991) trade classification algorithm. Order imbalances are calculated as absolute differences in shares traded on the bid and the offer, normalized by the total interval volume and signed by the trade side; these measure the price pressure in the direction of trade. We examine the intervals 5 minutes prior to a trade's arrival, 5 minutes after the arrival and 5 minutes after the last fill of the trade. In addition to market imbalances, we compute the imbalances generated by our trading algorithms to back out the net imbalances created by the rest of the market. To minimize potential biases, we exclude orders that may have been affected by our own prior trades in the same symbol and the orders that had fewer than 3 prints per 5-minute interval. The choice of the 5-minute interval seems to provide a reasonable trade-off between the level of noise in the Lee-Ready order imbalances and the short-term nature of opportunities that are exploited by HFT firms.

If the participation of HFT firms in front-running strategies is significant, we expect to observe order imbalances in the direction of our trade created by the market a few minutes prior to the trade's arrival and/or during the first few minutes of trade period, signaling the presence of competitive pressure. Trading algorithms incur the peak of market impact by the time of the last fill, potentially triggering HFT firms to unwind the position and lock in profit. Thus, we also expect post-trade order imbalances to be on the opposite side of the pre- and in-trade imbalances. In analyzing order flow profiles, we anticipate documenting statistically significant differences in the order imbalance profiles between *HiVLM* and *LoVLM* samples.

Market microstructure literature (Asquith et al. 2010) has documented a positive bias in the Lee-Ready imbalances because of the misclassification of short sells as buys on an uptick rule. While nothing similar to the uptick rule has been imposed on major European markets, Japan introduced the uptick rule during slump in the stock market in 2002 and it continued to be in effect in the first half of 2010. This prompted us to adjust stock level pre-, in- and post-trade order imbalances observed in Japanese stocks by the average 5-minute Lee-Ready imbalance measured for that stock during the entire period.

### 6.1.1. UK Market

In the introduction to this article, we discussed the concern that liquidity is increasingly being shifted toward a smaller subset of highly liquid stocks, while the less liquid universe remains expensive to trade. This shift becomes a self-fulfilling prophecy because liquidity begets liquidity, and HFT firms have more reasons to focus on a handful of liquid instruments as institutional investors avoid hard-to-trade securities. As we were matching our trades to *HiVLM* and *LoVLM* sets, it became apparent that our traded volumes in less liquid instruments were significantly more dispersed. To collect a sufficiently large sample in *LoVLM*, we had to extend the time period from 6 months to 15 months, and we had to assume that the same *HiVLM* from the top of the FTSE 100 were still favored by HFT firms throughout March of 2011 and that the lower liquidity *LoVLM* remained unpopular for the entire period. We have analyzed market activity in both sets throughout a 15-month period, and this analysis gave us no indication that our assumption is incorrect.

Table 12 reports averages for 5 minute pre-, in- and post-trade order imbalances for UK trades. We find that pre- and post-trade order imbalances are statistically insignificant for both sets. The in-trade imbalance is split into the imbalance created by our own trading activity and the imbalance created by the rest of the market. As expected, our trading strategy creates order imbalances in the direction of trade. The rest of the market trades on the opposite side, which offsets our trade imbalance. Moreover, in *HiVLM*, the market is clearly more two-sided with more neutral overall in-trade imbalance such that the sum of imbalances created by us and by “the rest of the market” is statistically insignificant.

For *LoVLM*, we find this difference to be statistically significant at the 5% confidence level. This suggests that HFT activity is associated with providing liquidity to the market and thereafter profiting from capturing liquidity rebates and earning the spread. This result is consistent with the arguments presented earlier.

### 6.1.2. Japanese Market

We employ the same methodology for Japanese data to estimate 5 minute pre-, in- and post- trade imbalances around our orders arrivals. Table 13 shows a summary of the findings. The results are similar to those obtained for the UK market. We do not observe front-running behavior by the rest of the market. Pre- and post-trade imbalances are statistically insignificant, which implies no competitive pressure prior to order arrivals and no detectable arbitrage opportunities at the completion of trades. The rest of the market trades on the opposite side during the first 5 minutes of our trade execution, signaling liquidity provision. We also confirm a more two-sided market in the in-trade period for *HiVLM*.

We conjecture that for liquid stocks from broad equity indices, HFT firms are involved primarily in liquidity provisioning rather than predatory front-running strategies. Notably, the results in Table 14 indicate that close-to-open price returns are small for *HiVLM* suggesting the absence of short-term alpha. In the situation of no short-term alpha, passive liquidity provisioning that aims at capturing rebates and bid-ask spread is more profitable than any active strategy that will compete with LT investor orders and may be forced to cross the spread and chase the price.

Our findings are in line with Schoeneborn and Schield (2009), who find that liquidity provision is the most profitable behavior in the market where the temporary price impact dominates the permanent price impact. This is a case of low short-term alpha. In such a market, it is optimal to cooperate with a buyer by selling some assets to the buyer and buying them at a later point in time.

By contrast, the authors argue that a predatory strategy would be optimal in a market in which the permanent price effect of a trade outweighs the temporary effect. In such a situation, it is profitable to keep buying in parallel with a buyer and selling back at a later point in time. It would be useful to test for front running by HFT firms using a set of trades with short-term alpha. Whereas passive orders come with the positive externality of liquidity supply, aggressive HFT orders may create the negative externality of an adverse impact on the trading costs of LT investors; in any event, we will leave this topic to future research. One possibility will be to study a subset of trades executed in the morning. The results from Section 3 for the Japanese market indicated that HFT firms and LT investors, on average, tend to be competitors, ie, trading on the same side at the opening of the day.

### 6.2. The Effect of HFT Presence on Trading Costs Incurred by LT Investors

In this section, we are looking for further support for the argument that HFT is mostly involved in liquidity provisioning rather than predatory front running. If HFT adds liquidity to the market, then we expect to see shortfall reduction for trades in stocks in which HFT activity is high.

To detect the effect of HFT on trading shortfall, we must control for other factors that affect trading costs. Realized implementation shortfall is typically compared to so-called "expected post-trade cost" – a combination of expected pre-trade cost, in-trade broad market momentum and in-trade stock volatility. Other factors, such as the liquidity interaction of a trading strategy that affect trading costs, are outside the scope of this paper. Expected pre-trade cost models are calibrated on historical data and typically take into account the average bid-ask spread, a measure of daily volatility and the order size normalized by average daily volume. In this study, we use pre-trade cost estimates obtained from the ITG ACE model.

In-trade momentum approximates for short-term alpha associated with broad market movements. We assume that execution of an individual trade does not affect broad market dynamics. In-trade volatility is measured as the daily average of the 5-minute HL volatility. This term accounts for the effect of accentuated short-term volatility associated with HFT presence.

We normalize the implementation shortfall, pre-trade cost, market return and intraday volatility to their respective z-scores. The presence of HFT is a dummy variable equal to 1 for actively traded stocks by HFT, and 0 otherwise[1]. We expect that some of our control variables are correlated. To select the most relevant control variables, we first report cross-correlation patterns for the proposed control and target variables and then perform OLS analysis. The sample of trades includes only daily orders with a minimum trade duration of 1 minute.

### 6.2.1. Trading Costs, UK Market

Table 15 summarizes the correlation results among potential explanatory variables for the difference between realized and pre-trade costs for the UK market. Of these explanatory variables, market return shows the highest positive correlation with

[1] We also tested HFT proportion to the tape volume during trade execution as a proxy for HFT presence

implementation shortfall, suggesting that broad market movement is the most influential factor adversely affecting the IS, followed by the pre-trade estimate[2]. Short-term volatility exhibits positive association with realized costs. Finally, HFT is in negative correlation with IS costs and pre-trade estimates.

It is not surprising that the results suggest that HFT is positively correlated with 5-minute HL volatility, as discussed in Section 3 above. The negative relationship between HFT and trading costs is the result of the activity of HFT firms in stocks from a high liquidity class with typically low bid-ask spreads, which are further compressed by the market making activity of HFT firms. We also expect that liquidity provisioning by HFT reduces the magnitude of stock movement relative to the market and therefore reduces our market impact net of market momentum. We observe no association between HFT activity and market returns over the trade duration suggesting that there are no effects of HFT on broad market movements.

Table 15 also includes implied volatility and time of day variables, which are later dropped from the list of control variables because their marginal contribution to IS is insignificant. We regress IS over pre-trade, market return, the daily average 5-minute HL volatility and the presence of HFT using the PCA analysis presented in Table 16.

The results from the PCA regression suggest that IS is adversely affected by broad market movements and pre-trade cost. HFT helps to reduce IS costs for AllianceBernstein's buy-side trades in UK stocks through liquidity provisioning. The effect of short-term volatility on IS is adverse but not statistically significant. This finding suggests that, although HFT firms tend to create an accentuated short-term volatility in liquid stocks, the overall savings outweigh the cost associated with heightened volatility.

[2] Pre-trade, IS and sector returns are signed as +1/-1 for buys/sells, respectively.

We believe the savings come in the form of compressed realized spreads that lessen the impact of smaller orders and also as a reduction of relative price movements caused by the market impact of large aggressive orders.

We would like to note that this conclusion applies to liquid stocks with a flat daily close-to-open profile, ie, where passive liquidity provisioning is a dominant strategy for electronic market makers. Order size distribution and the level of execution aggressiveness also affect the result, which should therefore not be generalized to all LT investors. For example, we can expect that the spread reduction will not offset the effect of higher short-term volatility for large orders. This may be shown by examining a typical pre-trade cost model in which market impact is expressed as a sum of the bid-ask spread term and volatility that is multiplied by a power function of order size (a square root). As order size increases, the second term explains most of the effect and is linearly proportional to the volatility level. Value-style investors who predominantly use passive trading strategies may also find HFT adversely affecting their performance because they compete with HFT firms in providing liquidity and will likely end up being adversely selected or having to trade more aggressively to finish their orders because of their technological disadvantage. This may explain the conflicting results from the early literature that attempted to evaluate the aggregate HFT effect because the outcome may be sample-dependent. What we present here is rather a general methodology of evaluating the effect of HFT on the trading costs of a particularly large asset manager.

**6.2.2. Trading Costs, Japanese Market**

We choose the identical explanatory variables as the analysis of the European data, ie, the pre-trade, market return, the daily average 5-minute HL volatility and HFT's presence[3]. The cross-correlation structure of the control and target variables for the Japanese data is presented in Table 17. Similar to the UK market, we find that trading costs have the highest positive correlation with market movement during trade execution and pre-trade estimate. HFT shows negative correlation with trading costs. We apply a principal component analysis (PCA) to analyse the data, and the results are shown in Table 18. As with the UK market, the results suggest that LT investors' implementation shortfall is adversely affected by broad market movements and pre-trade cost. Short-term volatility has no statistically significant effect on IS. Finally, the results provide supporting evidence that HFT reduces trading costs for AllianceBernstein's trades. The same disclaimers listed at the end of Section 6.2.1 apply in this scenario, as well.

## SECTION 7. CONCLUSION

HFT is successfully penetrating new geographies and new asset classes, profoundly changing the market microstructure along the way. Many Asia-Pacific exchanges, including Singapore's SGX, Malaysia's BURSA, Hong Kong and Australia's ASX are following the lead of the TSE by beefing up their infrastructure and adopting a regulatory environment that accommodates HFT. These developments are advertised to create economic opportunities for various groups of market participants. Exchanges generally experience higher levels of liquidity and new revenue derived from selling market data and co-location services. The sell-side benefits from eventual marketplace fragmentation, which lowers their execution costs. The resulting increase in algorithmic usage also helps brokers improve trading efficiency. The traditional buy-side community

[3] We tested a time of day variable and did not find a statistically significant effect on LT investor's implementation shortfall.

may expect to enjoy higher levels of execution immediacy, compressed bid-ask spreads and lower overall transaction costs. For an investor, this type of trading environment presents an opportunity to rebalance portfolios more frequently, which enhances information ratio, at least in theory. Clearly, if one portrays HFT solely as a liquidity transfer agent that is more efficient at pricing liquidity than the rest of the market participants, its presence should contribute to more efficient markets and ultimately benefit its trading counterparties. However, the resulting picture is more complex as a result of the conflicting interests of market participants.

In this article, we examined and contrasted the Japanese market in its early post-Arrowhead period with the more mature UK market. We find that HFT activity is heavily concentrated in a small subset of liquid mega-cap and large-cap stocks that populate the top of broad country indices. We confirm that HFT is indeed predominantly involved in market-making in these stocks, and in the aggregate it provides liquidity to long-term and retail investors.

LT investors, however, must realize the peculiarities of this liquidity provision. First, the concentration of liquidity among top stocks results in a significant disparity in expected transaction costs per dollar traded. High correlations among stocks, which we have observed lately, limit the divergence of expected excess returns and forces portfolio optimizers to prefer cheaper-to-trade securities, which ultimately contributes to crowdedness of the trade, further increases in correlations, and more liquidity polarization. HFT, however, is not serving liquidity on the terms of LT investors. Alternatively, we find that the distribution of liquidity demand by LT investors matches the liquidity supply by HFT in neither magnitude nor intraday volume characteristics.

Tight risk controls force HFT to severely scale back liquidity provisioning when the probability to trade against informed flow or inventory risk increases – such as during market opening, close, around news, etc. – whenever LT investors' demand for liquidity is high.

Competition among HFTs has also led to the dominance of a few large players. Smaller market makers and brokers are being squeezed out from the less risky and more profitable segment of the market, and their ability to provide liquidity and capital in less liquid stocks is also diminishing. TSE statistics offer a clear picture of this trend; between 1H 2010 and 1H 2012, the market share of HFT has increased from 10% to approximately 40%. At the same time, the total traded volume decreased in both *LoVLM* and *HiVLM* by 5% and 4% (in shares) and 17% and 20% by notional, respectively. The latter is in line with the declining activity of global LT investors who tend to invest proportionally to MSCI country weights, which went down by 15% for Japan over this period. All this suggests that HFT gained market share at the expense of existing market makers and smaller brokers.

For long-term investors, the concentration of trading counterparties implies higher liquidity risks and fewer opportunities to execute anonymously even moderately sized orders, while it also indicates compressed bid-ask spreads but higher short-term volatility. Indeed, we show that intraday volatility has risen in stocks in which HFT activity is high. In other words, HFT adds a volatility layer over and above the fundamental volatility level. In Japan, we find that within a year from Arrowhead implementation, the 5-minute high-to-low stock volatility increased by 10% while quoted spreads reduced by 3% in low-priced stocks. Likewise, in the higher price category between 2000 ¥ and 5000 ¥, the

5-minute high-to-low volatility increased by 8%, and the bid-ask spread was reduced by approximately 12%. The drastic change in the quoted spread was the result of the reduction in minimum tick size.

Analysis of UK data for 2010 also revealed excessive short-term volatility in stocks with high HFT activity. We find that the level of 5-minute high-to-low volatility is 30% higher in stocks with significant HFT presence compared to stocks less traded by HFT. Evidence of an accentuated level of short-term volatility in the mature UK market can serve as a predictive implication for a future rise in the level of volatility in Tokyo. We suggest that increased short-term volatility is likely because of the decline of quoted depth as a result of narrowed spreads. We leave validation of this fact for future research.

How should LT investors adopt to the new market environment that absorbs information about new orders faster and more efficiently? Proper, systematic alignment of liquidity demand against underlying alpha becomes crucial: order sizes and trade aggressiveness should be scaled appropriately. It is important to recognize intraday patterns for various sources of liquidity and stage intraday trades accordingly. Traders should also realize how quickly available liquidity drops below the top 50-70 stocks and keep significantly more flexibility and clear price targets to execute less liquid orders.

Analyzing our own trades, we found that, in the aggregate, HFT translates into net cost reduction for our orders in both the UK and Japanese markets primarily because of liquidity provisioning by HFT. On average, we found no evidence of front running in our orders. Notably, our results relate to liquid stocks with relatively low short-term alpha. Opportunistic liquidity provisioning in these stocks is perhaps more profitable for a market maker than engaging in active predatory trading. An interesting avenue for future research would be an analysis of trading costs for order flow with a significant short-term alpha that is presumably more attractive to be exploited by predatory strategies.

APPENDIX A.

The TSE implemented the following tick size rules at the beginning of 2010 (source: the TSE).

| **Stock Price, ¥** | **Tick Size ¥, Before Revision** | **Tick Size ¥, After Revision** |
|---|---|---|
| Up to 2,000 | 1 | 1 |
| **2,000-3,000** | **5** | **1** |
| **3,000-5,000** | **10** | **5** |
| 5,000-30,000 | 10 | 10 |
| 30,000-50,000 | 50 | 50 |
| 50,000-300,000 | 100 | 100 |
| **300,000-500,000** | **1,000** | **500** |
| 500,000-3,000,000 | 1,000 | 1,000 |
| **3,000,000-5,000,000** | **10,000** | **5,000** |
| 5,000,000-20,000,000 | 10,000 | 10,000 |
| **20,000,000-30,000,000** | **50,000** | **10,000** |
| **30,000,000-50,000,000** | **100,000** | **50,000** |
| Over 50,000,000 | 100,000 | 100,000 |

APPENDIX B.

The Difference-in-Differences method estimates the treatment effect in the following regression:

$$y_{i,t} = \alpha + \beta * T_i + \gamma * P_t + \delta * T_i * P_t + \varepsilon_{i,t}$$

where $y_{i,t}$ is the outcome for group i in period t, $T_i$ is a binary variable that takes 1 if the group receives treatment and zero otherwise, $P_t$ is a binary variable that indicates the time period, eg, takes 1 in the second period and zero in the first, $\varepsilon_{i,t}$ is the error term, and $\alpha$, $\beta$, γ and $\delta$ are regression estimates. Specifically, $\delta$ reproduces the DID estimates.

In the absence of other covariates in the regression, the DID estimates can be easily obtained through simple differences, eg,

$$\delta = (\bar{y}_{2,2} - \bar{y}_{1,1}) - (\bar{x}_{2,2} - \bar{x}_{1,1})$$

where $\bar{y}_{2,2}$ is the average outcome in the treatment group for the second period and $\bar{y}_{1,1}$ is the average outcome for the treatment group in the first period. The second term shows the time difference between the average outcomes in the control group.

There have been debates about inconsistency in the standard errors for the DID. First, it has been argued that the estimated effect of the event is valid under the assumption that changes in the outcome variable over time would have been exactly the same in both control and treatment stocks if they had not been treated. We believe that, in the absence of treatment, the main driver behind stock short-term volatility for each group is market volatility; therefore, there should be a parallel volatility shift in time for *HiVLM* and *LoVLM*. Additionally, we checked how the 5-minute HL volatility changed for two groups in 2009, ie, in pre-HFT era in Tokyo. Specifically, we contrasted daily average 5-minute HL volatility in the first and second half of 2009 for each group. We first calculate flat average 5-minute HL volatility per stock for each day. Then, we take flat averages of these numbers for a period and group of stocks. The results suggest that the difference between 5-minute HL volatility in the first and second half of 2009 for *HiVLM* is 12.18 +/- 1.98 bps. This number corresponds to 9.97 +/-1.76 bps for *LoVLM*. The change in stock short-term volatility between the two groups is 2.22+/-2.65 bps, which is statistically insignificant at the 5% confidence level.

Second, the debates point to an additional uncertainty in the sampling error in estimating the means of each group time/period combination. DID standard errors are often derived from OLS in repeated cross-sections of data. However, serially correlated outcomes may cause over-estimation of t-statistics and significance levels. A correction technique that has been proposed by Bertrand et al. (2003) alleviates the problem. This technique proposes removing the time series dimension by aggregating the data into two periods, pre- and post-treatment and running OLS on these averaged outcome variables. We replicated this technique and did not show large shifts in statistical significance of the HFT effect estimates on volatility and spreads.

Finally, to check the robustness of the estimated coefficients, we added covariates in regression. Specifically, we added spread and implied volatility into regression for short-term volatilities. In regression for the spread, we added short-term volatility because of a bi-directional causality between the spread and stock volatility (Chung and Kim 2009). Estimated coefficients did not change much. Table B.1 shows an example of regression results for 5-minute stock volatility for *HiVLM* in a price category below 2000¥.

Table B.1[4].

$$HL_{i,t} = \alpha + \beta * T_i + \gamma * P_t + \delta * T_i * P_t + \varepsilon_{i,t}$$

where HL is 5-minute volatility.

R-squared = 0.2%

| Variable | Coefficient | Std. Err. | T-statistics | 95% CI |
|---|---|---|---|---|
| $\beta$ | -2.50 | 0.05 | -43.77 | -2.61 -2.38 |
| γ | -1.87 | 0.05 | -34.66 | -1.97 -1.76 |
| $\delta$ | 2.63 | 0.08 | 30.47 | 2.46 2.80 |
| $\alpha$ | 30.27 | 0.03 | 829.53 | 30.20 30.34 |

Adding more covariates:

$$HL_{i,t} = \alpha + \beta * T_i + \gamma * P_t + \delta * T_i * P_t + \lambda VXJ_{i,t} + \varepsilon_{i,t}$$

where $VXJ$ is implied volatility.

R-squared = 7%

| Variable | Coefficient | Std. Err. | T-statistics | 95% CI |
|---|---|---|---|---|
| $\beta$ | -2.69 | 0.05 | -48.69 | -2.80 -2.58 |
| γ | -1.26 | 0.05 | -24.12 | -1.36 -1.15 |
| $\delta$ | 2.68 | 0.08 | 32.13 | 2.52 2.85 |
| $\alpha$ | 9.38 | 0.07 | 119.92 | 9.23 9.54 |
| VXJ | 0.82 | 0.002 | 298.88 | 0.81 0.83 |

[4] This table shows unadjusted standard errors.

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Figure 1. The European market is presented by the Euro Stoxx 50 and the DAX volatility index, V2X.

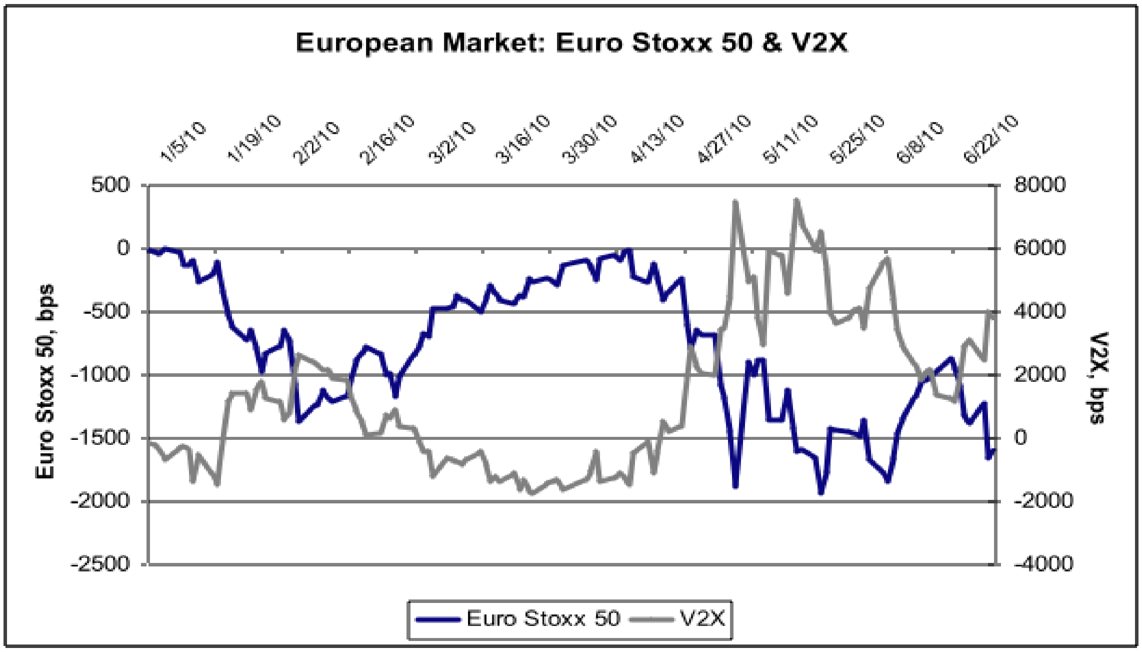



Table 1. The table shows a flat average of stock beta, daily bid-ask spread in bps, medium daily volume in mln. shares and daily HL volatility in percent for the UK market.

| *Hi VLM* | **Beta** | **Spread (bps)** | **MDV (mln. shares)** | **HL (%)** |
|---|---|---|---|---|
| Avg. | 1.08 | 6.56 | 17.25 | 2.56 |
| Median | 0.99 | 6.34 | 5.82 | 2.13 |
| Std. dev | 0.35 | 2.27 | 36.56 | 1.49 |
| *Lo VLM* | | | | |
| Avg. | 1.01 | 13.66 | 2.83 | 2.76 |
| Median | 1.01 | 11.22 | 1.28 | 2.34 |
| Std. dev | 0.25 | 7.35 | 4.12 | 1.61 |

Table 2. This table shows Spearman's rank correlations for market, HFT and LT investor daily volumes. Volumes are expressed in % MDV. All correlation coefficients are statistically significant at the 5% confidence level. The difference between correlations for the most- and least-traded stocks is statistically significant at the 5% confidence level.

*HiVLM*, UK Market

| | **Market** | **HFT** | **LT** |
|---|---|---|---|
| Market | 1 | | |
| HFT | 0.40 | 1 | |
| LT | 0.50 | 0.28 | 1 |

*LoVLM*, UK Market

| | **Market** | **HFT** | **LT** |
|---|---|---|---|
| Market | 1 | | |
| HFT | 0.25 | 1 | |
| LT | 0.37 | 0.21 | 1 |

Figure 2. The chart shows cumulative close-to-close returns for the Nikkei 225 and Japan volatility index, VXJ.

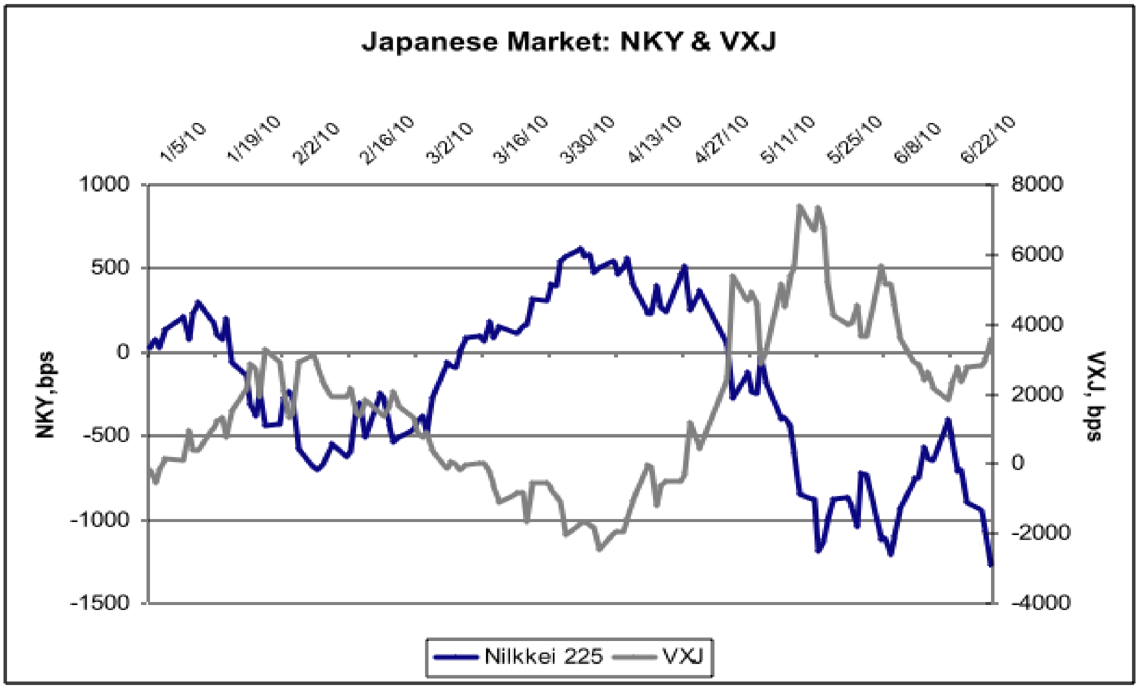



Table 3. The table shows the flat average of stock beta, daily bid-ask spread in bps, medium daily volume in mln. shares and daily HL volatility in percent for the Japanese market.

| *HiVLM* | **Beta** | **Spread (bps)** | **MDV (mln. shares)** | **HL (%)** |
|---|---|---|---|---|
| Avg. | 1.14 | 13.14 | 8.26 | 2.21 |
| Median | 1.18 | 12.07 | 3.64 | 1.98 |
| Std. dev | 0.20 | 6.11 | 14.46 | 1.06 |
| *LoVLM* | | | | |
| Avg. | 1.09 | 27.10 | 4.12 | 2.22 |
| Median | 1.11 | 25.40 | 2.49 | 2.00 |
| Std. dev | 0.22 | 11.99 | 5.02 | 1.07 |

Table 4. This table shows Spearman's rank correlations for market, HFT and LT investor daily volumes. Volumes are expressed as a percentage of MDV. All correlation coefficients are statistically significant at the 5% confidence level. The difference between correlations for the most- and least-traded stocks is statistically significant at the 5% confidence level.

*HiVLM*, Japanese Market

| | **Market** | **HFT** | **LT** |
|---|---|---|---|
| Market | 1 | | |
| HFT | 0.39 | 1 | |
| LT | 0.31 | 0.27 | 1 |

*LoVLM*, Japanese Market

| | **Market** | **HFT** | **LT** |
|---|---|---|---|
| Market | 1 | | |
| HFT | 0.28 | 1 | |
| LT | 0.22 | 0.10 | 1 |

Table 5. The table shows cross correlations for buy and sell volumes as a percentage of MDV executed by HFT and LT investors and Spearman's rank correlations for market, HFT and LT investor daily volumes as a percentage of MDV. All correlation coefficients are statistically significant at the 5% confidence level. The difference between correlations for the most- and least-traded stocks is statistically significant at the 5% confidence level.

*HiVLM*, Japanese Market

| | **HFT BUY** | **HFT SELL** | **LT BUY** | **LT SELL** |
|---|---|---|---|---|
| HFT BUY | 1 | | | |
| HFT SELL | 0.93 | 1 | | |
| LT BUY | 0.21 | 0.23 | 1 | |
| LT SELL | 0.26 | 0.25 | 0.28 | 1 |

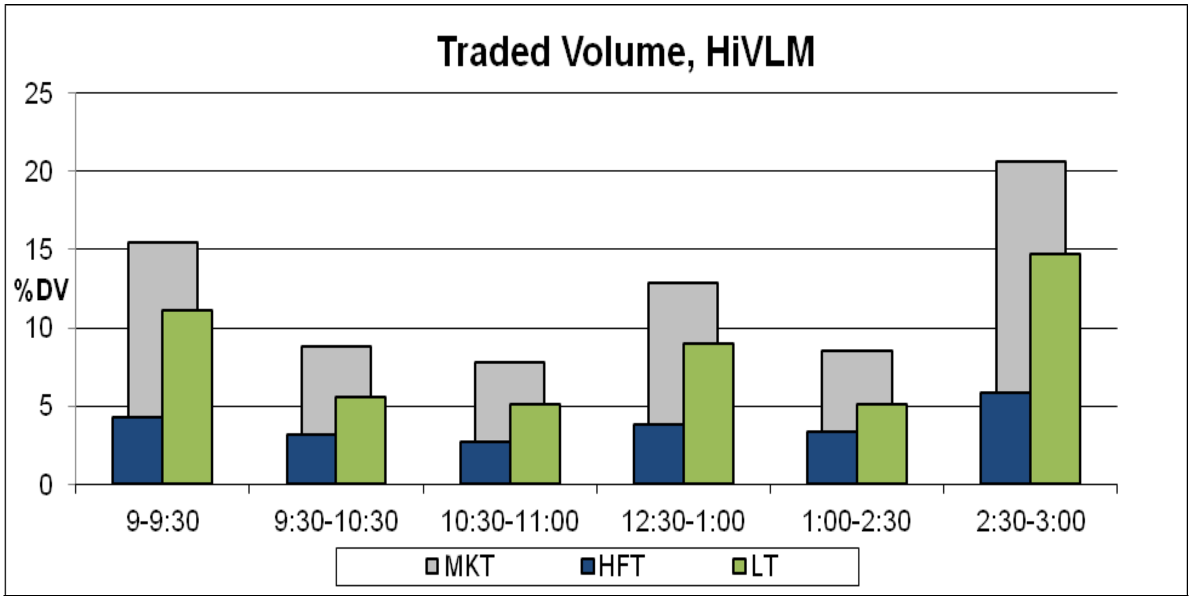
*LoVLM*, Japanese Market

| | **HFT BUY** | **HFT SELL** | **LT BUY** | **LT SELL** |
|---|---|---|---|---|
| HFT BUY | 1 | | | |
| HFT SELL | 0.79 | 1 | | |
| LT BUY | 0.03 | 0.04 | 1 | |
| LT SELL | 0.05 | 0.04 | 0.16 | 1 |

Table 6. This table reports absolute daily order imbalances (%) for LT investor and HFT volumes for *HiVLM* and *LoVLM* .

| | ***HiVLM*, HFT** | ***HiVLM*, LT** | ***LoVLM*, HFT** | ***LoVLM*, LT** |
|---|---|---|---|---|
| Avg. | 11.08 | 52.97 | 28.58 | 66.13 |
| Median | 7.50 | 53.76 | 19.64 | 74.21 |
| Std. dev | 11.96 | 30.43 | 26.05 | 31.51 |

Figure 3. This figure shows average trading volume as a percentage of daily volume (DV) per 30 minutes in intraday intervals for market, HFT and LT investors in *HiVLM* and *LoVLM*.



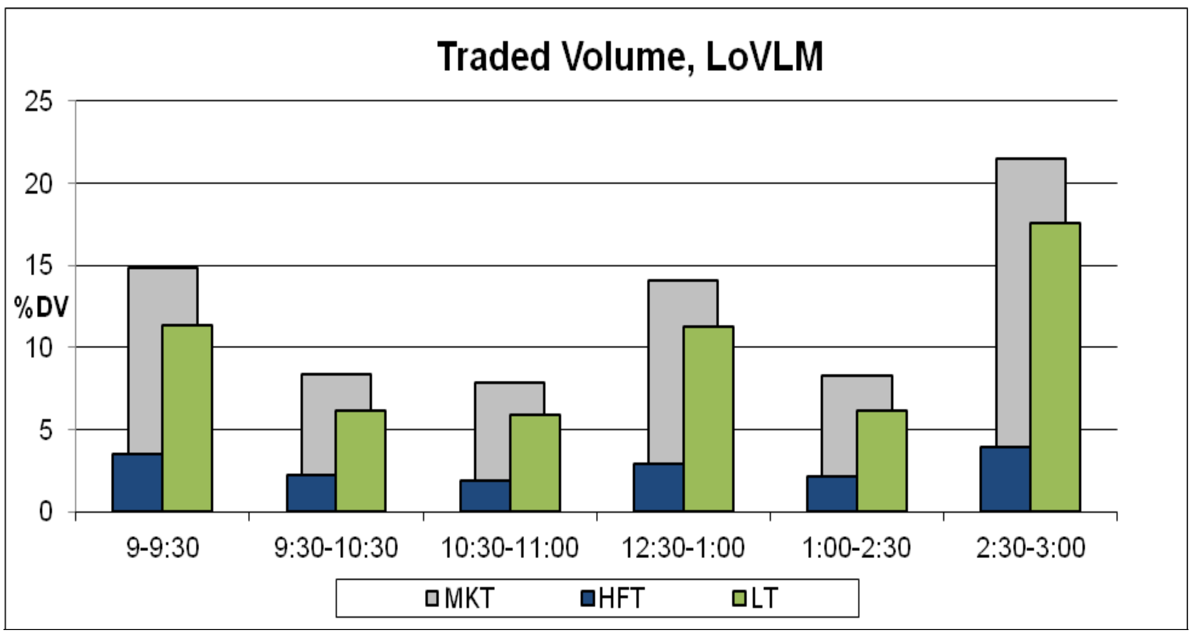
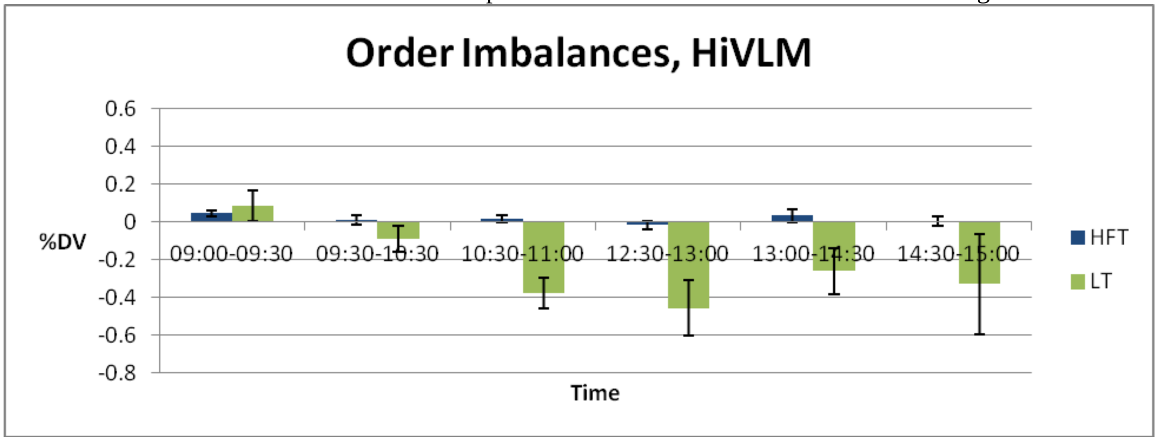



Figure 4. This figure displays order imbalances as a percentage of daily volume (DV) created by HFT and LT investors in *HiVLM* and *LoVLM* around open and close and in the middle of each trading session.



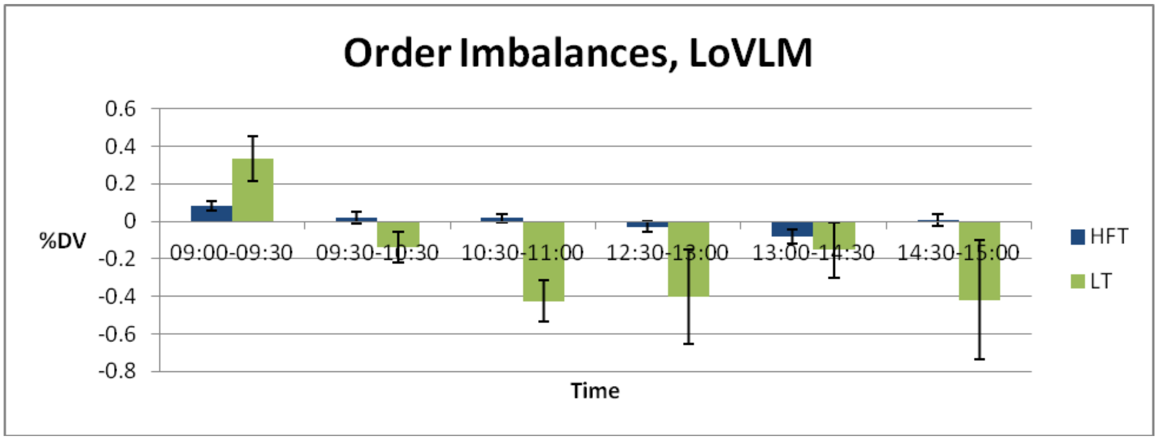




Figure 5. This figure displays the average daily HFT and LT investor order imbalances as a percentage of daily volume (DV) for *HiVLM* and *LoVLM*.

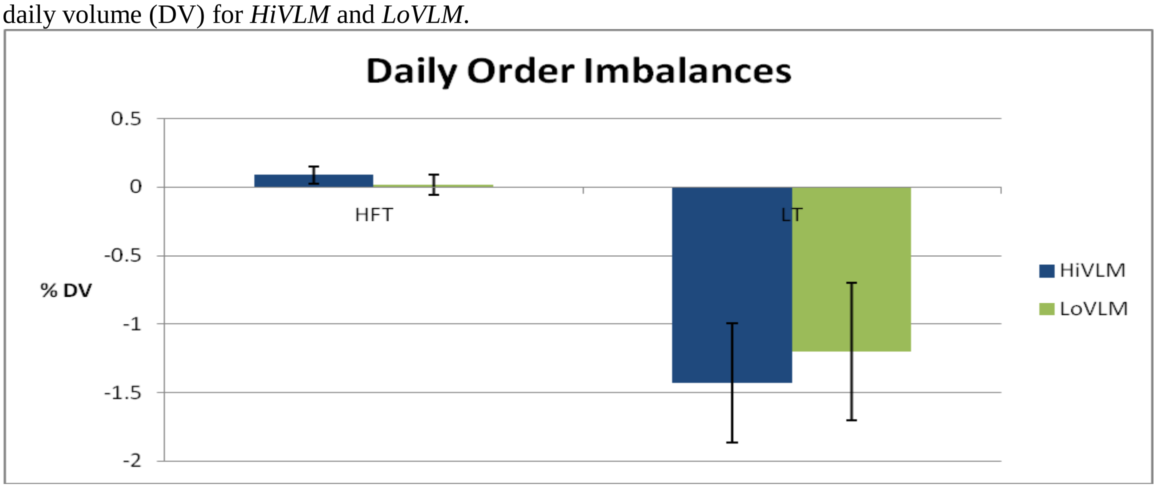


Table 7. This table shows means (bps) of short-term volatilities, quoted spread and tick size for each intraday interval for *HiVLM* and *LoVLM* in 2010 and 2011. Time periods with index 1 refer to the morning session. Time periods with index 2 indicate the afternoon session.

**Year 2010**

***LoVLM***

| | ***Open1*** | ***Midday1*** | ***Close1*** | ***Open2*** | ***Midday2*** | ***Close2*** |
|---|---|---|---|---|---|---|
| HL5 | 45.02 | 29.61 | 27.42 | 30.77 | 26.35 | 30.67 |
| HL10 | 67.92 | 43.35 | 38.88 | 44.47 | 36.34 | 39.93 |
| HL30 | 124.86 | 76.24 | 66.20 | 78.16 | 59.93 | 61.67 |
| HL | 167.80 | 167.80 | 167.80 | 167.80 | 167.80 | 167.80 |
| CO | 66.65 | 66.65 | 66.65 | 66.65 | 66.65 | 66.65 |
| Quoted Spread | 31.57 | 27.91 | 27.37 | 27.86 | 26.28 | 26.05 |
| Tick size | 24.45 | 23.92 | 24.25 | 24.12 | 24.38 | 24.47 |

***HiVLM***

**<=2000 ¥**

| | ***Open1*** | ***Midday1*** | ***Close1*** | ***Open2*** | ***Midday2*** | ***Close2*** |
|---|---|---|---|---|---|---|
| HL5 | 47.07 | 28.70 | 25.31 | 28.75 | 22.95 | 25.62 |
| HL10 | 69.11 | 41.87 | 36.56 | 41.55 | 32.54 | 35.24 |
| HL30 | 125.58 | 74.14 | 64.36 | 74.72 | 55.91 | 58.06 |
| HL | 170.02 | 170.02 | 170.02 | 170.02 | 170.02 | 170.02 |
| CO | 69.46 | 69.46 | 69.46 | 69.46 | 69.46 | 69.46 |
| Quoted Spread | 16.31 | 13.78 | 13.56 | 13.63 | 12.69 | 12.41 |
| Tick size | 11.27 | 10.94 | 10.93 | 10.94 | 10.82 | 10.91 |

***HiVLM***

**2000-5000 ¥**

| | ***Open1*** | ***Midday1*** | ***Close1*** | ***Open2*** | ***Midday2*** | ***Close2*** |
|---|---|---|---|---|---|---|
| HL5 | 41.06 | 24.44 | 21.41 | 24.13 | 19.18 | 21.98 |
| HL10 | 59.82 | 35.12 | 30.50 | 34.48 | 27.02 | 30.48 |
| HL30 | 109.26 | 60.77 | 53.10 | 61.07 | 45.60 | 51.29 |
| HL | 156.72 | 156.72 | 156.72 | 156.72 | 156.72 | 156.72 |
| CO | 64.88 | 64.88 | 64.88 | 64.88 | 64.88 | 64.88 |
| Quoted Spread | 11.20 | 9.18 | 8.96 | 9.09 | 8.29 | 8.18 |
| Tick size | 7.32 | 7.04 | 6.98 | 7.05 | 6.91 | 7.01 |

**Year 2011**

***LoVLM***

| | *Open1* | *Midday1* | *Close1* | *Open2* | *Midday2* | *Close2* |
|---|---|---|---|---|---|---|
| HL5 | 40.01 | 27.93 | 25.91 | 29.48 | 25.66 | 31.71 |
| HL10 | 63.35 | 42.04 | 37.73 | 43.88 | 36.68 | 43.32 |
| HL30 | 120.96 | 75.92 | 66.09 | 78.45 | 62.63 | 70.11 |
| HL | 159.45 | 159.45 | 159.45 | 159.45 | 159.45 | 159.45 |
| CO | 66.74 | 66.74 | 66.74 | 66.74 | 66.74 | 66.74 |
| Quoted Spread | 33.19 | 29.65 | 25.82 | 29.28 | 25.54 | 27.78 |
| Tick size | 25.24 | 25.07 | 25.53 | 25.24 | 25.44 | 25.65 |

***HiVLM***
**<=2000 ¥**

| | *Open1* | *Midday1* | *Close1* | *Open2* | *Midday2* | *Close2* |
|---|---|---|---|---|---|---|
| HL5 | 46.12 | 29.78 | 26.52 | 29.90 | 24.87 | 28.81 |
| HL10 | 69.13 | 43.86 | 37.58 | 43.68 | 35.64 | 39.90 |
| HL30 | 130.01 | 77.32 | 63.77 | 78.39 | 61.27 | 67.00 |
| HL | 168.03 | 168.03 | 168.03 | 168.03 | 168.03 | 168.03 |
| CO | 71.20 | 71.20 | 71.20 | 71.20 | 71.20 | 71.20 |
| Quoted Spread | 18.17 | 16.05 | 15.50 | 15.81 | 14.81 | 14.52 |
| Tick size | 13.45 | 13.09 | 12.98 | 13.05 | 12.84 | 12.96 |

***HiVLM***
**2000-5000 ¥**

| | *Open1* | *Midday1* | *Close1* | *Open2* | *Midday2* | *Close2* |
|---|---|---|---|---|---|---|
| HL5 | 40.18 | 24.68 | 21.13 | 24.88 | 19.96 | 23.32 |
| HL10 | 59.47 | 35.51 | 29.56 | 35.72 | 28.26 | 32.13 |
| HL30 | 108.79 | 61.10 | 49.51 | 63.27 | 48.08 | 53.54 |
| HL | 148.47 | 148.47 | 148.47 | 148.47 | 148.47 | 148.47 |
| CO | 65.59 | 65.59 | 65.59 | 65.59 | 65.59 | 65.59 |
| Quoted Spread | 12.30 | 10.62 | 10.20 | 10.52 | 9.62 | 9.49 |
| Tick size | 8.64 | 8.35 | 8.25 | 8.31 | 8.08 | 8.23 |

Table 8. This table displays DID estimates of percentage changes in volatilities and quoted spreads from 2010 to 2011 in the presence of growing HFT liquidity. Additionally, it shows the percentage change in quoted spread improvement over tick size. Quoted spread improvement over tick size is taken as a percentage. Statistically significant estimates at the 5% confidence level are bolded.

**Price Category <=2000 ¥**

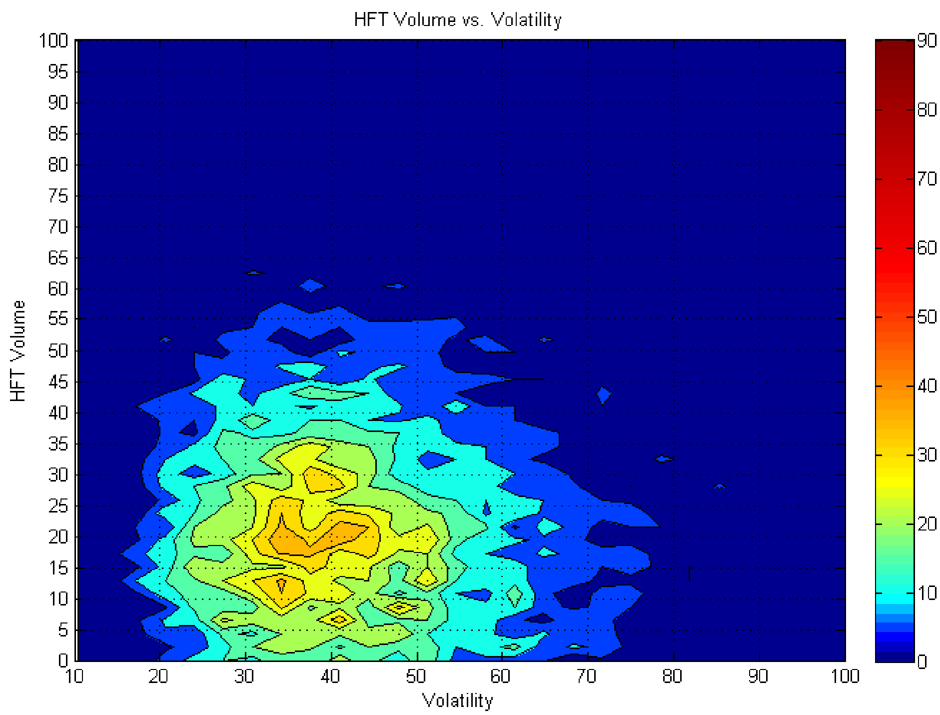
| **% Change** | **Mean** | **Std. Err.** | **T-statistics** |
|---|---|---|---|
| HL5 | **9.48** | 0.28 | 33.57 |
| HL10 | **1.79** | 0.31 | 5.79 |
| HL30 | 1.47 | 0.41 | 3.59 |
| HL | 1.24 | 1.17 | 1.06 |
| CO | 4.19 | 3.18 | 1.32 |
| Quoted spread | **-3.33** | 0.34 | -9.76 |
| Quoted spread improvement over  tick size | **-28.11** | 0.78 | -36.18 |

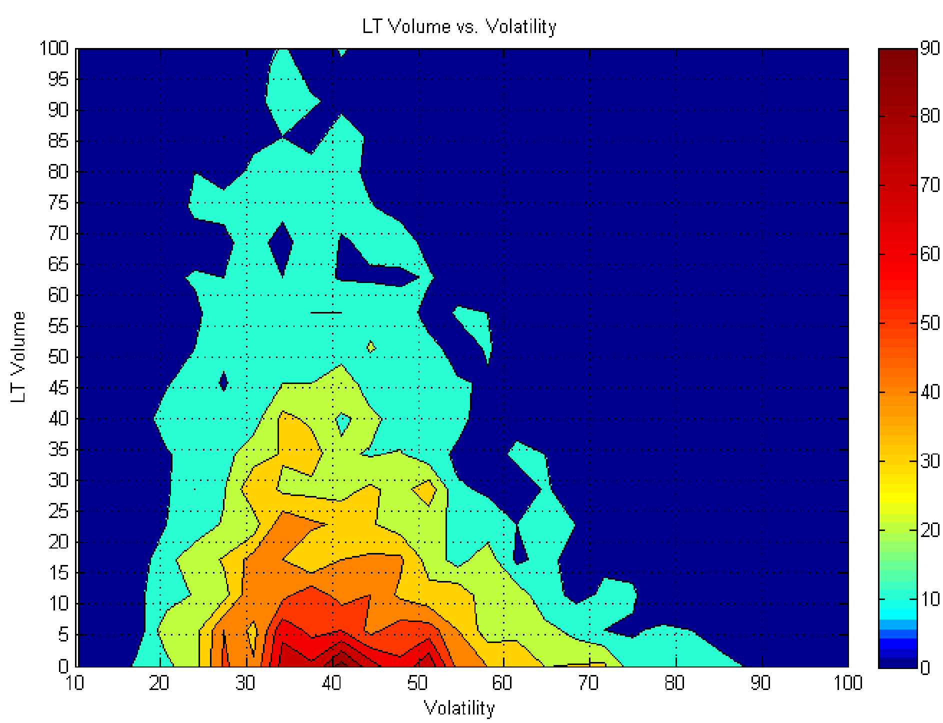
**Price Category 2000-5000 ¥**

| **% Change** | **Mean** | **Std. Err.** | **T-statistics** |
|---|---|---|---|
| HL5 | **7.83** | 0.43 | 18.08 |
| HL10 | **1.20** | 0.45 | 2.67 |
| HL30 | -0.23 | 0.57 | -0.41 |
| HL | 0.03 | 1.10 | 0.02 |
| CO | 1.00 | 2.76 | 0.36 |
| Quoted spread | **-11.55** | 0.68 | -16.96 |
| Quoted spread improvement over tick size | **-26.48** | 0.60 | -44.06 |

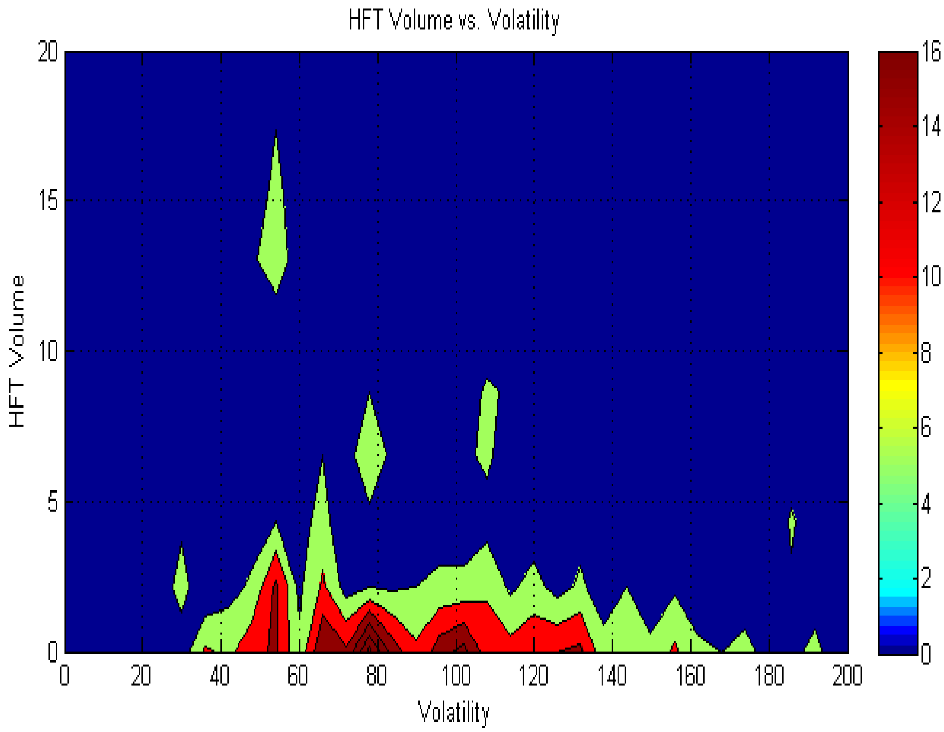
Figure 6. This figure displays HFT and LT investor traded volumes as a percentage of market volume in the first 30 minutes following market open vs. high-to-low volatility (bps).

***HiVLM*:**

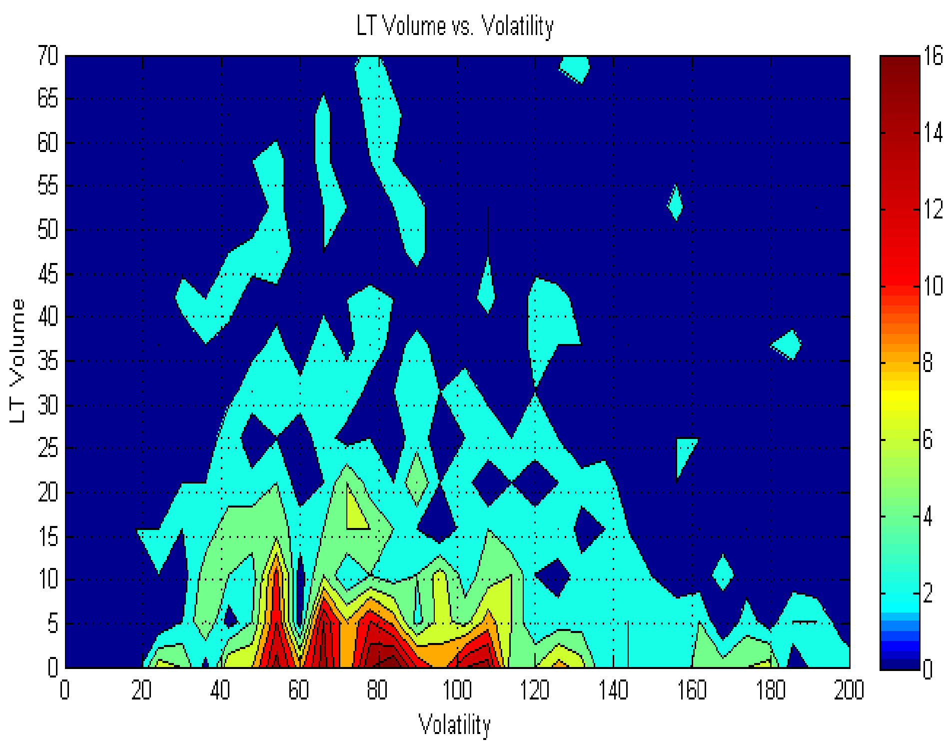


***LoVLM*:**



HFT Volume vs. Volatility
HFT Volume
Volatility
0
5
10
15
20
0
20
40
60
80
100
120
140
160
180
200
0
2
4
6
8
10
12
14
16

LT Volume vs. Volatility
LT Volume
Volatility
0
5
10
15
20
25
30
35
40
45
50
55
60
65
70
0
20
40
60
80
100
120
140
160
180
200
0
2
4
6
8
10
12
14
16

Table 9. This table shows the linear regression results of executed volumes by HFT and LT investor in the first 30 minutes of the trading day against 30-minute HL volatility. Executed volumes are scaled to their z-scores.

**HFT, *HiVLM***

# Obs. 6023
R-squared = 0.1%

| HFT volumes | Coefficient | Std. Err. | T-statistics | 95% CI |
|---|---|---|---|---|
| volatility | -0.0226 | 0.0128 | -1.76 | -0.0478 0.0026 |

**LT, *HiVLM***

# Obs. 5661
R-squared = 1%

| LT volumes | Coefficient | Std. Err. | T-statistics | 95% CI |
|---|---|---|---|---|
| volatility | -0.07388 | 0.0132 | -5.57 | -0.0998 -0.0478 |

**HFT, *LoVLM***

# Obs. 1186
R-squared = 3%

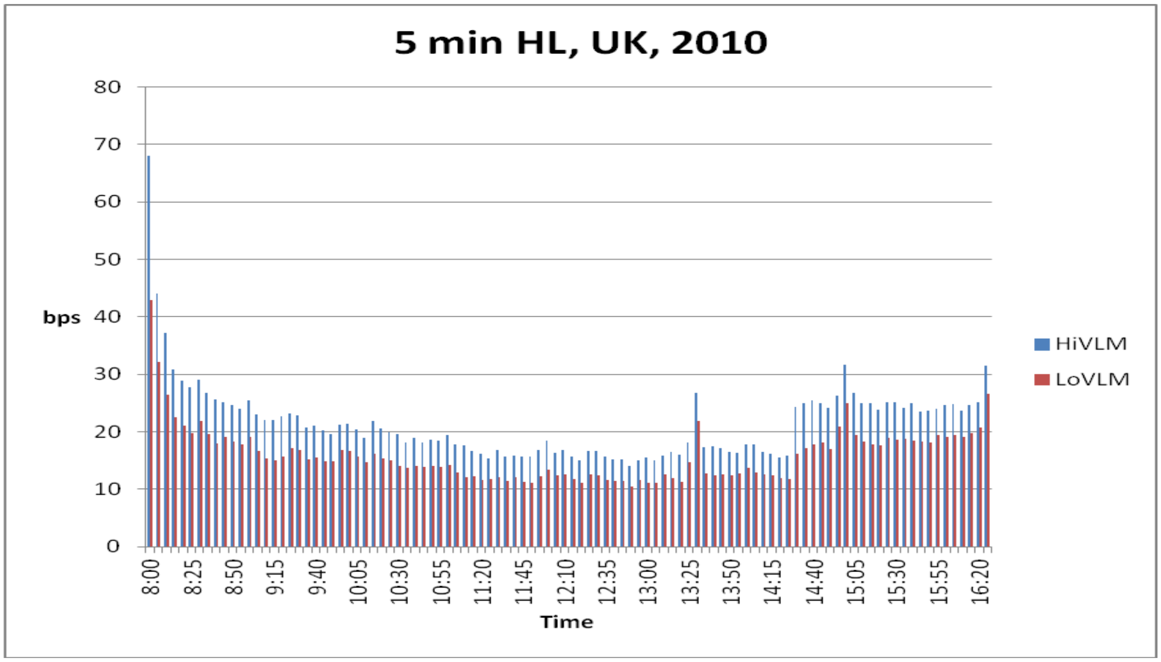
| HFT volumes | Coefficient | Std. Err. | T-statistics | 95% CI |
|---|---|---|---|---|
| volatility | -0.1632 | 0.0286 | -5.69 | -0.2194 -0.1069 |

**LT, *LoVLM***

# Obs. 1066
R-squared = 0.1%

| LT volumes | Coefficient | Std. Err. | T-statistics | 95% CI |
|---|---|---|---|---|
| volatility | -0.0400 | 0.0306 | -1.31 | -0.1001 0.0200 |

Figure 7. This figure shows 5-minute HL volatility and bid-ask spreads for *HiVLM* and *LoVLM* in the first half of 2010. Time buckets are formed from the opening session accounting for daylight saving time. Time buckets are shown in the chart in standard time.



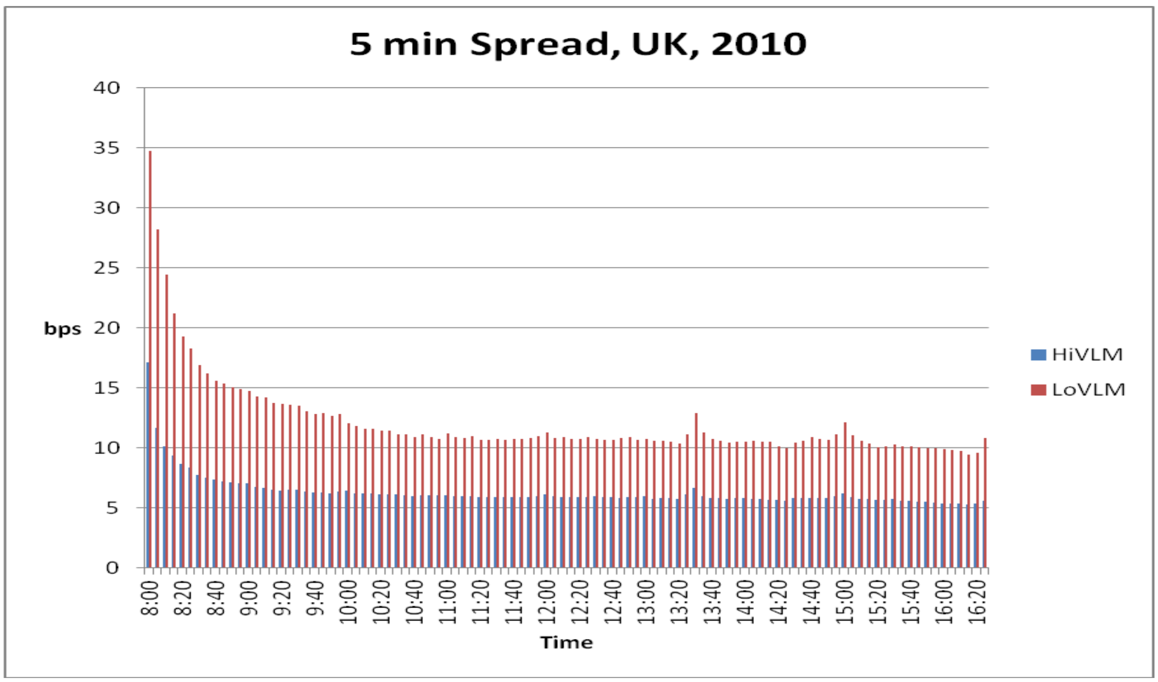



Table 10. This table shows regression results of daily HFT volumes over LT investor volumes, Quarterly Earnings Announcements and implied volatility. Daily volumes are expressed as a percentage of MDV. Daily volumes and implied volatility are scaled to present z-scores.

$$HFT_{i,t} = \alpha_1 + Q_{i,t}\ \beta_{11} + VX_t\beta_{12} + LT_{i,t}\beta_{13} + \epsilon_{1i,t},$$

$$LT_{i,t} = \alpha_2 + Q_{i,t}\ \beta_{21} + VX_t\beta_{22} + HFT_{i,t}\beta_{23} + \epsilon_{2i,t},$$

where HFT and LT investor are volumes traded by HFT and LT investors expressed as a percentage of MDV in stock i on day t, and $Qi,t$ is a dummy variable that equals one for stock i if t is a day of Quarterly Earnings Announcements, and zero otherwise and VX is implied volatility index. Implied volatility for European market is captured by the DAX volatility index, V2X.

R-squared=12%

| HFT activity | Coefficient | Std. Err. | T-statistics | 95% CI |
|---|---|---|---|---|
| LT investor's activity | 0.3137 | 0.0038 | 81.87 | 0.3062 0.3212 |
| Earnings Announcements | 0.0907 | 0.0377 | 2.41 | 0.0168 0.1646 |
| Implied Volatility | 0.1625 | 0.0038 | 42.52 | 0.1549 0.1699 |
| Constant term | -0.0009 | 0.0038 | -0.25 | -0.0084 0.0065 |
| R-squared = 4% | | | | |
| **LT investor's activity** | **Coefficient** | **Std. Err.** | **T-statistics** | **95% CI** |
| HFT activity | 0.3215 | 0.0039 | 81.87 | 0.3138 0.3292 |
| Earnings Announcements | 0.6515 | 0.0381 | 17.11 | 0.5769 0.7261 |
| Implied Volatility | -0.0179 | 0.0031 | -4.57 | -0.0256 -0.0102 |
| Constant term | -0.0067 | 0.0038 | -1.75 | -0.0144 0.0008 |

Table 11. This table shows the regression results of daily HFT volumes over LT investor volumes, Quarterly Earnings Announcements and implied volatility. Daily volumes are expressed as a percentage of MDV. Daily volumes and implied volatility are scaled to present z-scores.

$$HFT_{i,t} = \alpha_1 + Q_{i,t}\ \beta_{11} + VX_t\beta_{12} + LT_{i,t}\beta_{13} + \epsilon_{1i,t},$$

$$LT_{i,t} = \alpha_2 + Q_{i,t}\ \beta_{21} + VX_t\beta_{22} + HFT_{i,t}\beta_{23} + \epsilon_{2i,t},$$

where HFT and LT are volumes traded by HFT and LT investors expressed as a percentage of MDV in stock i on day t, and $Qi,t$ is a dummy variable that equals one for stock i if t is a day of Quarterly Earnings Announcements, and zero otherwise and VX is implied volatility index. Japan market implied volatility is presented by the VXJ index.

R-squared = 8%

| HFT activity | Coefficient | Std. Err. | T-statistics | 95% CI |
|---|---|---|---|---|
| LT investor's activity | 0.1355 | .0059 | 22.90 | 0.1239 0.1471 |
| Earnings Announcements | 0.1077 | .0463 | 2.32 | 0.0168 0.1985 |
| Implied Volatility | 0.1921 | .0059 | 32.43 | 0.1805 0.2037 |
| Constant term | -0.0019 | .0059 | -0.32 | -0.0136 0.0097 |
| R-squared = 3% | | | | |
| **LT investor's activity** | **Coefficient** | **Std. Err.** | **T-statistics** | **95% CI** |
| HFT activity | 0.1407 | 0.0061 | 22.90 | 0.1286 0.1527 |
| Earnings Announcements | 0.1662 | 0.0472 | 3.52 | 0.0736 0.2587 |
| Implied Volatility | -0.0291 | 0.0061 | -4.74 | -0.0412 -0.0171 |
| Constant term | -0.0027 | 0.0060 | -0.45 | -0.0146 0.0091 |

Table 12. This table shows order imbalances around trades for *HiVLM* and *LoVLM* in UK Market. Order imbalances are expressed as a percentage of the tape during execution.

*HiVLM*, UK Market
Sample size =1831

| Variable | Mean | Std. Err. | 95% CI |
|---|---|---|---|
| Pretrade Imbalance | -0.8510 | 1.0306 | -2.8724 1.1704 |
| Algo Imbalance | 12.6301 | 2.5892 | 7.5518 17.7080 |
| Intrade Market Imbalance | -9.9003 | 2.7633 | -15.3200 -4.4806 |
| Posttrade Imbalance | -1.3555 | 1.0293 | -3.3743 0.6633 |

*LoVLM*, UK Market
Sample size = 414

| Variable | Mean | Std. Err. | 95% CI |
|---|---|---|---|
| Pretrade Imbalance | -2.5009 | 3.0406 | -8.4781 3.4762 |
| Algo Imbalance | 18.9041 | 1.9486 | 15.0738 22.7347 |
| Intrade Market Imbalance | -7.0339 | 3.4821 | -13.8789 -0.1890 |
| Posttrade Imbalance | 0.75899 | 2.9040 | -4.9496 6.4676 |

Table 13. This table displays order imbalances around trades for *HiVLM* and *LoVLM* in the Japanese Market. Order imbalances are expressed as a percentage of the tape during execution.

*HiVLM*, Japanese market

Sample size = 2940

| Variable | Mean | Std. Err. | 95% CI |
|---|---|---|---|
| Pretrade Imbalance | -0.0902 | 0.7737 | -1.6074 1.4268 |
| Algo Imbalance | 6.8849 | 0.8333 | 6.7181 7.0516 |
| Intrade Market Imbalance | -4.4451 | 0.6706 | -5.7863 -3.1039 |
| Posttrade Imbalance | 1.0922 | 0.7796 | -0.4365 2.6210 |

*LoVLM*, Japanese Market
Sample size = 681

| Variable | Mean | Std. Err. | 95% CI |
|---|---|---|---|
| Pretrade Imbalance | 0.1635 | 2.8625 | -5.4570 5.7841 |
| Algo Imbalance | 6.0455 | 0.5622 | 4.9403 7.1507 |
| Intrade Market Imbalance | -1.2859 | 2.8435 | -6.8744 4.3026 |
| Posttrade Imbalance | 3.6730 | 2.2419 | -0.7289 8.0750 |

Table 14. This table displays daily close-to-open (CO) returns signed by the side of AllianceBernstein's trades.

UK Market

| Variable | Mean | Std. Err. | 95% CI |
|---|---|---|---|
| CO, *HiVLM* | -3.8406 | 1.9804 | -7.7623 0.0806 |
| CO, *LoVLM* | 4.3272 | 3.8944 | -3.3103 11.9649 |

Japanese Market

| Variable | Mean | Std. Err. | 95% CI |
|---|---|---|---|
| CO, *HiVLM* | -2.1283 | 1.3457 | -4.7663 0.5095 |
| CO, *LoVLM* | -5.5087 | 3.2545 | -11.8900 0.8724 |

Table 15. The table reports Spearman's rank correlations. Correlation coefficients that are significant at the 5% confidence level are bolded. A positive/negative value of shortfall means costs/savings. The implied volatility index is VX2. The market is a broad market index, ISF.LN.

Sample size =11069

| | **Shortfall** | **Pretrade** | **Market Return** | **Daily Average 5 min HL** | **VX2** | **HFT** | **Time of Day** |
|---|---|---|---|---|---|---|---|
| Shortfall | 1 | | | | | | |
| Pretrade | **0.08** | 1 | | | | | |
| Market Return | **0.26** | **-0.02** | 1 | | | | |
| Daily average 5 min HL volatility | **0.05** | **0.15** | 0.00 | 1 | | | |
| VX2 | -0.01 | **0.19** | -0.01 | **0.30** | 1 | | |
| HFT | **-0.03** | **-0.25** | 0.00 | **0.11** | **0.02** | 1 | |
| Time of Day | 0.03 | **-0.15** | 0.01 | **-0.03** | **-0.08** | 0.01 | 1 |

Table 16. The table summarizes results from a PCA regression of IS over the pre trade costs C, market return R, the daily average of 5-minute HL volatility and HFT presence. Pre-trade, market return, the daily average of 5-minute HL volatility and shortfall are expressed in basis points and normalized to their z-scores.

$$IS_{i,t} = \alpha + C_{i,t}\,\beta 1 + R_{i,t}\,\beta 2 + HL_{i,t}\,\beta 3 + HFT_{i,t}\,\beta 4 + \epsilon_{i,t},$$

where HFT is a dummy variable that takes 1 for stocks where HFT is active and 0 otherwise.

Principal Components:

| **Component** | **Eigenvalue** | **Difference** | **Proportion** | **Cumulative** |
|---|---|---|---|---|
| Comp1 | 1.2536 | 0.1554 | 0.3134 | 0.3134 |
| Comp2 | 1.0981 | 0.1027 | 0.2745 | 0.5879 |
| Comp3 | 0.9953 | 0.3424 | 0.2488 | 0.8368 |
| Comp4 | 0.6529 | | 0.1632 | 1.0000 |

| **Variable** | **Comp1** | **Comp2** | **Comp3** | **Comp4** |
|---|---|---|---|---|
| Pretrade | -0.7129 | 0.2905 | 0.1108 | -0.6285 |
| Market Return | 0.1016 | -0.1394 | 0.9849 | -0.0059 |
| Daily average 5 min HL volatility | -0.0338 | 0.8746 | 0.1301 | 0.4657 |
| HFT | -0.6930 | -0.3621 | 0.0240 | 0.6228 |

OLS regression of LT investor IS costs over the first three principal components:

$$IS_{i,t} = \alpha + Comp1_{i,t}\,\beta 1 + Comp2_{i,t}\,\beta 2 + Comp3_{i,t}\,\beta 3 + Comp4_{,i,t}\,\beta 4 + \epsilon_{i,t},$$

#obs. 11069
R-squared = 10%

| Variable | Coefficient | Std. Err. | T-statistics | 95% CI |
|---|---|---|---|---|
| Comp1 | -0.0868 | 0.0114 | -7.56 | -0.1093 -0.0643 |
| Comp2 | -0.0222 | 0.0097 | -2.29 | -0.0412 -0.0032 |
| Comp3 | 0.3035 | 0.0090 | 33.58 | 0.2858 0.3213 |
| Constant term | 0.0193 | 0.0213 | 0.91 | -0.0610 0.0224 |

Loading back explanatory variables, we obtain:

R-squared = 10%

| Variable | Coefficient | Std. Err. | T-statistics | 95% CI |
|---|---|---|---|---|
| Pretrade | 0.0890 | 0.0158 | 5.62 | 0.0573 0.1208 |
| HFT presence | -0.0755 | 0.0169 | -4.45 | -0.1094 -0.0415 |
| Market Return | 0.2933 | 0.0108 | 26.94 | 0.2715 0.0315 |
| Daily average 5 min HL volatility | 0.0230 | 0.0278 | 0.82 | -0.0326 0.0786 |
| Constant term | 0.0193 | 0.0213 | 0.91 | -0.0224 0.0610 |

Table 17. The table reports Spearman's rank correlations. Correlation coefficients that are significant at the 5% confidence level are bolded. A positive/negative value of shortfall means costs/savings. The implied volatility index is VXJ. The market is a broad market index, TOPIX.

Sample size = 14730

| | **Shortfall** | **Pretrade** | **Market Return** | **Daily Average 5 min HL** | **VXJ** | **HFT** |
|---|---|---|---|---|---|---|
| Shortfall | 1 | | | | | |
| Pretrade | **0.10** | 1 | | | | |
| Market Return | **0.19** | **-0.03** | 1 | | | |
| Daily average 5 min HL volatility | **0.03** | **0.30** | -0.01 | 1 | | |
| VXJ | -0.02 | **0.02** | -0.01 | **0.33** | 1 | |
| HFT | **-0.04** | **-0.31** | -0.02 | **0.32** | **0.02** | 1 |

Table 18. The table summarizes results from PCA regression of IS over the pre trade costs C, market return R, the daily average of 5-minute HL volatility and HFT presence. Pre-trade, market return, the daily average of 5-minute HL and shortfall are expressed in basis points and normalized to their z-scores.

$$IS_{i,t} = \alpha + C_{i,t}\beta 1 + R_{i,t}\beta 2 + HL_{i,t}\beta 3 + HFT_{i,t}\beta 4 + \epsilon_{i,t},$$

where HFT is dummy variable that takes 1 for stocks where HFT is active and 0 otherwise.

Principal Components:

| Component | Eigenvalue | Difference | Proportion | Cumulative |
|---|---|---|---|---|
| Comp1 | 1.5313 | 0.4759 | 0.3063 | 0.3063 |
| Comp2 | 1.0554 | 0.0568 | 0.2111 | 0.5173 |
| Comp3 | 0.9985 | 0.2183 | 0.1997 | 0.7170 |
| Comp4 | 0.7801 | 0.1456 | 0.1560 | 0.8731 |
| Comp5 | 0.6345 | | 0.1269 | 1.0000 |

Principal Components

| Variable | Comp1 | Comp2 | Comp3 | Comp4 | Comp5 |
|---|---|---|---|---|---|
| Pretrade | 0.5979 | 0.2413 | 0.0784 | 0.3525 | -0.6737 |
| Market Return | -0.0010 | 0.2890 | -0.9507 | -0.0963 | -0.0585 |
| Daily average 5 min HL volatility | -0.4494 | 0.5075 | 0.0724 | 0.7129 | 0.1644 |
| HFT | -0.5782 | 0.2651 | 0.1627 | -0.4263 | -0.6223 |

OLS regression of LT investor IS costs over the first four principal components:

$$IS_{i,t} = \alpha + \text{Comp1}_{i,t}\,\beta_1 + \text{Comp2}_{i,t}\,\beta_2 + \text{Comp3}_{i,t}\,\beta_3 + \text{Comp4}_{,i,t}\,\beta_4 + \epsilon_{i,t},$$

#obs. 14730
R-squared = 6%

| Variable | Coefficient | Std. Err. | T-statistics | 95% CI |
|---|---|---|---|---|
| Comp1 | 0.0869 | 0.0084 | 10.26 | 0.0703 0.1035 |
| Comp2 | 0.0707 | 0.0064 | 10.99 | 0.0580 0.0833 |
| Comp3 | -0.2313 | 0.0078 | -29.33 | -0.2468 -0.2159 |
| Comp4 | 0.0777 | 0.0093 | 8.28 | 0.0593 0.0961 |
| Constant term | 0.0558 | 0.0147 | 3.78 | 0.0269 0.0847 |

Loading back explanatory variables, we obtain:

| Variable | Coefficient | Std. Err. | T-statistics | 95% CI |
|---|---|---|---|---|
| Pretrade | 0.0783 | 0.0117 | 6.66 | 0.0550 0.1015 |
| HFT presence | -0.1023 | 0.0126 | -8.07 | -0.1274 0.0771 |
| Market Return | 0.2328 | 0.0163 | 14.24 | 0.2004 0.2652 |
| Daily average 5 min HL volatility | -0.0354 | 0.0203 | -1.74 | -0.0757 0.0047 |
| Constant term | -0.0558 | 0.0147 | 3.78 | 0.0269 0.0847 |