Extreme Market Condition, High-Frequency Trading and Liquidity

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December 31, 2017

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Abstract

This paper examines the impact of High-Frequency Trading (HFT) activity on market liquidity and liquidity commonality during extreme market situations and different timing with a unique sample of NASDAQ trades and quotes that explicitly identify HFT participation from 2008 to 2009. We obtain the following interesting results by daily and intraday examinations: (1) High-Frequency traders (HFTs) are more likely to provide liquidity for large-cap stocks and which is more likely to happen during extreme market downward and upward situations; (2) HFTs still provide liquidity during the first ten minutes of the market but shift to be liquidity taker at lunch time and the last ten minute of the U.S. stock market; and (3) HFTs become liquidity taker as larger orders enter the market for all stocks (4) Commonality in liquidity is reduced during the period when HFT activity is high for large-cap stocks but increased for small-cap stocks.

Keyword: High-frequency trading, Liquidity, Liquidity commonality, Market conditions

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I. Introduction

The financial crisis in 2008 and the Flash Crash in May 2010 cause that the relationship between asset liquidity and High-Frequency Trading (HFT) has received much attention. High-Frequency Traders (HFTs) can be classified into two groups: (1) passive market making HFTs and (2) opportunistic HFTs (i.e., arbitrage, structural, directional). Therefore, HFTs could take the liquidity and also be a liquidity provider. Most of the recent empirical literature documents that HFT makes positive effects on market quality which reduces bid-ask spread and increases market liquidity, reduces short term price volatility and increases market price discovery (see Hedndershott and Menkveld (2011), Brogarrd (2011), Heendershott and Riordan (2012), Carrion (2013), Hagstromer and Norden (2013), Hasbrouck and Saar (2013), Brogard, et al. (2014), Brogard et al. (2017) and others). But, HFTs could selectively provide liquidity or only during some specific periods. Hence, this study investigates the impact of HFT on various dimensions of liquidity, including: (1) daily as well as intraday variation in liquidity; (2) timings with and without extreme price movements; and (3) commonality in liquidity.

SEC (2010) debates that HFTs would withdraw the liquidity during the extreme market condition since the flash crash, which is also found by Kirilenko, Kyle, Samadi and Tuzun (2015). Moreover, as HFTs submit orders at the same side in the extreme market in a short time period, traders would face a serious commonality risk. Several theoretical models demonstrate that HFTs in market stress conditions can reduce market liquidity, increase short term price volatility and create adverse selection cost for slow traders (see Brubno, Faoucault and Monias (2012), Cartea and Penalva (2012), Jarrow and Protter (2012), Ait-Sahalia and Saglam (2013), and Martinz and Rosen (2013)). Only a few empirical papers (see Kirilenko et al. (2011), Zhang (2010) and Boehmer, Fung and Wu (2012) document the negative effects of HFT on market quality such as increasing market volatility and bid ask spread. But, Brogaard et al. (2015) indicate that, during extreme price movements, HFTs still act as net liquidity suppliers, while non-high-frequency traders take liquidity. The empirical results are mixed. Even, there is no study to focus on intraday effects of HFT. Furthermore, there are a few previous empirical literature examines the impact of HFT on market liquidity and systemic market liquidity under market stress conditions and the results are mixed. The natural question is therefore raised that under what conditions are that HFTs provide liquidity, and what the corresponding conditions are that HFT will shift to be liquidity demanders.

This paper has three particular purposes: First, we examine the impact of HFT on market liquidity under extreme market conditions. There is a hypothesis that passive market making, HFTs will make profits under the price stable situations. However, under extreme market stress situations (such as extreme market decline and high volatility periods), HFTs will face extreme order balance, have inventory imbalance and suffer heavy losses. In this situation, they may switch to become liquidity demanders rather suppliers or they just exit the market because they are voluntary market makers. Under this situation, the market has liquidity crisis and short-term price volatility and bid-ask would increase.

Second, we consider the influences of intraday effect and order size. HFTs are assumed to be informed trader and therefore they would act as those investors who have information advantage. For example, we assume that HFTs would shift to be liquidity takers at the opening and closing time of a market which are shown to be the period with informed traders. Besides, informed investors are also found to be active during lunch time. Hence, we include the intraday dummy into our model. Besides information asymmetry, HFTs will change their trading strategy as some abnormal trading enters the market. Korajczyk and Murphy (2016) suggest that HFTs will compete with the large order and they will change to be aggressive. Thus, we further take the order size dummy into our model.

Third, we investigate whether HFT will increase systemic liquidity risk during extreme downward and upward market conditions. We verify the hypothesis, suggesting that opportunity HFTs use the same information and see common signals for small-cap companies, which could be the realization of market related events or a mispricing. Then, the HFT transacts instantaneously based on this same signal. If all HFTs do the same trade at the same time, they may act independently, but in unison, and they collectively act like large traders. These collective actions have a quantity impact on market prices, and systemic liquidity risk if market makers cannot provide adequate liquidity supply (Jarrow and Protter (2012)).

Previous literature related to our work includes the following papers. Using Tokyo Stock Exchange data from 2007 to 2010, Moriyasu, Wee and Yu (2013) find that algorithmic trading (AT) increases stock liquidity in normal time, but AT trading narrows the quoted spreads to a much lesser extent following extreme market declines. They also document that AT trading decreases commonality in liquidity in Tokyo Stock Exchange. By contrast, using the introduction of hybrid market in New York Stock Exchange from June 1, 2006, to May 31, 2007, as a natural experiments setting, Huh (2011) demonstrates increase in intraday liquidity co-movement in five-minute and daily intervals. He attributes the increase in liquidity co-movement to the growth in algorithmic trading. However, Huh (2011) does not observe whether an individual trade comes from an algorithm or not. His analysis rests on the assumption that hybridization increases automatic capacity; it would have benefitted algorithmic traders the most. Thus, algorithmic trading would have increased. He indirectly looks at decreases in average trade sizes and increases in numbers of trades as proxy data to support his claim that algorithmic trading increases due to hybridization of exchange.[1]

Boehmer and Shanker (2014) examine the impact of algorithm trading (AT) in equities on co-movement of order flow, returns and volatility with order-level data of selected stocks traded in National Stock Exchange of India. They find that more intense AT reduces order commonality in order flow, return, liquidity and volatility, and therefore reduces the market's susceptibility to systemic risk. Using NASDAQ HFT database, Brogaard et al. (2015) document that during extreme price movements HFTs act as net liquidity suppliers, while non-HFTs act as net liquidity demanders. Therefore, they claim that their evidence is consistent with the hypothesis that HFT performs a stabilizing function in extreme market conditions.

Our work differs from the existing empirical papers in two important aspects. First, Huh (2011) uses trading records of NYSE with high trading frequency, small trade size with large trading volume as a proxy for AT trading over sample period. Certainly this type of proxy is very difficult to distinguish AT trading from retail trading. We employ NASDAQ HFT data set that explicitly identifies HFT versus non-HFT. Thus, our data set is free from misclassification error of HFT versus non-HFT participations in our sample data. Besides, both Moriyau et al. (2013) and Boehmer and Shanker (2014) examine the impacts of AT trading on various measures of liquidity and commonality in liquidity with Tokyo Stock Exchange and National Stock of Exchange of India, respectively. But, they do not consider the extreme market conditions, the asymmetry of buy and sell behavior and the effects of capitalization size. Second, Brogarrd et al. (2015) examine the impact of HFT on liquidity under extreme decline market and jump events with the same data set we use, but they do not examine the impact of HFT on liquidity commonality under various market situations and different intraday periods. Furthermore, Brogarrd et al. (2015) only discuss large-cap companies and do not consider the asymmetry behavior of buy and sell sides.

[1] Reuters (2012), INTERVIEW-High-frequency trading distorts commodities prices.

Using a unique sample of NASDAQ trades and quotes that explicitly identify HFT versus non-HFT participation from 2008 to 2009, we have obtained several interesting results:

(1) According to our exploratory data analysis results, we find that HFT provides liquidity for all stocks during normal, extreme downward and extreme upward markets because the liquidity supply is greater than the liquidity demand by HFT on both buy and sell sides, respectively. By contrast, HFT is not net liquidity demander for medium- and small-cap stocks. These differences are statistically significant at one percent level. On the other hand, liquidity supply is less than liquidity demand for all stocks by non-HFTs in these two extreme market conditions; alternatively, the reverse results are found for the other size stocks. Moreover, we investigate the intraday pattern of liquidity supply and demand, and present HFT trader are more likely to supply liquidity for large stocks.

(2) Our empirical results are consistent with the previous finding of Hameed et al. (2010) that market decline causes asset illiquidity. Furthermore, this paper presents new evidence that the impacts of large market downward and upward on liquidity are weaker when HFT participation is active for large stocks but is more serious for small stocks. Besides, we show that large orders result in higher liquidity but HFT investors become liquidity taker as the order enter the market.

(3) We find that HFT reduces commonality in liquidity (measured in terms of liquidity beta) under normal and extreme market situations for large-cap companies, but leads a higher commonality for small-cap companies. These results suggest that, on average, HFT does not increase systemic liquidity risk for large stocks during our sample period.

The reminder of the paper is organized as follows: Section II discuss the unique feature of NASDAQ HFT database and the supplementary data used in our analysis. Empirical models and measurement of variables are presented in Section III. Section IV reports empirical results. Section V concludes the paper.

II. The data

2.1 Data

We use a unique NASDAQ data set that directly identifies HFT and Non-HFT (nHFT) participations. The sample period covers from 2008 to 2009. The sample consists of 40 large cap stocks, 40 medium cap stocks and 40 small cap stocks. The dataset provides the following data information: (a) symbol; (b) date; (c) time stamped in milliseconds; (d) shares; (e) prices; (f) indicators on initiated buy and sell trades; (g) trade type by (HH, HN, NH, NN). The type of variable HH indicates that a HFT demands liquidity and another HFT provides liquidity in a trade.

HN indicates the HFT demands liquidity and nHFT (non-HFT) provides liquidity in a trade. NN indicates that a Non-HFT (nHFT) demands liquidity and a nHFT supplies liquidity in a trade. NH is the reverse situation HN. We define HFT_D demand liquidity as the sum of HH and HN. HFT_S supply liquidity is the sum of HH and NH. The total trading activity is the total sum of the following variables: HH, HN, NN and NH. We can also use the buy and sell indicators to estimate HFT_D and HFT_S trading activity on buy sides versus sell sides. Similarly, we can use buy and sell indicators information to estimate HFT and nHFT demand and supply of liquidity trading activity on either buy or sell sides, respectively.

Our data set is also supplemented with the National Best Bid and Ask Offer (NBBO) from TAQ. We employ the NNBO to measure the best prices prevailing across all markets. Both NBBO and NASDAQ BBO data sets are used to estimate various measures of the spreads.

2.2 Summary statistics

We present daily summary statistics of market returns, quoted spread, share volume of HFT and nHFT, the number of trades of HFT and nHFT and turnover under three market situations in Table 1. We use S&P 500 daily returns as proxy for market situation. Market situations are partitioned into three cases: (a) normal market situation; (b) extreme decline market situation; and (c) extreme upward market situation. This paper defines the extreme market by the 95th percentile of all price movements.[2] Extreme decline market return situation is defined when market returns are less than 5th percentile of all market returns distribution, and extreme upward market situation is defined when the market returns are greater than the 95th percentile of all market returns distribution. The normal market situation is between these two extreme market situations.

The daily average quoted spreads under upward and decline markets are 0.0048 and 0.0045, respectively. These two spreads are about 30 % higher than daily average quoted spread (i.e., 0.0037) under normal market condition. These results confirm that market become relatively illiquid when liquidity demand (selling and buying pressure) is greater than liquidity supply. It is expected that magnitude of turnover under two extreme market conditions is higher than daily average turnover under normal market (see last column in Table 1).

Under normal market, the volumes of HFTV (1,226,945) and nFTHV (1,514,355) are lower than share volume of HFTV (2,312,204) and nHFTV (2,640,821) under upward and HFTV

[2] We also use75 th percentile of all price movements to proxy the extreme market conditons and get the similar results with the proxy of 95 th percentile. The most related paper, Brogaard et al. (2015), use the 99.9th percentile of all price movements.

(2,281,972) and nHFTV (2,644,917) under decline market, respectively. We find the similar results hold for the number of trades of HFT versus the number of trades of nHFT under three market conditions. Under normal market, HFTV accounts for about 44% of the total share volume (i.e., HFTV+nHFTV). Under upward and decline markets, the percentage of share volume of HFT increases to about 47% of the total share volume. Number of trades of HFTs under extreme market conditions increases about 100% more than the number of trades under normal markets. However, the number of trades of nHFTs also increases but only 77% more than the number of trades under normal markets. This result suggests that HFT plays a more influential role in affecting market quality under extreme market situations.

[INSERT TABLE I]

III. Empirical models and measurement of variables

3.1 Liquidity, past market returns and HFT

We specify the following regression model to examine the impact of HFT on liquidity under extreme market conditions. The basic framework of our regression model is based on the spirit of regression models used by Hameed, Kang and Viswanathan (2010). The regression model is as follows:

$$\begin{aligned} L_{i,t} = {} & \alpha_i + \beta_{i,1} R_{M,t-1} + \beta_{HFT,i,1} HFT_{i,t-1} + \beta_{down,t-1} R_{M,t-1} * ICM_{M,t-1} + \\ & \beta_{down,HFT,i,t-1} R_{M,t-1} * IC_{M,t-1} * HFT_{i,t-1} + \beta_{up,i,t-1} R_{M,t-1} * DL_{M,t-1} + \\ & \beta_{up,HFT,i,t-1} R_{M,t-1} * DL_{M,t-1} * HFT_{i,t-1} + \gamma_i Z_{i,t} + \varepsilon_{i,t} \end{aligned} \quad (1)$$

The notations and measurement of the variables used in the regression model (1) are explained in the following.

$L_{i,t}$ is the daily average of quoted spread of ith stock at tth day, which equals to (ask $_{i,j,t}$ – bid $_{i,j,t}$)/q $_{i,j,t}$ where q $_{i,j,t}$ is the midpoint of the reference bid and ask quotes, which is assumed to be the true value of the asset.

$HFT_{i,t}$ is a dummy variable that take the value of one if the high frequency trading volume of stock *i* on day *t* is larger than its' the 75th percentile

$R_{M,t}$ presents the average market return on day *t;* we use S&P 500 daily return as a proxy for market return on day t . $R_{i,t}$ presents the daily return for stock *i* on day *t.*

$DL_{M,t}$ and $IC_{M,t}$ are the dummies of market decline and market growth. The dummy of $DL_{M,t}$ equals 1 as the market return is less than the 5th percentile of all of those negative returns and zero otherwise; similarly, the dummy of $IC_{m,t}$ equals 1 if the market return is bigger than the 95th percentile of the positive market return and zero otherwise.

Z_{it} denotes the column vector of control variables, which include trading day of week dummies, a dummy for days around holidays, daily volatility of market returns, daily volatility of individual stock, daily changes in turnover and fixed firm effects.

We expect there is a positive relationship between large negative market returns and firm's bid-ask spreads because market participants engage in a panic selling (a demand effect) and market makers withdraw from providing liquidity (a supply effect) due to capital funding constraints (Brunnermeier and Pedersen (2009) and Hameed et al. (2010)). If the coefficients of ($R_{m,t-1}$*$DL_{m,t-1}$*$HFT_{i,t-1}$) and ($R_{m,t-1} * IC_{M,t-1} * HFT_{i,t-1}$) are positive and negative statistically significant, then these results suggest that the impact of large negative (positive) market return on liquidity is weaker on the days when HFT participation is high. We expect that the coefficients of volatility of stock i at t and t-1 are positive and significant because these variables are used as proxies for inventory risk and adverse information risk facing by market makers. The relationship between daily turnover and bid ask spread is negative because large turnover (volume) indicates that market makers can quickly adjust their inventory risk (Stoll (1978)).

Besides, in order to look into the intraday and order size effects on the liquidity and HFT participants' behavior, we revise our model as follows:

$$\begin{aligned} L_{i,t} = {} & \alpha_i + \beta_{HFT,i,t-1} HFT_{i,t-1} + \beta_{up,i,t-1} IC_{M,t-1} + \beta_{up,HFT,i,t-1} HFT_{i,t-1} * IC_{M,t-1} + \beta_{down,i,t-1} DL_{M,t-1} + \\ & \beta_{down,HFT,i,t-1} HFT_{i,t-1} * DL_{M,t-1} + \beta_{large,i,t-1} Large_{i,t-1} + \beta_{large,HFT,i,t-1} Large_{i,t-1} * HFT_{i,t-1} + \\ & \beta_{medium,i,t-1} Medium_{i,t-1} + \beta_{medium,HFT,i,t-1} Medium_{i,t-1} * HFT_{i,t-1} + \beta_{open,t-1} Open_{t-1} + \\ & \beta_{open,HFT,i,t-1} Open_{t-1} * HFT_{i,t-1} + \beta_{lunch,t-1} Lunch_{i,t-1} + \beta_{lunch,HFT,i,t-1} Lunch_{t-1} * HFT_{i,t-1} + \\ & \beta_{close,t-1} Close_{t-1} + \beta_{close,HFT,i,t-1} Close_{t-1} * HFT_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

where $HFT_{i,t}$ is a dummy variable that take the value of one if the high frequency trading volume of stock *i* on day *t* is larger than its' the 75th percentile and the $DL_{M,t}$ and $IC_{M,t}$ are the dummies of market decline and market growth. The dummy of $DL_{M,t}$ equals 1 as the market return is less than the 5th percentile of all of those negative returns; similarly, the dummy of $IC_{M,t}$ equals 1 if the market return is bigger than the 95th percentile of the positive market return. $Medium_{i,t}$ and $Large_{i,t}$ are trade size indicator variables. Medium trades are defined as at least 500 but less than 1000 shares, and large trades are 1000 shares or more. Open, Lunch and Close are the timing indicators which equals 1 if it is 9:30, 12:00 or 4:00, respectively.

We employ an asymptotic efficient two–step Generalized Least Squares estimator to estimate the parameters of the equation (1) with cross-section contemporaneous correlated and heteroskedastic errors. (Beck and Katz (1995))

3.2 Commonality in liquidity and HFT

In this section, we present our regression model to test the hypothesis that HFT may increase commonality in liquidity (systemic risk) during extreme market condition because HFT may have correlated trading behavior because they use same information, see common signal which could be the realization of market related events. If the HFT transacts instantaneously based on this same signal, they may act independently, but in unison, they collectively act like large traders and will have a large impact on system liquidity. Furthermore, Reuters news agency (2012) suggests that liquidity commonality in equity and commodity increases since the introduction of HFT. Following the work of Chordia et al. (2002) and Hameedt et al. (2010), we specify the following liquidity market model to investigate the impacts of HFT on commonality in liquidity under various market conditions.

$$
\begin{aligned}
L_{i,t} = \alpha_{i,} + \kappa_{1,i} L_{m,t} + \kappa_{2,i} HFT_{i,t} + \kappa_{3,i} L_{m,t} * HFT_{i,t} + \kappa_{up,i} L_{m,t} * IC_{M,t} + \\
\kappa_{up,HFT,i} L_{m,t} * HFT_{i,t} * IC_{M,t} + \kappa_{down,i} L_{m,t} * DL_{M,t} + \qquad , \qquad (3) \\
\kappa_{down,HFT,i} L_{m,t} * HFT_{i,t} * DL_{M,t} + \eta_i Q_{i,t} + \varepsilon_{i,t}
\end{aligned}
$$

where $L_{m,t}$ presents the daily average quoted spread of all stocks that we have in our sample except the i^{th} stock. $L_{i,t}$ presents the quoted spread for stock i on day t. $HFT_{i,t}$ is a dummy variable that take the value of one if the high frequency trading volume of stock i on day t is larger than the 75^{th} percentile. The $DL_{M,t}$ and $IC_{M,t}$ are the dummies to represent extreme negative and positive market return situations. The dummy of $DL_{M,t}$ equals 1 as the market return is less than the 5^{th} percentile of all market returns distribution in the sample period and zero otherwise; similarly, the dummy of $IC_{M,t}$ equals 1 if the market return is bigger than the 95^{th} percentile of the all market return distribution and zero otherwise. In order to control the other effects, $Q_{i,t}$ denotes the column vector of control variables, which include day of week dummies, a dummy for days around holidays, one lead and lag of the daily average market liquidity, one day lag and lag return of stock i at day t, daily volatility of market returns, daily turnover of i^{th} stock and fixed firm effect.

We employ an asymptotic efficient two–step Generalized Least Squares estimator to estimate the parameters of the equation (3) with cross-section contemporaneous correlated and heteroskedastic errors.

IV. Empirical results

4.1. Exploratory data analysis of liquidity supply versus liquidity demand

In this section, we estimate the daily liquidity supply and demand behaviors of HFT and nHFT under three market situations. Tables 2, 3 and 4 present our estimates of liquidity supply versus demand by HFT versus nHFT at buy and sell sides for the large-, medium- and small-cap companies around normal and extreme market conditions, respectively.

In Table 2, we find that are net liquidity suppliers for large-cap stocks in term of trading volumes at both buy and sell sides under three market return situations. For example, in Table 2, Panel A–Normal market, we find that HFT_S_B (second column) is greater than HFT_D_B (first column) and their difference (Column 3) is statistically significant at 1 % level. We find the similar results for HFT as net liquidity supplier at the sell side under normal market. From Panel B and C, we observe the similar results that HFTs are net liquidity suppliers at the buy and sell side, respectively, under upward and decline market conditions. However, depending on Panels B and C of Table 2, although we also observe that HFTs are net liquidity suppliers at the buy and sell side, respectively, under upward and decline market conditions. But, the analysis tells that the significances decrease, which could indicate that part of HFT changes to be liquidity demanders under extreme market conditions. Conrad’s (2015) finding, algorithms trading prefer marketable orders during periods where the return exhibits extreme behavior.

By contrast, Table 2 indicates that nHFT are net liquidity demanders for large-cap stocks at the buy and sell sides under all market conditions. Panel A of Table 2 presents that the share volumes of nHFT_D_B (column 7) are greater than the share volume of nHFT_S_B (column 8) and their difference is statistically significant at 1% level. We find that share volumes of nHFT demand are greater than the corresponding share volumes of nHFT supply at the buy and sell side, respectively.

Alternatively, the empirical results of Table 3 and 4 suggest that HFTs on medium and small-cap stocks are net liquidity demander at the both buy and sell sides under all market conditions; but, nHFTs are net liquidity suppliers on medium and small cap stocks at the buy and sell sides under all three market conditions. These results suggest that HFT, on daily average, is less active in medium and small cap stocks. We confirm that large cap stocks attract HFT because large cap stocks have high turnover and are more liquid than small cap stocks.

[INSERT TABLE 2, 3, 4]

4.2 Liquidity, past return and HFT

Although we have provided evidence that HFTs are liquidity suppliers, and which results are even hold on days with extreme returns, but it is only for large-cap companies. This section introduces a set of firm-specific variables and market condition to control for other sources of intertemporal variation in liquidity. We present empirical results of model (1) for whole sample in column 2, large-cap, medium-cap and small-cap stocks in columns 3, 4 and 5 of Table 5, respectively.

First, our analysis shows that the coefficients of $R_{m,t-1}$ and $R_{m,t-1} * HFT_{i,t-1}$ are not significantly correlated with trading cost. Second, the coefficients of $HFT_{i,t-1}$ presents that HFTs significantly help to increase the liquidity. However, Table 5 provides a complementary evidence for the decreases in statistical significance for the difference between liquidity supply and demand in Tables 2-4. Although we find that the coefficients of $R_{m,t-1} * IC_{m,t-1} * HFT_{i,t-1}$ is not significant for the entire sample, the coefficient for large stocks is significantly negative which suggest that HFTs provide more liquidity to the market during there are big positive shocks. But for medium stocks, the coefficients of $R_{m,t-1} * IC_{m,t-1} * HFT_{i,t-1}$ are significantly positive, implying that part of HFT trader shift to be liquidity demander. But, HFT does not significantly affect the liquidity for small stocks.

During the opposite extreme market condition as there is a big decline in the market return, the coefficient of $R_{m,t-1} * DL_{M,t-1}$ illustrates that the liquidity will decline, which is in line with results of Hameed et al. (2010) and implications from funding constraints theoretical model by Brunnermerier and Pedersen (2009). But, in this situation, HFTs do not significantly change their trading strategies; and, even the influence of ($R_{m,t-1} * DL_{M,t-1} * HFT_{i,t-1}$) on stock liquidity for large stocks are positive. Although the number is not significant, it provides a weak evidence to confirm that HFT participation is helpful for the stock liquidity. Hence, in our Model 1, we can only conclude that overall HFTs still provide liquidity during extreme market, but some of HFT can change to be liquidity demander, which is especially significant for medium and small stocks.

Other than market conditions, we use daily S&P 500 VIX to proxy for market return volatility. We find that some of the signs of the coefficients of market return volatility at time t and lagged one period for all four equations are positive and some of the signs are negative. Thus, in our case, we cannot draw a definite conclusion on the impact of market return volatility on liquidity. However, the coefficients of volatility of individual stock are positive and significant for all four equations. These results are expected in microstructure literature because increase in volatility of individual stock usually is due to increase in inventory adjust risk or/and adverse selection risk faced by market makers. The coefficients of turnover lagged one period ($TURN_{i,t-1}$) are negative and significant for all four equations. This is also expected because higher turnover implies higher trading chance for market practitioners to reduce their inventory risk (see Stoll (1978)).

Chordia, Roll, and Subrahmanyam (2002) present that order imbalances correlate with spreads and suggest that it could be resulted from that the market maker's difficulty in adjusting quotes during periods of large order imbalances. The coefficients of $OIB\_H_{i,t-1}$ and $OIB\_nH_{i,t-1}$ illustrate that the order imbalance is positive with spread. First, the result of $OIB\_H_{i,t-1}$ suggests that HFTs are more likely to make profit by information advantage from small stock and we hence suggest that HFTs would take more liquidity from others in small stocks. Additionally, the positive relationship between $OIB\_nH_{i,t-1}$ and spread would support Chordia et al's (2002) suggestion since we always assume that HFTs are the market maker in the new trading system.

In summary, part of our empirical result is consistent with previous findings of Hameed et al. (2010) that market decline lead to asset illiquidity, but only for smaller stocks. Furthermore, we provide new evidence that upward market enlarges and reduces firm's liquidity for large and medium stocks, respectively. Previous literature (i.e., Brogaard et al. (2014) and Carrion (2013)) shows that HFT improves market liquidity in the normal time periods, while we provide new evidence that HFT improves market liquidity for large cap stock not only under normal but also under extreme market conditions.

[INSERT TABLE 5]

4.3 Intraday Analysis

Section 4.2 gives a big picture that HFTs overall supply liquidity to the market. Results in Section 4.2 even suggest HFT continuously provide liquidity to the market during extreme market conditions, but it is more likely to happen for large-cap companies only. However, Jovanovic and Menkveld (2015) build up a theoretical work to suggest that HFT will stop to supply liquidity if they find there exists information asymmetry risk. Similarly, the theoretical work of Foucault, Hombert and Rosu (2016) shows that HFT will not trade if they are slower relative to dealers. Literature shows that informed trader has the greatest advantage when the market first opens (see

Foster and Viswanathan (1990)). On the other hand, Ito et al. (1998) indicate informed traders enter the market to trade with their private information as the other traders do not pay attention to the market during the lunch time. On the other hand, research documentes that HFTs are used to clear their position, and therefore, those studies suggest that HFT would shift to be liquidity demander around the close time. Hence, to better understand HFTs' and nHFTs' relative roles in liquidity, we revise our model and include intraday effects and extreme market condition into our model to explore role of HFT at the beginning trading time period, lunch time and close time period, which represents 9:30-9:40, 12:00-12:10 and 15:50-16:00, respectively.

Table 6 indicates there exist significantly negative relations between trading cost and HFT for whole sample, large-, medium- and small-cap companies. Hence, after we consider the intraday effects, we still find HFTs are more likely to supply liquidity. Karpoff (1987) suggests that the trading volume is relatively heavy during bull market. The increase in trading volume makes contribution to liquidity and we therefore find the reduction in trading cost. Based on the effects of extreme market conditions, we find that liquidity significantly increase as market return sharply move up. But, the effect does not happen for large-cap. Connecting with Section 2, the finding would further give us an evidence to believe that HFTs are used to provide liquidity for large stocks. Moreover, the coefficients of $IC_{m,t-1} * HFT_{i,t-1}$ are positive for whole sample, medium- and small-cap, which suggest that HFTs will take the liquidity while there is a big shock which lead to a large move up in market returns. This finding shows that HFTs become liquidity taker and are more likely to take liquidity for medium and small stocks which is consistent with our previous finding of $OIB\_H_{i,t-1}$.

On the other hand, the coefficient of $DL_{m,t-1}$ is only significant positive for large stocks. During the extreme downside market, liquidity is more prone to decrease for large stocks. But, we still fine the coefficients of $DL_{m,t-1} * HFT_{i,t-1}$ is significantly negative for large stocks, but positive for medium and small stocks. Thus, we suggest that HFTs provide liquidity to large stocks during most investors need liquidity; by contrast, part of HFTs become liquidity demanders for medium and small stocks.

Besides extreme market, in our Model (2), we include the trade size indicator variables into our model. Korajczyk and Murphy (2016) suggest that HFTs will compete with the large order and they will change to take liquidity. This paper therefore discusses the influence of order size. Table 6 reports that the coefficients of $Large_{i,t-1}$ are significantly negative for whole sample, large- and small-cap. By contrast, the intersection term of $Large_{i,t-1}$ and $HFT_{i,t-1}$ predicts that HFTs will shift to be liquidity demander as investors submit large size orders. The finding supports Korajczyk and Murphy's (2016) competition hypothesis. Likely, the coefficients of $Medium_{i,t-1}$ give the similar results to support the competition theory.

Considering information asymmetry theory and inventory management, we include intraday dummy to discuss intraday pattern of liquidity supply and demand. This paper assumes that HFTs would shift to be liquidity demander or stop to trade at beginning of the market since the traders who have information advantage will exploit the overnight information to make profits. Table 6 presents that the trading cost actually increases at the first ten minute as the begging of the market, supporting that the information risk become larger and results in lower liquidity. But, contrast to our assumption which HFTs shift to be liquidity demander based on their information advantage, the coefficients of $Open_{i,t-1} * HFT_{i,t-1}$ are negative for whole sample and large- and small-cap companies. We suggest the consequence is results from that HFTs used to clear their position every day, and they do not act as the general informed traders to trade on their private information at the begging

Literature suggests that as investors go to lunch and pay less attention to the financial market, informed traders will enter the market to exploit their information advantage. But, in our analysis, we find that the liquidity increases at the lunch time. Although literature suggests that information risk increase at lunch time, we suggest that the HFTs change the environment of financial market. People go to have lunch but computers do not. Yet, HFTs are the liquidity takers during the period. We conjecture that HFTs would use lunch time to manage their position based on our previous results that trading cost decrease during the time.

Moreover, depending on the traditional market microstructure model, the probability of an informed trading increases around the closed time of the market, and HFTs are shown that they clear their inventory every day, and therefore HFT would need liquidity at the end of the market. This study analyzes the intraday pattern of liquidity demand and supply by the last ten minutes. Our analysis provides evidence to support that liquidity actually become lower at the last ten minutes for all capitalizations, presenting that information risk is higher than the other trading periods. Also, in the analysis of interaction term of $Clsoe_{i,t-1} * HFT_{i,t-1}$, we show that HFTs take liquidity to arrange their inventory. Although it is not significant for large- and medium-cap companies, we find the coefficients of $Clsoe_{i,t-1} * HFT_{i,t-1}$ is positive. We thus conclude that HFTs shift to be liquidity demander since they must adjust their position or information risk. Our intraday analysis supports the arguments of Jovanovic and Menkveld (2015) and Foucault, Hombert and Rosu (2016).

Overall, our Model (2) indicates that although HFTs usually play a role to supply liquidity, but they shift to be liquidity demander during extreme market, high information risk or around the close time. Moreover, HFTs are more likely to become liquidity takers for medium-and small-cap companies.

[INSERT TABLE 6]

4.4 HFT and commonality in liquidity

In this section, we estimate regression model (2) to test the hypothesis that HFT may increase commonality in liquidity during various market conditions. Table 7 presents the regression results for whole sample, large-cap, medium-cap and small-cap firms, respectively.

The coefficients of market liquidity ($L_{m,t}$) are all positive and statistically significant for whole sample as well as three different capital size firms. This result is consistent with Chordia et al. (2000), stock liquidities actually co-move. We also find that beta coefficient of small size firm is larger than that of large and medium size firms. Kamara et al. (2008) documente the similar results for magnitude of betas based on capitalization size of firms.

Considering the effect of HFT on liquidity commonality, our empirical results illustrate negative relations between HFT and liquidity commonality, and statistically significant for whole sample, large-cap and small-cap stocks. The consequence confirms that HFT reduces commonality in liquidity in normal time but only contain statistical significance for small stocks. Our results are consistent with the findings of Moriyasu et al. (2013) and Behmer and Shanker (2014), who find that HFT reduces commonality in liquidity in Tokyo Stock Exchange and India Stock Exchange, respectively.

Depending on extreme market condition, Table 7 indicates HFT reduces liquidity commonality for large capitalization firms during market upward periods because the coefficients of ($L_{m,t} * IC_{M,t} * HFT_{i,t}$) are negative and significant. Likely, we provide evidence to support that HFT reduces commonality in liquidity under market decline conditions. But, the coefficient for small stocks is significantly positive, suggesting the HFTs lead to a more serious risk of liquidity commonality.

In summary, this section partly supports the hypothesis that HFT increases liquidity commonality (systematic liquidity risk) during extreme market condition for small stocks. Thus, we show that the HFTs have heterogeneity in trading strategies all the time.

[INSERT TABLE 7]

V. Conclusion

This paper separately examines the impacts of HFT versus non-HFT on liquidity and liquidity commonality under market stress conditions and different timing of a day over large-, medium- and small-cap stocks. HFTs are helpful to reduce the trading cost and increase the market liquidity for all-cap stocks during normal periods, which is in line with previous literature that uses does not consider the market conditions. However, our empirical evidence presents that HFTs are more likely to be net liquidity supplier for large-cap stocks collectively during extreme market conditions only, but not for medium- and small-cap stocks. Hameed et al. (2010) that market decline causes asset illiquidity and we hence conjecture that some HTFs would shift to take liquidity for medium- and small-cap stocks during illiquid market condition.

Considering the information asymmetry and intraday effects, our study suggests that HFTs do not act as the informed traders to take liquidity during the begging of the market. But during lunch time and the end of the market, we show that the HFTs shift to take liquidity and we suggest that they try to exploit their information advantage and clean their position during those trading periods.

As the systematic risk, we overall document that HFT reduces commonality for all stocks. Nevertheless, in liquidity under normal and extreme market conditions, HFT only results in decreases in liquidity commonality for large stocks, but leads to higher commonality in liquidity for small stocks. Thus, our results only support to the hypothesis suggesting that HFT may increase systemic liquidity risk because HFT may use the same trading strategies during extreme market conditions for small-cap companies.

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Table 1 Summary Statistics

This table presents the description statistics for return, quoted spread (QSF), Effective spread (ESF), the share volume of HFT and nHFT (HFTV; nHFTV), and the numbers of trade of HFT and nHFT (NHFT; nNHFT) during Jan. 1, 2008 to Dec. 31, 2009. This paper calculates the return by the change in mid-quote of the closing price. Quoted spread equals to (ask_t-bid_t)/Q_t which Q_t is mid-quote at time t. Turnover is the trading volume divide total trading volume divided by shares outstanding for firm i. Panel A presents the results during the days without extreme market return. Panels B and C present the results for days with market returns which are larger than the 95 quartile and smaller than the 5 quartile, respectively.

	RETURN	**QSF**	**HFTV**	**nHFTV**	**NHFT**	**NHFT**	**TURNOVER**
Panel A-Normal market							
Mean	-0.0026	0.0037	1,226,945	1,514,355	6,691	283,967	11.7630
Median	0.0000	0.0017	96,035	207,756	944	58,608	9.1246
Std. De.	12.4759	24.6754	6.2583	6.6866	4.6427	6.9753	15.5498
Observations	40100	40100	40100	40100	40100	40100	40100
Panel B-Upward market							
Mean	0.7710	0.0048	2,312,204	2,640,821	13,494	433,866	17.4058
Median	0.5288	0.0025	170063	380440	1582.5	98381	14.7136
Std. De.	-11.7739	5.4208	5.0152	4.3340	3.8861	3.8071	3.2761
Observations	1158	1158	1158	1158	1158	1158	1158
Panel C-Decline market							
Mean	-0.9855	0.0045	2,281,972	2,644,917	13,771	504,546	15.8649
Median	-0.6163	0.0027	160,412	364,881	1,523	107,198	13.2632
Std. De.	-5.9173	4.5429	4.3471	4.0754	3.4554	3.6301	6.6789
Observations	1114	1114	1114	1114	1114	1114	1114

Table 2 Trading volume of demand and supply sides around extreme market conditions for large-cap companies

This table reports the direction of trading volume around normal, market increase and market decline conditions for large-cap companies according to asset size. We identify the days as market increase while the market returns are larger than their 95 percentile and the market decline is the days with returns which are less than the 5 percentile of market return. HFT_D_B and HFT_D_B are share volume of demand and supply side of HFT for buy orders. HFT_D_S and HFT_D_S are share volume of demand and supply side of HFT for sell orders. Similarly, nHFT_D_B and nHFT_D_B are share volume of demand and supply side of nHFT for buy orders; for sell orders, nHFT_D_S and nHFT_D_S are share volume of demand and supply side of nHFT. This paper further to use Satterthwaite-Welch *t*-test to identify the differences of demand and supply sides for HFT and nHFT buy and sell sides, which shown in Colums (3), (6), (9) and (12). ***, ** and * indicate significant at the 1%, 5% and 10%.

Variable	(1) HFT_ D_B	(2) HFT_ S_B	(3) (1)-(2) *t*-value	(4) HFT_ D_S	(5) HFT_ S_S	(6) (4)-(5) *t*-value	(7) nHFT _D_B	(8) nHFT _S_D	(9) (7)-(8) *t*-value	(10) nHFT _D_S	(11) nHFT _S_S	(12) (10)-(11) *t*-value
Panel A-Normal market												
Mean	886,278	1,146,349	-13.86***	887,027	1,148,786	-13.89***	1,469,970	1,209,899	11.44***	1,483,946	1,222,187	11.43***
Std. Dc.	1,164,985	1,895,215		1,172,354	1,901,811		2,240,383	1,495,854		2,255,626	1,508,936	
Observations	14,053	14,053		14,053	14,053		14,053	14,053		14,053	14,053	
Panel B-Upward market												
Mean	1,756,999	2,166,086	-2.03**	1,738,567	2,136,879	-1.98**	2,562,805	2,153,718	2.14**	2,411,719	2,013,407	2.14**
Std. Dc.	2,291,420	3,399,207		2,341,459	3,352,513		3,245,661	2,140,910		3,131,121	2,116,547	
Observation	412	412		412	412		412	412		412	412	
Panel C-Decline market												
Mean	1,724,083	2,066,118	-1.82*	1,753,775	2,069,118	-1.68*	2,348,701	2,006,665	1.87*	2,562,952	2,247,609	1.60
Std. Dc	2,157,145	3,090,589		2,178,372	3,061,430		3,000,949	2,085,164		3,201,922	2,308,318	
Observation	400	400		400	400		400	400		400	400	

Table 3 Trading volume of demand and supply sides around extreme market conditions for medium-cap companies

This table reports the direction of trading volume around normal, market increase and market decline conditions for medium-cap companies according to asset size. We identify the days as market increase while the market returns are larger than their 95 percentile and the market decline is the days with returns which are less than the 5 percentile of market return. HFT_D_B and HFT_D_B are share volume of demand and supply side of HFT for buy orders. HFT_D_S and HFT_D_S are share volume of demand and supply side of HFT for sell orders. Similarly, nHFT_D_B and nHFT_D_B are share volume of demand and supply side of nHFT for buy orders; for sell orders, nHFT_D_S and nHFT_D_S are share volume of demand and supply side of nHFT. This paper further to use Satterthwaite-Welch t-test to identify the differences of demand and supply sides for HFT and nHFT buy and sell sides, which shown in Colums (3), (6), (9) and (12). ***, ** and * indicate significant at the 1%, 5% and 10%.

Variable	**(1) HFT_ D_B**	**(2) HFT_ S_B**	**(3) (1)-(2) *t*-value**	**(4) HFT_ D_S**	**(5) HFT_ S_S**	**(6) (4)-(5) *t*-value**	**(7) nHFT _D_B**	**(8) nHFT _S_D**	**(9) (7)-(8) *t*-value**	**(10) nHFT _D_S**	**(11) nHFT _S_S**	**(12) (10)-(11) *t*-value**
Panel A-Normal market												
Mean	49,965	36,395	16.06***	49,830	36,184	16.22***	96,764	110,334	-7.90***	29,420	32,689	-5.05***
Std. Dc.	67,286	71,730		66,316	72,024		143,283	139,309		48,827	53,488	
Observations	13,547	13,547		13,547	13,547		13,547	13,547		12,500	12,500	
Panel B-Upward market												
Mean	80,251	47,060	5.52***	77,677	45,227	5.53***	146,063	179,254	-2.73***	135,269	167,720	-2.68***
Std. Dc.	89,060	83,005		84,339	83,749		170,538	177,037		174,806	172,183	
Observation	410	410		410	410		410	410		410	410	
Panel C-Decline market												
Mean	74,425	40,320	5.83***	77,066	40,685	6.22***	121,712	155,816	-3.33***	140,609	176,990	-3.13***
Std. Dc	85,277	79,623		89,465	74,981		140,009	148,528		154,931	172,608	
Observation	398	398		398	398		398	398		398	398	

Table 4 Trading volume of demand and supply sides around extreme market conditions for small-cap companies

This table reports the direction of trading volume around normal, market increase and market decline conditions for small-cap companies according to asset size. We identify the days as market increase while the market returns are larger than their 95 percentile and the market decline is the days with returns which are less than the 5 percentile of market return. HFT_D_B and HFT_D_B are share volume of demand and supply side of HFT for buy orders. HFT_D_S and HFT_D_S are share volume of demand and supply side of HFT for sell orders. Similarly, nHFT_D_B and nHFT_D_B are share volume of demand and supply side of nHFT for buy orders; for sell orders, nHFT_D_S and nHFT_D_S are share volume of demand and supply side of nHFT. This paper further to use Satterthwaite-Welch t-test to identify the differences of demand and supply sides for HFT and nHFT buy and sell sides, which shown in Colums (3), (6), (9) and (12). ***, ** and * indicate significant at the 1%, 5% and 10%.

Variable	**(1) HFT_ D_B**	**(2) HFT_ S_B**	**(3) (1)-(2) *t*-value**	**(4) HFT_ D_S**	**(5) HFT_ S_S**	**(6) (4)-(5) *t*-value**	**(7) nHFT _D_B**	**(8) nHFT _S_D**	**(9) (7)-(8) *t*-value**	**(10) nHFT _D_S**	**(11) nHFT _S_S**	**(12) (10)-(11) *t*-value**
Panel A-Normal market												
Mean	7,903	4,633	19.25***	7,933	4,538	20.32***	29,420	32,689	-5.05***	29,470	32,865	-5.56***
Std. Dc.	15,861	10,437		15,421	10,546		48,827	53,488		46,254	50,125	
Observations	12,500	12,500		12,500	12,500		12,500	12,500		12,500	12,500	
Panel B-Upward market												
Mean	12,604	6,089	5.10***	12,881	5,715	4.64***	48,222	54,737	-1.25	41,997	49,162	-1.54
Std. Dc.	20,365	11,574		25,911	11,399		63,480	71,874		52,786	67,199	
Observation	336	336		336	336		336	336		336	336	
Panel C-Decline market												
Mean	10,499	4,088	7.07***	12,560	4,529	7.23***	33,308	39,719	-2.09**	43,634	51,665	-2.01**
Std. Dc	15,119	5,593		18,451	7,011		34,105	42,455		44,435	55,262	
Observation	316	316		316	316		316	316		316	316	

Table 5 Daily Spreads, Returns and HFT

This table reports estimated coefficients from the following regressions of stock liquidity:

$$L_{i,t} = \alpha_i + \beta_{i,1}R_{M,t-1} + \beta_{HFT,i,1}HFT_{i,t-1} + \beta_{downi,t-1}R_{M,t-1} * IC_{M,t-1} + \beta_{downHFT,i,t-1}R_{M,t-1} * IC_{M,t-1} * HFT_{i,t-1} + \beta_{up,i,t-1}R_{M,t-1} * DL_{M,t-1} + \beta_{up,HFT,i,t-1}R_{M,t-1} * DL_{M,t-1} * HFT_{i,t-1} + \gamma_i Z_{i,t} + \varepsilon_{i,t}$$

where $L_{i,t}$ is the daily average of quoted spread of i[th] stock at t[th] day, which equals to (ask $_{i,j,t}$ – bid $_{i,j,t}$)/q $_{i,j,t}$ where q $_{i,j,t}$ is the midpoint of the reference bid and ask quotes. $R_{M,t}$ presents the average market return on day t, $R_{i,t}$ presents the daily return for stock i on day t, and the $DL_{M,t}$ and $IC_{M,t}$ are the dummies of market decline and market growth. The dummy of $DL_{M,t}$ equals 1 as the market return is less than the 5[th] percentile of all of those negative returns; similarly, the dummy of $IC_{M,t}$ equals 1 if the market return is bigger than the 95[th] percentile of the positive market return. $HFT_{i,t}$ is a dummy variable that take the value of one if the high frequency trading volume of stock i on day t is larger than its' the 75[th] percentile. In order to control the other effects, Z_{it} denotes the column vector of control variables which include day of week dummies, a dummy for days around holidays, contemporaneous and lagged daily volatility of market returns and daily volatility of individual stock, lagged daily turnover and firm fixed effect. An asymptotic efficient two–steps Generalized Least Squares estimator is used to estimate the parameters of the above equation with cross-section contemporaneous correlated and heteroskedastic errors ***, ** and * indicate significant at the 1%, 5% and 10%.

Variable	All	Large-Cap	Medium-Cap	Small-Cap
C (*10E+3)	0.0024***	0.0003***	0.0015***	0.0058***
	18.56	25.99	16.36	15.60
$R_{M,t-1}$	0.0028	-0.0001	-0.0008	0.0095
	0.99	-0.78	-0.40	1.16
$HFT_{i,t-1}$	-0.0010***	-0.0001***	-0.0004***	-0.0018***
	-9.47	-7.73	-4.68	-6.56
$R_{M,t-1}*IC_{M,t-1}$	0.0025	0.0002	-0.0008	-0.0035
	0.35	0.61	-0.20	-0.23
$R_{M,t-1}*IC_{M,t-1}*HFT_{t-1}$	-0.0075	-0.0006**	0.0062**	-0.0017
	-1.11	-2.40	2.48	-0.12
$R_{M,t-1}*DL_{M,t-1}$ (*10E+6)	0.0081*	-0.0009	-0.0008	0.0247**
	1.85	-0.99	-0.25	2.04
$R_{M,t-1}*DL_{M,t-1}*HFT_{t-1}$	-0.0008	0.0013	0.0025	-0.0082
	-0.26***	1.47	0.66	-1.16
$STD_{M,t}$ (*10E+6)	-25.4	6.14***	16.6*	-79.1***
	-1.61	3.10	1.90	-1.79
$STD_{M,t-1}$(*10E+6)	34.7**	-0.427	-1.68	113**
	2.14	-0.21	-0.19	2.37
$STD_{i,t}$(*10E+6)	0.0338***	0.0025***	0.0134***	0.0483***
	3.47	3.35	5.41	2.56
$STD_{i,t-1}$(*10E+6)	0.0365***	0.0023**	0.0151***	0.0532***
	5.43	2.24	3.25	4.09
OIB_H (*10E+6)	0.0087	0.0013	-0.0067	2.0900*
	0.82	0.75	-0.10	1.76
OIB_nH(*10E+6)	-0.00755	0.0038***	-0.00698	-0.363
	-0.59	3.36	-0.12	-0.48
$TRUM_{i,t}$(*10E+6)	-25.5000***	0.3010	-9.7000***	-72.6000***
	-5.02	0.56	-3.84	-4.66

Table 6 Intraday Spreads, Returns and HFT

This table reports estimated coefficients from the following regressions of stock liquidity:

$$
\begin{aligned}
L_{i,t} = {} & \alpha_i + \beta_{HFT,i,t-1} HFT_{i,t-1} + \beta_{up,M,t-1} IC_{M,t-1} + \beta_{up,HFT,i,t-1} HFT_{i,t-1} * IC_{M,t-1} + \beta_{down,i,t-1} DL_{M,t-1} + \\
& \beta_{down,HFT,i,t-1} HFT_{i,t-1} * DL_{M,t-1} + \beta_{large,i,t-1} Large_{i,t-1} + \beta_{large,HFT,i,t-1} Large_{i,t-1} * HFT_{i,t-1} + \\
& \beta_{medium,i,t-1} Medium_{i,t-1} + \beta_{medium,HFT,i,t-1} Medium_{i,t-1} * HFT_{i,t-1} + \beta_{open,i,t-1} Open_{t-1} + \\
& \beta_{open,HFT,i,t-1} Open_{t-1} * HFT_{i,t-1} + \beta_{lunch,i,t-1} Lunch_{t-1} + \beta_{lunch,HFT,i,t-1} Lunch_{t-1} * HFT_{i,t-1} + \\
& \beta_{close,i,t-1} Close_{t-1} + \beta_{close,HFT,i,t-1} Close_{t-1} * HFT_{i,t-1} + \varepsilon_{i,t}
\end{aligned}
$$

where $L_{i,t}$ is the daily average of quoted spread of ith stock at tth day, which equals to (ask $_{i,j,t}$ – bid $_{i,j,t}$)/q $_{i,j,t}$ where q $_{i,j,t}$ is the midpoint of the reference bid and ask quotes. $HFT_{i,t}$ is a dummy variable that take the value of one if the high frequency trading volume of stock i on day t is larger than its' the 75th percentile and the $DL_{M,t}$ and $IC_{M,t}$ are the dummies of market decline and market growth. The dummy of $DL_{M,t}$ equals 1 as the market return is less than the 5th percentile of all of those negative returns; similarly, the dummy of $IC_{M,t}$ equals 1 if the market return is bigger than the 95th percentile of the positive market return. *MEDIUM* are defined as at least 500 but less than 1000 shares, and *LARGE* are 1000 shares or more. $Open_t$, $Lunch_t$ and $Close_t$ are the timing indicators which equals 1 if it is 9:30, 12:00 or 4:00, respectively. An asymptotic efficient two–steps Generalized Least Squares estimator is used to estimate the parameters of the above equation with cross-section contemporaneous correlated and heteroskedastic errors ***, ** and * indicate significant at the 1%, 5% and 10%.

Variable	All	Large-Cap	Medium-Cap	Small-Cap
C (*10E+3)	0.0068***	0.0013***	0.0070***	0.0118***
	50.82	53.48	41.33	50.01
HFT_{t-1}	-0.0052***	-0.0007***	-0.0058***	-0.0088***
	-39.92	-27.33	-34.50	-38.62
$IC_{M,\ t-1}$	-0.0019***	-0.0001	-0.0016***	-0.0042***
	-3.38	-1.12	-2.46	-4.03
$IC_{M,\ t-1}$*HFT_{t-1}	0.0015***	0.0000	0.0019***	0.0042***
	2.87	0.47	2.96	4.27
$DL_{M,t-1}$	-0.0004	0.0004**	-0.0002	-0.0019
	-0.65	2.12	-0.18	-1.64
$DL_{M,t-1}$ *HFT_{t-1}	0.0005	-0.0003**	0.0009*	0.0028***
	0.88	-2.00	1.08	2.56
$Large_{t-1}$	-0.0026***	-0.0008***	-0.0003	-0.0063***
	-11.79	-14.68	-0.12	-19.60
$Large_{t-1}$*HFT_{t-1}	0.0065***	0.0009***	0.0015	0.0093**
	34.53	20.10	0.56	2.00
$Medium_{t-1}$	-0.0019***	-0.0008***	-0.0052***	-0.0084**
	-15.87	-27.08	-5.26	-1.81
$Medium_{t-1}$*HFT_{t-1}	0.0055***	0.0008***	0.0056***	0.0101*
	33.62	8.74	5.26	1.86*
$Open_{t-1}$	0.0316***	0.0067***	0.0346***	0.0530***
	23.03	22.19	20.68	19.45
$Open_{t-1}$*HFT_{t-1}	-0.0214***	-0.0014**	-0.0131	-0.0388***
	-15.52	-2.50	-1.55	-4.63
$Lunch_{t-1}$	-0.0055***	-0.0009***	-0.0060***	-0.0093***
	-40.35	-38.60	-36.60	-38.53
$Lunch_{t-1}$*HFT_{t-1}	0.0052***	0.0006***	0.0057***	0.0088***
	36.41	26.05	33.80	34.42
$Close_{t-1}$	0.0199***	0.0035***	0.0150***	0.0419***
	14.84	8.09	9.47	16.47
$Close_{t-1}$*HFT_{t-1}	0.0070***	0.0012	0.0003	0.0098***
	4.25	0.96	0.17	3.17

Table 7 Liquidity commonality and HFT

This table reports estimated coefficients from the following regressions of stock liquidity:

$$L_{i,t} = \alpha_{i,} + \kappa_{1,i} L_{m,t} + \kappa_{2,i} HFT_{i,t} + \kappa_{3,i} L_{m,t} * HFT_{i,t} + \kappa_{up,i} L_{m,t} * IC_{M,t} +$$

$$\kappa_{up,HFT,i} L_{m,t} * HFT_{i,t} * IC_{M,t} + \kappa_{down,i} L_{m,t} * DL_{M,t} +$$

$$\kappa_{down,HFT,i} L_{m,t} * HFT_{i,t} * DL_{M,t} + \eta_i Q_{i,t} + \varepsilon_{i,t}$$

where $L_{m,t}$ presents the average quoted spread of all stocks except the ith stock, $L_{i,t}$ presents the quoted spread for stock i and the $DL_{M,t}$ and $IC_{M,t}$ are the dummies of market decline and market growth. The dummy of $DL_{M,t}$ equals 1 as the market return is less than the 5th percentile of all of those negative returns; similarly, the dummy of $IC_{M,t}$ equals 1 if the market return is bigger than the 95th percentile of the positive market return. $HFT_{i,t}$ is a dummy variable that take the value of one if the high frequency trading volume of stock i on day t is larger than its' the 75th percentile. In order to control the other effects, Z_{it} denotes the column vector of control variables which include day of week dummies, a dummy for days around holidays, one lead and lag of the market average liquidity, one-day lag market return and return of stock i, daily volatility of market returns, daily turnover and firm fixed effect. An asymptotic efficient two – steps Generalized Least Squares estimator is used to estimate the parameters of the above equation with cross-section contemporaneous correlated and heteroskedastic errors. ***, ** and * indicate significant at the 1%, 5% and 10%.

Variable	All	Large-Cap	Medium-Cap	Small-Cap
C	0.4067***	0.0002***	0.0008***	0.0032***
	7.91	13.17	4.28	5.61
$L_{m,t}$	0.0006***	0.0148***	0.2545***	1.1014***
	5.65	3.01	3.32	5.93
HFT_t	-0.1721***	0.0000	0.0000	-0.0002
	-6.24	-0.89	0.16	-0.22
$L_{m,t}*HFT_t$	-0.0365	-0.0049	-0.1081	-0.5015**
	-0.45	-0.72	-1.23	-2.55
$L_{m,t}*IC_{M,t}$	-0.0652	0.0295	0.0482	-0.3019**
	-0.94	1.23	0.72	-2.06
$L_{m,t}*IC_{M,t}*HFT_t$	0.0835	-0.0280*	-0.0615	-0.0044
	1.34	-1.75	-0.88	-0.03
$L_{m,t}*DL_{M,t}$	-0.0206	0.0120**	0.0225	-0.0393
	-0.29	2.45	0.91	-0.35
$L_{m,t}*DL_{M,t}*HFT_t$	0.4067***	-0.0108**	0.0006	0.4478**
	7.91	-2.35	0.01	2.46