Figuring Out Flash Crash: Is VPIN a Good Indicator of the August 24th, 2015 Crash?

Jinhua Wang Zi Yuan Yang

Financial Market Microstructure, University of Toronto

Professor: Andreas Park[1]

Submission date: Nov. 26th, 2015

Abstract

This paper examines data from a stock market crash that happened on August 24th, 2015, for a large cross section of 19 US stocks. Easley, Lopez de Prado, and O'Hara (Easley, Lopez de Prado, and O'Hara, 2012) introduced volume-synchronized Probability of Informed Trading (VPIN) as an indicator of order flow toxicity. We showed that an increase in VPIN does not necessarily correlated with a decrease in price in the near term. Our results suggest that VPIN metric is a weak indicator of oncoming crashes in the stock market.

[1] We want to thank Professor Andreas Park for putting up with a lot of emails and steering us in the right direction when we got lost.

1. Introduction

On August 24th, 2015, U.S stock markets experienced a huge flash crash with some stocks and exchange-traded funds (ETFs) halting in trading multiple times throughout the day. Some securities saw their bid ask spreads increase to astronomical amounts. The Dow Jones Industrial Average (DJIA) dropped some 1100 points in the first five minutes of trading and has never gone higher than the opening price throughout the whole day. No doubt, the cost of the crash is huge. A crash like the one we have seen on August 24th could cause certain financial instruments to trigger and thus depressing prices even more. A downwards-positive feedback loop could occur and cause systemic risk. Although the cause of the crash may never be known, some people invariably speculate the cause may have something to do with technical advances in computation, namely high frequency trading.

The Volume-synchronized Probability of Informed trading (VPIN) is a measure developed in response to HFT environment (Abada and Yagüe, 2012). VPIN is a measure of flow toxicity based on volume imbalances and trade intensity (Easley, Lopez de Prado, and O'Hara, 2012). Based on research done by Easley, Lopez de Prado, and O'Hara (2012), it is shown that VPIN is a good indicator of flash crashes. The authors found that such results to be not only fascinating but also harbors practicality. Imagine a way to predict the next crash before it happens, that is a powerful idea.

This paper aims to use microstructure data to examine the question of whether VPIN is a good indicator of the crash on August 24th, 2015. To this end, we obtained data from before the crash (August 19th, 2015) and compared the VPIN with the VPIN from the day of the crash (August 24th, 2015). We also plotted 4 different graphs (VPIN-Buckets, Price-Buckets, Volume-Buckets, and Effective Spread (Basis Points) – Buckets) for some selected companies (*See Appendix*). We used the graphs to examine how well VPIN predicted the crash. We predict that our results should be consistent with that of O'Hara et al that VPIN is a good indicator of the crash.

2. Data and Metrics

We obtained our data from FactSet Research Systems Inc. We downloaded the data of each stock with the variables time, price, trade date, volume, exchange, bid, and bid size, ask, and ask size, cumulative volume, and volume weighted average price. We downloaded the data for August 19th, 2015 and August 24th, 2015. There was a flash crash in the stock market on August 24th, 2015, but there was no crash on August 19th, 2015. Therefore, we can use August 19th, 2015 as a control and compare it to August 24th 2015.

2.1 Sample Construction

Our aim is to construct a sample that is drawn from a random sample pool, which will then, by definition, be independent and identically distributed (i.i.d). The amount of trade data of halted ETFs available for August 24th, 2015 was limited (<1000). Therefore, we constructed a random sample pool of stocks with trade volumes greater than 100,000 per day (per stock). We believe that the latter way of sampling will still preserve the qualities of i.i.d[2]. We then used a random process to generate a sample of 19 stocks (*Appendix A*).

We believe that the stocks we selected are appropriate for the question that we pose because these stocks are sufficiently big in size and the prices of these stocks decreased on the day of the crash. We dropped trades with volume less than 100 and we paneled together all 19 stocks' trade data for Aug 19 2015 and Aug 24 2015 into one. The concatenated data had close to *2 million* observations.

3. Methods

In this section, we describe the mathematical and stochastic model that was used. We begin with describing VPIN construction as well as how we classify buys and sells using Lee-Ready

[2] To obtain proper VPIN, we cut down the sample space. Therefore, our analysis is based on the question "if VPIN is a good indicator of crashes for stocks with more than 100,000 trades per day".

algorithm. Then, we describe how we did our graphical construction and regression construction.

3.1 VPIN Construction

Volume-synchronized Probability of Informed trading (VPIN) is the measurement of the toxicity of the order flows. VPIN is derived from PIN (Probability of Informed Trading) (Easley, Kiefer, OHara, Paperman, 1996):

$$\boldsymbol{PIN} = \frac{\boldsymbol{\alpha\mu}}{\boldsymbol{\alpha\mu + 2\mu}}$$

Where,

α is the probability of an event

μ is the probability of an investor that is informed

$\alpha\mu + 2\mu$ is the arrival rate of orders, and $\alpha\mu$ is the arrival rate of informed orders

PIN is clock time-synchronized. Since the frequency of trade order arrivals is irregular, and the weights of information revealed for each trade is usually different, PIN could suffer from intraday seasonality based on clock time.

Therefore, we choose to volume-synchronize the trades. We use Lee-Ready algorithm (Lee & Ready (JFM, 1991)) to determine buy-initiated trades and seller-initiated trades:

$$\boldsymbol{midpoint} = \frac{\boldsymbol{bid + ask}}{\boldsymbol{2}}$$

Where,

Buyer-initiated trade occurs when a market-buy order is submitted and matched to a limit-sell order.

Seller-initiated trade occurs when a market-sell order is submitted and matched to a limit-buy order.

If the trade price > midpoint, we treat the trade as a buyer-initiated trade.

If the trade price < midpoint, we treat the trade as a seller-initiated trade.

If the price = midpoint, we cannot determine the direction of the trade. Therefore, we choose to drop the data.

The downside of using Lee-Ready Algorithm is that it sometimes misclassifies short sales, as regulations require short sales at a price above last transaction price.

We use STATA[3] to calculate VPIN using the following formula (Park, 2015):

$$\boldsymbol{VPIN = \ Moving\ Average\left(\sum_{i-1}^{n}\left|Vol_i^b - Vol_i^s\right|\right) * \frac{1}{V}}$$

Where,

Moving Average takes the average of nearby 9 observations.

N = 100 buckets.

$$\frac{\sum_{i-1}^{n}|Vol_i^b - Vol_i^s|}{n} = E\,[|Vol^b - Vol^s|] \approx \alpha\mu$$

$$V = E\,[|Vol^b + Vol^s|] \approx \alpha\mu + 2\epsilon = \frac{Total\ Volume\ of\ the\ Day}{100}$$

3.2 Graphical Construction

We constructed four types of graphs with STATA™. All of the four graphs are drawn against the series of buckets after volume bucketing. We observe the correlation between 1) VPIN and Price, 2) VPIN and Volume, 3) VPIN and Effective Spread when the crash happened on August 24, 2015 (Graph 1, Graph2 and Graph 3).

3. STATA is statistical software.

Graph Type I

VPIN-Buckets: Each bucket's VPIN value on the vertical axis, and the bucket number on the horizontal axis.

Graph Type II

Price-Buckets: Average price of each bucket on vertical axis, and the bucket number on the horizontal axis.

Graph Type III

Volume-Buckets: Average volume of each bucket on vertical axis, and the bucket number on the horizontal axis.

Graph Type IV

Effective Spread (Basis Points) – Buckets: Average effective spreads in basis point on vertical axis, and the bucket number on the horizontal axis.

3.3 Regression Construction

Since we know that August 24^{th}, 2015 is when the crash happened, we defined VPIN on bad times to be "*VPIN_bad*". We then call our control (August 19^{th}, 2015) "*VPIN_good*". Therefore, VPIN in good times is defined to be *VPIN_good* and VPIN in bad times is defined to be *VPIN_bad* in our regression model.

We used a regression framework to test the question of whether VPIN is different in good times than in bad times. To this end, we use ordinary least squares (OLS) estimation to get estimators for the coefficients, α and β.

We define:

Event = 0, if *VPIN_good*

Event = 1, if *VPIN_bad*

$$Spread = \rho + \alpha VPIN\_good + \beta VPIN\_bad + U$$

Where,

Spread = quoted spread in basis points

ρ = intercept term

VPIN_good = VPIN in good times (August 19^{th}, 2015)

VPIN_bad = VPIN in bad times (August 24^{th}, 2015)

U = unobservable

We then performed the following hypothesis test.

$$H_0: \alpha = \beta$$

$$H_1: \alpha \neq \beta$$

We used an F-test to test to determine if the coefficients are the same.

$$\boldsymbol{F = \frac{(SSRr - SSRur)/q}{SSRur/(n-k-1)}} \sim F_{q,\, n\text{-}k\text{-}1}$$

Where,

SSRr = sum of square residual restricted

SSRur = sum of square residual unrestricted

q = number of restrictions

n = number of observations

k = number of repressors

(*See appendix C for F-test values*)

We believe OLS estimator is good because it satisfies assumptions A.1 to A.4 (*Appendix B*), which makes the estimators unbiased and consistent. However, we have reason to believe that the data is not homoscedastic from the regressions we ran. Therefore, we cannot conclude that OLS, in this case, is BLUE (best linear unbiased estimator) from the Gauss-Markov theorem, which is to say that the variance isn't the most efficient.

Since we are only testing for if the regression coefficients are the same, we do not need the homoscedastic assumption. It should be noted that we are not trying to draw any causal conclusions. Hence it is why, we believe the above way of setting up the regression is a good way.

4. Empirical Results

4.1 Graphical Analysis

The green bands in graph 1, graph 2, and graph 3 (*Appendix D*) marked the period that the flash crash happened on August 24, 2015.

Graph 1 is the observation of United Technologies Corporation (UTX). The VPIN increased rapidly to 0.8 in the beginning, and then gradually decrease to below 0.2. The effective spread increases first, and as the VPIN decreases, it decreases. Graph 1 also observes significant increase in trading volume. The price increased first, and then dropped 1%.

Graph 2 is the observation of Yelp Inc. (YELP). The VPIN increased rapidly in the beginning to 0.8, and gradually dropped to below 0.4. The price dropped 5%, and the effective spread dropped 60% during the crash. The transaction volume increased rapidly when the crash happened.

Graph 3 is the observation of Yum! Brands, Inc. (YUM). The VPIN increased rapidly to nearly 0.8 in the beginning of the crash. The volume increased rapidly, the effective spread increased while the VPIN increase, and it dropped following the drop of VPIN. The price dropped one percent during the stock market crash.

Graph 4 is the observed VPIN of the panel data[4]. The VPIN increased rapidly during the August 24th crash.

4.2 Regression analysis

Table 2 reports the results from our regression. Based on our regression analysis, we found that VPIN in good times and bad times are statistically different than 0 at the 0.05 alpha risk level (see appendix), which is expected. The R^2 is 0.6039, which says that roughly 60% of the quoted spread is explained by the repressors *VPIN_good* and *VPIN_bad*. The intercept is 7464.087 basis points. The coefficient for *VPIN_good* is 6376.027 basis points and *VPIN_bad* is 8910.233 basis points.

5. Discussion

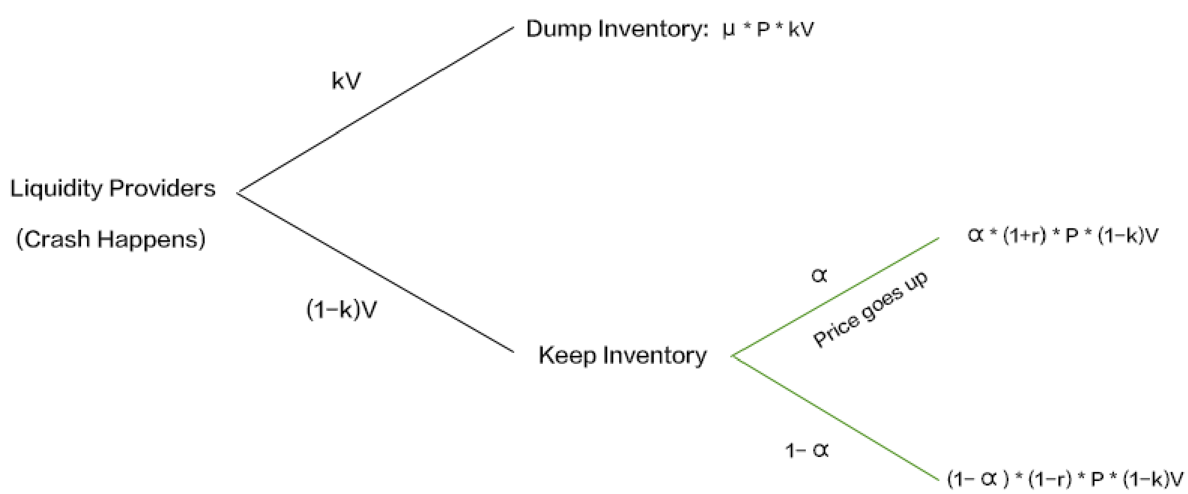
The main purpose of this paper is to determine whether VPIN is a good indicator of stock market crashes. Our analysis from the graphs (*Appendix D*) suggests that VPIN is a weak indicator of stock market crashes. We found that rises in VPIN sometimes happens before the crash and sometimes after the crash. For United Technologies (*Graph 1 Appendix D*), the stock price went up with VPIN when the stock crash happened in the morning. Only as the VPIN started to decrease did we see a decrease in prices. Our results are consistent with Anderson and Bondarenko (2013). However, the graph from Yelp Inc. shows opposite results. As VPIN went up, the price of Yelp Inc. went down 5%. This seems to suggest that VPIN is a good indicator of the crash, which is consistent with Easley, Lopez de Pardo and O'Hara (2012). Yet, if we graph from YUM Brands suggests that increases in VPIN does not have any effect on the

[4] The panel data includes trade data of 19 stocks on Aug 19 2015 and Aug 24 2015, respectively.

prices of the stock. Based on our data of 19 stocks, we found that VPIN of 16 stocks exhibits no significant correlation with prices. Our graphical analysis suggests that VPIN is at best a weak indicator of the crash. However, VPIN shows positive correlation with volume and quoted spread. VPIN is also statistically different in good and bad times.

5.1 VPIN and Inventory Risk Model

Graph 1, Graph 2 and Graph 3 showed significant increase in trading volume when the crashed happened on Aug 24, 2015. The graphs also suggest positive correlation between VPIN and trading volume upon Crash.



Suppose liquidity providers with inventory choose to sell kV shares when the crash happened. Coefficient μ is the percentage loss caused by toxicity of orders indicated by high VPIN. P is the price before the inventory dump.

$$Proceeds = \mu * P * KV$$

Suppose the liquidity provider also chooses to keep (1-k) V shares in inventory. This investor is subject to $1-\alpha$ chance that the price might go down by r percent, and α chance that the price goes up after time t.

$$E(proceeds) = \alpha * (1+r) * P * (1-k)V + (1-\alpha) * (1-r) * P * (1-k)V$$

Therefore, if E (proceeds) < Proceeds, the liquidity holders will sell more save less, we also have k > 0.5, and the following equation holds:

$$\mu > (2\alpha r + 1 + r) * (1-k)/k$$

Therefore, when the toxicity of orders exceeds a certain value, investors would choose to dump the inventory to reduce further risk. This can explain the reason of the big volume climb.

5.2 VPIN and Liquidity

Our statistics results suggest that the quoted spread increases with VPIN when the crash happened. VPIN is a measurement of the toxicity of orders. Therefore, when VPIN increases, it is more likely that a random investor in the market is informed. Informed investors tend to take advantage of the uninformed traders who would then trade at a loss. Therefore, when the crash happens, it is likely that the uninformed traders reduced liquidity provision, widening the quoted spread. To mitigate the possible loss in values of stocks in inventory, uninformed traders would prefer placing market orders to reduce inventory when the crash happened. Therefore, we see a spike in spread when VPIN increases, and a significant increase in trading volume.

5.3 VPIN Good and VPIN Bad

According to the regression results, VPIN in good time is statistically different than VPIN in bad time. Consistently, Graph 4[5] also shows that VPIN increased significantly during the crash. This finding suggests that, although VPIN is not significantly correlated to stock prices, VPIN in good times is statistically different VPIN in bad times. We also find that VPIN in good times is negatively related to quoted spread while VPIN in bad time is positively related to quoted

[5] Graph 4 is the VPIN-Bucket relation of panel data.

spread. This indicates that high VPIN in good times helps to feed liquidity into the market. It is likely that as the number of informed traders increases when market is going up, information efficiency improves, reducing the quoted spread and increasing the liquidity. However in bad times, uninformed investors are more afraid of the loss caused by informed trading. Therefore, they reduce liquidity provision.

Although we didn't find direct and statistically significant relationships between VPIN and stock prices, VPIN still predicts the change in liquidity and trading volumes in the crash. We also find that VPIN in good time is statistically different from VPIN in bad time. Therefore, we conclude that VPIN is a weak indicator of the crash.

6. Conclusion

This paper presents an empirical analysis of Volume-synchronized Probability of Informed Trading or VPIN flow toxicity metric. We examined the VPIN of 19 companies from before and on the day of the crash on August 24th, 2015. Our results suggest that VPIN is a weak indicator of the crash. We believe that VPIN has limited predictability power of the crash. Therefore, financial institutions, policy makers, and regulators should use VPIN with a pinch of salt.

Our findings also suggest that the search for a metric that can predict a stock market crash is still high up on the list. We hope that the analysis done in this paper will be helpful for future researchers who are looking for a said indicator for the crashes in the future.

Appendix

A. Stocks in the sample pool:

1. American Express
2. Boeing
3. Berkshire Hathaway
4. Coca Cola
5. Disney
6. Facebook
7. General electric
8. Home depot
9. Intel
10. JP Morgan
11. McDonalds
12. Pfizer
13. Procter and Gamble
14. Tesla
15. Twitter
16. United Technologies
17. Walmart
18. Yelp
19. Yum

B. OLS Estimator Assumptions

A.1 Linear in parameters

A.2 Zero conditional mean

A.3 independent and identically distributed

A.4 No perfect co-linearity

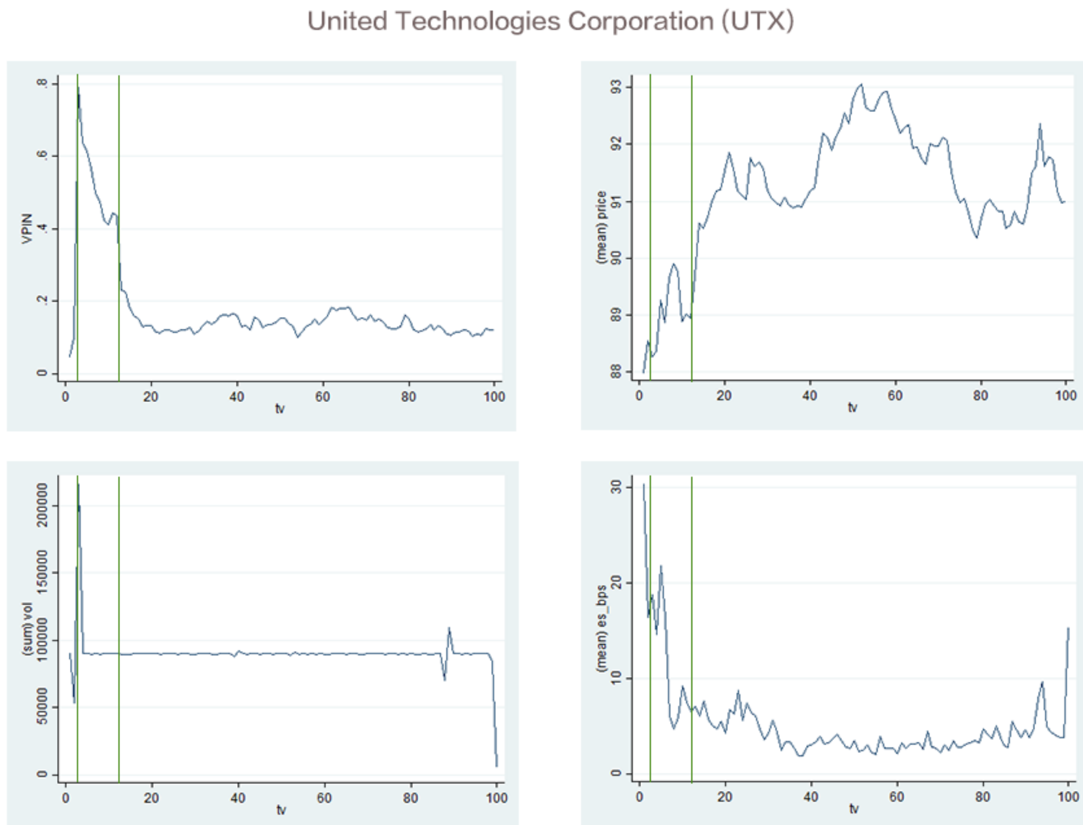
C. Table 2: Regression Output for Testing VPIN on spread

Variable	
Intercept	7464.087
	(14.6)**
VPIN_bad	8910.233
	(11.74)**
VPIN_good	6376.027
	(6.15)**
Observations	385
R^2	60.39%
F-statistic for H_0: $\alpha = \beta = 0$	216.38
F-statistic for H_0: $\alpha = \beta$	43.74

t-statistic is reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5% and 10% respectively.

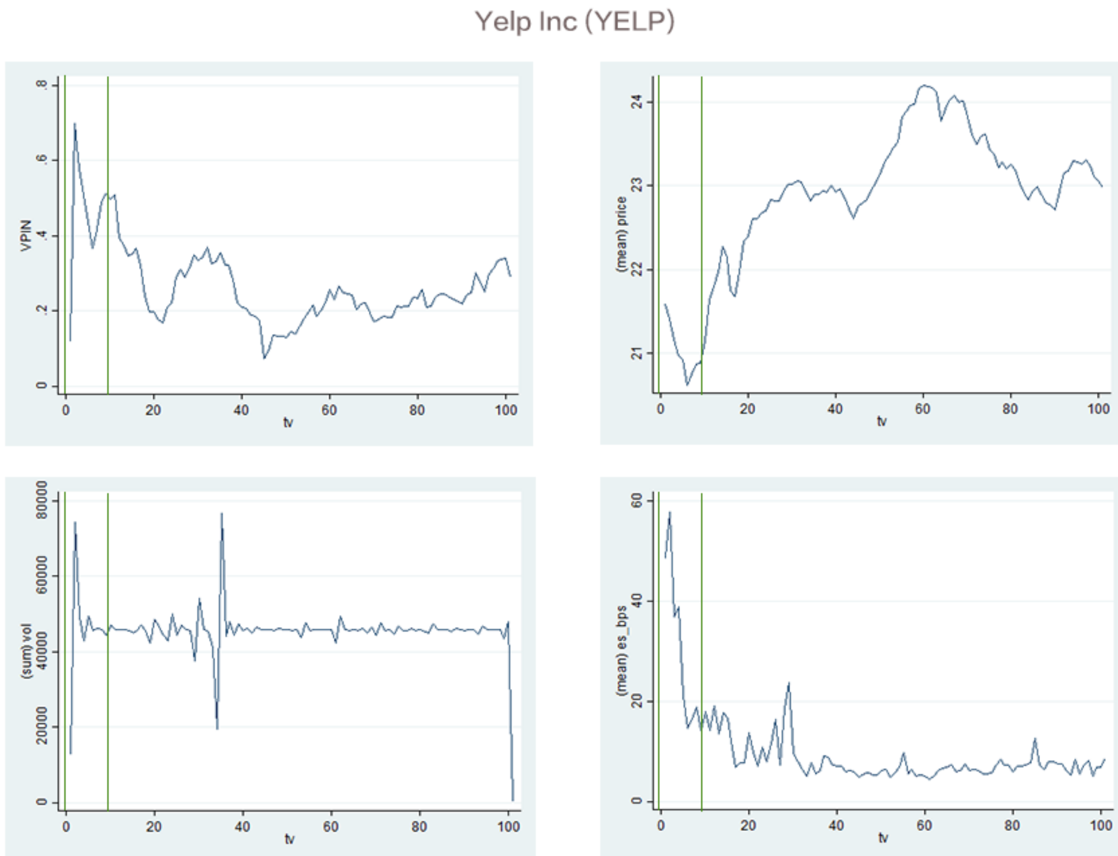
D. Graphs[6] of VPIN-Buckets, Price-Buckets, Volume-Buckets, and Effective Spread (Basis Points) – Buckets.

Graph 1

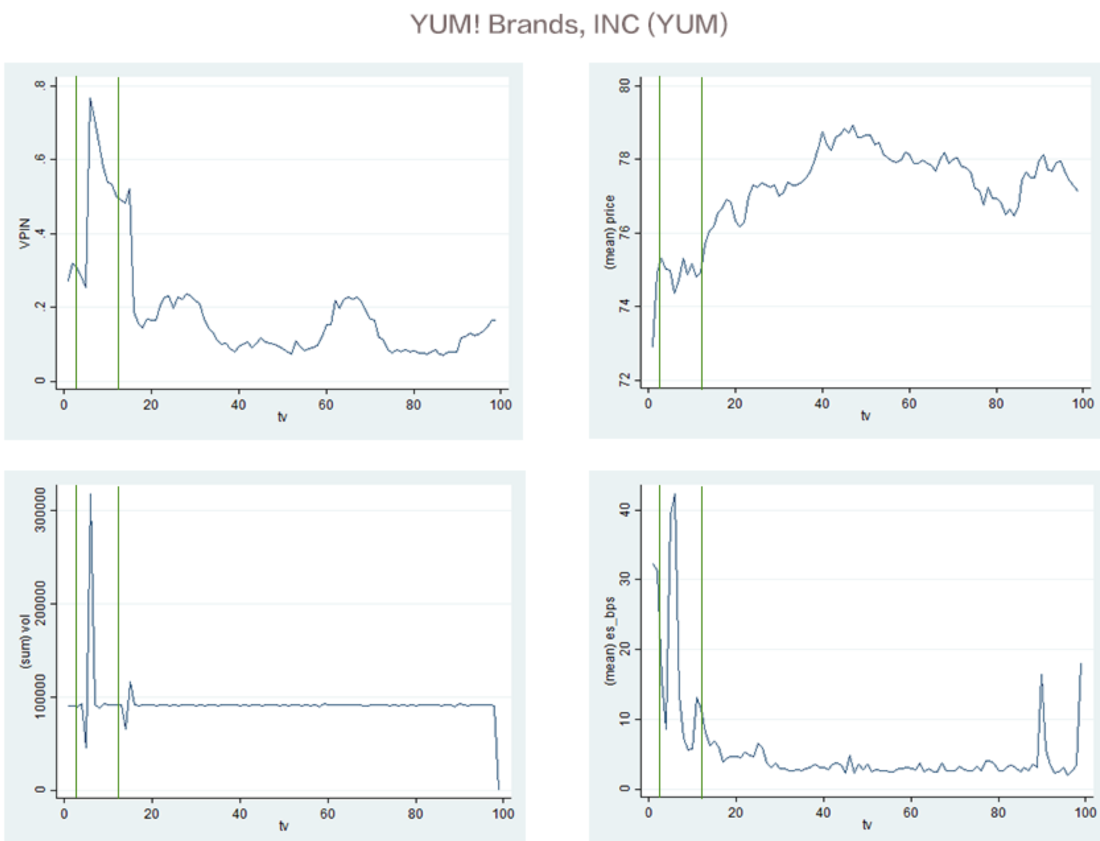


[6] We constructed 3 graphs out of the 19 stocks as a sample of VPIN being positively correlated with prices, VPIN negatively correlated with prices, and VPIN seem to have no correlations with the crash. We could have graphed all 19 stocks but generally the other 3 stocks fall into one of these 3 categories.

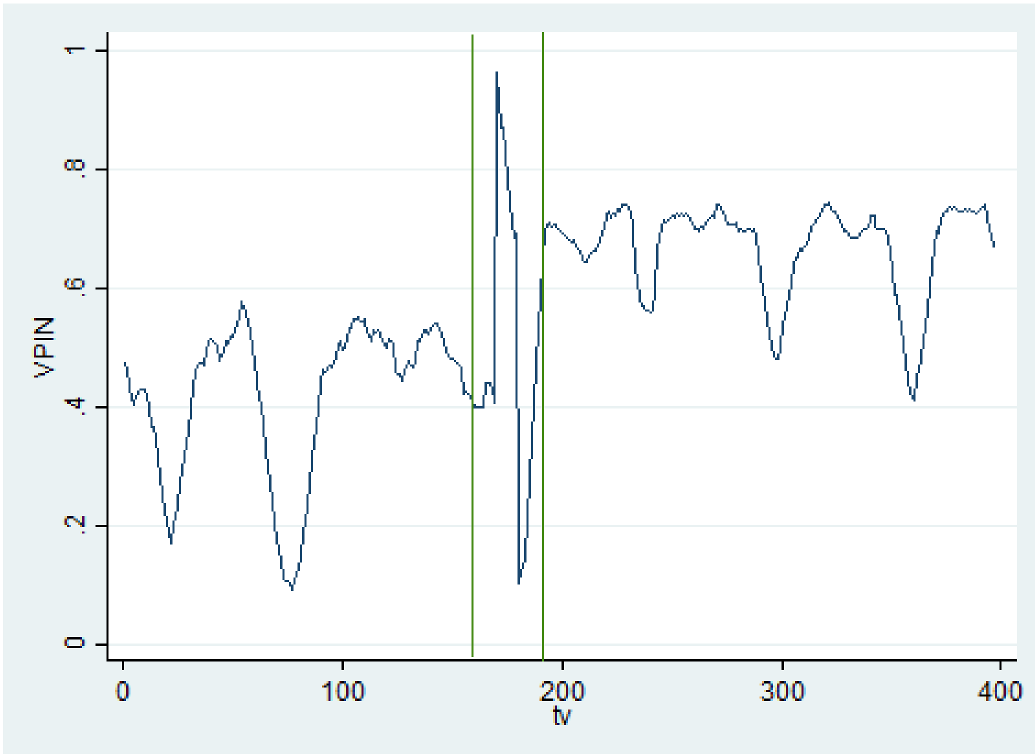
Graph 2



Graph 3



Graph 4 (VPIN-Bucket relation of the panel data.[7])



[7] The panel data includes trade data of 19 stocks on August 19th, 2015 and August 24th, 2015, respectively.

References

Abad, David., Yague, Jose., 2012. “From PIN to VPIN: An introduction to order flow toxicity.” The Spanish Review of Financial Economics, Vol 10, pp. 74-83

Anderson, Torben., Bondarenko, Oleg., 2013. “VPIN and the Flash Crash.” Journal of Financial Markets, Vol. 17, pp. 1-46, 2014

Andreas Park, Lecture on VPIN and STATA Calculation, ECO463 Financial Market Microstructure, University of Toronto, Nov 2015.

Easley, David., Lopez de Prado, Marcos., and O’Hara, Maureen. 2012. “Flow Toxicity in a High Frequency World.” Review of Financial Studies, Vol. 25, No. 5, pp. 1457-1493

Easley, D., N. Kiefer, M. OHara, and J. Paperman. 1996. “Liquidity, Information, and Infrequently Traded Stocks.” Journal of Finance 51:140536.

Lee, Charles M.C. and Ready, Mark J., Inferring Trading Direction from Intraday Data, The Journal of Finance, Vol. 46, No.2 (Jun., 1991), 733-746