Flow Toxicity of High Frequency Trading and Its Impact on Price Volatility: Evidence from the KOSPI 200 Futures Market

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JEL classification: G14

Keywords: high frequency traders; order flow toxicity; short-term price volatility; VPIN

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Abstract

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1 Introduction

Market making helps markets to achieve market efficiency by facilitating the process of price discovery, which is one of the most important roles of the market. In the late 20th century when floor markets were still pervasive, market making was primarily conducted by so-called exchange specialists (the NYSE's designated market makers and NASDAQ market makers, for example). After the transformation to electronic limit order book (LOB) markets and regulatory changes (Reg NMS (2005)), the bids and asks from endogenous liquidity providers (ELPs) or proprietary market makers have replaced those of the traditional market makers. Furthermore, as algorithmic trading becomes a trend in modern markets, high frequency traders (HFTs) take considerable part of market making by generating a number of orders from complex computer algorithms.

Those new type of traders, who are now the main liquidity providers by employing algorithms, are reported to behave differently compared to the traditional market makers. For example, Kirilenko *et al.* (2017) show that inventory changes of HFTs are positively associated with contemporaneous price changes while those of market makers are negatively associated with contemporaneous price changes in the one-second clock-time interval in the E-mini S&P 500 futures market. Brogaard *et al.* (2018) and Kang *et al.* (2018) present similar evidences in the NASDAQ market and in the KOSPI 200 futures market, respectively. Notably, Kang *et al.* (2018) indicate that during extreme price movements (EPMs) HFTs reveal directional trading whereas other types of traders including market makers absorb volume imbalances created by HFTs in the KOSPI 200 futures market. Therefore, the shift to high frequency markets after the emergence of HFTs changes the shape of liquidity provision/demand and market making.

If adverse selection cost is widespread in a market, liquidity providers reduce their bids and asks in a limit order book, and enlarge a bid-ask spread to compensate possible loss incurred from the adversely selected trades (Glosten and Milgrom (1985)). In more severe cases, they will even liquidate their positions and exit the market, which makes it unstable. If large orders enter into the market during those periods, liquidity-driven market crash can take place even in the absence of fundamental shocks. Together with the fact that HFTs with high speed order submission and cancellation now dominate liquidity provision, the market can collapse in few minutes.

A typical example is the 2010 Flash Crash. On May 6, 2010, the U.S. financial markets underwent one of the most turbulent periods when the price of the E-mini S&P 500 stock index futures and its related index prices collapsed and recovered in 36 minutes; the Dow Jones Industrial Average plunged nearly 1,000 points within several minutes and rebounded about 70% of the drop until the market close. According to the 2010 joint report issued by the Commodity Futures Trading Commission and the U.S. Securities and Exchange Commission (CFTC-SEC), the Flash Crash was triggered by large sell orders of the E-mini S&P 500 future contracts against a backdrop of unusually high volatility and illiquidity. Kirilenko *et al.* (2017) show that, unlike traditional market makers, HFTs did not alter the trading strategy during the "down" phase but tried to short accumulated contracts during the "up" phase, which was possible to further accelerate the crash.

Order flow is said to be "toxic" if it induces liquidity providers on adverse selection. In high frequency markets where market conditions, such as liquidity and volatility, change rapidly, it is important to develop a real-time intraday measure of the market-wide order flow toxicity. Easley *et al.* (2012a) suggest the *Volume-Synchronized Probability of Informed Trading (VPIN)* as a measure of order flow toxicity, and assert that it is a useful predictor of short-term toxicity-induced volatility in the U.S. futures markets. In contrast to the original PIN measure, it is straightforward to calculate and is updated in real time by construction, which is easily implementable for traders and regulators in a high frequency market environment. Furthermore, Easley *et al.* (2011) demonstrate that their VPIN metric reached its all-time historical high right before the Flash Crash and alarmed a warning signal for possible market turbulence in the E-mini S&P 500 futures market.

The VPIN metric is widely adopted as a successful proxy of order flow toxicity in many subsequent papers. To name a few, Chordia *et al.* (2017) propose that the volatility of order flow (VOIB), which is the similar to VPIN[4], well measures informational asymmetry and predicts stock returns in the cross section in the U.S. stock markets. Low *et al.* (2018) support the applicability of VPIN in international equity markets. Cheung *et al.* (2015) use mandatory call events (MCEs) of the callable bull/bear contracts (CBBC) in the Hong Kong Stock Exchange to show that high level of VPIN indicates high market risk around MCEs. Bhattacharya and

[4] The VPIN metric is calculated as a moving average of the absolute values of imbalances while the VOIB metric is basically a moving standard deviation of signed imbalances. Although both metrics are slightly different in the calculation, the main ideas behind the measurement are in fact the same. Our results are qualitatively similar when we choose the VOIB metric as a measure of order flow toxicity.

Chakrabarti (2014) study the evolution of adverse selection in the IPO aftermarket by adopting VPIN as a proxy for adverse selection.

There are some criticisms about the application of the VPIN metric, on the other hand. For instance, Andersen and Bondarenko (2014a) and Andersen and Bondarenko (2014b) refute the findings of Easley *et al.* (2012a). They argue that VPIN is mechanically related to the underlying trading intensity, and its predictability is subsumed by trading intensity and realized volatility in the E-mini S&P 500 futures market. Abad *et al.* (2018) show that VPIN is limited to forecast large intraday price changes leading to single-stock circuit breakers in the Spanish stock market. While there are ongoing debates about the applicability of VPIN in various markets, it is valuable to see whether VPIN is applicable in the KOSPI 200 futures market that is one of the most active derivative markets in the world.

Prior to calculate the VPIN metric, one needs to distinguish buy volume and sell volume to compute order imbalances. The most common classification in market microstructure is the Lee and Ready (1991) algorithm. It classifies buy volume and sell volume trade-by-trade based on the proximity to the prevailing quote except for the midpoint. Its variations with slight changes and better performances are also introduced in subsequent papers, such as Ellis *et al.* (2000) and Chakrabarty *et al.* (2007). However, as pointed out by O'Hara (2015), those tick rule-based classifications become more problematic in the world of high frequency trading in the following points: (1) the difficulty to infer the prevailing BBO due to varying latencies between the market information system and market centers and high order cancellation/resubmission rates, (2) the trading norm that traders with information do not necessarily cross the spread but use passive orders to execute trades at favorable prices with order-splitting behaviors. Easley *et al.* (2016) find that bulk volume classification (BVC) better discerns information-based trading than tick rule in high frequency markets, and Easley *et al.* (2012a) advocate the use of BVC in the calculation of VPIN. However, Pöppe *et al.* (2016) argue that VPIN is not robust to the choice of trade classification scheme between tick rule-based and bulk-volume classifications in Deutche Boerse. Hence, it is also necessary to test which classification algorithm discerns informed trading better and is more appropriate for the calculation of the VPIN metric in the KOSPI 200 futures market.

When HFTs make markets, their speed advantage enables themselves to increase the probability that they avoid "*being picked off*" by informed traders and provide liquidity skillfully, which leads to be more likely for other investors to find them as trading counterparties. Moreover, as pointed out in Brogaard *et al.* (2014), they facilitate the process of price discovery, which reduces informational asymmetry between informed traders and slow liquidity providers. Collectively, they tend to decrease order flow toxicity. On the other hand, using the speed advantage, they can pick off slow traders, which increases adverse selection and then the level of flow toxicity. During a market experiences stressful periods like the Flash Crash, while the traditional market makers (the specialists) were expected (obligated) to maintain a bid and an ask, HFTs do not have any obligation to stabilize the market. According to Kang *et al.* (2018), they trade in the same direction of the price movement during stressful states, which implies their order flow could be highly toxic. Considering those conflicting standpoints, it is vital to examine the relation between order flow toxicity and high frequency trading, depending on market conditions.

Understanding the effect of HFTs on price volatility is crucial to researchers, practitioners, and policy makers, and is widely studied in numerous papers. Theoretically, Cartea and Penalva (2012) present a model that shows HFTs increase price volatility. Jarrow and Protter (2012) show that HFTs can create a self-induced mispricing that exploit against slow traders. However, many empirical papers including Brogaard (2010), Hasbrouck and Saar (2013), Hagströmer and Nordén (2013) report that HFTs are helpful to reduce price volatility in the U.S. equity markets while Boehmer *et al.* (2015) reach different conclusions for international equity markets that HFTs have a positive relation with volatility. Moreover, as indicated by recent papers (Kirilenko *et al.* (2017), Brogaard *et al.* (2018), and Kang *et al.* (2018)), there would be a difference in the effect of HFTs on price volatility during normal versus stressful times. Thus, it is a critical issue how HFTs affect price volatility, especially under stressful times like the Flash Crash, in the KOSPI 200 index futures market.

To summarize, the purposes of this paper are fourfold: in the KOSPI 200 index futures market, (1) we examine that the VPIN metric is applicable; (2) we analyze which classification algorithm, the true initiator versus BVC, is better to capture the underlying information, and therefore is more suitable to calculate the VPIN metric, (3) we investigate flow toxicity of orders produced by HFTs who are now dominant intermediaries but different to traditional market makers; and (4) we study how HFTs affect price volatility during both normal and stressful times.

Following Easley *et al.* (2012a), we construct the VPIN metric as a measure of order flow toxicity, and examine the relations among the VPIN metric, high frequency trading, and price volatility in the KOSPI 200 index futures market. We utilize the high-quality data that encompasses all transaction records for the KOSPI 200 index futures from January 2010 to June 2014. Our dataset has a number of advantages as follows. First, it has encrypted account information in the bid and ask side for each transaction, which allow us to classify a particular account as a high frequency trader (HFT) or non-high frequency trader (nHFT) based on its pure trading activities. Second, we further classify the group of HFTs into foreign, individual, and institutional HFTs from the investor group identifier. Third, we are able to infer the true trade initiator for each transaction by comparing order acceptance numbers in the bid and ask sides. For example, if order acceptance number in the bid side is greater than that in the ask side, it implies that order from the bid side is accepted in the Korea Exchange (KRX) later, and thereby that the bid side initiates the transaction against the ask side. Fourth, in contrast to the NASDAQ HFT dataset, our testing market does not suffer from market fragmentation. The KOSPI 200 futures market is consolidated so that all futures contracts are exclusively traded on the market. Lastly, due to negligible transaction cost and no tax in the KOSPI 200 futures market, it is favorable for HFTs who establish and liquidate their positions frequently.

Our empirical results can be summarized as follows. First, the volume-synchronized probability of informed trading using bulk-volume classification (BV-VPIN) strongly predicts future short-term price volatility. And its predictability still remains significant even after controlling for realized volatility, trading intensity, and illiquidity, which discernibly contradicts to Andersen and Bondarenko (2014a). Furthermore, BV-VPIN reached unusually high level before and during the historical events when the market experienced extremely unstable periods. Accordingly, we conclude that BV-VPIN successfully measures the market-wide order flow toxicity in the KOSPI 200 futures market. Second, BVC discerns informed trading better than trade classification using the true trade initiator, both in the aspect of illiquidity and profitability. In contrast to BV-VPIN, the volume-synchronized probability of informed trading using the true trade initiator (TR-VPIN) is negatively associated with future price volatility. Therefore, we urge to use bulk-volume classification when calculating the VPIN metric, even if we know the accurately identified initiator. Third, high frequency trading (HFT) is negatively related to order flow toxicity in normal times, which is consistent with that it reduces informational asymmetry between informed traders and liquidity providers by facilitating the price discovery. However, during intense trading times and extremely volatile times, it is positively related to order flow toxicity, compared to normal times. This pattern is consistent with "*its picking-off slow traders*" during those stressful states. Finally, HFT decreases short-term price volatility in normal times, but turns to increase when the market-wide order flow is toxic and the price is extremely volatile. This HFT behavior is consistent with what happened in the Flash Crash.

This paper contributes to the literature in the following aspects. First, we take sides in favor of the application of VPIN in high frequency markets as Easley *et al.* (2012a), but sharply contrast to Andersen and Bondarenko (2014a). Thus, the VPIN metric can be utilized as a measure of adverse selection, a risk management tool for practitioners, or a reliable indicator for the exchange in the KOSPI 200 futures market. Second, our study is the first to show order flow toxicity of HFTs depending on market conditions, who dominates liquidity provision in today's markets. Third, we show that HFTs can differently behave in stressful states; they produce more toxic orders, and they increase price volatility. Our results about the effect of HFT on price volatility is consistent with Kirilenko *et al.* (2017). At last, as argued in Easley *et al.* (2016), we advocate the use of BVC in high frequency markets, since it captures the underlying information better than the true initiator. We present an additional evidence that the initiator identified by BVC trades at more favorable prices than the true initiator. It implies that immediacy is no longer a good proxy for informed trading.

The rest of the paper is organized as follows. Section 2 describes the environment of the KOSPI 200 index futures market. In Section 3, we detail our dataset, and explain the procedures of the VPIN calculation and the HFT identification. Section 4 deals with the predictability of BV-VPIN on future price volatility. Section 5 clarifies the relations among BV-VPIN, HFT, and price volatility. Section 6 takes an in-depth look at TR-VPIN and issues on the choice of trade classification. We checks robustness in Section 7, and leave concluding remarks in Section 8.

2 The KOSPI 200 Futures Market

Since the Korea Exchange (KRX) listed the KOSPI 200 index futures and options on May 1996 and July 1997, respectively, the markets have rapidly developed notwithstanding their short histories. In particular, the Futures Industry Association (FIA) reported that the KOSPI 200 index derivatives were the most actively traded derivative contracts in the world in 2011.[5] During our sample period spanning from January 2011 to June 2014, the KOSPI 200 index futures and options markets were regarded as one of the major derivative markets in the world.

The KOSPI 200 index futures are traded exclusively on the KRX trading platform. Therefore, in contrary to the studies that deal with the U.S. financial markets, our results are unaffected by market fragmentation.[6] The KOSPI 200 index futures market is a fully electronic limit order market without floor traders and specialists. The market opens at 9:00 a.m. and closes at 3:15 p.m., 15 minutes after the closing time of the stock market. The opening price is determined by a batch auction at a one-hour pre-opening session (8:00 a.m. to 9:00 a.m.), and for the last ten minutes until the market closes (3:05 p.m. to 3:15 p.m.) orders are executed in the closing batch auction. The market adopts the price-time priority, a rule that orders which offer better prices will be firstly executed, and if the prices are the same orders which come first will be executed. The minimum tick size of the market is 0.05 index point, and one index point had its value of KRW500,000 during our sample period, implying the minimum tick value was $0.05 \times \text{KRW}500{,}000 = \text{KRW}25{,}000$.

One notable feature of the KOSPI 200 index futures market is that it requires negligible transaction cost and no tax, which is a crucial advantage to (foreign) HFTs. The KRX imposes 0.3% tax of transaction on the sale of equity. However, for exchange-traded derivatives, investors are not required to pay capital gains tax as well as tax of transaction. As a result, our testing market provides a favorable market environment for HFTs who frequently establish and liquidate their positions.

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[5] According to the FIA Annual Volume Survey in 2011, the KOSPI 200 options took the 1st rank of global equity index futures & options contracts with 3,671,662,258 cumulative contracts during 2011. The KOSPI 200 futures took the 15th rank with 86,214,025 cumulative contracts during 2011. After the increase in the option multiplier in March 2012, the number of contracts traded and/or cleared in the KOSPI 200 futures and options in 2012 declined by 28.5% and 57.1%, respectively, compared to 2011. Still, the KOSPI 200 options and futures took the 1st and 20th rank of global equity index futures & options contracts in 2012.

[6] As dark trading volume executed in alternative trading systems (ATS) has increased sharply in recent years, how market fragmentation is affecting market quality becomes the critical issue in market microstructure. However, the empirical evidence about that issue is mixed: for instance, O'Hara and Ye (2011) find that fragmentation enhances market quality in the aspects of transaction costs, execution speed, and market efficiency while Hatheway *et al.* (2017) show that the effects of dark-venue order segmentation are damaging to overall market quality except for the execution of large transactions and trading in small stocks.

3 Data and Methodology

3.1 Data

Offered from the KRX, our high-quality data encompass all transaction-by-transaction trade records for all trading days from January 2010 to June 2014 (1,115 trading days). Our sample period is very long relative to other studies related to HFTs.[7] Each transaction is time-stamped in a millisecond unit and has data fields including encrypted account information, investor group identifier (foreign, individual, and institutional), bidder-asker identifier and order acceptance number. The encrypted account information allows us to look into trading activities account-by-account. Therefore, after we see the trading activity of each account, we can categorize each trader into HFT or nHFT. Based on the investor group identifier, we can further classify HFTs as foreign, individual, and institutional HFTs. The bidder-asker identifier and the time-ordered order acceptance number enable us to identify reliably whether each transaction is buyer-initiated or seller-initiated without depending on tick rule-based algorithms. For example, if order acceptance number in the bid side is larger than that in the ask side, it implies that order from the bid side is accepted in the KRX later, and thereby that the bid side initiates the transaction against the ask side. We use only the front-month futures contracts since longer-maturity futures contracts are rarely traded. In constructing the VPIN metric, we only focus on continuous normal trading hours, from 9:00 am. to 3:05 pm., excluding the opening and closing auctions and overnight trading sessions. The reason is that our main focus is to examine the relation between the VPIN metric and the trading activity of HFTs who use algorithms restricted in continuous trading hours.

3.2 Methodology

3.2.1 VPIN

We follow Easley *et al.* (2012a) to calculate the VPIN metric. First, all sequential trades are grouped into equal volume "buckets" of an exogenously defined size V, which is set to one-fiftieth of the average daily trading

[7] For example, Kirilenko et al. (2017) examine only four days around the Flash Crash, and datasets of Andersen and Bondarenko (2014) and Easley et al. (2011) span less than three years. Easley et al. (2012a) investigate the period from January 2008 to August 2011, which is less than four years. Andersen and Bondarenko (2015) especially cover a longer period from February 10, 2006 to March 22, 2011, but our sample period includes more recent events, such as the downgrade of the U.S. credit rating in August 2011 and the upgrade of the Korean credit rating on September 2012.

volume over the sample period. Second, to calculate a trade imbalance for each bucket, one needs to classify the bucket volume into buy volume and sell volume. To do this task, we employ bulk volume classification (BVC) using volume bars of size 1,000 contracts; for bucket τ, buy volume (V_τ^B) and sell volume (V_τ^S) is computed as:

$$V_\tau^B = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \times Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right) \tag{1}$$

$$V_\tau^S = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \times \left[1 - Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right)\right] = V - V_\tau^B \tag{2}$$

where $t(\tau)$ is the index for the last volume bar in bucket τ, V_i is the bar size, P_i is the last trade price in volume bar i, and $\sigma_{\Delta P}$ is the standard deviation of changes in the last price between consecutive volume bars. Then trade imbalance for bucket τ is computed as $V_\tau^B - V_\tau^S$. Finally, we compute the VPIN metric as a moving average of the absolute values of trade imbalances over 50 buckets, which is equivalent to one trading day, divided by the bucket size, $V = V_\tau^B + V_\tau^S$, and is updated for each bucket. We denote this VPIN metric as BV-VPIN. One crucial advantage of VPIN in comparison to the original PIN (Easley *et al.* (1996)) is to require no estimation procedure of non-observable parameters, so that it is easy to compute for traders in high frequency markets.

As noted in Section 3.1, one of the advantages of our dataset is that we can exactly figure out the true trade initiator without depending on tick rule-based algorithms. Previously, Andersen and Bondarenko (2014a) raise a doubt on validity of the VPIN metric and insist that the BVC scheme is inferior to a standard tick rule-based classifications (the Lee and Ready (1991) algorithm and its variants). We mainly follow the original inventors of the VPIN metric (Easley *et al.* (2012a)) advocate to utilize BV-VPIN instead of TR-VPIN, but to further examine the issue suggested by Andersen and Bondarenko (2014a), we also compute the VPIN metric using classification using the true trade initiator, denoted as TR-VPIN, and compare it with BV-VPIN in Section 6.

3.2.2 Volume intervals

Our empirical analyses are based on volume intervals not on time intervals. Our approach is supported by Easley *et al.* (2012b), which point out that machines which HFTs heavily rely on trade on an internal clock that is event-based, such as volume-clock metric. They advocate volume interval because it partially recovers normality and the *i.i.d.* assumption for the distribution of price changes, and mitigates intraday seasonal effects. Hence, we group sequential trades into volume intervals (buckets), and then compute VPIN (by construction), HFT participation ratios and other intraday measures for each volume interval.

3.2.3 HFT identification

There are no floor traders and designated market makers with formal obligations in the KOSPI 200 futures market. Thus, all intraday intermediaries in the market are endogenous liquidity providers. Following Kirilenko *et al.* (2017), we adopt a data-driven approach and define intraday intermediaries as traders who consistently buy and sell throughout a trading day while maintaining low levels of inventory. Specifically, for each trading day *d*, an account *i* is defined as an intraday intermediary if:

(i) The account *i* must trade 10 or more contracts,

$$VOL_{i,d} \geq 10 \tag{3}$$

(ii) The absolute value of the ratio of the account *i*'s end-of-day net position to its daily trading volume does not exceed 5%,

$$\frac{|NP_{i,d,t=365}|}{VOL_{i,d}} \leq 5\% \tag{4}$$

(iii) And the square root of the account *i*'s daily mean of squared end-of-minute net position deviations from its end-of-day net position over its daily trading volume does not exceed 1%

$$\sqrt{\frac{1}{365}\sum_{t=1}^{365}\left(\frac{NP_{i,d,t} - NP_{i,d,t=365}}{VOL_{i,d}}\right)^2} \leq 1\% \tag{5}$$

where $VOL_{i,d}$ is trading volume of the account *i* on day *d*, and $NP_{i,d,t}$ is a net inventory position of the account *i* in minute *t* of day *d*. Among intraday intermediaries, for each trading day, we identify the 20 most active accounts in terms of daily trading volume as *high frequency traders (HFTs)* and the remaining accounts as *market makers (MMs)*. Though the cutoff values and the number of HFTs are specific to the KOSPI 200 futures market, our empirical results are robust to admissible changes in those values.

[Insert Table 1 about here]

Summary statistics for each trader category are reported in Table 1. Panel A of Table 1 shows that HFTs, who consist of 20 traders by construction, account for nearly 40% of trading volume in the KOSPI 200 futures market. On average, they trade 2.51 contracts per one transaction, which are executed from 30.42 contracts they sent to the exchange. They primarily use limit orders (marketable as well as non-marketable) and rarely use other types of orders. More than half of their trades (52.89%) are resulted from marketable orders (market orders and marketable limit orders). Interestingly, they are more aggressive than *Others* trader group which includes fundamental buyers and sellers. It is contrary to the U.S. case that HFTs are less aggressive than any of fundamental buyers/sellers, opportunistic traders, and small traders (Kirilenko *et al.* (2017)).

After identifying HFTs, we calculate their participation ratios. First, all transactions are divided into four trade types: HH, HN, NH, and NN. 'H' denotes HFTs and 'N' denotes nHFTs. The first letter represents the initiating party, and the second the counterparty who are initiated. For instance, trades categorized into 'HN' corresponds to trades that HFTs initiate against nHFTs. Then for each bucket, we aggregate trading volume by each trade type, and the participation ratios are defined as follows:

$$HFT \quad = \frac{(HH + HN + NH)}{(HH + HN + NH + NN)} \tag{6}$$

$$HFT\_M \quad = \frac{(HH + HN)}{(HH + HN + NH + NN)} \tag{7}$$

$$HFT\_L \quad = \frac{(HH + NH)}{(HH + HN + NH + NN)} \tag{8}$$

HFT_M signifies the trading activity of HFTs participating into trades as its initiators while *HFT_L* the trading activity of HFTs participating into the trades as the counterparty who are initiated. And *HFT* signifies the overall trading activity of HFTs participating into either sides of trades.

[Insert Table 2 about here]

Panel A of Table 2 shows HFT participation ratios. In Panel A, HFTs involve 63% of trading volume, about 20% of which is occupied by trades between HFTs (HH) and about 80% of which is occupied by trades between HFTs and nHFTs (HN + NH). Trading volumes which are initiated by HFTs against nHFTs (HN) are similar to volumes which are initiated by nHFTs against HFTs (NH).

3.2.4 Other intraday measures

We further investigate other intraday measures as well as VPIN metrics and how they relate to each other. First, price volatility is measured by the high-low price (*Price H-L*). We get the high price and the low price for each bucket, and take their difference. One cautious thing is that some volume buckets reflect overnight price changes. To adjust for overnight returns, we follow the Corwin and Schultz (2012)'s correction. Specifically, we calculate overnight price changes as the difference between the day t close price and the day t+1 low (high) price if the day t+1 low (high) price is higher (lower) than the day t close price. In other cases, overnight changes are set to zero. Then we deduct the overnight changes from the high-low prices for buckets which contain overnight trading hours. Another volatility measure is the return standard deviation (*Return Std. Dev.*), which is calculated as the standard deviation of returns in each bucket. Although we mainly document the empirical results for the high-low price (*Price H-L*), our results are not sensitive to the choice of volatility measure.

Next, we measure illiquidity by the Corwin and Schultz (2012)'s High-Low spread (*H-L spread*). They exploits a simple insight that the true variance of the price is proportional to the length of the time period while the bid-ask spread does not. They derive the High-Low spread by solving two equations, the first a function of the price high-low ratios on two consecutive one-day period and the second a function of the price high-low ratio from a single two-day period. The High-Low spread is easily implementable, and is reported to outperform other low-frequency spread estimators. In this paper, we apply the same technique as above except for calculating the spreads not in daily intervals but in intraday volume intervals (buckets).

Lastly, we proxy trading intensity by *Time duration* which elapses to fill the bucket size. Note that the less time duration corresponds to the higher trading intensity in volume intervals, different to time intervals in which the higher trading volume corresponds to the higher trading intensity. If a bucket includes overnight trading hours, we subtract those hours from its time duration.

In Panel B of Table 2, the volume bucket size, which is the one-fiftieth of the average daily trading volume over our sample period, is nearly 5,000 contracts. And about seven minutes are needed to fill this volume size. The resulting BV-VPIN in the KOSPI 200 futures market has its mean of 0.18 with the standard deviation of 0.04. Both statistics are slightly lower than those of VPIN in the S&P 500 E-mini futures market, where the VPIN has its mean of 0.2251 with the standard deviation 0.0575, reported in Easley *et al.* (2012a). The BV-VPIN reached its maximum 0.41 during the period when the shock from the downgrade of the U.S. credit rating struck the Korean financial markets on August 8-9, 2011, leading to circuit breakers in the KOSPI 200 futures market. The TR-VPIN are distributed with lower mean and lower standard deviation compared to the BV-VPIN, and reached its maximum 0.24 when the Bank of Korea decided to rise the base interest rate from 2.5% to 2.75% on January 13, 2011.

The correlation structure of the variables is reported in Panel C of Table 4. First, *Time duration* is negatively related to *Return Std. Dev.* and *Price H-L*, but is positively related to *H-L spread*. That is, as trading intensity becomes higher, the price moves more volatile and illiquidity decreases. Second, BV-VPIN has strong positive association with *Return Std. Dev.*, *Price H-L*, and *H-L spread*, which indicates that BV-VPIN may partially capture volatility and illiquidity to some extent. However, TR-VPIN shows the opposite pattern: TR-VPIN is negatively related with *Return Std. Dev.*, *Price H-L*, and *H-L spread*. It implies that trade classification matters when calculating the VPIN metric. In fact, Easley et al. (2016) report the consistent results that the tick rule-based and the BVC order flow imbalances show substantially different relations with those spreads, and suggest that the aggressor side of a trade might not be a good indicator of order flow informativeness. The differences between the TR-VPIN and the BV-VPIN in our results may also stem from order flow informativeness differently captured depending on classification methods, and thus we further investigate this issue in Section 6. The relations among price volatility, BV-VPIN (and TR-VPIN), and HFT participation ratios are more closely examined in the following sections by employing various regression analyses.

4 Predictability of BV-VPIN on Price Volatility

In this section, we examine whether BV-VPIN can predict the future (short-term) price volatility as Easley et al. (2012a) report in the E-mini S&P 500 futures (CME) and the WTI crude oil futures contract (NYMEX). Toxic orders are defined as orders that induce adverse selection on liquidity providers. Glosten and Milgrom (1985) show that market makers widen the bid-ask spread to compensate possible loss incurred from trades with informed traders. Though those market makers were meant to be traditional market makers, their finding still holds in today's market microstructure where market making is mainly done by ELPs or proprietary traders. When adverse selection (induced by informed traders) is prevalent in a market, they are reluctant to intermediate trades by broadening the bid-ask spread or by retreating their quotes. In more severe cases, they can liquidate their accumulation and exit the market, which leads to make the price extremely volatile.

Consequently, if BV-VPIN truly measures order flow toxicity, it should predict short-term (toxicity-induced) price volatility. To investigate this predictability, we estimate the following OLS regression (Model 1):

$$PRC\_VOL_t = \alpha + \beta_1 \times \ln(VPIN_{t-1}) + \epsilon_t \tag{9}$$

where PRC_VOL_t is the price volatility in the bucket *t* measured by *Price H-L* and *Return Std. Dev.*, and $\ln(VPIN_t)$ is the logarithm of BV-VPIN in the bucket *t*.

On the other hand, in contrast to Easley et al. (2012a), Andersen and Bondarenko (2014a) argue that, even if the VPIN metric predicts short-term volatility, it is derived from its mechanical relation with trading intensity and realized volatility. Reflecting their argument, we estimate the following OLS regressions (Model 2-5):

$$PRC\_VOL_t = \alpha + \beta_1 \times \ln(VPIN_{t-1}) + \boldsymbol{\gamma}'\boldsymbol{Conrols_{t-\sigma}} + \epsilon_t \tag{10}$$

$$\begin{aligned} PRC\_VOL_t = \alpha_1 + \alpha_2 \times 1_{t-1}^{TOXIC} + \beta_1 \times \ln(VPIN_{t-1}) + \beta_2 \times (1_{t-1}^{TOXIC} \times \ln(VPIN_{t-1})) \\ + \boldsymbol{\gamma}'\boldsymbol{Conrols_{t-\sigma}} + \epsilon_t \end{aligned} \tag{11}$$

where $\boldsymbol{Conrols_{t-\sigma}}$ denotes a vector of lagged *Price H-L, Time durations*, and *H-L spreads* with $\sigma = 1, \ldots, 5$, and 1_t^{TOXIC} is a dummy variable that is equal to 1 if $CDF(VPIN_t) \geq 0.9$ and 0 otherwise. That is, the first regression explores the additional information content of BV-VPIN on future price volatility after controlling for realized volatility, trading intensity, and illiquidity. The second equation adds the dummy variable and its interaction with BV-VPIN to check whether the high level of BV-VPIN signals turbulent price movement in the next bucket.

[Insert Table 3 about here]

The estimation results are reported in Table 3. The coefficient of $\ln(VPIN_{t-1})$ in Model 1 is statistically significant with *t*-value 24.74, which indicates that it strongly predicts the high-low price in the next bucket *t*. The coefficients of $\ln(VPIN_{t-1})$ in Model 2-4 clarify that the predictability of $\ln(VPIN_{t-1})$ on *Price H-L* is not subsumed by lagged *Price H-L* (realized volatility), *Time duration* (trading intensity), and *H-L spread* (illiquidity). Hence, BV-VPIN has additional information about future price volatility to realized volatility, trading intensity, and illiquidity in the KOSPI 200 futures market. In Model 5, the coefficients of the toxic dummy and its interaction with $\ln(VPIN_{t-1})$ are strongly significant, implying that high toxic periods signal future price swing and strengthen the predictability of $\ln(VPIN_{t-1})$. Our results are strictly contradictory to Andersen and Bondarenko (2014a). Meanwhile, *Price H-L* has significant serial correlations, lagged *Time duration* (trading intensity) negatively (positively) predicts *Price H-L*, and lagged *H-L spread* (illiquidity) positively predicts *Price H-L*. Lastly, the empirical results are qualitatively the same if we measure price volatility by *Return Std. Dev*.

Next, we search historical episodes when the KOSPI 200 futures market experienced extremely unstable periods, and examine how BV-VPIN had moved before, during, and after those periods. In specific, if BV-VPIN effectively captures order flow toxicity, it might show unusually high value before the episodes. We consider the following episodes (in a chronological order):

1. Expiration-day effect of KOSPI 200 options on November 11, 2010
2. Fukushima Daiichi nuclear disaster following the 2011 Tohoku earthquake and tsunami on March 11, 2011
3. Downgrade of the U.S. credit rating on August 5, 2011
4. Upgrade of the Korean credit rating on September 14, 2012

[Insert Figure 1 about here]

The time-series of the KOSPI 200 futures price, BV-VPIN, and its CDF value for each event are illustrated in Figure 1. In Panel A of Figure 1, November 11, 2010 was the maturity day of the KOSPI 200 options. During the last ten minutes (14:50 ~ 15:00) of trading on that day (the closing batch auction), large sell orders that were unwound by Deutsche Bank AG's Hong Kong Branch entered into the Korean stock market, which led to a sharp drop of the KOSPI 200 index from 254.62 points to 247.51 points (2.8% drop). The level of BV-VPIN in the KOSPI 200 futures market gradually rose before the maturity due to the expiration effect. In the morning of the next day, however, BV-VPIN unusually increased further and CDF(BV-VPIN) reached its 0.9 threshold, because investor suspected the credibility of the Korean derivatives markets. After that, as sell orders came into the market when the market-wide order flow was highly toxic, the price declined from 253.60 points to 247.60 in the rest of the morning. Concurrently, BV-VPIN raised further during the decline, indicating that BV-VPIN did not peak but reached significantly high level prior to the market crash and raised further during the market crash.

Panel B of Figure 1 depicts the market turmoil caused by Fukushima Daiichi nuclear disaster following the 2011 Tohoku earthquake and tsunami on March 11, 2011. The earthquake and tsunami occurred in the morning of March 11, 2011 (Friday), and the news about the resulting nuclear crisis spread out on the worldwide financial markets on March 14, 2011 (Monday). On that day, BV-VPIN gradually increased until the market close and exceed its threshold of 0.9 CDF value. On the next day, March 15, 2011, the KOSPI 200 futures price plunged from 263.75 points to 250.15 points until 1 p.m. and quickly recovered to 254.90 points until the market close. BV-VPIN persisted in extremely high level during the market crash and the rebound.

Next, we exhibit the crisis following the downgrade of the U.S. credit rating in Panel C of Figure 1. After the U.S. credit rating was reduced from AAA to AA+ on August 5, 2011 (Friday), the Korean stock market experienced extremely stressful periods on August 8 and 9; particularly, on August 9, the KOSPI endured its steepest one-day decline in history at that time. BV-VPIN was unusually high during the preceding days (August 4-5) before the crash, which warned vulnerable market states to large orders due to the occurrence of order flow toxicity. Following the market opening of trading on August 8, the market was in panic as the announcement of the S&P broke out; as large sell orders arrived the market, the KOSPI 200 futures price declined from 253.13 points to 231.35 points in the morning of August 8, quickly rebounded to 241.75 points until the market close of August 8; on next day, it dropped further to 218.50 points during the morning, and recovered to 232.30 points until the market close. Circuit breakers were set off on both dates. During those periods, BV-VPIN stayed exceptionally high and reached its historical maximum on August 9. Hence, this example illustrates that during periods when BV-VPIN was persistently extremely high, the price volatility was substantial.

The last panel of Figure 1 shows the case for the upgrade of the Korean credit rating from AA- to A+ announced by S&P on September 14, 2012. Since the day before the announcement, BV-VPIN had soared above its threshold of its 0.9 CDF value, indicating that the market were aware of the upcoming event. The price jumped up from 256.60 points to 265.00 points during the following overnight session, and then on the announcement day, BV-VPIN backed to the normal level gradually. Thus, BV-VPIN signaled the positive shock on the market in advance, which caused the huge positive price jump.

From the anecdotal evidences above, we obtain several interesting observations. First, BV-VPIN reaches the significantly high level in advance before toxicity-induced market turbulences. However, it does not necessarily achieve its maximum before the turbulences, and increases further during the turbulences, which is in part consistent with Andersen and Bondarenko (2014b) who argue that VPIN did not attain a historical high prior to the Flash Crash. Nevertheless, we emphasize that BV-VPIN is still considerably high prior to market turbulences as we expected. It indicates that BV-VPIN signals the prevalent order flow toxicity as Easley et al. (2011) show in the E-mini S&P 500 futures market. If large orders come to the market during that period, trades are executed in one-sided and the price moves much accordingly, which makes BV-VPIN raise further. Second, if BV-VPIN sequentially remains in the high level over a number of buckets, the price is considerably more volatile reflecting both price declines and (partial) price recoveries during those buckets. Third, all big price movements are not necessarily signaled by the high level of BV-VPIN, since all price volatilities may not be toxicity-induced.

5 Relations among Order Flow Toxicity, High Frequency Trading, and Price Volatility

5.1 Order flow toxicity of high frequency traders

The newly emerged traders, HFTs, may reveal different trading behaviors compared to traditional market makers when they make markets. On the one hand, their speed advantage enables themselves to increase the probability to avoid "*being picked off*" by informed traders and provide liquidity skillfully, which leads to be more likely for other investors to find them as trading counterparties. Besides, as Brogaard *et al.* (2014) demonstrate, they are helpful to facilitate the process of price discovery, which reduces information asymmetry between informed traders and liquidity providers. Working together, HFTs may reduce the level of order flow toxicity. On the other hand, they can utilize the speed advantage to pick off slow traders including slow liquidity providers, which rises adverse selection and then the level of order flow toxicity. And their impact on order flow toxicity may be altered when a market bears stressful times like the Flash Crash, the periods when order flow toxicity is high, trading activity intensifies, and price is highly volatile, compared to normal times.

Given the validity of BV-VPIN in the KOSPI 200 futures market, to clarify order flow toxicity of HFTs depending on market conditions, we employ the following OLS regressions (Model 1-4):[8]

$$\begin{aligned}\Delta \ln(VPIN_t) = \alpha + \sum_{i=1}^{5} \beta_i (Participation\ Rates_{t-i}) + \delta \ln(VPIN_{t-1}) \\ + \sum_{i=1}^{5} \zeta_i \Delta \ln(VPIN_{t-i}) + \epsilon_t\end{aligned} \tag{12}$$

$$\begin{aligned}\Delta \ln(VPIN_t) = \alpha + \sum_{i=1}^{5} \beta_i (Participation\ Rates_{t-i}) \\ + \gamma \left(1_{t-1}^{(EVENT)} \times (Participation\ Rates_{t-1})\right) + \delta \ln(VPIN_{t-1}) \\ + \sum_{i=1}^{5} \zeta_i \Delta \ln(VPIN_{t-i}) + \epsilon_t\end{aligned} \tag{13}$$

where $\Delta \ln(VPIN_t)$ is the first difference of BV-VPIN in the bucket *t*, $(Participation\ Rates_t)$ is a HFTs' activity (*HFT*, *HFT_M*, or *HFT_L*) in the bucket *t*. To see whether order flow toxicity of HFTs depends on the

[8] In all specifications considered in this section, we take the first difference on BV-VPIN. Although BV-VPIN is highly persistent by construction, it follows a stationary process since the current BV-VPIN are independent of BV-VPIN calculated 50 buckets earlier (When the VPIN metric is updated, the first of the previous 50 buckets is excluded and the new bucket is added). Therefore, we test other specifications with the level of BV-VPIN as a dependent variable. The results are qualitatively similar when we consider other econometric specifications. The detail on this issue is covered in Section 7.

market state or condition, we add dummy variables and their interaction term with HFTs' participation rates. In specific, $1_t^{(EVENT)}$ is a dummy variable that indicates extreme states of the bucket *t*. 1_t^{Toxic} is equal to 1 if $CDF(VPIN_t) \geq 0.9$ and zero otherwise, 1_t^{Short} is equal to 1 if *Time duration* of the bucket *t* is less than or equal to its 1% percentile (=0.976 minutes) and 0 otherwise, and $1_t^{Volatile}$ is equal to 1 if *Price H-L* of the bucket *t* is greater than or equal to its 99% percentile (=1.527 points) and 0 otherwise.

Even if HFT is positively associated with BV-VPIN, it may be derived from the mechanical imbalance between HFTs. To control for this effect, we add imbalance generated by HFTs, calculated as $|IMBAL^{HFT}| = \frac{|HFT_{BUY} - HFT_{SELL}|}{TOTVOL}$, in the right-hand side of the regression of Mode 2-4 as follows (Model 5-7):

$$\begin{aligned} \Delta \ln(VPIN_t) = \alpha + \sum_{i=1}^{5} \beta_i (Participation\ Rates_{t-i}) + \gamma_1 \left(1_{t-1}^{(EVENT)} \times (Participation\ Rates_{t-1})\right) \\ + \gamma_2 \left(1_{t-1}^{(EVENT)} \times |IMBAL_{t-1}^{HFT}|\right) + \delta \ln(VPIN_{t-1}) + \sum_{i=1}^{5} \zeta_i \Delta \ln(VPIN_{t-i}) \\ + \sum_{i=1}^{5} \eta_i \left|IMBAL_{t-i}^{HFT}\right| + \epsilon_t \end{aligned} \tag{14}$$

[Insert Table 4 about here]

The estimation results are reported in Table 4. In all specifications, the coefficients of the level of BV-VPIN and the lagged differences in BV-VPIN until *t*-2 are significantly negative, which shows the mean-reverting property of BV-VPIN. In Model 1, the coefficient of HFT_{t-1} is significantly negative with *t*-value -3.37, which is consistent with the view that HFTs reduce order flow toxicity by using their speed advantage in normal times. Though the coefficient of its interaction with *Toxic* dummy is insignificant in Model 2, the coefficient of its interaction with *Short* dummy or *Volatile* dummy is positively significant in Model 3 and 4. Hence, during intensely traded times and highly volatile times, HFTs produce toxic orders compared to normal times. The significance of the interaction term in Model 3 is subsumed after controlling for the mechanical imbalances of HFTs (Model 6), which implies that positive order flow toxicity during intensely traded times mainly stems from imbalances between HFTs. On the contrary, the coefficient of the interaction between HFT_{t-1} and *Volatile* dummy is still significant in Model 7, which indicates that HFTs increase order flow toxicity by trading against nHFTs during highly volatile times. It is consistent with the view that HFTs utilize their speed advantage to pick off nHFTs when there are large price movements.

Then we examine flow toxicity of market orders and limit orders produced by HFTs separately. Though the table for this examination is omitted here for brevity, we observed qualitatively similar results with overall HFT activity in Table 4. Both type of orders diminishes flow toxicity in normal times (Model 1), and the pattern does not change in toxic times (Model 2). When trade executions are intensely occurred, the effect of HFTs' limit orders on toxicity are positively significant while the effect of HFTs' market orders are insignificant (Model 3). Thus, HFTs elevate toxicity by producing limit orders rather than market orders in intensely traded times. In buckets with big price swing, both type of orders contribute to higher toxicity (Model 4). Toxicity of both type of orders is subsumed by imbalances between HFTs during buckets with short time interval (Model 6). During buckets with large price changes, HFTs generate toxicity by trading against nHFTs with the use of both type of orders (Model 7).

5.2 Impact of high frequency trading on price volatility

It is vital for both investors and policy makers to understand the impact of HFTs on short-term price volatility. For a theoretical standpoint, however, how they affect volatility is unclear. If HFTs are liquidity suppliers, they contribute to reduce transitory price changes. However, if they are liquidity demanders, they rather generate transitory price changes. In addition, if HFTs take the blame for liquidity-driven market crashes, such as the Flash Crash, they would raise short-term price volatility. Although the impact of HFTs on volatility has been extensively studied, the empirical results are mixed.[9] We investigate this issue in our setting by employing the following OLS regression (Model 1):

$$PRCHL_t = \alpha + \sum_{i=1}^{5} \beta_i (Participation\ Rates_{t-i}) + \boldsymbol{\gamma' Conrols_{t-\sigma}} + \epsilon_t \tag{15}$$

where $PRCHL_t$ is the High-Low price in the bucket *t*, $(Participation\ Rates_t)$ is a HFTs' activity (*HFT*, *HFT_M*, or *HFT_L*) in the bucket *t*, and $\boldsymbol{Conrols_{t-\sigma}}$ denotes a vector of lagged BV-VPIN, *Price H-L, Time*

9 We expect that one possible explanation for these mixed empirical results is different definitions of HFTs. We mainly follow Kirilenko *et al.* (2017) utilizing the account information of each trader, and Kirilenko *et al.* (2017) stress that their methodology is solely based on directly observed individual inventory and trading volume patterns of traders unlike others using a variety of qualitative and quantitative criteria (Kurov and Lasser (2004); Biais et al. (2016). More importantly, Kirilenko *et al.* (2017) show that according to their classification HFTs show clear differences from other investor groups. Utilizing our unique dataset including the account information, we expect to clearly distinguish HFTs from other traders, and thus provide the reliable empirical evidence.

durations, and *H-L spreads* with $\sigma = 1, \dots, 5$.

To see whether HFTs affect price volatility dissimilarly in toxic times, intensively traded times, and volatile times, we add dummy variables and their interaction term with HFTs' participation rates as follows (Model 2-4):

$$PRCHL_t = \alpha + \sum_{i=1}^{5} \beta_{1i}(Participation\ Rates_{t-i}) + \beta_2 \left(1_{t-1}^{(EVENT)} \times (Participation\ Rates_{t-1})\right) + \boldsymbol{\gamma' Conrols_{t-\sigma}} + \epsilon_t \tag{16}$$

where $1_t^{(EVENT)}$ is a dummy variable that indicates a state of the bucket *t*; Specifically, 1_t^{Toxic} is equal to 1 if $CDF(VPIN_t) \geq 0.9$ and zero otherwise, 1_t^{Short} is equal to 1 if *Time duration* of the bucket *t* is less than or equal to its 1% percentile (=0.976 minutes) and 0 otherwise, and $1_t^{Volatile}$ is equal to 1 if *Price H-L* of the bucket *t* is greater than or equal to its 99% percentile (=1.527 points) and 0 otherwise.

[Insert Table 5 about here]

Table 5 displays the estimation results. The coefficient of HFT_{t-1} is significantly negative with *t*-value -18.20 in Model 1, implying that HFTs normally decrease price volatility after controlling for lagged volatilities, order flow toxicity, trading intensities, and illiquidities. The interaction between HFT_{t-1} and *Toxic* dummy is positively significant in Model 2, which indicates that HFTs increase price volatility during in toxic buckets. Considering the magnitudes of coefficients of HFT_{t-1} and its interaction with *Toxic* dummy in Model 2, the positive impact of HFTs on price volatility during toxic buckets compared to normal buckets is not considerable. However, the interaction between HFT_{t-1} and *Volatile* dummy is positively significant in Model 4, and its magnitude is much larger than the magnitude of the interaction with *Toxic* dummy. It is consistent with the evidence that during extremely volatile times HFTs switch to trade more in the same direction of price movements which make the price more volatile (Kang *et al.* (2018)). In Model 3, the interaction between HFT_{t-1} and *Short* dummy is significantly negative, which is consistent with that HFTs decline price volatility more by supplying liquidity. Finally, when we consider participation rates involving HFTs' market orders and limit orders separately, the results are similar with those for overall HFT participation rates, which are dropped here to save space.

5.3 VAR results

In previous sections, we examine the relation of each pair of endogenous variables: price volatility, BV-VPIN, and HFT participation rates. However, those variables influence each other intertemporally, which may affect our empirical results. Therefore, to estimate multiple equations simultaneously, we run the Vector Autoregression (VAR) model of price volatility, BV-VPIN, and HFT participation rates as follows:[10]

$$\begin{aligned} PRCHL_t = \alpha_1 + \beta_{11} PRCHL_{t-1} + \beta_{12} \ln(VPIN_{t-1}) + \beta_{13} (Participation\ Rates_{t-1}) \\ + \sum_{i=1}^{5} \gamma_{1i} (Time\ Duration_{t-i}) + \sum_{i=1}^{5} \delta_{1i} (HL\ Spread_{t-i}) + \epsilon_{1t} \end{aligned} \tag{17}$$

$$\begin{aligned} \ln(VPIN_t) = \alpha_2 + \beta_{21} PRCHL_{t-1} + \beta_{22} \ln(VPIN_{t-1}) + \beta_{23} (Participation\ Rates_{t-1}) \\ + \sum_{i=1}^{5} \gamma_{2i} (Time\ Duration_{t-i}) + \sum_{i=1}^{5} \delta_{2i} (HL\ Spread_{t-i}) + \epsilon_{2t} \end{aligned} \tag{18}$$

$$\begin{aligned} (Participation\ Rates_t) \\ = \alpha_3 + \beta_{31} PRCHL_{t-1} + \beta_{32} \ln(VPIN_{t-1}) + \beta_{33} (Participation\ Rates_{t-1}) \\ + \sum_{i=1}^{5} \gamma_{3i} (Time\ Duration_{t-i}) + \sum_{i=1}^{5} \delta_{3i} (HL\ Spread_{t-i}) + \epsilon_{3t} \end{aligned} \tag{19}$$

where $PRCHL_t$ is *Price H-L* in the bucket *t*, $\ln(VPIN_t)$ is the logarithm of BV-VPIN in the bucket *t*, and $(Participation\ Rates_t)$ is a HFTs' activity (*HFT*, *HFT_M*, or *HFT_L*) in the bucket *t*. Since BV-VPIN is highly autocorrelated, we choose one as the maximum lag of endogenous variables in the VAR model. In addition, we include exogenous variables, *Time duration* and *H-L spread*, as a proxy for trading intensity and illiquidity, respectively.

[Insert Table 6 about here]

The estimated coefficients in the VAR model is reported in Table 6. Similar to the results in Table 5 obtained from the OLS regressions, BV-VPIN strongly predicts future short-term price volatility, and HFTs (both their market orders and limit orders) contribute to decline both flow toxicity and volatility. In the VAR analysis, we could analyze how HFTs change their trading activity as order flow toxicity and price volatility increase. The result is that HFTs lessen their trading activities of both market orders and limit orders when order flow is more toxic. It is consistent with the view that, when order flow toxicity is high, adverse selection is induced on

[10] Though other VAR specifications are considered, the results are qualitatively similar to those of the above VAR model. We discuss it more in Section 7 as robustness check.

intraday intermediaries which then let them participate less. However, when the price is more volatile, HFTs trade less with market orders while they trade more with limit orders. Offsetting those asymmetric behavior, overall HFT participation rates become less as the price changes more.

6 Issues on Trade Classification and TR-VPIN

In this section, we construct TR-VPIN that utilizes the true trade initiator in classifying buy and sell volume, and compare its empirical performance with that of BV-VPIN. The VPIN metric is widely adopted as a successful proxy of order flow toxicity in many subsequent papers (Bhattacharya and Chakrabarti (2014); Cheung *et al.* (2015); Low *et al.* (2018)). In constructing the VPIN metric, all transactions should be categorized into either buy or sell transactions but there is an ongoing debate on the classification methodology. Pöppe *et al.* (2016) argue that VPIN is not robust to the choice of trade classification scheme in Deutche Boerse. In fact, our results in Table 2 also show that TR-VPIN and BV-VPIN have totally different relations with *Return Std. Dev.*, *Price H-L*, and *H-L spread*, implying that trade classification matters when calculating the VPIN metric. Easley *et al.* (2016) originally suggest the use of BVC in the calculation of VPIN and provide the supportive evidence that BVC better discerns information-based trading than tick rule in high frequency markets, but Andersen and Bondarenko (2014a) argue that BVC is inferior to the tick rule.

One of the critical advantages of our dataset is that we can figure out the true initiator of each transaction. By comparing order acceptance numbers in a bid and ask side for each trade, we accurately identify which side initiates it. Taking this advantage, we examine the issue on the trade classification methodology in twofold. In Section 6.1, we construct TR-VPIN, which is based on the true initiator information[11], and compare its predictability for short-term price volatility with that of BV-VPIN. Next, in Section 6.2, we investigate whether BVC better captures the information-based trading than the true initiator in high frequency markets as Easley et al. (2016) address.

6.1 TR-VPIN and short-term price volatility

First, we investigate the prediction of TR-VPIN on short-term price volatility. The estimation procedure is the same as in Section 4 except that we replace BV-VPIN with TR-VPIN, and the results are reported in Table 7.

[Insert Table 7 about here]

[11] More precisely, we calculate trade imbalances based on the true initiator for each bucket, and then TR-VPIN, a moving average of the absolute trade imbalances over 50 buckets.

Strikingly, the coefficient of TR-VPIN is significantly negative in all model specifications, implying that TR-VPIN negatively predicts short-term price volatility in contrast to BV-VPIN. Our result for TR-VPIN is much different to results from other markets where TR-VPIN and BV-VPIN show a similar pattern to some extent.

[Insert Figure 2 about here]

Next, we look at how TR-VPIN evolved before and during the episodes considered in Section 4, which is illustrated in Figure 2. The TR-VPIN results are different from the BV-VPIN results in Figure 1. TR-VPIN increases before the market crashes, but its magnitude is not as large as it does with BV-VPIN. For example, when the Korean financial markets were shocked by the downgrade of the U.S. credit rating on August 8 and 9, TR-VPIN did not exceed its value with 0.6 CDF value. More critically, TR-VPIN were decreasing or maintained low levels during the crashes and the immediate recoveries (if exists). It seems to be highly unlikely that volume imbalance was decreasing or matched during those periods when the price movements were extreme.

In sum, our results in Table 7 and Figure 2 show that TR-VPIN fails to signal the prevalent order flow toxicity before the market turbulences as opposed to BV-VPIN. Therefore, we advocate to use BVC rather than the true initiator (tick rule-based classifications, in general) in calculating the VPIN metric in the KOSPI 200 futures market.

6.2 Trade classification and informed trading

The conflicting results between BV-VPIN and TR-VPIN lead to the ongoing debates about the proper choice of trade classification in high frequency markets. In this subsection, we present evidences showing that BVC better discerns information-based trading than the true initiator (and tick rule-based classifications in general), and thereby support our choice of BV-VPIN instead of TR-VPIN in the main empirical analysis.

First, following Easley *et al.* (2016), we examine the relation between illiquidity, measured by Corwin and Schultz (2012)'s High-Low spread, and trade imbalances for BV and TR, respectively. Easley *et al.* (2016) note (p.280), "a measure of order imbalance that accurately reflects actual order imbalance should at least be positively correlated with the high-low spread estimate regardless of whether they primarily reflect spreads or other liquidity effects." Thus, we compute the High-Low spread for each bucket, and compare it with trade imbalances for BV and TR bucket-by-bucket. Table 8 shows summary statistics of those variables.

[Insert Table 8 about here]

In Table 8, Panel A shows the summary statistics of High-Low spread and order imbalances based on BVC (OI_BV) and the true initiator (OI_TR), and Panel B presents the correlation among them. Panel A of Table 8 shows substantial differences in distribution of OI_BV and OI_TR. Specifically, OI_BV has higher average and standard deviation compared to OI_TR, but percentiles show that distribution of OI_TR is highly skewed. In Panel B of Table 8, the absolute value of trade imbalances for BV has a positive correlation with the High-Low spread while the absolute value of trade imbalances for TR has a negative correlation. Those differences between OI_BV and OI_TR may contribute to different performances of BV-VPIN and TR-VPIN in the previous subsection.

[Insert Table 9 about here]

In Table 9, we employ the OLS regressions suggested by Easley et al. (2016) (Eq. (6)) with the High-low spread as a dependent variable and the absolute values of trade imbalances for BV and/or TR as independent variables to more directly examine whether BVC successfully captures the informed trading. The coefficient of $|OI_{\tau}^{TR}|$ is strongly negative with *t*-value -51.56 in Panel A while the coefficient of $|OI_{\tau}^{BV}|$ is strongly positive with *t*-value 13.45. The result are qualitatively the same when both $|OI_{\tau}^{TR}|$ and $|OI_{\tau}^{BV}|$ are included in the right-hand side. Therefore, we conclude that bulk volume classification is better linked to informed trading than the true initiator because the former is positively associated with illiquidity while the latter is negatively associated.

[Insert Figure 3 about here]

Finally, in Figure 3, we group buckets into 10 deciles based on the absolute trade imbalances for BV and TR, and then average High-Low spreads over buckets within the same decile. Again, this figure ensures us that BV discerns the underlying information in trade better than TR.

The result suggests the important implication. Aggressiveness is not a good indicator of order flow information. Our results instead suggest that the more aggressive orders, the less informed order flows. It is consistent with that informed investors do not necessarily cross the spread but use passive orders to execute trades at favorable prices with order-splitting strategy. Consistent with Easley et al. (2016) and in contrast to Andersen and Bondarenko (2015), bulk volume classification, which does not depend on the initiator, captures order flow information well, and is more suitable for calculating the VPIN metric.

Second, we compare the profitability of the TR-initiator and BV-initiator. If BV discerns information-based trading better than TR, the BV-initiator should trade at more favorable prices than the TR-initiator unconditionally. To investigate this issue, we follow (and modify to our setting) (Choe *et al.* (2005)) to calculate the price ratio for buy and sell trades separately by each of the TR-initiator and BV-initiator. Specifically, we first calculate the volume-weighted average price (vwap) for each 50 buckets (equivalent to one trading day, on average) using all trades included in those 50 buckets, denoted as A_d, and then calculate the volume-weighted average price for all buy and sell trades separately for each initiator, denoted as B_d^j as follows:

$$A_d = \frac{\sum_t P_{dt} V_{dt}}{\sum_t V_{dt}} \tag{20}$$

$$B_d^j = \frac{\sum_t P_{dt}^j V_{dt}^j}{\sum_t V_{dt}^j} \tag{21}$$

where the index *d* is the enumeration of 50 buckets, P_{dt} is the price for trade *t* in the *d*-th 50 buckets, V_{dt} is the trading volume for trade *t* in the *d*-th 50 buckets, and the index *j* is the investor class *j*, either BV-initiator or TR-initiator. Finally, we calculate the price ratio, B_d^j/A_d, for all buy and sell trades separately for each initiator.

The calculation of the price ratio is based on averaging prices in a trade-by-trade basis, which is not directly applicable to BVC that classifies buy and sell volume in bulk (in volume bar). To apply this methodology to BVC, we assign constant buy rate and sell rate to all trades within the same volume bar. For instance, if a buy rate in the bar is 0.6, then for each trade filling the bar 60% of trading volume is assigned as buy volume and the remaining as sell volume. Then we are able to compute the price ratio for the BV-initiator by using Equation (20) and (21). This method is equivalent to that one volume bar is treated as one trade with the volume-weighted average price using all trades in the bar as the trade price of that bar.

Choe *et al.* (2005) use the price ratio to investigate whether an investor trades at advantage. For example, if the buy price ratio is larger than 1 (100%), then it indicates that the investor (buyer) purchases the asset at a price higher than the average price on that day. Consequently, it implies that the investor purchases the asset at disadvantage on average. We expect that if BVC is better than TR in capturing the informed trading, the buy price ratio based on BVC will be lower than that based on TR and the sell price ratio based on BVC will be higher than that based on TR.

[Insert Table 10 about here]

Table 10 reports average buy and sell price ratios for the TR-initiator and the BV-initiator to the average trading price. Though the buy (sell) price ratios for both the TR- and BV-initiators are higher (lower) than 100%, the ratios for the TR- and BV-initiators show substantial differences. In comparison to the average trade price over 50 buckets, the TR(BV)-initiator buy at 0.0115% (0.0012%) more expensive price which is statistically significant with *t*-value 31.58 (2.81). More importantly, when comparing average buy price of two types of initiators, the BV-initiator buy at 0.0102% cheaper price than the TR-initiator, which is statistically significant with *t*-value -31.74. In sell sides, the results are similar: the BV-initiator sell at 0.0102% more expensive price than the TR-initiator which is statistically significant with *t*-value 32.49. Collectively, the initiator identified by BVC trades at more favorable prices than the true trade initiator, which supports that BVC better discerns informed trading than the true trade initiator and tick rule-based classifications in general.

7 Robustness Checks

7.1 Other econometric specifications

To show that our empirical results are not specific to econometric specifications, we conduct robustness check with other model specifications. First, we examine the relation between order flow toxicity and HFTs by employing the following OLS regressions:

$$\ln(VPIN_t) = \alpha + \sum_{i=1}^{5} \beta_i (Participation\ Rates_{t-i}) + \epsilon_t \tag{22}$$

$$\ln(VPIN_t) = \alpha + \sum_{i=1}^{5} \beta_i (Participation\ Rates_{t-i}) + \gamma \ln(VPIN_{t-1}) + \epsilon_t \tag{23}$$

In the main analysis, we take the first difference on $\ln(VPIN_t)$ in the left-hand side since it is highly autocorrelated. However, $\ln(VPIN_t)$ is also highly stable because it is memoryless after 50 buckets. Above specifications use the level of $\ln(VPIN_t)$ as dependent variables, accordingly. Also we repeat to run the OLS regression included the dummy variables. The corresponding empirical results remain to be qualitatively similar. For brevity, we do not report the whole results, which can be obtained from the authors upon request.

Second, we conduct the VAR estimation with different model specifications as follows:

$$\begin{aligned} PRCHL_t = \alpha_1 &+ \sum_{i=1}^{5} \beta_{1i} PRCHL_{t-i} + \sum_{i=1}^{5} \gamma_{1i} (Participation\ Rates_{t-1}) + \delta_1 \ln(VPIN_{t-1}) \\ &+ \sum_{i=1}^{5} \zeta_{1i} (Time\ Duration_{t-i}) + \sum_{i=1}^{5} \eta_{1i} (HL\ Spread_{t-i}) + \epsilon_{1t} \end{aligned} \tag{24}$$

$$\begin{aligned} &(Participation\ Rates_t) \\ &= \alpha_2 + \sum_{i=1}^{5} \beta_{2i} PRCHL_{t-i} + \sum_{i=1}^{5} \gamma_{2i} (Participation\ Rates_{t-1}) + \delta_2 \ln(VPIN_{t-1}) \\ &+ \sum_{i=1}^{5} \zeta_{2i} (Time\ Duration_{t-i}) + \sum_{i=1}^{5} \eta_{2i} (HL\ Spread_{t-i}) + \epsilon_{2t} \end{aligned} \tag{25}$$

This VAR model is specified by two endogenous variables, *Price H-L* and HFT participation rates with maximum lag 5, and also includes three exogenous variables, BV-VPIN, *Time duration*, and *H-L spread*. Finally other VAR specification is considered:

$$PRCHL_t = \alpha_1 + \sum_{i=1}^{5} \beta_{1i} PRCHL_{t-i} + \sum_{i=1}^{5} \gamma_{1i} \Delta \ln(VPIN_{t-i}) + \sum_{i=1}^{5} \delta_{1i} (Participation\ Rates_{t-i}) + \zeta_1 \ln(VPIN_{t-1}) + \sum_{i=1}^{5} \eta_{1i} (Time\ Duration_{t-i}) + \sum_{i=1}^{5} \theta_{1i} (HL\ Spread_{t-i}) + \epsilon_{1t} \tag{26}$$

$$\Delta \ln(VPIN_t) = \alpha_2 + \sum_{i=1}^{5} \beta_{2i} PRCHL_{t-i} + \sum_{i=1}^{5} \gamma_{2i} \Delta \ln(VPIN_{t-i}) + \sum_{i=1}^{5} \delta_{2i} (Participation\ Rates_{t-i}) + \zeta_2 \ln(VPIN_{t-1}) + \sum_{i=1}^{5} \eta_{2i} (Time\ Duration_{t-i}) + \sum_{i=1}^{5} \theta_{2i} (HL\ Spread_{t-i}) + \epsilon_{2t} \tag{27}$$

$$(Participation\ Rates_t) = \alpha_3 + \sum_{i=1}^{5} \beta_{3i} PRCHL_{t-i} + \sum_{i=1}^{5} \gamma_{3i} \Delta \ln(VPIN_{t-i}) + \sum_{i=1}^{5} \delta_{3i} (Participation\ Rates_{t-i}) + \zeta_3 \ln(VPIN_{t-1}) + \sum_{i=1}^{5} \eta_{3i} (Time\ Duration_{t-i}) + \sum_{i=1}^{5} \theta_{3i} (HL\ Spread_{t-i}) + \epsilon_{3t} \tag{28}$$

This VAR model has three endogenous variables, *Price H-L*, difference in BV-VPIN, and HFT participation rates with maximum lag 5, and also includes three exogenous variables, BV-VPIN, *Time duration*, and *H-L spread*. The results are qualitatively similar to the main VAR results which can be obtained from the authors upon request.

7.2 HFTs by investor group

As addressed in Section 3.1, our unique dataset includes the investor group identifier indicating if a trader is foreign, (domestic) individual, or (domestic) institutional investors. Previous studies on the HFTs categorize all market participants into HFTs and nHFTs based on various definitions of HFT (Kurov and Lasser (2004); Biais et al. (2016); Kirilenko *et al.* (2017)), but do not further distinguish HFTs by the investor type and investigate whether even within the HFT group they trade differently depending on their type. However, as a body of the finance literature has reported that foreign, individual, and institutional investors have distinctive trading behaviors ((Barber and Odean (2007)); Richards (2005)), it seems to be worth enough to examine whether foreign, individual, and institutional HFTs also exhibit some differences, and more importantly they have different impacts on order flow toxicity and short-term price volatility (depending on market conditions).

To do so, in this subsection, we further classify HFTs into three investor groups: foreign, individual, and institutional HFTs. Based on this classification of HFTs, we first examine the summary statistics on trading of each investor group. We revisit our analysis in Section 3.2.3 and Panels A and B of Table 11 show the results as we report in Tables 1 and 2, respectively.

[Insert Table 11 about here]

Panel A of Table 11 shows the statistics for further classification of HFTs. Among the 20 traders, foreigners, who are about 8 traders, account for more than half (53.42%) of HFTs' trading volume. They exclusively utilize limit orders, and their aggressiveness is much higher than other HFT subgroup (64.81%), implying that the aggressiveness of HFTs actually stems from that of foreign HFTs. Institutional HFTs consist of 10-11 traders on average, mostly account for the other half of HFTs' trading volume (44.34%), and their aggressiveness is similar to *market makers* (39.90%). Although there exist averagely 1.74 traders classified as individual HFTs, their trading activity is negligible.

In Panel B of Table 11, we define the participation ratios for each of foreign, individual, and institutional HFTs as we define the (general) participation ratio in Section 3.2.3. For example, *HFT_FOR_M* is the ratio of trades that foreign HFTs initiate to total trades in each bucket. Other participation ratios are similarly defined. In Panel B, foreign HFTs participate in 36% of trading volumes. Consistent with the results in Panel A of Table 11, foreign HFTs seem to take aggressive trades relative to others. Their participation is more likely to be engaged in the initiating party (26%) than in the counterparty who are initiated (14%). The participation rate of institutional HFTs is 31% which is close to that of foreign HFTs, except that they are more likely to be initiated (21%) than to initiate trades (14%). The trading activity of individual HFTs are negligible; they involve in 2% of trading volumes.

In this way, as we expected, even within HFTs, foreign, individual, and institutional investors show different trading behaviors. In specific, foreign and institutional investors account for most of HFTs but their trading patterns, especially aggressiveness of trading, show a sharp contrast. We expect that this difference may also result in different impact on order flow toxicity.

Next, to answer this question, we explore how each HFT investor group affects order flow toxicity and short-term price volatility depending on market conditions. Since the trading activity of individual HFTs is negligible, their participation ratio is often zero in some buckets. Thus, in this analysis, we consider two subgroups: foreign HFTs and domestic (individual + institutional) HFTs.

[Insert Table 12 about here]

To see the impact of foreign and domestic HFTs on order flow toxicity and price volatility, we repeat the OLS regressions in Section 5.1 and Section 5.2. The estimation results are reported in Panel A and Panel B of Table 12, respectively. Panel A of Table 12 shows that, in normal times, foreign HFTs do not significantly affect flow toxicity while domestic HFTs decrease flow toxicity. Limit orders from foreign HFTs rather increase order flow toxicity in normal times. However, in intensely traded times or extremely volatile times, both HFT subgroups produce toxic orders compared to normal times. In Panel B of Table 12, the impact of foreign and domestic HFTs on price volatility is disparate in normal times; the former declines volatility while the latter raises. In toxic times or extremely volatile times, both subgroups have a positive effect on price volatility. In particular, considering the magnitude of coefficients, foreign HFTs turn to increase price volatility in extremely volatile times. In intensely traded times, domestic HFTs have a significantly negative effect on price volatility while foreign HFTs have no significant effect.

8 Concluding Remarks

We leave several concluding remarks here. First, we show the validity of VPIN as a measure of flow toxicity in the KOSPI 200 futures market to the extent that it strongly predicts future short-term price volatility. Hence, we urge to utilize VPIN as a measure of adverse selection, a risk management tool for practitioners, or a reliable indicator for the exchange in the KOSPI 200 futures market.

Second, we investigate flow toxicity of high frequency traders by examining the relation between VPIN and their participation rates. HFTs show an asymmetric behavior; they normally decrease the level of flow toxicity, but in stressful times, they rather produce toxic orders. The similar pattern is appeared in the relation between HFTs and price volatility. They reduce short-term price volatility in normal times while they turns to increase in stressful times. Collectively, it is unclear whether HFTs are helpful to improve market qualities.

Lastly, we emphasize the applicability of BVC instead of tick rule-based classifications (e.g. Lee and Ready (1991) algorithm) in high frequency markets when classifying buy and sell volume. We provide two clear evidences. Consistent with Easley *et al.* (2016), trade imbalance classified by BVC is positively correlated with the high-low spread estimate while trade imbalance classified by the true initiator is negatively correlated. Furthermore, we argue that the initiator identified by BVC trades at more favorable prices than the true trade initiator. These evidences imply that aggressiveness is no longer a good indicator or order flow information. It is consistent with recent trading environment where informed investors do not necessarily cross the spread but use passive orders to execute trades at favorable prices with order-splitting strategy.

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Table 1. Summary statistics of trader categories

Panel A. Traders by trader type

	# Traders	% Dollar Volume	% Share Volume	Trade Size	Order Size	Limit Orders, % Volume	Aggressiveness, % Volume
HFT	20.00	37.72%	37.97%	2.51	30.42	99.70%	52.89%
MM	100.43	9.96%	10.03%	1.69	4.74	96.71%	38.07%
Others	4,956.58	52.32%	52.00%	2.02	16.59	94.94%	50.19%
	# Traders	Dollar Volume	Share Volume	Trade Size	Order Size	Limit Orders, % Volume	Aggressiveness, % Volume
All	5,077.00	$ 62,709,223,833,093	550,505,976	2.14	19.57	96.93%	50.00%

Panel B. Traders by investor group

	# Traders	% Dollar Volume	% Share Volume	Trade Size	Order Size	Limit Orders, % Volume	Aggressiveness, % Volume
FOR	201.28	35.83%	35.31%	2.29	21.53	99.17%	63.17%
IND	4,280.42	28.84%	28.80%	1.69	11.01	92.20%	42.68%
INS	595.30	35.33%	35.89%	2.51	27.66	98.50%	42.92%
	# Traders	Dollar Volume	Share Volume	Trade Size	Order Size	Limit Orders, % Volume	Aggressiveness, % Volume
All	5,077.00	$ 62,709,223,833,093	550,505,976	2.14	19.57	96.93%	50.00%

Table 2. Summary statistics of measures for HFT participation ratios, trading intensity, volatility, illiquidity, and flow toxicity

Panel A. HFT participation ratios

	Mean	Std. Dev.	Min	P25	P50	P75	Max
HFT	0.63	0.11	0.02	0.56	0.63	0.70	0.99
HFT_M	0.40	0.11	0.02	0.33	0.40	0.48	0.96
HFT_L	0.36	0.08	0.00	0.30	0.35	0.41	0.70
HH	0.13	0.07	0.00	0.09	0.12	0.17	0.60
HN	0.27	0.07	0.02	0.23	0.27	0.31	0.58
NH	0.23	0.04	0.00	0.20	0.22	0.25	0.47
NN	0.37	0.11	0.01	0.30	0.37	0.44	0.98

Panel B. Summary statistics of measures for trading intensity, volatility, illiquidity and flow toxicity

	Mean	Std. Dev.	Min	P25	P50	P75	Max
Volume Bucket Size (contracts)	4,937	.	.	.	.	.	.
Time duration (minutes)	7.30	5.94	0.12	3.46	5.70	9.17	77.59
Return (bp)	0.04	16.40	-491.05	-7.55	0.00	7.56	375.21
Return Std. Dev. (bp)	0.72	0.27	0.23	0.59	0.67	0.78	10.13
Price H-L (points)	0.47	0.34	0.05	0.30	0.40	0.55	11.75
H-L spread (points)	4.80.E-04	6.15.E-04	0.00	0.00	2.25.E-04	8.29.E-04	1.22.E-02
BV-VPIN	0.18	0.04	0.08	0.15	0.18	0.21	0.41
TR-VPIN	0.15	0.02	0.09	0.13	0.15	0.16	0.24

Panel C. Correlation structure

	Time Duration	Return Std. Dev.	Price H-L	H-L spread	BV-VPIN	TR-VPIN	HFT
Time Duration	1.00	-0.33	-0.16	0.10	-0.03	-0.17	0.09
Return Std. Dev.	.	1.00	0.82	0.05	0.28	-0.12	-0.30
Price H-L	.	.	1.00	0.14	0.40	-0.21	-0.28
H-L spread	.	.	.	1.00	0.21	-0.13	0.10
BV-VPIN	.	.	.	.	1.00	-0.37	-0.11
TR-VPIN	.	.	.	.	.	1.00	0.08
HFT	.	.	.	.	.	.	1.00

Table 3. The predictability of BV-VPIN on short-term price volatility

Volatility Specifications	$PRCHL_t$					$RETVOL_t$				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Const.	1.4078	0.8806	0.9107	0.8690	0.8185	1.2271	0.3737	0.4180	0.3672	0.3248
	35.30	30.31	28.73	27.86	29.74	23.31	20.21	17.72	16.74	17.27
1_{t-1}^{TOXIC}					1.1294					0.8880
					5.71					7.20
$\ln(VPIN_{t-1})$	0.5461	0.3377	0.3448	0.3286	0.2909	0.2928	0.0842	0.0913	0.0670	0.0234
	24.74	28.93	28.35	28.50	26.94	10.01	10.35	10.81	9.30	4.04
$1_{t-1}^{TOXIC} \times \ln(VPIN_{t-1})$					0.7796					0.6026
					5.47					6.82
$Volatility_{t-1}$		0.1063	0.1026	0.0978	0.0892		0.3277	0.3115	0.3082	0.2971
		11.58	10.92	10.83	10.99		20.64	19.26	19.14	18.78
$Volatility_{t-2}$		0.0730	0.0705	0.0657	0.0576		0.1278	0.1226	0.1200	0.1111
		11.91	11.04	11.30	11.10		18.25	17.13	17.33	15.11
$Volatility_{t-3}$		0.0686	0.0665	0.0607	0.0529		0.0880	0.0867	0.0841	0.0758
		10.23	9.66	9.67	10.19		20.35	18.90	18.51	19.47
$Volatility_{t-4}$		0.0564	0.0534	0.0473	0.0398		0.0724	0.0711	0.0663	0.0581
		9.06	8.36	8.30	9.50		16.43	15.11	15.64	16.31
$Volatility_{t-5}$		0.0559	0.0539	0.0480	0.0405		0.0677	0.0666	0.0591	0.0492
		9.66	9.28	9.46	10.35		15.67	14.22	14.36	13.47
$(Time\ \ Duration_{t-1})$			-0.1529	-0.1957	-0.1808			-0.4595	-0.4793	-0.4825
			-6.48	-7.82	-7.32			-18.14	-18.32	-18.92
$(Time\ \ Duration_{t-2})$			0.0645	0.0579	0.0645			0.2043	0.1888	0.1830
			2.59	2.23	2.50			10.79	9.68	9.50
$(Time\ \ Duration_{t-3})$			-0.0458	-0.0586	-0.0513			0.0369	0.0149	0.0127
			-1.76	-2.10	-1.85			2.06	0.77	0.65
$(Time\ \ Duration_{t-4})$			-0.0490	-0.0422	-0.0333			0.0171	0.0193	0.0199
			-1.72	-1.37	-1.08			0.88	0.91	0.95
$(Time\ \ Duration_{t-5})$			0.0250	0.0557	0.0773			0.0105	0.0221	0.0314
			0.88	1.94	2.77			0.62	1.26	1.81
$(HL\ \ Spread_{t-1})$				0.1720	0.1432				0.0924	0.0706
				6.78	5.71				5.20	3.99
$(HL\ \ Spread_{t-2})$				0.1200	0.0894				0.1052	0.0814
				4.98	3.78				6.01	4.64
$(HL\ \ Spread_{t-3})$				0.1331	0.1002				0.1460	0.1197

				3.12	2.59				4.44	3.94
$(HL\ \ Spread_{t-4})$				0.0901	0.0547				0.0941	0.0654
				2.92	1.82				3.86	2.76
$(HL\ \ Spread_{t-5})$				0.0752	0.0354				0.1266	0.0942
				2.00	1.04				4.61	3.67
Adjusted R^2	0.133	0.165	0.166	0.168	0.175	0.057	0.307	0.312	0.315	0.321

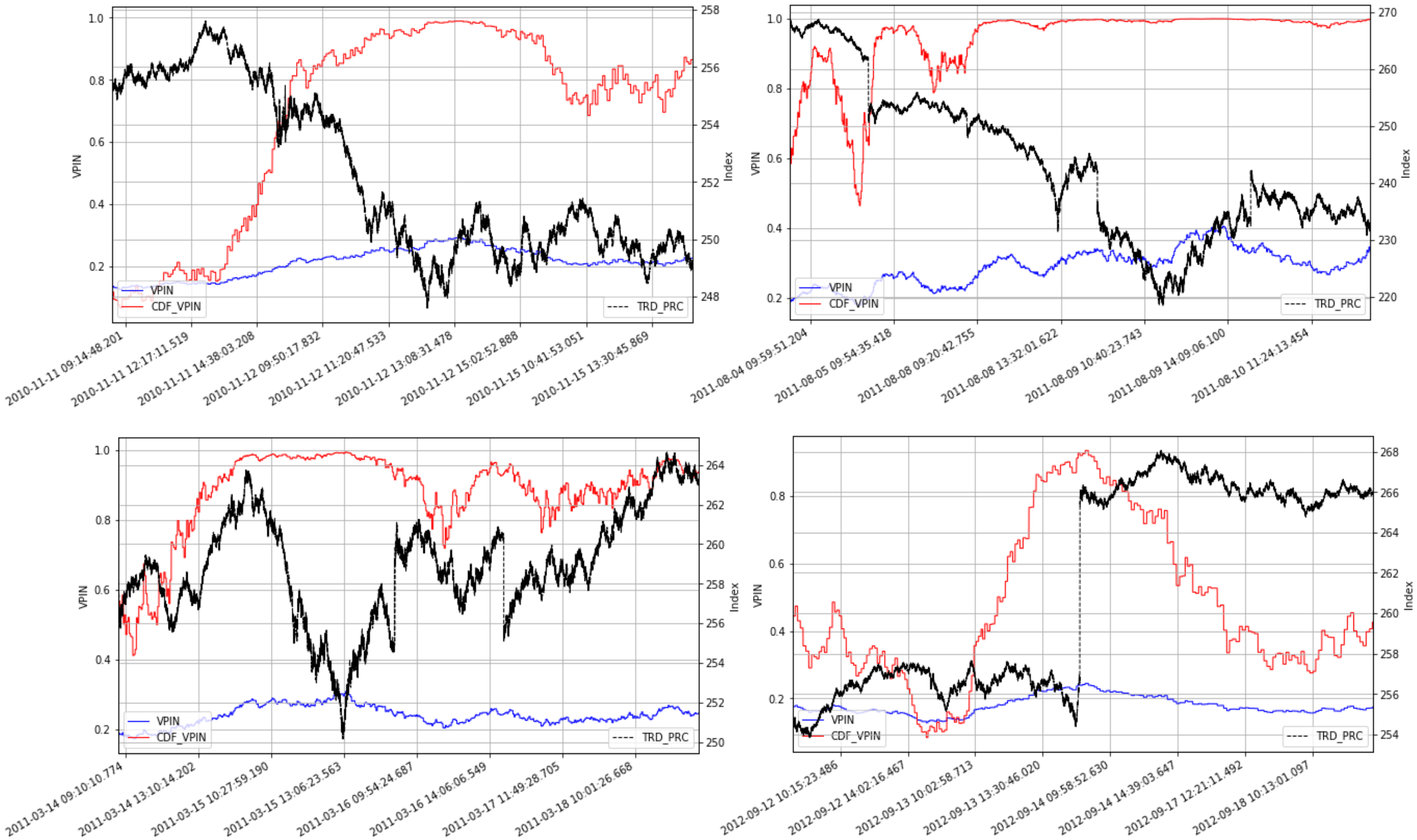

Figure 1. BV-VPIN around extreme price volatilities

The left top panel (Panel A), the left bottom panel (Panel B), the right top panel (Panel C), and the right bottom panel (Panel D) describe the following episodes respectively: (1) Expiration-day effect of KOSPI 200 options (11/11/2010), (2) Fukushima Daiichi nuclear disaster following the 2011 Tohoku earthquake and tsunami (03/11/2011), (3) Downgrade of the U.S. credit rating (08/05/2011), and (4) Upgrade of the Korean credit rating (09/14/2012)

Table 4. Flow toxicity of high-frequency trading

Participation Rates	HFT						
Specifications	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Const.	-0.0016	-0.0019	-0.0016	-0.0020	-0.0037	-0.0036	-0.0040
	-1.70	-1.84	-1.72	-2.19	-3.46	-3.67	-4.12
$(Participation\ \ Rates_{t-1})$	-0.0037	-0.0037	-0.0036	-0.0033	-0.0041	-0.0040	-0.0037
	-3.37	-3.41	-3.30	-3.02	-3.72	-3.65	-3.35
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{TOXIC}$		0.0004			-0.0002		
		0.72			-0.19		
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{SHORT}$			0.0035			0.0005	
			1.98			0.18	
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{VOLATILE}$				0.0077			0.0101
				3.80			2.93
$(Participation\ \ Rates_{t-2})$	-0.0022	-0.0022	-0.0021	-0.0020	-0.0029	-0.0029	-0.0028
	-1.81	-1.81	-1.76	-1.70	-2.40	-2.35	-2.29
$(Participation\ \ Rates_{t-3})$	-0.0019	-0.0019	-0.0019	-0.0019	-0.0025	-0.0026	-0.0025
	-1.57	-1.57	-1.61	-1.57	-2.10	-2.13	-2.10
$(Participation\ \ Rates_{t-4})$	0.0004	0.0004	0.0004	0.0003	0.0000	0.0000	0.0000
	0.32	0.32	0.31	0.28	0.03	0.03	-0.02
$(Participation\ \ Rates_{t-5})$	-0.0033	-0.0033	-0.0033	-0.0034	-0.0039	-0.0039	-0.0040
	-3.05	-3.06	-3.04	-3.17	-3.54	-3.53	-3.66
$\ln(VPIN_{t-1})$	-0.0048	-0.0050	-0.0048	-0.0049	-0.0061	-0.0060	-0.0061
	-11.32	-9.96	-11.28	-11.75	-11.35	-12.69	-13.03
$\Delta \ln(VPIN_{t-1})$	-0.0103	-0.0103	-0.0108	-0.0106	-0.0124	-0.0130	-0.0125
	-2.33	-2.34	-2.46	-2.41	-2.29	-2.41	-2.32
$\Delta \ln(VPIN_{t-2})$	-0.0123	-0.0123	-0.0131	-0.0121	-0.0220	-0.0226	-0.0219
	-2.75	-2.76	-2.92	-2.71	-4.01	-4.11	-3.99
$\Delta \ln(VPIN_{t-3})$	0.0130	0.0130	0.0127	0.0133	0.0062	0.0060	0.0064
	2.77	2.76	2.70	2.82	1.11	1.06	1.15
$\Delta \ln(VPIN_{t-4})$	0.0066	0.0066	0.0064	0.0067	0.0025	0.0024	0.0027
	1.46	1.46	1.43	1.50	0.46	0.45	0.50
$\Delta \ln(VPIN_{t-5})$	0.0139	0.0139	0.0139	0.0137	0.0056	0.0056	0.0054
	3.20	3.19	3.19	3.15	1.04	1.04	1.01
$\lvert IMBAL_{t-1}^{HFT} \rvert$					0.0015	0.0016	0.0018
					0.73	0.84	0.93
$\lvert IMBAL_{t-1}^{HFT} \rvert \times 1_{t-1}^{TOXIC}$					0.0018		
					0.47		
$\lvert IMBAL_{t-1}^{HFT} \rvert \times 1_{t-1}^{SHORT}$						0.0167	
						1.23	
$\lvert IMBAL_{t-1}^{HFT} \rvert \times 1_{t-1}^{VOLATILE}$							-0.0119
							-0.93
$\lvert IMBAL_{t-2}^{HFT} \rvert$					0.0065	0.0064	0.0066
					3.49	3.46	3.54
$\lvert IMBAL_{t-3}^{HFT} \rvert$					0.0047	0.0047	0.0047
					2.47	2.46	2.50
$\lvert IMBAL_{t-4}^{HFT} \rvert$					0.0030	0.0030	0.0030
					1.54	1.53	1.54
$\lvert IMBAL_{t-5}^{HFT} \rvert$					0.0056	0.0056	0.0055
					3.05	3.04	3.02
Adjusted R^2	0.005	0.005	0.005	0.005	0.005	0.005	0.005

Table 5. The impact of high-frequency trading on price volatility

Participation Rates	HFT			
Specifications	Model 1	Model 2	Model 3	Model 4
Const.	1.1050	1.0629	1.1036	1.1526
	25.06	24.12	24.99	30.96
$(Participation\ \ Rates_{t-1})$	-0.4467	-0.4543	-0.4478	-0.4524
	-18.20	-18.56	-18.24	-18.46
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{TOXIC}$		0.0928		
		7.34		
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{SHORT}$			-0.0674	
			-3.48	
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{VOLATILE}$				0.4073
				4.23
$(Participation\ \ Rates_{t-2})$	-0.1336	-0.1360	-0.1340	-0.1285
	-7.16	-7.29	-7.18	-6.86
$(Participation\ \ Rates_{t-3})$	0.0502	0.0474	0.0515	0.0480
	2.62	2.48	2.68	2.53
$(Participation\ \ Rates_{t-4})$	0.1040	0.1002	0.1043	0.1023
	5.69	5.51	5.70	5.67
$(Participation\ \ Rates_{t-5})$	0.0920	0.0865	0.0915	0.0890
	5.87	5.52	5.83	5.76
$PRCHL_{t-1}$	0.0580	0.0557	0.0584	0.0195
	5.83	5.66	5.85	1.73
$PRCHL_{t-2}$	0.0409	0.0384	0.0420	0.0409
	6.21	5.91	6.32	6.82
$PRCHL_{t-3}$	0.0546	0.0520	0.0549	0.0546
	7.52	7.31	7.56	8.03
$PRCHL_{t-4}$	0.0530	0.0502	0.0530	0.0524
	8.07	7.78	8.09	8.67
$PRCHL_{t-5}$	0.0572	0.0544	0.0572	0.0568
	9.74	9.42	9.75	10.43
$\ln(VPIN_{t-1})$	0.3306	0.2978	0.3296	0.3455
	28.08	25.47	27.88	32.15
$(Time\ \ Duration_{t-1})$	-6.1688	-5.0502	-6.6420	-8.7846
	-2.49	-2.04	-2.69	-3.53
$(Time\ \ Duration_{t-2})$	4.0930	4.6277	4.1149	6.0153
	1.59	1.80	1.60	2.30
$(Time\ \ Duration_{t-3})$	-12.7479	-12.2493	-12.7782	-13.1445
	-4.46	-4.30	-4.47	-4.59
$(Time\ \ Duration_{t-4})$	-10.9938	-10.4870	-10.9845	-11.0865
	-3.58	-3.43	-3.58	-3.62
$(Time\ \ Duration_{t-5})$	-1.5744	-0.6483	-1.6014	-1.5795
	-0.54	-0.22	-0.55	-0.55
$(HL\ \ Spread_{t-1})$	0.2772	0.2636	0.2751	0.2875
	10.60	9.99	10.50	10.97
$(HL\ \ Spread_{t-2})$	0.1950	0.1835	0.1936	0.1938
	7.71	7.34	7.66	7.70
$(HL\ \ Spread_{t-3})$	0.1588	0.1481	0.1577	0.1577
	3.71	3.47	3.69	3.76
$(HL\ \ Spread_{t-4})$	0.0873	0.0763	0.0866	0.0866
	2.84	2.49	2.82	2.91
$(HL\ \ Spread_{t-5})$	0.0682	0.0560	0.0680	0.0686
	1.79	1.47	1.78	1.83
Adjusted R^2	0.188	0.190	0.188	0.189

Table 6. Price volatility, flow toxicity, and high-frequency trading: Vector autoregression (VAR) analysis

Participation Rates	HFT			HFT_M			HFT_L		
Dependent Variables	$PRCHL_t$	$\ln(VPIN_t)$	$(Part.Rates_t)$	$PRCHL_t$	$\ln(VPIN_t)$	$(Part.Rates_t)$	$PRCHL_t$	$\ln(VPIN_t)$	$(Part.Rates_t)$
Const.	1.4270	-0.0079	0.2169	1.3208	-0.0094	0.1504	1.2600	-0.0097	0.1051
	93.47	-7.82	51.73	94.16	-10.06	38.85	87.97	-10.30	36.50
$PRCHL_{t-1}$	0.0700	0.0017	-0.0027	0.0709	0.0016	-0.0091	0.0943	0.0019	0.0025
	15.86	5.62	-2.24	16.15	5.57	-7.48	21.57	6.57	2.88
$\ln(VPIN_{t-1})$	0.4179	0.9934	-0.0084	0.4151	0.9933	-0.0057	0.4116	0.9932	-0.0224
	63.02	999.00	-4.60	62.61	999.00	-3.13	61.17	999.00	-16.53
$(Participation\ Rates_{t-1})$	-0.4684	-0.0070	0.6580	-0.4887	-0.0077	0.6499	-0.3928	-0.0082	0.6212
	-37.87	-8.52	193.73	-39.28	-9.31	189.28	-23.20	-7.37	182.50
$(Time\ Duration_{t-1})$	-11.0901	0.5749	-10.4001	-6.2338	0.6608	-9.1084	-24.8566	0.3565	-5.4511
	-3.50	2.73	-11.95	-1.96	3.12	-10.38	-7.81	1.70	-8.52
$(Time\ Duration_{t-2})$	-6.2408	-0.1935	0.7870	-5.1756	-0.1781	-0.8190	-6.2706	-0.2043	1.6838
	-1.76	-0.82	0.81	-1.46	-0.75	-0.84	-1.75	-0.86	2.34
$(Time\ Duration_{t-3})$	-14.7702	-0.7858	0.8465	-15.5035	-0.8002	0.9916	-12.0574	-0.7499	-1.4161
	-4.14	-3.32	0.86	-4.35	-3.38	1.01	-3.36	-3.16	-1.96
$(Time\ Duration_{t-4})$	-10.7792	-0.5171	-0.9590	-11.5888	-0.5333	-1.4407	-8.1515	-0.4875	-0.8803
	-3.03	-2.19	-0.98	-3.26	-2.26	-1.47	-2.28	-2.06	-1.22
$(Time\ Duration_{t-5})$	0.1803	-0.2355	-5.9944	-1.3233	-0.2659	-5.9615	5.1488	-0.1816	-4.6140
	0.06	-1.14	-7.00	-0.42	-1.28	-6.92	1.64	-0.88	-7.31
$(HL\ Spread_{t-1})$	0.3342	0.0070	-0.0574	0.3426	0.0073	-0.0469	0.2737	0.0064	-0.0268
	15.08	4.78	-9.43	15.46	4.92	-7.66	12.31	4.35	-5.99
$(HL\ Spread_{t-2})$	0.2322	0.0036	-0.0261	0.2400	0.0038	-0.0252	0.2091	0.0034	-0.0110
	10.58	2.47	-4.32	10.94	2.58	-4.16	9.46	2.30	-2.48
$(HL\ Spread_{t-3})$	0.2189	0.0048	-0.0084	0.2243	0.0049	-0.0062	0.2065	0.0046	-0.0003
	9.99	3.27	-1.40	10.24	3.34	-1.02	9.35	3.17	-0.07
$(HL\ Spread_{t-4})$	0.1590	0.0035	0.0025	0.1639	0.0036	0.0021	0.1491	0.0034	0.0033
	7.26	2.43	0.41	7.49	2.50	0.34	6.75	2.36	0.73
$(HL\ Spread_{t-5})$	0.1402	0.0016	0.0012	0.1443	0.0017	0.0042	0.1270	0.0014	0.0038
	6.48	1.09	0.21	6.67	1.15	0.70	5.82	0.99	0.86

Table 7. The predictability of TR-VPIN on short-term price volatility

Volatility Specifications	$PRCHL_t$					$RETVOL_t$				
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 1	Model 2	Model 3	Model 4	Model 5
Const.	-0.5527	-0.2841	-0.3047	-0.2825	-0.3298	0.2456	0.0777	0.0709	0.1144	0.0784
	-7.84	-9.80	-10.10	-10.35	-8.91	3.14	3.03	2.70	5.20	2.81
1_{t-1}^{TOXIC}					0.3140					0.0797
					3.09					0.82
$\ln(VPIN_{t-1})$	-0.5283	-0.2634	-0.2863	-0.2671	-0.2912	-0.2471	-0.0696	-0.0918	-0.0663	-0.0848
	-14.03	-17.51	-16.91	-17.60	-15.12	-5.89	-6.50	-7.64	-6.49	-6.48
$1_{t-1}^{TOXIC} \times \ln(VPIN_{t-1})$					0.1760					0.0385
					2.96					0.67
$Volatility_{t-1}$		0.1391	0.1350	0.1267	0.1264		0.3328	0.3164	0.3110	0.3107
		16.77	15.97	15.33	15.35		21.01	19.59	19.33	19.32
$Volatility_{t-2}$		0.1040	0.1013	0.0928	0.0926		0.1318	0.1263	0.1219	0.1217
		19.33	18.09	17.83	17.86		18.70	17.43	17.57	17.52
$Volatility_{t-3}$		0.0997	0.0975	0.0877	0.0875		0.0919	0.0903	0.0859	0.0857
		16.42	15.78	15.24	15.28		20.52	19.21	18.78	18.86
$Volatility_{t-4}$		0.0880	0.0845	0.0741	0.0739		0.0767	0.0747	0.0679	0.0677
		15.61	14.78	14.43	14.50		16.69	15.48	16.02	16.12
$Volatility_{t-5}$		0.0891	0.0853	0.0749	0.0746		0.0734	0.0711	0.0609	0.0605
		17.00	16.42	16.18	16.25		16.22	14.91	14.89	14.98
$(Time\ \ Duration_{t-1})$			-0.1551	-0.2027	-0.2025			-0.4655	-0.4884	-0.4885
			-6.47	-7.88	-7.87			-17.93	-18.17	-18.18
$(Time\ \ Duration_{t-2})$			0.0721	0.0613	0.0612			0.2042	0.1860	0.1855
			2.83	2.31	2.30			10.76	9.53	9.51
$(Time\ \ Duration_{t-3})$			-0.0421	-0.0595	-0.0599			0.0358	0.0119	0.0114
			-1.60	-2.10	-2.11			1.99	0.61	0.59
$(Time\ \ Duration_{t-4})$			-0.0530	-0.0504	-0.0506			0.0138	0.0151	0.0149
			-1.84	-1.62	-1.63			0.71	0.71	0.70
$(Time\ \ Duration_{t-5})$			-0.0420	0.0001	-0.0005			-0.0047	0.0133	0.0126
			-1.41	0.00	-0.02			-0.27	0.75	0.71
$(HL\ \ Spread_{t-1})$				0.2045	0.2037				0.1092	0.1088
				7.87	7.85				6.17	6.16
$(HL\ \ Spread_{t-2})$				0.1564	0.1557				0.1225	0.1222
				6.45	6.44				6.95	6.95
$(HL\ \ Spread_{t-3})$				0.1762	0.1754				0.1638	0.1634

				4.20	4.19				4.94	4.94
$(HL\ \ Spread_{t-4})$				0.1401	0.1393				0.1125	0.1119
				4.62	4.60				4.68	4.67
$(HL\ \ Spread_{t-5})$				0.1371	0.1364				0.1464	0.1460
				3.74	3.73				5.31	5.31
Adjusted R^2	0.052	0.145	0.146	0.151	0.151	0.017	0.304	0.309	0.314	0.314

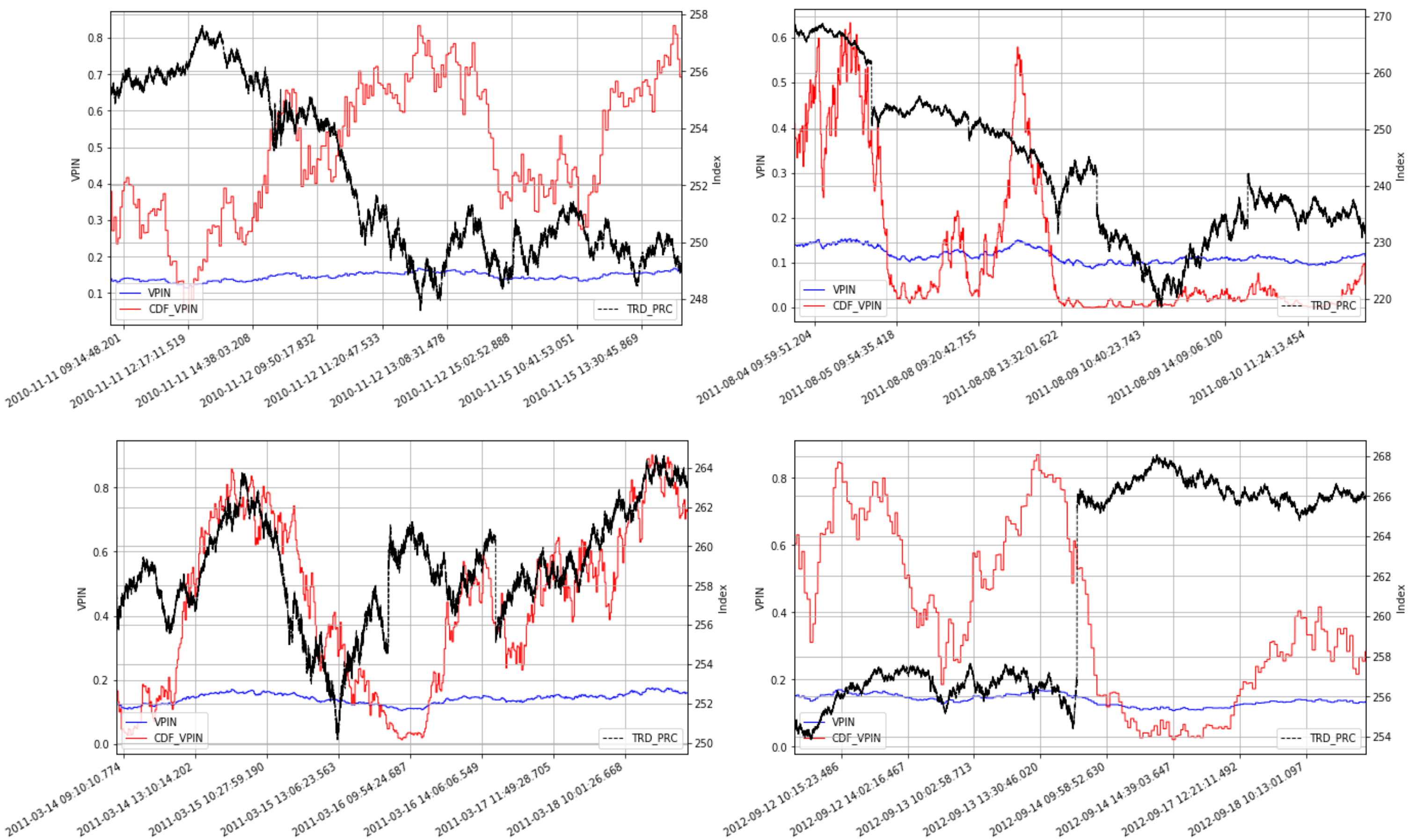

Figure 2. TR-VPIN around extreme price volatilities

The left top panel (Panel A), the left bottom panel (Panel B), the right top panel (Panel C), and the right bottom panel (Panel D) describe the following episodes respectively: (1) Expiration-day effect of KOSPI 200 options (11/11/2010), (2) Fukushima Daiichi nuclear disaster following the 2011 Tohoku earthquake and tsunami (03/11/2011), (3) Downgrade of the U.S. credit rating (08/05/2011), and (4) Upgrade of the Korean credit rating (09/14/2012)

Table 8. Summary statistics of Corwin-Schultz (2012) high-low spreads and order imbalances for BV and TR

Panel A. Summary statistics

Statistics	High-Low spread	OI_BV	OI_TR
Number of obs.	55,745	55,745	55,745
Mean	4.800.E-04	0.442	0.147
Std. Dev.	6.150.E-04	0.280	0.108
Min	0.000	0.000	0.000
Q1	0.000	0.234	0.060
Q2	2.250.E-04	0.448	0.126
Q3	8.290.E-04	0.628	0.212
Max	1.225.E-02	1.000	0.935

Panel B. Correlation

	High-Low spread	OI_BV	OI_TR
High-Low spread	1.000	0.104	-0.245
OI_BVC	0.104	1.000	0.480
OI_TR	-0.245	0.480	1.000

Table 9. Corwin-Schultz (2012) high-low spreads and order imbalances for BV and TR: OLS analysis

Panel A. High-low spreads and order imbalances for TR

$S_\tau = \alpha + \beta_1 S_{\tau-1} + \beta_2 |OI_\tau^{TR}| + \epsilon_\tau$

	Estimate	t-Statistic	Adjusted R^2
Intercept	0.0006	90.54	0.066
$S_{\tau-1}$	0.0756	9.25	
$\|OI_\tau^{TR}\|$	-0.0014	-51.56	

Panel B. High-low spreads and order imbalances for BV

$S_\tau = \alpha + \beta_1 S_{\tau-1} + \beta_2 |OI_\tau^{BV}| + \epsilon_\tau$

	Estimate	t-Statistic	Adjusted R^2
Intercept	0.0004	48.17	0.016
$S_{\tau-1}$	0.0687	8.81	
$\|OI_\tau^{BV}\|$	0.0002	13.45	

Panel C. High-low spreads and order imbalances for BV and TR

$S_\tau = \alpha + \beta_1 S_{\tau-1} + \beta_2 |OI_\tau^{TR}| + \beta_3 |OI_\tau^{BV}| + \epsilon_\tau$

	Estimate	t-Statistic	Adjusted R^2
Intercept	0.0005	81.93	0.126
$S_{\tau-1}$	0.0456	6.55	
$\|OI_\tau^{TR}\|$	-0.0022	-46.97	
$\|OI_\tau^{BV}\|$	0.0006	32.48	

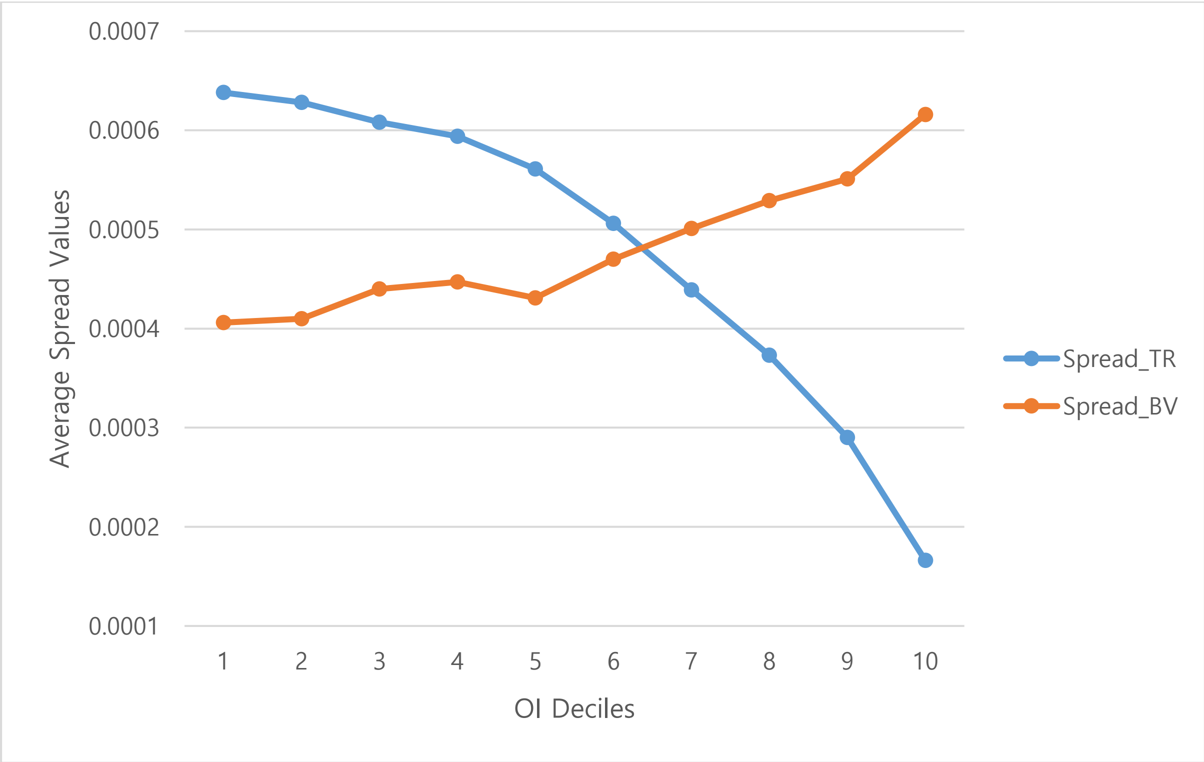

Figure 3. Corwin-Schultz (2012) high-low spread against order imbalances for BV and TR

Table 10. Average buy and sell price ratios for the TR-initiator and the BV-initiator relative to the average trading price

	TR-initiator	BV-initiator
Buy trades		
Mean of buy price ratio (%)	100.0115	100.0012
(t-Statistic: H_0 = 100)	31.58	2.81
Std. of buy price ratio (%)	0.0121	0.0146
Difference of buy price ratio (%) from TR-initiator		-0.0102
(t-Statistic: H_0 = 0)		-31.74
Sell trades		
Mean of sell price ratio (%)	99.9887	99.9988
(t-Statistic: H_0 = 100)	-31.46	-2.78
Std. of sell price ratio (%)	0.0120	0.0143
Difference of sell price ratio (%) from TR-initiator		0.0102
(t-Statistic: H_0 = 0)		32.49

Table 11. Summary statistics of HFT subgroups

Panel A. HFTs by investor group

	# Traders	% Dollar Volume	% Share Volume	Trade Size	Order Size	Limit Orders, % Volume	Aggressiveness, % Volume
HFT, FOR	8.25	53.42%	52.36%	2.40	25.31	100.00%	64.81%
HFT, IND	1.74	2.23%	2.23%	1.36	3.10	90.49%	37.32%
HFT, INS	10.77	44.34%	45.41%	2.77	39.93	99.80%	39.90%
	# Traders	Dollar Volume	Share Volume	Trade Size	Order Size	Limit Orders, % Volume	Aggressiveness, % Volume
HFT, All	20.00	$ 23,653,162,881,856	209,039,257	2.51	30.42	99.70%	52.89%

Panel B. HFT participation ratios by investor group

	Mean	Std. Dev.	Min	P25	P50	P75	Max
HFT_FOR	0.36	0.15	0.00	0.26	0.37	0.47	0.87
HFT_FOR_M	0.26	0.11	0.00	0.18	0.26	0.33	0.70
HFT_FOR_L	0.14	0.09	0.00	0.07	0.12	0.19	0.63
HFT_IND	0.02	0.02	0.00	0.00	0.01	0.03	0.22
HFT_IND_M	0.01	0.01	0.00	0.00	0.00	0.01	0.19
HFT_IND_L	0.01	0.01	0.00	0.00	0.01	0.02	0.19
HFT_INS	0.31	0.14	0.01	0.20	0.30	0.41	0.93
HFT_INS_M	0.14	0.09	0.00	0.07	0.12	0.19	0.86
HFT_INS_L	0.21	0.10	0.00	0.13	0.20	0.27	0.64

Table 12. Price volatility, flow toxicity, and high-frequency trading by HFT subgroups

Panel A. Flow toxicity of high-frequency trading by HFT subgroups

	HFT_FOR				HFT_FOR_M				HFT_FOR_L			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
$(Participation\ \ Rates_{t-1})$	0.0004	0.0004	0.0005	0.0005	-0.0011	-0.0011	-0.001	-0.001	0.0061	0.0061	0.0061	0.0061
	0.44	0.43	0.53	0.52	-1.00	-1.00	-0.89	-0.86	3.25	3.20	3.23	3.21
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{TOXIC}$		0.0000				0.0000				0.0007		
		0.03				0.04				0.41		
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{SHORT}$			0.0101				0.0136				0.0192	
			2.42				2.07				2.28	
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{VOLATILE}$				0.0195				0.0307				0.0346
				5.54				5.23				5.22
Control for the VPIN level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for the VPIN differences	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for the imbalances between HFTs	No	No	No	No	No	No	No	No	No	No	No	No
Adjusted R^2	0.003	0.003	0.003	0.004	0.004	0.004	0.004	0.004	0.003	0.003	0.003	0.003

	HFT_DOM				HFT_DOM_M				HFT_DOM_L			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
$(Participation\ \ Rates_{t-1})$	-0.0043	-0.0043	-0.0044	-0.0042	-0.0038	-0.0039	-0.0040	-0.0038	-0.0080	-0.0081	-0.0082	-0.0081
	-3.93	-3.95	-4.03	-3.89	-2.62	-2.64	-2.72	-2.59	-5.09	-5.12	-5.20	-5.11
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{TOXIC}$		0.0005				0.0008				0.0011		
		0.44				0.31				0.62		
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{SHORT}$			0.0054				0.0088				0.0083	
			2.24				1.88				2.22	
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{VOLATILE}$				0.0112				0.0261				0.0160
				3.79				3.77				3.69
Control for the VPIN level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for the VPIN differences	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for the imbalances between HFTs	No	No	No	No	No	No	No	No	No	No	No	No
Adjusted R^2	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.004	0.004	0.004	0.004

Panel B. The impact of high-frequency trading on price volatility by HFT subgroups

	HFT_FOR				HFT_FOR_M				HFT_FOR_L			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
$(Participation\ \ Rates_{t-1})$	-0.4776	-0.4817	-0.4783	-0.4770	-0.5466	-0.5534	-0.5478	-0.5477	-0.6656	-0.6783	-0.6657	-0.6618
	-21.62	-21.81	-21.64	-21.79	-20.67	-21.03	-20.69	-20.84	-19.51	-19.58	-19.52	-19.61
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{TOXIC}$		0.0858				0.1102				0.2434		
		5.15				5.00				5.22		
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{SHORT}$			-0.0992				-0.1723				0.0335	
			-1.23				-1.45				0.21	
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{VOLATILE}$				0.9479				1.4686				1.8234
				6.49				6.26				6.50
Control for lagged volatility	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for flow toxicity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for trading intensity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for illliquidity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.197	0.197	0.197	0.200	0.191	0.192	0.191	0.194	0.187	0.188	0.187	0.190

	HFT_DOM				HFT_DOM_M				HFT_DOM_L			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
$(Participation\ \ Rates_{t-1})$	0.1473	0.1326	0.1497	0.1457	0.0728	0.0463	0.0762	0.0695	0.2140	0.1954	0.2172	0.2124
	7.16	6.66	7.25	7.09	2.92	1.96	3.04	2.80	7.20	6.68	7.29	7.13
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{TOXIC}$		0.1768				0.4310				0.2324		
		5.44				5.60				4.82		
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{SHORT}$			-0.0903				-0.1487				-0.1429	
			-4.75				-3.38				-5.22	
$(Participation\ \ Rates_{t-1}) \times 1_{t-1}^{VOLATILE}$				0.1573				0.5777				0.1026
				1.88				2.46				0.99
Control for lagged volatility	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for flow toxicity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for trading intensity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for illliquidity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.171	0.172	0.171	0.171	0.169	0.169	0.169	0.169	0.171	0.172	0.171	0.171