The Role of HFTs in Order Flow Toxicity and Stock Price Variance, And Predicting Changes in HFTs' Liquidity Provisions.

Serhat Yildiz
University of Mississippi
syildiz@bus.olemiss.edu

Robert A. Van Ness
University of Mississippi
rvanness@bus.olemiss.edu

Bonnie F. Van Ness
University of Mississippi
bvanness@bus.olemiss.edu

February 23, 2016

Abstract

This study examines relations between high frequency trading, order flow toxicity, stock price volatility during normal and high order flow toxicity periods, and predictability of changes in high frequency traders' liquidity supply and demand. By employing Volume-synchronized probability of informed trading (VPIN) flow toxicity metric, we find a negative relation between high frequency trading and order flow toxicity. Our results also show that VPIN can be a good predictor of high frequency traders' liquidity supply and demand changes. Finally, we find that high frequency traders' impacts on stock price variance are not uniform and change with order flow toxicity levels of markets and stock volume.

The Role of HFTs in Order Flow Toxicity and Stock Price Variance, And Predicting Changes in HFTs' Liquidity Provisions.

Introduction

High frequency trading is a subset of algorithmic trading that aims to profit from trading at very high speeds. The 26 high frequency trading firms, identified in the NASDAQ high frequency dataset (which includes 120 stocks) participate in 74% of all trades that execute on NASDAQ (Brogaard, 2010). The upper boundary for estimated annual profits of aggressive high frequency traders (HFTs) on the US market is around $21 billion (Kearns et al., 2010). Theoretical work implies that HFTs may be harmful or beneficial for market quality depending on certain conditions.[1] However, empirical studies generally find that HFTs appear to be mostly beneficial for markets.[2]

Our study answers three questions related to HFTs. First, how do HFTs' liquidity supply and demand affect order flow toxicity in equity markets? Second, can we predict periods in which HFTs are dropping out of the market or decreasing their liquidity provisions? Third, how do HFTs affect stock price variance during normal and high order flow toxicity periods?

Two empirical studies, Brogaard et al. (2014) and Carrion (2013), are related to our study. Brogaard et al. find that while HFTs' liquidity demanding orders increase price efficiency their liquidity supplying orders may be adversely selected. Carrion finds that HFTs provide liquidity when spreads are wider and take liquidity when spreads are tighter. Carrion's results about HFTs' adverse selection costs to other liquidity providers are mixed. While examining possible high

[1] Cartea and Penalva (2012), Jarrow and Protter (2012) and Biais, Foucault, and Moinas (2015) develop theoretical models to describe the impacts of HFTs.
[2] Brogaard (2010), Kearns, Kulesza, and Nevmyvaka (2010), Menkveld (2013), Kirilenko, Kyle, Samadi, and Tuzun (2012), Brogaard, Hendershott, and Riordan (2014) and Carrion (2013) empirically examine HFTs from different perspectives.

frequency trading generated adverse selection, Brogaard et al. and Carrion focus on HFTs' impact on the permanent price change component.

As opposed to Brogaard et al. (2014) and Carrion (2013), our first question approaches HFTs' impacts on market liquidity with a different framework; order flow toxicity, measured with VPIN. According to Easley et al. (2011), when there is a lot of information-based trades, VPIN will be high. During high VPIN periods market makers will be on the wrong side of the market, and they will accumulate or lose inventory on the wrong side of the market. Accumulation of losses by market makers may force them to leave the market. Thus, order flow toxicity may harm market liquidity.

Instead of focusing on price changes over a clock time interval, our approach, measuring toxicity with VPIN, focuses on volume, order imbalances, and the number of trades over a trade time interval. The importance of our approach is supported with findings of Easley and O'Hara (1992), Jones, Kaul and Lipson (1994) and Blume, Easley and O'Hara (1994). Research shows that the number of trades is an important signal of information flow, and the sequence of trades provides additional information that is not conveyed by individual transactions (Easley and O'Hara, 1992), the frequency of trades contains information regarding trading (Jones, Kaul and Lipson, 1984), and volume provides information about the quality of traders' information (Blume, Easley and O'Hara, 1994). In other words, VPIN is designed to capture volume information rather than price information (Easley et al., 2011). Thus, different from previous studies our approach examines the impact of HFTs on market liquidity by focusing on volume information.

Another uniqueness of our approach is to employ a trade time clock rather than clock time. While examining HFTs' impact on market liquidity a trade time clock can be more appropriate. Specifically, Clark (1973) introduces the idea that clock time may not be appropriate for measuring time in financial markets. Consistently, Ane and Geman (2000) find that in high frequency world, trade time rather than clock time is a more appropriate measure to use in sampling information sets. Particularly, Ane and Geman find that the cumulative number of trades is an appropriate stochastic clock for generating virtually perfect normality in returns. Also, Easley et al. (2012) show that volume time reduces the impact of volatility clustering, and the distribution of price changes calculated in volume time is closer to a normal distribution and is less heteroscedastic than price changes calculated in clock time.

Second, we study the predictability of periods in which high frequency liquidity providers change their liquidity supply and demand. Sudden changes in liquidity provisions can have significant impacts on market liquidity. For instance, Kirilenko et al. (2012) and Easley et al. (2011) find that the May 6, 2010 Flash Crash is a liquidity event in which some liquidity providers dropped out the market. Such liquidity events can have devastating implications for investors. So, predicting liquidity shocks is an important issue. To this end, we examine whether high VPIN levels can detect changes in HFTs' liquidity supply and demand.

Lastly, we examine the impact of HFTs on stock price variance. Similar to our study, Brogaard (2010) compares volatility in one minute intervals with and without HFT initiated trades and concludes that HFTs may decrease stock price variance. Our approach differs from Brogaard in two aspects. First, we employ a volume time clock rather than clock time. The importance of focusing on volume time rather than clock time in a high frequency world is emphasized by the findings of Clark (1973), Ane and Geman (2000) and Easley et al. (2012). Thus, by using a more relevant clock to calculate volatility, our study increases our understanding of the relation between HFTs and stock price variance. Second, we examine impact of HFTs on stock price variance during two different periods: normal and high order flow toxicity environments. This analysis is important because Kirilenko et al. (2012) find that HFTs did not start the Flash Crash, but HFT's did exacerbated stock price volatility during the Flash Crash. Thus, HFTs' impact on stock price variance may be different during normal times (as in Brogaard) than during high toxicity times (as in Kirilenko et al.). Kirilenko et al. analyze a single high toxicity event, whereas we examine the relation between HFTs and stock price variance during all high toxicity periods over the year 2009. Thus, we provide a more comprehensive analysis of HFTs' impact on stock price variance in different order flow toxicity environments.

Our main findings are as follows. The trades in which HFTs trade with other HFTs and non-HFTs are negatively associated with order flow toxicity. rades in which non-HFTs trade with each other are positively associated with order flow toxicity. These findings are robust across different volume samples. Our findings show that HFTs do not increase order flow toxicity, and trades of non-HFTs with other non-HFTs are the main sources of order flow toxicity during our sample period. We also find that VPIN can detect changes in HFTs' market participation, liquidity supply and demand around 10 volume buckets in advance. Thus, market participants and regulators can track VPIN in real time and predict when high frequency liquidity suppliers will change their liquidity provisions. Lastly, HFTs' relation to stock return volatility is not uniform, and depend on stock volume and toxicity level in the market. Specifically, during normal periods HFTs participation can decrease stock return variance in high and medium volume stocks but increase the volatility in low volume stocks. HFTs continue to decrease stock return volatility of high volume stocks even during the high toxicity periods. However, HFTs do not affect stock return variance of medium and low volume stocks during the high toxicity periods.

2. VPIN as a measure of order flow toxicity

Volume-synchronized probability of informed trading (VPIN) is developed by Easley et al. (2012), and we follow their methods. Similar to our application, VPIN is used to measure order flow toxicity by Easley et al. (2011; 2012), Menkveld and Yueshan (2013), Bethel et al. (2012), Abad and Yague (2012), Wu et al. (2013) and Wei et al. (2013).

Using S&P 500 futures data, Easley et al. (2011) employ VPIN to study toxicity around the May 6, 2010, Flash Crash, and find high levels of toxicity around the Flash Crash. Menkveld and Yueshan (2013) present VPIN and the change in VPIN as toxicity measures in the Flash Crash. Bethel et al. (2012) find that VPIN gives strong signals ahead of the Flash Crash. Using E-mini S&P 500 futures and WTI crude oil futures from January 1, 2008 to June 6, 2011, Easley et al. (2012) report high levels of VPIN around the Flash Crash and the Fukushima nuclear crisis on March 14, 2011. Easley et al. (2012) conclude that high VPIN levels indicate order flow toxicity. Abad and Yague (2012) find that certain specifications of VPIN can proxy for adverse selection risk, and that VPIN can be a helpful device in Spanish financial markets. Wu et al. (2013) examine the performance of VPIN in predicting volatility events in 94 futures contracts from January 2007 to July 2012, and conclude that VPIN is a strong predictor of liquidity-induced volatility. Using VPIN as a toxicity measure, Wei et al. (2013) find that VPIN affects quote imbalances and intraday price volatility of 30 stocks in Australian financial markets. On the other hand, using E-mini S&P 500 data from February 10, 2006 to March 22, 2011, Andersen and Bondarenko (2014b) find that after controlling for trading intensity and volatility, VPIN calculated with bulk volume classification has no additional predictive power of future volatility.

We do not aim to resolve the conflicting results about VPIN's predictive power for future volatility after controlling for certain factors in futures market. Consistent with the order flow toxicity literature, we use VPIN as a measure of HFT and non-HFT generated toxicity in equity markets. Also, while VPIN estimations are sensitive to trade classification algorithms, our data indicate if the trade is a buy or sell. Thus, our calculations are free from biases caused by certain trade classification algorithms.

3. Hypotheses development

3.1 HFTs and order flow toxicity

Theoretical work proposes that HFTs can benefit or harm market quality depending on certain conditions. Cartea and Penalva (2012) propose that HFTs can cause losses to both liquidity traders and market makers, increase price volatility and volume, but do not improve liquidity. Jarrow and Protter (2012) show that HFTs may increase market volatility and create their own profit opportunities at the expense of ordinary traders in a frictionless financial market. However, Biais, Foucault, and Moinas (2015) find that increases in the level of high frequency trading, up to a threshold level, may increase the probability that investors will find a trading counterparty and, thereby, increase trading volume and profits. On the other hand, high levels of high frequency trading can impose adverse selection costs on slow traders, and reduce volume, profits, and cause slow traders to drop out of the market.

Empirically, Hendershott, Jones, and Menkveld (2011) and Hendershott and Riordan (2013) find that algorithmic trading improves liquidity in U.S. and Germany stock markets, respectively. Brogaard et al. (2014) find that HFTs play a significant role in information dissemination and price discovery. We reason that HFTs' impact on price discovery may be beneficial to other liquidity providers, and lower order flow toxicity. Specifically, high information asymmetry between liquidity providers and informed traders generates losses for liquidity providers. HFTs speed up information incorporation into stock prices (as in Brogaard et al., 2014), thus possible information asymmetry between informed traders and liquidity providers will be reduced faster. Due to the decreased information asymmetry, possible losses of liquidity suppliers will be reduced, and order flow toxicity will be lower. Based on the empirical findings of Brogaard et al., we argue that by increasing price informational efficiency, HFTs reduce informational asymmetry between informed traders and liquidity providers and become negatively related to order flow toxicity.

Hypothesis 1: High frequency trading is negatively associated with order flow toxicity in equity markets.

3.2 Predicting HFTs' liquidity provision changes

In the finance literature, extreme VPIN values are used as signals for important liquidity events. Easley et al. (2012; 2011), Bethel et al. (2012) and Wu et al. (2013) document that VPIN gives strong signals ahead of the Flash Crash. Wu et al. (2014) find that VPIN can detect some events that resulted in liquidity issues in the market, such as the Countrywide Financial liquidity crunch (08/2007), a FOMC weak outlook warning (01/2008), a significant drop in the DOW Jones index (09/2008), and the U.S.'s credit rating downgrade (08/2011). Also, Easley et al. (2012) document high levels of VPIN around the Fukushima nuclear crisis on March 14, 2011. Abad and Yague (2012) find that VPIN can proxy for adverse selection risk in Spanish financial markets.

As empirical findings suggest that VPIN can signal important liquidity events, we ask a different question: can VPIN signal the periods in which liquidity suppliers are changing their liquidity supply and demand? Identifying when liquidity suppliers increase or decrease their market participation is important. If we can detect those periods, regulators and market participants can take precautions and prevent sudden high frequency trading related liquidity crises. To this end, we test whether high levels of VPIN can detect changes in HFTs' liquidity supply and demand.

Hypothesis 2: High levels of VPIN can signal changes in HFTs' liquidity supply and demand.

3.3 HFTs' impact on stock price variance

Cartea and Penalva's (2012) and Jarrow and Protter's (2012) theoretical models predict that HFTs can increase stock price volatility, yet, empirical findings for HFTs' impact on stock price volatility are mixed. Brogaard (2010) finds that HFTs may reduce price volatility. On the other hand, Kirilenko et al. (2012) find that HFTs lead to an increase in volatility during the Flash Crash. Additionally, Zhang (2010) finds that HFTs may increase stock price volatility.

We approach the relation between HFTs and stock price variance with a volume clock approach rather than a time clock approach. A volume time clock approach to HFTs and stock price variance relation can be more suitable than a clock time approach, particularly as Clark's (1973) and Ane and Geman's (2000) findings support the idea that trade time rather than clock time is more appropriate in financial markets. Moreover, Easley et al. (2012) show that the distribution of price changes calculated in volume time is closer to a normal distribution and is less heteroscedastic than price changes calculated in clock time. In addition, volume time reduces the impact of volatility clustering.

Our second contribution is that we examine HFTs and stock price variance relation during normal and high order flow toxicity periods. Kirilenko et al. (2012) find that HFTs increased stock price variance during a single high order flow toxicity event; the Flash Crash. Different than Kirilenko et al., we examine HFTs' impact on stock price variance during all high toxicity periods throughout the year 2009. Thus, we provide a comprehensive analysis of HFTs' impact on stock price variance during normal and high toxicity periods. Since theoretical studies predict a positive relation between HFTs and stock price variance, and empirical findings are mixed, we test a null hypothesis regarding HFTs and stock price volatility relation.

Hypothesis 3: HFTs' liquidity demand and supply do not affect stock price variance during normal and high order flow toxicity periods.

4. The VPIN metric calculation

We calculate volume-synchronized probability of informed trading, the VPIN toxicity measure, following Easley, Prado, and O'Hara (2012). This methodology is followed by Easley, Prado, and O'Hara (2011), Abad and Yague (2012), Bethel et al. (2012), Wu et al. (2013), and Wei et al. (2013). VPIN captures the imbalances between buying and selling pressure and is designed to capture volume information rather than price information (Easley et al., 2011). Empirical research shows that trade classification algorithms used to calculate VPIN can affect the VPIN measure. However, our data identify buy and sell trades, and we use actual trades without any classification algorithm. Thus, our measure is free from classification algorithm bias.

We define VPIN as:

$$VPIN = \frac{\sum_{\tau=1}^{n} \left| V_\tau^S - V_\tau^B \right|}{nV}$$

Where V is volume bucket size, n is the number of buckets, $V_\tau^{S(B)}$ is total sell (buy) volume in a given volume bucket (τ). Easley et al. (2012) and Abad and Yegue (2012) show that the choice of the number of buckets has little impact on final value of VPIN. Hence, we choose most commonly used value (50). We define bucket size as one-fiftieth of the average daily volume. Easley et al. (2012) show the choice of bucket size and number of buckets are robust to alternative specifications.

5.1 Sample overview

We use the NASDAQ HFT dataset. This dataset contains trades for 120 stocks. The sample includes 40 large cap, 40 medium cap and 40 small cap stocks. Half of the stocks are listed on NASDAQ and the other half are listed on the New York Stock Exchange (NYSE). The 26 high frequency trading firms are identified by NASDAQ based on analysis of firms' trading patterns, such as order duration, order to trade ratio, and how frequently net trading in a day crosses zero. The data contain following items: Symbol, Date, Time in milliseconds, Shares, Price, a Buy/Sell indicator, and Type (HH, HN, NH, NN).

Symbol is the NASDAQ trading symbol for a stock, and trades are time-stamped to the millisecond. Shares indicates the number of shares traded in a given transaction. The Buy/Sell indicator identifies if the trade was buyer- or seller-initiated. The Type item indicates liquidity demanding and liquidity supplying parties in the transaction; the first participant is demanding liquidity and second one is supplying liquidity. Specifically, a trade with high frequency trading firms on both sides of the transaction is categorized as HH, a trade with a high frequency trading firm initiating the trade and a non-high frequency trader providing liquidity is classified as HN. When a non-high frequency trader initiates a trade and a high frequency trading firm provides liquidity, this trade termed as an NH trade. An NN trade is one with no high frequency trading firms participating.

We calculate HFTs' overall participation, liquidity demand, and liquidity supply using Type item (HH, HN, NH, NN). Consistent with Brogaard, Hendershott, and Riordan (2014) and Carrion (2013) we define:

$HFT\_ALL = (HH+HN+NH)/(HH+HN+NH+NN)$,

HFT_DEMAND=(HH+HN)/(HH+HN+NH+NN), *(Eq.1)*

HFT_SUPPLY=(HH+NH)/(HH+HN+NH+NN).

In addition, using Type item (HH, HN, NH, NN) we define trade type participation variables as follows:[3]

HH_participation=(HH)/(HH+HN+NH+NN),

HN_participation=(HN)/(HH+HN+NH+NN), *(Eq.2)*

NH_participation = (NH)/(HH+HN+NH+NN),

NN_participation = (NN)/(HH+HN+NH+NN).

Table 1 shows price, market capitalization and volume information of the full sample and subsamples by listing exchange and market capitalization. Price, volume, market capitalization and exchange listing data are from the Center for Research in Security Prices (CRSP) as of December 31, 2009. Volume is calculated as the average number of shares traded per month during the year 2009 (in hundred thousands). The average market capitalization of our sample is around $18 billion and average stock price is around $34. While NASDAQ-listed stocks' volume and market capitalization are close to those of NYSE-listed stocks, NASDAQ-listed stocks have higher prices on average than the NYSE-listed stocks. Large cap stocks' volume is nearly 16 times larger than medium caps' volume, and 62 times larger than small caps' volume in our sample.

{Insert Table 1 here}

5.2 Descriptive statistics

Table 2 reports descriptive statics of full sample and three subsamples by volume. Our analysis utilizes all trade data reported by NASDAQ HFT dataset for the year 2009.[4] We find that

[3]These definitions are similar to some definitions of Brogaard (2010).

[4] We winsorize "price" at 0.01 and 99.9 percentiles to eliminate impact of any outliers as in Hendershott, Jones, and Menkveld (2011).

as volume increases average order flow toxicity decreases. Average order flow toxicity (mean VPIN) is 41.78% in overall sample, 23.78% in high volume sample, 40.01% in medium volume sample and 61.54 % in low volume sample. Thus, we observe the highest VPIN levels in low volume stocks and the lowest VPIN levels in high volume stocks. Similarly, we observe the lowest VPIN volatility in the high volume sample, and highest VPIN volatility in the low volume sample. The negative relation between volume and order flow toxicity is also observed between volume and return volatility. Specifically, the standard deviation of returns is 8.32% in the overall sample, 2.22% in the high volume sample, 7.18% in the medium volume sample and 16.33% in the low volume sample. We also observe that trade size and price are positively related to volume. Overall HFT participation, HFT liquidity demand, HFT liquidity supply, HH-participation, and NH-participation are increasing with volume while NN-participation is decreasing with volume. HN participation is highest in medium volume and lowest in low volume stocks. Table 2 Panel C results show that the mean differences we discussed so far are statistically significance at 1% level.

{Insert Table 2 here}

6.1 HFTs and order flow toxicity

We examine HFTs' association with order flow toxicity with the following model:

$$ln\, VPIN_{i,\tau} = \alpha_{i,\tau} + \beta_1 ln\, participation\ rate_{i,\tau-1} + \beta_2 ln\, trade\ size_{i,\tau-1} + \beta_3 ln\, price_{i,\tau-1} + \varepsilon_{i,\tau}.$$

VPIN method is explained in section 4. *"τ"* is a volume bucket for a given firm *"i"*. Participation rate refers to HFT all, HH-, HN-, NH-, and NN-participations as in equations 1 and 2. Trade size is average number of shares traded per trade in a given volume bucket. Price is the average stock price in a given volume bucket.

Consistent with the related literature (e.g., Easley, Engle, O'Hara, and Wu, 2008; Andersen, and Bondarenko, 2014a, 2014b), we estimate the regressions using generalized methods of moments, with the weighting matrix calculated according to Newey and West (1987) with 50 lags. Thus, our analysis is based on the t-statistics that reflect heteroskedasticity and autocorrelation consistent standard errors with 50 lags. In addition, when examining VPIN and HFT participation relations (Tables 3 and 4), we normalize all variables with natural log. Our approach is supported by empirical evidence that VPIN values may be better described with lognormal distribution (Wu, Bethel, Gu, Leinweber, and Ruebel, 2013). Also, consistent with our approach, Easley, de Prado, and O'Hara (2012) calculate natural log of VPIN values in their VPIN and volatility analysis section.

Table 3 reports impacts of HFT all, HH-, HN-, NH- and NN-participation on order flow toxicity with models 1, 2, 3, 4, and 5 respectively. Model 1 shows that overall HFT activity is negatively associated with order flow toxicity. Models 2 and 3 find that HFTs' trade with each other (HH), and HFTs' liquidity demand from non-HFTs (HN) are negatively associated with order flow toxicity. However, when non-HFTs trade with each other (NN) is positively related to order flow toxicity (model 5). These findings are statistically significant at 5% or higher levels. In addition, we find that trade size is positively associated with order flow toxicity in all models, while price is statistically insignificant.

{Insert Table 3 here}

Since, trading activities and HFTs' market participation are heterogeneous across volume samples (e.g., Table 2 Panel C), our findings in Table 3 may differ with volume. Thus, we examine the impact of volume on HFTs' relation to order flow toxicity in Table 4. Specifically, in Table 4 we divide the overall sample into high-, medium- and low-volume subsamples with 40 stocks each. Then, we employ the empirical approach of Table 3 in each subsample. In Table 4, the comparison of slopes panel, we test statistical significance of HFT participation's slope differences across subsamples. In the comparison of slopes tests, as in Ahn, Hwang, and Kim (2010), we follow the methods suggested by Paternoster, Brame, Mazerolle, and Piquero (1998).

Table 4 Panel A shows that overall HFT participation is negatively associated with order flow toxicity across all subvolume samples. Comparison of slopes shows that the negative impact is more pronounced in the high and medium volume samples compared to the low volume sample. Panel B and C find that when HFTs' trades with each other (HH), and HFTs' liquidity demand from non-HFTs (HN) are negatively related to order flow toxicity in high and medium volume samples. Comparisons of slopes show that negative impact of HH-participation is greater in high volume sample compared to medium and low volume samples. Table 4 Panel E shows that when non-HFTs' trades with each other (NN), we find a positive relation to order flow toxicity across all sub-volume samples. Comparison of slopes shows that the positive impact is more pronounced in the high and medium volume samples compared to the low volume sample. In all models of Table 4 trade size is positively associated with order flow toxicity.

Overall, and consistent with the findings in Table 3, our findings in Table 4 show that even after controlling for volume differences across stocks, HFTs are negatively related to order flow toxicity. Moreover, order flow toxicity is a positively related to non-HFTs' trading with other non-HFTs and trade size.

{Insert Table 4 here}

The findings in Table 3 and Table 4 are consistent with our first hypothesis that HFTs are negatively associated with order flow toxicity. One possible explanation of this finding is that when information asymmetry is high between the liquidity providers and informed traders, losses to the liquidity providers will be high and order flow toxicity will increase. Since, HFTs are better at observing markets (Hendershott and Riordan, 2013) and increase price efficiency (Brogaard et al., 2014), they reduce the information asymmetry in the markets. With short lived information asymmetry, losses to liquidity suppliers decrease and HFTs' participations become negatively related to order flow toxicity.

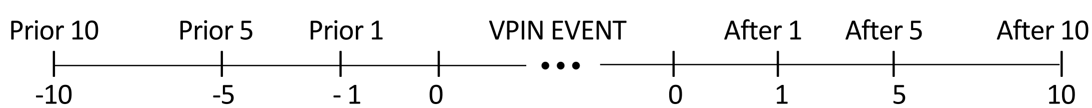
6.2 Predicting HFTs' liquidity provision changes

We examine if VPIN can detect changes in HFTs' market participations, liquidity supply and demand with univariate and multivariate (probit) approaches.

6.2.1 Predicting HFTs' liquidity provision changes univariate approach

We start univariate approach by defining VPIN events. When the VPIN level in a volume bucket is two standard deviations above the sample's mean VPIN level, we define that volume bucket as a VPIN event bucket (similar to Wu et al., 2013). VPIN event buckets are considered to be high toxicity periods. We examine HFTs' liquidity supply and demand activities in different volume bucket windows around and during the VPIN events.

Below, the volume bucket line represents the way we create the volume bucket windows. The first bucket in which VPIN is two standard deviations above the sample mean is considered as the start of a VPIN event. The last bucket extreme VPIN observed is considered as the end of VPIN event. Prior 10, 5, and 1 windows start at 10, 5, and 1 buckets before the VPIN event starts. All Prior event windows end at the beginning of the VPIN event.



Mean 0 is the average liquidity supply/demand throughout the entire sample period, excluding VPIN event periods and the window itself. Mean 1 is the average liquidity supply/demand in the stated volume bucket window. We calculate the differences between Mean 0 and Mean 1 in each window, and test for statistical significance of the differences with T-Tests and Wilcoxon Two-Sample Tests. In addition, we test whether the distributions of liquidity supply and demand in six different windows and during the VPIN event are the same as the distributions of liquidity supply and demand during normal times. To this end, we apply the Kolmogorov-Smirnov test on the liquidity supply and demand distributions. Kolmogorov-Smirnov analysis tests if the distribution of a variable is same across different groups, and reports the probability that two compared sequences follow same distribution.[5]

Table 5-A Panel A presents comparison of HFTs' liquidity supply around the VPIN events. We find that in Prior 10, 5, and 1 windows the differences are positive. Thus, prior to the VPIN events HFTs' liquidity supply is decreasing compared to their liquidity supply during the normal times. The greatest decrease is observed during the VPIN events. In after 1, 5, and 10 windows all differences are negative, which means HFTs' liquidity supply is increasing after the VPIN events. We apply T-Tests and Wilcoxon Two-Sample tests and find that all differences in Panel A are statistically significant at the 1% level. In addition, the results of Kolmogorov-Smirnov test show that the distributions of HFTs' liquidity supply in the prior, during and after VPIN event windows are different than those during the normal toxicity periods. Thus, VPIN is able to predict the changes in HFTs' liquidity supply.

Table 5-A Panel B reports HFTs' liquidity demand around and during the VPIN events. HFTs' liquidity demand is decreasing in Prior 10, 5, and 1 windows compared to the liquidity demand during the normal periods. The differences are significant at 5% level.[6] During the VPIN

[5] We discuss the findings of Kolmogorov-Smirnov test, but do not report the results. The findings are available upon request.

[6] Exceptions are; After 1 window which is significant at 10% level, and After 5 window which is insignificant.

events HFTs' liquidity demand is lower than their liquidity demand during the normal times. After the VPIN events HFTs' liquidity demand starts to increase. Kolmogorov-Smirnov tests also show that the distributions of HFTs' liquidity demand around and during the VPIN events are different than the distributions of HFTs' liquidity demand during normal times. Thus, univariate findings are consistent with our hypothesis that VPIN can detect changes in HFTs' liquidity supply and demand.

{Insert Table 5-A here}

6.2.2 Predicting HFTs' liquidity provision changes multivariate (probit) approach

Table 5-B presents probit analysis in which VPIN events are dependent variables and HFT participations, price and trade size are independent variables. The probit regression is:

$$VPIN\ Event_{i,\tau} = \alpha_{i,\tau} + \sum_{j=1}^{10} \beta_j\ participation\ rate_{i,\tau-j} + \sum_{j=1}^{10} \Lambda_j\ price_{i,\tau-j} + \sum_{j=1}^{10} \Psi_j\ trade\ size_{i,\tau-j} + \varepsilon_{i,\tau}.$$

In the probit analysis, we examine how HFTs' market participations in the ten prior volume bucket is related to VPIN events, while controlling for price and trade size. We follow Wooldridge's (2012) method to calculate sums of coefficients of 10 lags and their standard errors. We cluster the standard errors at the firm level and report the robust t-statistics.

In the Table 5-B Panel A, we use overall sample's mean and standard deviations of VPIN values to calculate VPIN threshold and VPIN events. This examination is practical and uses all available information but does allow contemporaneous examination. In the Table 5-B Panel B, first, we divide our sample in two subsamples with equal number of volume buckets. Then, we calculate VPIN thresholds by using the data from the first sample. We use VPIN thresholds calculated from first sample to define VPIN events in the second sample. This approach allows for contemporaneous calculation, because VPIN events in second sample are defined based on realized VPIN values from the first sample.

Table 5-B Panel A-1 shows that overall HFT activity is negatively related to the likelihood of VPIN events. We examine HFT activity and VPIN event relation more specifically with HH, HN, and NH participations in Panels A-2, A-3, and A-4. These three panels also find a negative relation between HFT involved trades and the likelihood of a VPIN event. On the other hand Panel A-5 finds non-HFTs trade with each other (NN) is positively related to probability of a VPIN event. In all models, price and trade size are positively associated with probability of VPIN events. Table 5-B Panel B, contemporaneous examination shows consistent findings with Panel-A. Thus, VPIN events defined by using realized VPIN values can be useful to detect HFT activity changes in real time.

{Insert Table 5-B here}

Tables 5-A and 5-B provide supportive evidence that in addition to predicting important toxicity events, VPIN can be used to predict changes in HFTs' market participation, liquidity supply and demand. Market participants and regulators can benefit from this property of VPIN. By tracking VPIN in real time; market participants and regulators can predict when high frequency liquidity suppliers will drop out the market. Thus, sudden drops in liquidity due to high frequency liquidity supplier withdrawals can be foreseen and appropriate protection strategies can be implemented.

6.3 HFTs and stock price variance

We examine the relation between stock price variance and HFTs' market participation with the following model:

$$Std.dev.of\ returns_{i,\tau} = \alpha_{i,\tau} + \beta_1 participation\ rate_{i,\tau-1} + \beta_2 \ln trade\ size_{i,\tau-1} + \beta_3 \ln price_{i,\tau-1} + \varepsilon_{i,\tau}\ .$$

Standard deviation of returns is calculated in each volume bucket "τ" for a given firm "i". Returns are calculated using prices of consecutive trades. Participation rates are calculated as in equations 1 and 2. Controls variables are the natural logarithms of price and trade size. In the volatility and HFT participation examinations, we follow Andersen, and Bondarenko, 2014a, 2014b. We estimate the regressions using generalized methods of moments, with the weighting matrix calculated according to Newey and West (1987) with 50 lags. Hence, our analysis is based on the t-statistics that reflect heteroskedasticity and autocorrelation consistent standard errors with 50 lags.

Table 6 presents the relations between overall HFT-, HH-, HN-, NH- and NN-participation and stock price variance in model 1, 2, 3, 4, and 5 respectively. Models 1, 2 and 5 find that overall HFT participation, HFTs trades with other HFTs, and non-HFTs trades with other non-HFTs do not affect stock return variance in overall sample. Model 3 finds that trades in which HFTs demand liquidity from non-HFTs are negatively associated with return volatility. On the other hand, Model 4 shows that trades in which non-HFTs takes liquidity from HFTs are positively associated with stock return volatility. In all models, price is negatively related to stock return variance and trade size is statistically insignificant.

{Insert Table 6 here}

In Table 7 we examine the impact of HFT participation on stock return variance across high-, medium-, and low-volume subsamples. Table 7 Panel A models 1 and 2 find that overall HFT participation is negatively associated with stock return volatility in high and medium volume samples. However, Panel A model 3 shows that overall HFT participation is positively related to stock return volatility in the low volume sample. Comparisons of overall HFTs' slopes also show that overall HFT impact on volatility in high and medium volume stocks is different than that in low volume stocks. Panels B and D present that in high (low) volume sample HH and NH participations are negatively (positively) associated with stock return variance. Comparison of slopes also support these differences. Panel C finds that trades in which HFT demand liquidity from non-HFTs are negatively associated with stock return volatility in high and medium volume samples. Panel E shows that trades of non-HFTs are positively associated with stock return variance in high and medium volume samples and negatively associated in low volume sample. Comparison of non-HFTs' slopes provide supportive evidence about the statistical significance of impact differences.

{Insert Table 7 here}

Overall, Tables 6 and 7 provide evidence about the significant role of volume when examining impacts of HFTs on stock return volatility. Tables 6 and 7 results show that HFTs' impact on stock return variance is not uniform and varies with volume. HFTs' market participation can reduce stock return volatility in high and medium volume stocks but increase the volatility in low volume stocks. At the same time, non-HFTs' trades with each other can increase stock return volatility in high and medium volume samples, and decrease the volatility in low volume stocks. Hence, in terms of stock return volatility HFTs are mainly beneficial for high and medium volume stocks and can harm low volume stocks.

6.4 HFTs and stock price variance during high toxicity periods

Table 8 examines HFTs' impacts on stock price variance during high order flow toxicity periods. In this analysis, we follow the same regression model from section 6.3. The main difference is that we conduct our analysis only in high toxicity periods. We define high order flow toxicity periods as the volume buckets in which the VPIN level is two standard deviations above the sample's mean VPIN level (similar to Wu et al., 2013).

Table 8 Panel A model 1 finds that in high volume stocks overall HFT participation is negatively associated with stock return volatility even during high toxicity periods. Consistently, Panel C model 1 also finds a negative relation between HN participation and stock return volatility in high volume sample. On the other hand, Panel E model 1 finds a positive association with non-HFTs trades with each other and stock return volatility in high volume stocks. For medium and low volume stocks the results are mostly insignificant.

{Insert Table 8 here}

Consistent with the findings in Table 7, Table 8 results show that even during the high toxicity periods overall HFT participation is negatively related to stock return volatility in high volume stocks. While HFTs can be beneficial for high volume stocks during high toxicity periods, their impact in medium and low volume samples are insignificant. The differences in results of Tables 7 and 8 show that HFTs' impacts on stock price variance are changing during high order flow toxicity periods relative to normal periods. Thus, HFTs relation to stock return volatility is not uniform varies with market's order flow toxicity level.

7. Conclusion

A considerable amount of research is dedicated to understand the impacts of HFTs on the financial markets. Our study extends the empirical research on HFTs with three contributions. First, we examine the relation between high frequency trading and order flow toxicity in equity markets, and find a negative relation between high frequency trading and order flow toxicity in equity markets. We attribute this to HFTs' role in information dissemination and price discovery.

Second, we study predictability of changes in HFTs' market participation, liquidity supply and demand, and find that VPIN can detect changes in HFTs' liquidity demand and supply. Market participants and regulators can benefit from our finding by tracking the VPIN in real time; changes in HFTs' liquidity provisions can be detected and appropriate protection strategies can be implemented. Finally, we find that HFTs' impacts on stock price variance are not uniform, and vary with toxicity levels and stock volume. Overall HFTs participation is mostly beneficial for high and medium volume stocks while can increase stock return volatility in low volume stocks.

References

Abad, D., and Yague, J., (2012). From PIN to VPIN: an introduction to order flow toxicity. The Spanish Review of Financial Economics 10, 74–83.

Ahn, T. S., Hwang, I., & Kim, M. I. (2010). The impact of performance measure discriminability on ratee incentives. The Accounting Review, 85(2), 389-417.

Andersen, T. G., and Bondarenko, O. (2014a). VPIN and the flash crash. Journal of Financial Markets, 17, 1-46.

Andersen, T. G., and Bondarenko, O. (2014b). Assessing measures of order flow toxicity and early warning signals for market turbulence. Review of Finance, Forthcoming.

Ané, T., and Geman, H. (2000). Order flow, transaction clock, and normality of asset returns. The Journal of Finance, 55(5), 2259-2284.

Bethel, E. W., Leinweber, D., Rubel, O., and Wu, K., (2012). Federal market information technology in the post-flash crash era: roles for supercomputing. Journal of Trading 7 (2), 9–25.

Biais, B., Foucault, T., and Moinas, S. (2015). Equilibrium high-frequency trading. Journal of Financial Economics, 116(2), 292-313.

Blume, L., Easley, D., and O'Hara, M. (1994). Market statistics and technical analysis: The role of volume. The Journal of Finance, 49(1), 153-181.

Brogaard, J. (2010). High frequency trading and its impact on market quality. Northwestern University Kellogg School of Management Working Paper.

Brogaard, J., Hendershott, T., & Riordan, R. (2014). High-frequency trading and price discovery. Review of Financial Studies, 27(8), 2267-2306.

Carrion, A. (2013). Very fast money: High-frequency trading on the NASDAQ.Journal of Financial Markets, 16(4), 680-711.

Cartea, Á., and Penalva, J. (2012). Where is the value in high frequency trading?. The Quarterly Journal of Finance, 2(03).

Carrion, A. (2013). Very fast money: High-frequency trading on the NASDAQ.Journal of Financial Markets, 16(4), 680-711.

Clark, P. K. (1973). A subordinated stochastic process model with finite variance for speculative prices. Econometrica journal of the Econometric Society, 135-155.

Easley, D., and O'Hara, M. (1992). Time and the process of security price adjustment. The Journal of finance, 47(2), 577-605.

Easley, D., Engle, R. F., O'Hara, M., and Wu, L. (2008). Time-varying arrival rates of informed and uninformed trades. Journal of Financial Econometrics,6(2), 171-207.

Easley, D., López de Prado, M., and O'Hara, M. (2011). The microstructure of the 'Flash Crash': Flow toxicity, liquidity crashes and the probability of informed trading. The Journal of Portfolio Management, 37(2), 118-128.

Easley, D., de Prado, M. M. L., and O'Hara, M. (2012). Flow Toxicity and Liquidity in a High-frequency World. Review of Financial Studies, 25(5), 1457-1493.

Hendershott, T., Jones, C. M., and Menkveld, A. J. (2011). Does algorithmic trading improve liquidity?. The Journal of Finance, 66(1), 1-33.

Hendershott, T., and Riordan, R., Algorithmic Trading and the Market for Liquidity (2013). Journal of Financial and Quantitative Analysis, 48(4), 1001-1024.

Jarrow, R. A., and Protter, P. (2012). A dysfunctional role of high frequency trading in electronic markets. International Journal of Theoretical and Applied Finance, 15(03).
Jones, C. M., Kaul, G., and Lipson, M. L. (1994). Transactions, volume, and volatility. Review of Financial Studies, 7(4), 631-651.
Kearns, M., Kulesza, A., and Nevmyvaka, Y. (2010). Empirical limitations on high frequency trading profitability. Available at SSRN 1678758.
Kirilenko, A., Kyle, A., Samadi, M., and Tuzun, T. (2012). The Flash Crash: The impact of high frequency trading on an electronic market. Available at SSRN 1686004.
Menkveld, A. J. (2013). High frequency trading and the New-Market Makers. Journal of Financial Markets, 16(4), 712-740.
Menkveld, A. J., and Yueshen, B. Z., (2013), Anatomy of the Flash Crash (April 10,2013). Available from SSRN: http:/ssrn.com/abstract=2243520
Paternoster, R., Brame, R., Mazerolle, P., and Piquero, A. (1998). Using the correct statistical test for the equality of regression coefficients. Criminology,36, 859.
Wei, W. C., Gerace, D., and Frino, A., (2013). Informed trading, flow toxicity and the impact on intraday trading factors. Australian Accounting Business and Finance Journal7, 3–24.
Wooldridge, J. (2012). Introductory econometrics: A modern approach. Cengage Learning.
Wu, K., Bethel, W., Gu, M., Leinweber, D., and Rübel, O. (2013). A big data approach to analyzing market volatility. Algorithmic Finance (2013), 2, 3-4.
Zhang, F. (2010). High-frequency trading, stock volatility, and price discovery. Available at SSRN 1691679.

Table 1: Sample stock characteristics

Sample includes 120 NASDAQ stocks from NASDAQ provided high frequency trading dataset. Sample period is from January 2009 to December 2009. Price, volume, market capitalization and exchange listing data are from CRSP as of December 31, 2009. Volume (in 100,000's) is calculated as the average number of shares traded per month during 2009. Market Capitalization (MCAP) is in billions of dollars.

	Full sample	NYSE-listed stocks	NASDAQ-listed stocks	Large cap stocks	Medium cap stocks	Small cap stocks
N	120	60	60	40	40	40
Volume	1257.78	1266.26	1249.29	3504.90	212.70	55.72
Price	34.88	28.94	40.81	56.73	30.12	17.78
MCAP	17.99	18.26	17.72	51.80	1.75	0.41

Table 2: Descriptive statistics

This table reports descriptive statistics across volume buckets for 120 stocks traded on NASDAQ for the year 2009. *VPIN* calculation procedure is given in section 4 in detail. *Ret. Std. Dev.* is the standard deviation of returns, where returns calculated as $(((price_t / price_{t-1})-1)*100)$. *Trade size* is the average number of shares traded per trade in a given volume bucket. *Price* is the average stock price in a given volume bucket. *HH-, HN-, NH-, and NN-part*. are the participation rates which are calculated as (volume of trade type in a given volume bucket divided by total volume, as in eq.2). 'H' stands for high frequency trader and 'N' stands for non-high frequency trader. A trade with high frequency trading firms on both sides of the transaction is categorized as *HH*, a trade with a high frequency trading firm initiating the trade and a non-high frequency trader providing liquidity is classified as *HN.* When a non-high frequency trader initiates a trade and a high frequency trading firm provides liquidity, we term this trade as *NH* trade. An *NN* trade is one where there are no high frequency trading firms participating. *HFT all, HFT demand and HFT supply* are calculated following eq.1. Panel C reports if the differences in means are statistically significant. ***, ** and * represent significance at 1%, 5%, and 10% level, respectively.

Panel A: Overall sample						Panel A: High Volume sample					
Variable	Mean	Std. Dev	5th Pctl	Median	95th Pctl	Variable	Mean	Std. Dev	5th Pctl	Median	95th Pctl
VPIN	0.4178	0.1908	0.1761	0.3885	0.7744	VPIN	0.2378	0.0739	0.1497	0.2253	0.3657
Ret. Std. Dev.	0.0832	0.1464	0.0057	0.0382	0.2949	Ret. Std. Dev.	0.0222	0.0327	0.0071	0.0157	0.0522
Trade size	160.96	397.35	56.76	111.50	370.68	Trade size	196.45	578.90	90.29	142.86	400.19
Price	30.24	42.88	5.04	20.73	69.12	Price	43.31	64.25	7.88	28.22	95.19
HFT all	0.4938	0.2909	0.0000	0.5386	0.8988	HFT all	0.6890	0.1675	0.3662	0.7216	0.9004
HFT demand	0.3306	0.2463	0.0000	0.3247	0.7516	HFT demand	0.4268	0.1681	0.1453	0.4280	0.7021
HFT supply	0.2481	0.2243	0.0000	0.2003	0.6535	HFT supply	0.4262	0.1754	0.1268	0.4343	0.6986
HH part.	0.0848	0.1097	0.0000	0.0406	0.3036	HH part.	0.1640	0.1026	0.0227	0.1493	0.3545
HN part.	0.2458	0.2065	0.0000	0.2194	0.6330	HN part.	0.2628	0.1238	0.0754	0.2533	0.4805
NH part.	0.1633	0.1638	0.0000	0.1275	0.4684	NH part.	0.2622	0.1329	0.0715	0.2470	0.5010
NN part.	0.5062	0.2909	0.1012	0.4614	1.0000	NN part.	0.3110	0.1675	0.0996	0.2784	0.6338
Panel B: Medium volume sample						Panel B: Low volume sample					
Variable	Mean	Std. Dev	5th Pctl	Median	95th Pctl	Variable	Mean	Std. Dev	5th Pctl	Median	95th Pctl
VPIN	0.4001	0.1112	0.2445	0.3876	0.5981	VPIN	0.6154	0.1400	0.4024	0.6067	0.8586
Ret. Std. Dev.	0.0718	0.0915	0.0114	0.0508	0.1865	Ret. Std. Dev.	0.1633	0.2183	0.0000	0.1005	0.5279
Trade size	152.33	326.67	64.25	105.28	271.41	Trade size	134.11	172.50	41.51	91.42	393.76
Price	27.70	27.89	5.53	21.84	59.34	Price	19.72	17.93	3.22	12.89	59.21
HFT all	0.4751	0.2519	0.0495	0.4814	0.8793	HFT all	0.3174	0.3045	0.0000	0.2487	0.9342
HFT demand	0.3386	0.2353	0.0000	0.3151	0.7603	HFT demand	0.2263	0.2796	0.0000	0.1056	0.8337
HFT supply	0.2009	0.1822	0.0000	0.1550	0.5665	HFT supply	0.1171	0.1893	0.0000	0.0000	0.5233

HH part.	0.0643	0.0925	0.0000	0.0301	0.2540	HH part.	0.0260	0.0831	0.0000	0.0000	0.1744
HN part.	0.2743	0.2038	0.0000	0.2461	0.6512	HN part.	0.2003	0.2606	0.0000	0.0834	0.7708
NH part.	0.1365	0.1393	0.0000	0.1000	0.4110	NH part.	0.0911	0.1663	0.0000	0.0000	0.4370
NN part.	0.5249	0.2519	0.1207	0.5186	0.9505	NN part.	0.6826	0.3045	0.0658	0.7513	1.0000

Panel C: Diff. in Means	High Vol. vs. Med. Vol.	High Vol. vs. Low Vol.	Med Vol. vs. Low Vol.
VPIN	-0.1623***	-0.3776***	-0.2153***
Ret. Std. Dev.	-0.0496***	-0.1411***	-0.0915***
Trade size	44.1262***	62.3397***	18.2136***
Price	15.6117***	23.5877***	7.9759***
HFT all	0.2139***	0.3716***	0.1577***
HFT demand	0.0882***	0.2005***	0.1123***
HFT supply	0.2253***	0.3091***	0.0837***
HH part.	0.0996***	0.1379***	0.0383***
HN part.	-0.0114***	0.0625***	0.074***
NH part.	0.1257***	0.1712***	0.0454***
NN part.	-0.2139***	-0.3716***	-0.1577***

Table 3: HFTs' impact on order flow toxicity regression results

This table presents the results from estimating the regression given by $n\,VPIN_{i,\tau} = \alpha_{i,\tau} + \beta_1 ln\ participation\ rate_{i,\tau-1} + \beta_2 ln\ trade\ size_{i,\tau-1} + \beta_3 ln\ price_{i,\tau-1} + \varepsilon_{i,\tau}$. We estimate the regressions using generalized methods of moments, with the weighting matrix calculated according to Newey and West (1987) with 50 lags. The t-statistics in parentheses reflect heteroskedasticity and autocorrelation consistent standard errors with 50 lags. The dependent variable *VPIN* is calculated from NASDAQ provided HFT data from Jan 2009 to Dec. 2009. *"τ"* is a volume bucket for a given firm *"i"*. *HFT all* is calculated following eq.1. *HH-, HN-, NH-, and NN-participations* are calculated as in eq.2. *Trade size* is average number of shares traded per trade in a given volume bucket. *Price* is the average stock price in a given volume bucket. Sample size (N) is 120. ***, ** and * represent significance at 1%, 5%, and 10% level, respectively.

Models	Model 1	Model 2	Model 3	Model 4	Model 5
HFT ALL	-0.0315				
	(-3.03)***				
HH-part.		-0.0130			
		(-2.43)**			
HN-part.			-0.0158		
			(-2.63)**		
NH-part.				0.0067	
				(1.10)	
NN-part.					0.0321
					(3.57)***
Trade size	0.0954	0.0976	0.1025	0.1121	0.0925
	(5.96)***	(4.69)***	(6.46)***	(6.71)***	(6.72)***
Price	-0.0417	-0.0364	-0.0408	-0.0363	-0.0417
	(-0.70)	(-0.52)	(-0.67)	(-0.57)	(-0.72)
Intercept	-1.3669	-1.4143	-1.4083	-1.4436	-1.2979
	(-6.53)***	(-5.78)***	(-6.63)***	(-6.52)***	(-6.39)***
R-square	0.1050	0.0923	0.0996	0.0953	0.1217

Table 4: HFTs' impact on order flow toxicity across volume subsamples regression results

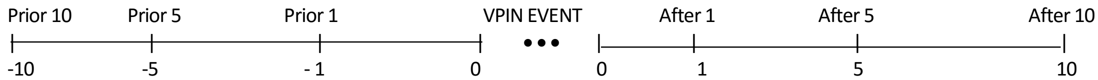
This table presents the results from estimating the regression given by $ln\,VPIN_{i,\tau} = \alpha_{i,\tau} + \beta_1 ln\,participation\,rate_{i,\tau-1} + \beta_2 ln\,trade\,size_{i,\tau-1} + \beta_3 ln\,price_{i,\tau-1} + \varepsilon_{i,\tau}$. We estimate the regressions using generalized methods of moments, with the weighting matrix calculated according to Newey and West (1987) with 50 lags. The t-statistics in parentheses reflect heteroskedasticity and autocorrelation consistent standard errors with 50 lags. The dependent variable *VPIN* is calculated from NASDAQ provided HFT data from Jan 2009 to Dec. 2009. *"τ"* is a volume bucket for a given firm *"i". HFT all is* calculated following eq.1. *HH-, HN-, NH-, and NN-participations* are calculated as in eq.2. *Trade size* is average number of shares traded per trade in a given volume bucket. *Price* is the average stock price in a given volume bucket. We compare slope differences following Paternoster, Brame, Mazerolle, and Piquero (1998). Each volume sample consists of 40 stocks. ***, ** and * represent significance at 1%, 5%, and 10% level, respectively.

Panel A	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
HFT all	-0.0544	-0.0319	-0.0081	-0.0225	-0.0463	-0.0239
	(-2.93)***	(-3.65)***	(-2.09)**	(-1.09)	(-2.44)**	(-2.50)**
Trade size	0.1159	0.10369	0.0666			
	(5.22)***	(6.46)***	(6.81)***			
Price	-0.0304	-0.0312	-0.0633			
	(-0.45)	(-0.52)	(-1.27)			
Intercept	1.9990	-1.4332	-0.6685			
	(-7.55)***	(-6.81)***	(-4.39)***			
R-square	0.1064	0.1245	0.0841			
Panel B	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
HH-part.	-0.0296	-0.00826	-0.0010	-0.0214	-0.0286	-0.0072
	(-4.01)***	(-1.96)*	(-0.23)	(-2.51)**	(-3.32)***	(-1.19)
Trade size	0.1146	0.12043	0.0576			
	(5.03)***	(5.61)***	(3.17)***			
Price	-0.0229	-0.0204	-0.0659			
	(-0.33)	(-0.29)	(-0.93)			
Intercept	-2.0531	-1.5491	-0.6404			
	(-7.81)***	(-6.27)***	(-2.86)***			
R-square	0.1086	0.1047	0.0636			
Panel C	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
HN-part.	-0.0232	-0.0202	-0.0041	-0.0029	-0.0191	-0.0161
	(-2.55)**	(-3.65)***	(-1.20)	(-0.27)	(-1.97)*	(-2.48)**
Trade size	0.1292	0.1104	0.0679			
	(6.44)***	(6.67)***	(6.20)***			
Price	-0.0229	-0.0355	-0.0641			
	(-0.33)	(-0.58)	(-1.20)			
Intercept	-2.1002	-1.4561	-0.6685			
	(-8.09)***	(-6.77)***	(-4.11)***			
R-square	0.1019	0.1153	0.0817			
Panel D	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
NH-part.	0.01755	0.0025	0.0002	0.0150	0.0174	0.0024
	(1.66)	(0.52)	(0.05)	(1.30)	(1.58)	(0.41)
Trade size	0.1492	0.1234	0.0636			
	(7.20)***	(7.06)***	(5.35)***			

Price	-0.0241	-0.0266	-0.0581			
	(-0.35)	(-0.42)	(-1.01)			
Intercept	-2.1398	-1.5149	-0.6759			
	(-8.19)***	(-6.76)***	(-3.77)***			
R-square	0.1032	0.1136	0.0690			
Panel E	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
NN-part.	0.0460	0.0352	0.0149	0.0108	0.0311	0.0203
	(4.28)***	(3.66)***	(2.27)**	(0.74)	(2.46)**	(1.74)*
Trade size	0.1117	0.0969	0.0690			
	(5.56)***	(7.40)***	(8.49)***			
Price	-0.0355	-0.0284	-0.0611			
	(-0.52)	(-0.47)	(-1.32)			
Intercept	-1.8756	-1.3571	-0.6611			
	(-7.11)***	(-6.65)***	(-4.69)***			
R-square	0.1133	0.1368	0.1149			

Table 5-A: Predicting HFTs' liquidity supply and demand changes univariate analysis

When VPIN level in a volume bucket is two standard deviations above the sample's mean VPIN level, we define that volume bucket as a VPIN event bucket (similar to Wu et al., 2013). VPIN event buckets are considered to be high toxicity periods. The first bucket VPIN is two standard deviations above the sample mean is considered as start of VPIN event. The last bucket extreme VPIN observed is considered as the end of VPIN event. Prior 10, 5, and 1 windows start at 10, 5, and 1 buckets before the VPIN event starts. All prior event windows end at the beginning of the VPIN event. After 1, 5, and 10 windows start at the end of the VPIN event and lasts for 1, 5, or 10 buckets, respectively.



Mean 0 is the average liquidity supply/demand throughout the entire sample period, excluding VPIN event periods and the window itself. Mean 1 is the average liquidity supply/demand in the stated volume bucket window. We calculate the differences between Mean 0 and Mean 1 in each window, and test statistical significance of differences with T-Tests and Wilcoxon Two-Sample Tests.

Panel A: HFT supply							
	Prior 10	Prior 5	Prior 1	During event	After 1	After 5	After 10
Mean 0	0.2497	0.2496	0.2494	0.2494	0.2493	0.2492	0.2492
Mean 1	0.2230	0.2241	0.2376	0.2144	0.2813	0.2706	0.2675
Difference	0.0267	0.0255	0.0118	0.0349	-0.0320	-0.0214	-0.0183
Panel B: HFT Demand							
	Prior 10	Prior 5	Prior 1	During event	After 1	After 5	After 10
Mean 0	0.3336	0.3333	0.3329	0.3328	0.3328	0.3328	0.3329
Mean 1	0.2680	0.2700	0.2901	0.2730	0.3406	0.3330	0.3282
Difference	0.0656	0.0633	0.0429	0.0598	-0.0078	-0.0002	0.0047

*All differences are statistically significant at 5% level. Except HFT demand in After 1 window which is significant at 10% level, and After 5 window which is insignificant.

**Wilcoxon Two-Sample Tests also produce consistent results and available upon request.

***Kolmogorov-Smirnov test statistics also support that distributions of liquidity supply and demand during event windows are different than the distributions during normal times. Results are available upon request.

Table 5-B: Predicting HFTs' liquidity supply and demand changes probit analysis

This table presents the results from estimating probit regression given by $VPIN\ Event_{i,\tau} = \alpha_{i,\tau} + \sum_{j=1}^{10} \beta_j\ participation\ rate_{i,\tau-j} + \sum_{j=1}^{10} Ʌ_j\ price_{i,\tau-j} + \sum_{j=1}^{10} \Psi_j\ trade\ size_{i,\tau-j} + \varepsilon_{i,\tau}$. We define VPIN threshold (similar to Wu et al., 2013) as mean VPIN plus two standard deviations of VPIN. When VPIN level in a volume bucket is above VPIN threshold, we define that volume bucket as a VPIN event bucket (similar to Wu et al., 2013). VPIN event buckets are considered to be high toxicity periods. In Panel A, we calculate VPIN thresholds using VPIN values over whole sample period. To allow on the fly examination, in Panel B, we divide our sample into two subsamples, which consist of equal number of volume buckets. Then, we use realized VPIN values of 1st subsample to calculate VPIN thresholds for the 2nd subsample. *HFT all is* calculated following eq.1. *HH-, HN-, NH-, and NN-participations* are calculated as in eq.2. *Trade size* is average number of shares traded per trade in a given volume bucket. *Price* is the average stock price in a given volume bucket. Sample size (N) is 120. We employ ten lags in each variable and report summation of the coefficients. We calculate t-statistics of summations based on robust standard errors that are clustered at firm level. ***, ** and * represent significance at 1%, 5%, and 10% level, respectively.

Panel A	Overall sample		Panel B	On the fly examination	
Panel A-1	Coeff	Robust t-stat	Panel B-1	Coeff	Robust t-stat
$\sum_1^{10} HFT\ all$	-1.0418	(-10.18)***	$\sum_1^{10} HFT\ all$	-0.9175	(-3.82)***
$\sum_1^{10} Price$	0.2589	(11.49)***	$\sum_1^{10} Price$	0.1714	(2.38)**
$\sum_1^{10} Trade\ size$	0.8873	(18.06)***	$\sum_1^{10} Trade\ size$	0.8753	(10.55)***
Intercept	-6.4735	(-24.98)***	Intercept	-6.0009	(-12.05)***
Pseudo R2	0.1269		Pseudo R2	0.1162	
Panel A-2	Coeff	Robust t-stat	Panel B-2	Coeff	Robust t-stat
$\sum_1^{10} HH\ Part.$	-3.4617	(-10.63)***	$\sum_1^{10} HH\ Part.$	-2.7907	(-3.94)***
$\sum_1^{10} Price$	0.2435	(10.34)***	$\sum_1^{10} Price$	0.1601	(2.35)**
$\sum_1^{10} Trade\ size$	0.9441	(19.26)***	$\sum_1^{10} Trade\ size$	0.9140	(10.95)***
Intercept	-6.9362	(-27.47)***	Intercept	-6.3601	(-12.59)***
Pseudo R2	0.1317		Pseudo R2	0.1178	
Panel A-3	Coeff	Robust t-stat	Panel B-3	Coeff	Robust t-stat
$\sum_1^{10} HN\ Part.$	-0.5617	(-2.20)**	$\sum_1^{10} HN\ Part.$	-1.3303	(-4.09)***
$\sum_1^{10} Price$	0.1825	(7.14)***	$\sum_1^{10} Price$	0.1570	(2.17)**
$\sum_1^{10} Trade\ size$	0.7821	(10.62)***	$\sum_1^{10} Trade\ size$	0.7496	(7.86)***
Intercept	-6.0886	(-15.30)***	Intercept	-5.4966	(-9.96)***
Pseudo R2	0.1001		Pseudo R2	0.1043	
Panel A-4	Coeff	Robust t-stat	Panel B-4	Coeff	Robust t-stat
$\sum_1^{10} NH\ Part.$	-1.6346	(-8.04)***	$\sum_1^{10} NH\ Part.$	-1.0221	(-2.23)**
$\sum_1^{10} Price$	0.1813	(7.83)***	$\sum_1^{10} Price$	0.0961	(1.42)
$\sum_1^{10} Trade\ size$	0.9473	(17.55)***	$\sum_1^{10} Trade\ size$	0.8710	(9.57)***
Intercept	-6.7685	(-24.75)***	Intercept	-5.9997	(-11.04)***
Pseudo R2	0.1186		Pseudo R2	0.1016	
Panel A-5	Coeff	Robust t-stat	Panel B-5	Coeff	Robust t-stat
$\sum_1^{10} NN\ Part.$	1.0418	(10.18)***	$\sum_1^{10} NN\ Part.$	0.9175	(3.82)***
$\sum_1^{10} Price$	0.2589	(11.49)***	$\sum_1^{10} Price$	0.1714	(2.38)**
$\sum_1^{10} Trade\ size$	0.8873	(18.06)***	$\sum_1^{10} Trade\ size$	0.8753	(10.55)***
Intercept	-7.5153	(-30.30)***	Intercept	-6.9183	(-12.22)***
Pseudo R2	0.1269		Pseudo R2	0.1162	

We also conduct the same analyses for *HFT demand* and *HFT supply*, and find negative relations to the VPIN events.

Table 6: HFTs' impact on stock price variance regression results

This table presents the results from estimating the regressions given by $Std.dev.of\ returns_{i,\tau} = \alpha_{i,\tau} + \beta_1 participation\ rate_{i,\tau-1} + \beta_2 \ln trade\ size_{i,\tau-1} + \beta_3 \ln price_{i,\tau-1} + \varepsilon_{i,\tau}$. We estimate the regressions using generalized methods of moments, with the weighting matrix calculated according to Newey and West (1987) with 50 lags. The t-statistics in parentheses reflect heteroskedasticity and autocorrelation consistent standard errors with 50 lags. The dependent variable *Standard deviation of returns* is calculated from NASDAQ provided HFT data from Jan 2009 to Dec. 2009. *"τ"* is a volume bucket for a given firm *"i"*. *Standard deviation of returns* is calculated in each volume bucket "*"τ"* for a given firm *"i"*. Returns are calculated using prices of consecutive trades. *HFT all is* calculated following eq.1. *HH-, HN-, NH-, and NN-participations* are calculated as in eq.2. *Trade size* is average number of shares traded per trade in a given volume bucket. *Price* is the average stock price in a given volume bucket. Sample size (N) is 120. ***, ** and * represent significance at 1%, 5%, and 10% level, respectively.

Models	Model 1	Model 2	Model 3	Model 4	Model 5
HFT ALL	-0.0070				
	(-1.09)				
HH-part.		0.0145			
		(0.86)			
HN-part.			-0.0123		
			(-1.81)*		
NH-part.				0.0202	
				(1.96)*	
NN-part.					0.0070
					(1.09)
Trade size	0.0013	0.0031	0.0026	0.0036	0.0013
	(0.34)	(0.77)	(0.66)	(0.36)	(0.34)
Price	-0.0718	-0.0717	-0.0719	-0.0735	-0.0718
	(-6.59)***	(-6.59)***	(-6.53)***	(-6.72)***	(-6.59)***
Intercept	0.2760	0.2608	0.2669	0.2628	0.2689
	(7.27)***	(6.85)***	(6.98)***	(6.92)***	(7.10)***
R-square	0.06760	0.0617	0.0639	0.0648	0.0676

Table 7: HFTs' impact on stock price variance across volume subsamples regression results

This table presents the results from estimating the regressions given by $Std.dev.of\ returns_{i,\tau} = \alpha_{i,\tau} + \beta_1 participation\ rate_{i,\tau-1} + \beta_2 \ln trade\ size_{i,\tau-1} + \beta_3 \ln price_{i,\tau-1} + \varepsilon_{i,\tau}$. We estimate the regressions using generalized methods of moments, with the weighting matrix calculated according to Newey and West (1987) with 50 lags. The t-statistics in parentheses reflect heteroskedasticity and autocorrelation consistent standard errors with 50 lags. The dependent variable *Standard deviation of returns* is calculated from NASDAQ provided HFT data from Jan 2009 to Dec. 2009. *"τ"* is a volume bucket for a given firm *"i"*. *Standard deviation of returns* is calculated in each volume bucket "*"τ"* for a given firm *"i"*. Returns are calculated using prices of consecutive trades. *HFT all is* calculated following eq.1. *HH-, HN-, NH-, and NN-participations* are calculated as in eq.2. *Trade size* is average number of shares traded per trade in a given volume bucket. *Price* is the average stock price in a given volume bucket. We compare slope differences following Paternoster, Brame, Mazerolle, and Piquero (1998). Each volume sample consists of 40 stocks. ***, ** and * represent significance at 1%, 5%, and 10% level, respectively.

Panel A	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
HFT all	-0.0242	-0.0139	0.0171	-0.0102	-0.0413	-0.0311
	(-6.08)***	(-2.57)**	(1.73)*	(-1.52)	(-3.86)***	(-2.75)***
Trade size	0.0095	0.0059	-0.0114			
	(4.60)***	(1.43)	(-2.10)**			
Price	-0.0182	-0.0616	-0.1353			
	(-7.06)***	(-7.44)***	(-6.21)***			
Intercept	0.0461	0.2288	0.5513			
	(3.27)***	(7.04)***	(8.21)***			
R-square	0.0973	0.0499	0.0556			
Panel B	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
HH-part.	-0.0142	-0.0064	0.0641	-0.0078	-0.01784	-0.0706
	(-3.97)***	(-0.46)	(1.97)*	(-0.54)	(-2.39)**	(-1.99)**
Trade size	0.0136	0.0075	-0.0119			
	(5.80)***	(1.80)*	(-2.20)**			
Price	-0.0175	-0.0619	-0.1358			
	(-6.71)***	(-7.50)***	(-6.24)***			
Intercept	0.0070	0.2154	0.5599			
	(0.48)	(6.62)***	(8.36)***			
R-square	0.0820	0.0480	0.0553			
Panel C	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
HN-part.	-0.0135	-0.0164	-0.0069	0.0029	-0.0065	-0.0095
	(-4.00)***	(-2.89)***	(-0.61)	(0.44)	(-0.55)	(-0.74)
Trade size	0.0135	0.0066	-0.0124			
	(5.89)***	(1.62)	(-2.29)**			
Price	-0.0169	-0.0630	-0.1357			
	(-6.31)***	(-7.56)***	(-6.17)***			
Intercept	0.0070	0.2276	0.5662			
	(0.48)	(7.02)***	(8.37)***			
R-square	0.0863	0.0504	0.0552			
Panel D	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
NH-part.	-0.0097	0.0151	0.0055	-0.0248	-0.0648	-0.0400
	(-2.38)**	(1.44)	(3.37)***	(-2.21)**	(-3.84)***	(-2.06)**
Trade size	0.0143	0.0079	-0.0114			
	(6.13)***	(1.91)*	(-2.11)**			

Price	-0.0178	-0.0638	-0.1387			
	(-6.81***)	(-7.65)***	(-6.35)***			
Intercept	0.0060	0.2190	0.5633			
	(0.43)	(6.74)***	(8.36)***			
R-square	0.0861	0.0514	0.0568			
Panel E	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
NN-part.	0.0241	0.0140	-0.0171	0.0102	0.0412	0.0311
	(6.08)***	(2.57)**	(-1.72)*	(1.52)	(3.86)***	(2.75)**
Trade size	0.0095	0.0059	-0.0114			
	(4.60)***	(1.45)	(-2.10)**			
Price	-0.0182	-0.0617	-0.1353			
	(-7.06)***	(-7.44)***	(-6.21)***			
Intercept	0.0219	0.2148	0.5703			
	(1.62)	(6.61)***	(8.43)***			
R-square	0.0973	0.0499	0.0555			

Table 8: HFTs' impact on stock price variance during high toxicity periods regression results

This table presents the results from estimating the regressions given by $Std.dev.of\ returns_{i,\tau} = \alpha_{i,\tau} + \beta_1 participation\ rate_{i,\tau-1} + \beta_2 \ln trade\ size_{i,\tau-1} + \beta_3 \ln price_{i,\tau-1} + \varepsilon_{i,\tau}$. We estimate the regressions using generalized methods of moments, with the weighting matrix calculated according to Newey and West (1987) with 30 lags*. The t-statistics in parentheses reflect heteroskedasticity and autocorrelation consistent standard errors with 30 lags. The dependent variable *Standard deviation of returns* is calculated from NASDAQ provided HFT data from Jan 2009 to Dec. 2009. *"τ"* is a volume bucket for a given firm *"i"*. *Standard deviation of returns* is calculated in each volume bucket "*"τ"* for a given firm *"i"*. Returns are calculated using prices of consecutive trades. *HFT all is* calculated following eq.1. *HH-, HN-, NH-, and NN-participations* are calculated as in eq.2. *Trade size* is average number of shares traded per trade in a given volume bucket. *Price* is the average stock price in a given volume bucket. We compare slope differences following Paternoster, Brame, Mazerolle, and Piquero (1998). Each volume sample consists of 40 stocks. ***, ** and * represent significance at 1%, 5%, and 10% level, respectively.

Panel A	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
HFT all	-0.0240	0.0036	0.0441	-0.0276	-0.0680	-0.0404
	(-2.30)**	(0.19)	(1.41)	(-1.30)	(-2.07)**	(-1.11)
Trade size	0.0068	0.0072	-0.0092			
	(1.72)*	(0.85)	(-0.62)			
Price	-0.0170	-0.0514	-0.0804			
	(-1.73)*	(-1.41)	(-1.21)			
Intercept	0.0536	0.1894	0.3713			
	(1.26)	(1.68)*	(1.86)*			
R-square	0.1037	0.0548	0.0511			
Panel B	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
HH-part.	-0.0125	0.0489	0.1621	-0.0614	-0.1746	-0.1132
	(-0.97)	(0.83)	(1.63)	(-1.02)	(-1.74)*	(-0.98)
Trade size	0.0114	0.0076	-0.0101			
	(2.57)**	(0.90)	(-0.68)			
Price	-0.0163	-0.0521	-0.0816			
	(-1.60)	(-1.42)	(-1.22)			
Intercept	0.0120	0.1881	0.3863			
	(0.29)	(1.68)*	(1.93)*			
R-square	0.0823	0.0534	0.0516			
Panel C	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
HN-part.	-0.0209	-0.0073	0.0113	-0.0136	-0.0322	-0.0186
	(-2.21)**	(-0.37)	(0.30)	(-0.62)	(-0.84)	(-0.44)
Trade size	0.0109	0.0066	-0.0112			
	(2.55)**	(0.79)	(-0.76)			
Price	-0.0161	-0.0520	-0.0825			
	(-1.57)	(-1.41)	(-1.22)			
Intercept	0.0175	0.1963	0.3973			
	(0.43)	(1.74)*	(1.95)*			
R-square	0.0876	0.0544	0.0468			
Panel D	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
NH-part.	-0.0095	0.0414	0.1148	-0.0509	-0.1244	-0.0734
	(-0.92)	(1.12)	(1.94)*	(-1.33)	(-2.07)**	(-1.05)
Trade size	0.0115	0.0080	-0.0095			
	(2.68)**	(0.35)	(-0.65)			

Price	-0.0168	-0.0535	-0.0821			
	(-1.65)	(-1.46)	(-1.27)			
Intercept	0.0153	0.1892	0.3810			
	(0.38)	(1.70)*	(1.96)*			
R-square	0.0868	0.0589	0.0583			
Panel E	High vol.	Med vol.	Low vol.	Comparison of slopes		
Models	Model 1	Model 2	Model 3	High vs Med	High vs Low	Med vs Low
NN-part.	0.0239	-0.0036	-0.0441	0.0276	0.0680	0.0404
	(2.30)**	(-0.19)	(-1.41)	(1.30)	(2.07)**	(0.27)
Trade size	0.0068	0.0072	-0.0092			
	(1.72)*	(0.85)	(-0.62)			
Price	-0.0170	-0.0514	-0.080			
	(-1.73)*	(-1.41)	(-1.21)			
Intercept	0.0296	0.193	0.4153			
	(0.76)	(1.73)*	(2.08)**			
R-square	0.1036	0.0548	0.0511			

*The low number of observations in some sub-volumes forced us to use thirty lags.