Order toxicity and liquidity crisis: An academic point of view on Flash Crash

Discussant

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11 May 2011

Introduction

We review two papers on the causes of the Flash Crash by Easley, De Prado and O'Hara:

- "The Microstructure of Flash Crash" (Working Paper November 2010)
- "Flow Toxicity and Volatility in High Frequency World" (Working Paper February 2011)

Summary

1. Flash Crash caused by severe mismatch in liquidity: liquidity providers withdraw from the market or even turned into liquidity takers.
2. Liquidity dries up due to "toxic" (unbalanced) order flows.
3. Authors propose a measure of order toxicity, the VPIN metric.
4. They show that this VPIN measure anticipated the Flash Crash.

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Recent trends in market structure

- Since 2009, HF trading firms ($\approx 2\%$ of total $20,000$ US firms) accounted for over 70% of U.S. equity trading volume.
- Many of these HF firms are in the business of “liquidity provision”, i.e. acting as market maker (MM) to “position takers”.
- HF MM generally do not make directional bets, but rather strive to earn razor thin margins on large numbers of trades.
- Their ability to do so depends on limiting their position risk by:
  - hold very small or zero inventory positions
  - have high inventory turnover (5 or more times a day)
  - control “adverse selection”
- $\Rightarrow$ Allow them to operate with very low capital, essentially using their speed of trading to control inventory risk.

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Market Microstructure Models

- Microstructure models view trading as a game between liquidity providers (or MM) and liquidity takers (or traders or position takers).
- MMs set the spread to be compensated for:
  - operational costs
  - inventory costs
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- Adverse selection arises because some traders may have better information on the future price than MM.
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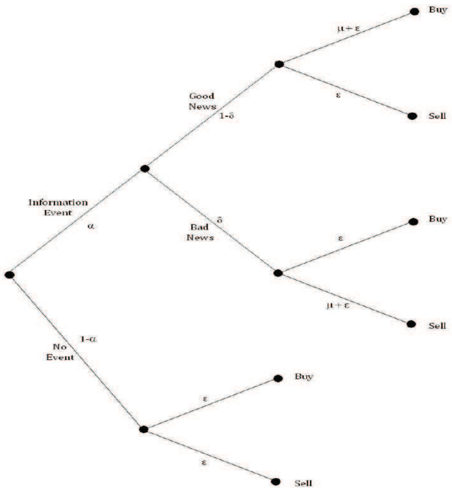
Sketch of a simple model of adverse selection



Market Microstructure Models

- If $\delta = 1/2$, it can be shown that the bid-ask spread simplified to

$$s = \frac{\alpha\mu}{\alpha\mu + 2\epsilon}\left[\,\overline{S_i} - \underline{S_i}\,\right]$$

where $\overline{S_i}$ and $\underline{S_i}$ are price predictions of informed trades in case of good and bad news.

- The probability that a trade in a period is information-based (PIN) is

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

where $\alpha\mu + 2\epsilon$ is the arrival rate for all orders and $\alpha\mu$ is the arrival rate for information-based orders.

- PIN is thus a measure of the fraction of orders that arise from informed traders relative to the total order flow.

- MMs need to correctly estimate their PIN in order to identify the optimal spread s.

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PIN estimation: VPIN theory

- Standard approach to estimate the PIN is to employ maximum likelihood estimation to get the unobservable parameters α, μ, ϵ and then derive PIN from those estimates.
- The Authors propose a more direct volume-based approach observing that:

  the expected trade imbalance is:

  $$\mathbb{E}\left[\left|V_\tau^S - V_\tau^B\right|\right] \approx \alpha\mu$$

  where V_τ^S is the sell volume and V_τ^B is the buy volume.

  and the expected arrival rate of total trades $V = V_\tau^S + V_\tau^B$ is:

  $$\mathbb{E}\left[V\right] = \alpha\mu + 2\epsilon$$

- Hence, the *Volume-Synchronized Probability of Informed Trading* VPIN is

  $$PIN = \frac{\alpha\mu}{\alpha\mu + 2\epsilon} \approx \frac{\alpha\mu}{V} \approx \frac{\sum_{\tau=1}^{n} \left|V_\tau^S - V_\tau^B\right|}{nV} = VPIN$$

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VPIN in practice

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

- Sample the prices in "Volume-time", i.e. in intervals having equal amount of volume V. They choose $V = 1/50$ of the average daily volume and $n = 50 \Rightarrow$ "daily" VPIN (on average).

- Volume Classification (in buy V_τ^B and sell V_τ^S volume).

  Trade classification is always problematic: more so in the HF world of electronic order book where applying standard tick-based algos over individual transactions would be "futile".

  $\Rightarrow$ propose to aggregate trades over short time intervals Δ (e.g. 1-minute) and sign the aggregated volume in that time interval as the corresponding transaction:

  An aggregated transaction is buy if either

  i $P_i > P_{i-\Delta}$ or
  ii $P_i = P_{i-\Delta}$ and the transaction $i - \Delta$ was also a buy.

  Otherwise, the transaction is a sell.

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VPIN of E-mini S&P500 over 3 years

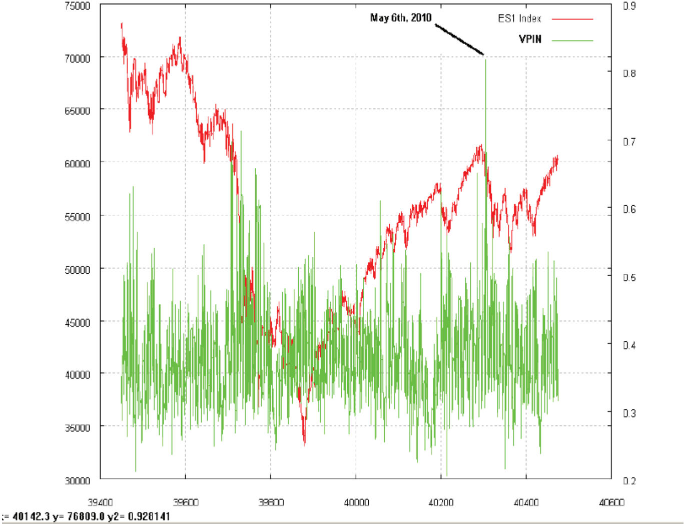

Figure 2 - VPIN metric between January 1st 2008 and October 30th 2010

VPIN: Historical PDF and CDF

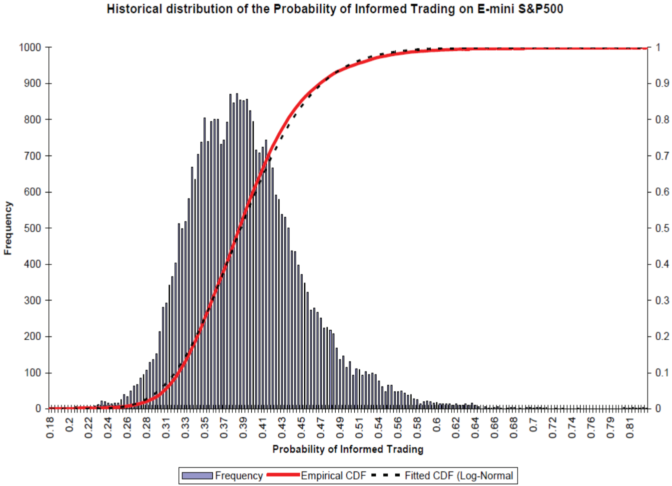

Figure 3 - The empirical CDF of the VPIN metric as fitted through a log-normal distribution

VPIN 1 week before the Flash Crash

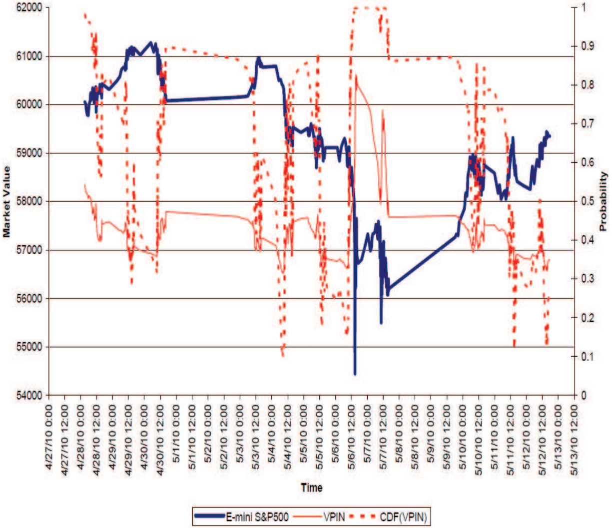

Figure 4 – E-mini S&P 500's VPIN metric one week before and after the flash crash

VPIN on the Flash Crash day

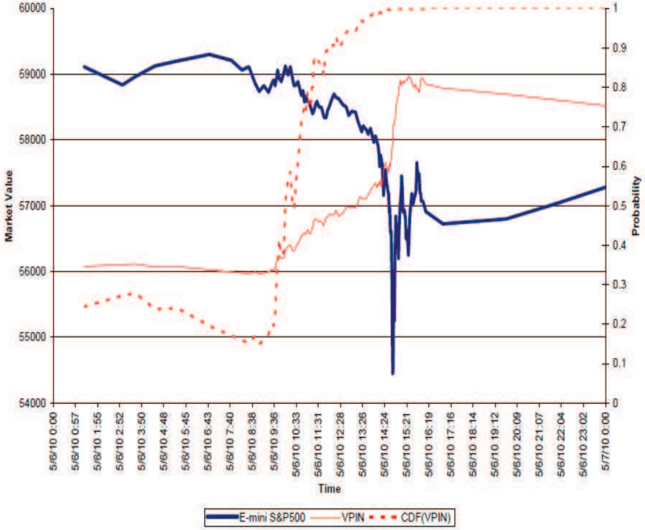

Figure 5 – E-mini S&P 500's VPIN metric on May 6th

VPIN vs VIX

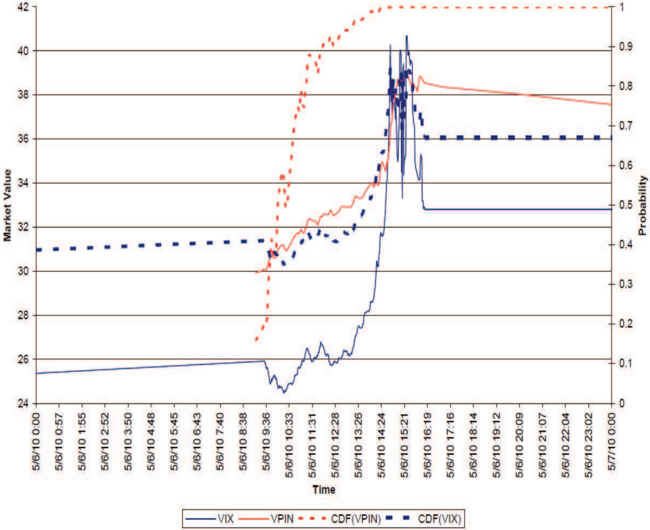

Figure 6 – VIX and E-mini's VPIN metric during the crash

Point of caution: Impact trade aggregation interval

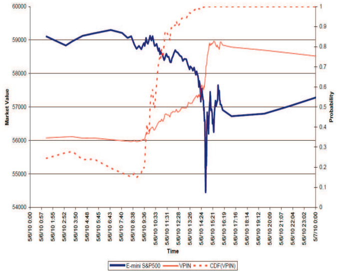

Figure 8(a) – VPIN estimated with One-Minute Time Bars

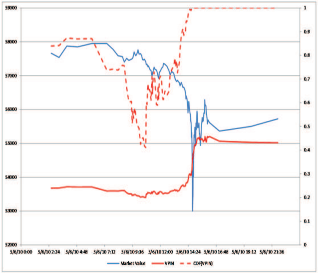

Figure 8(b) – VPIN Estimated with Ten-Second Time Bars

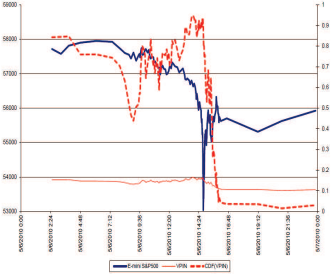

Figure 8(c) – VPIN Estimated with Trade-by-Trade Data

VPIN of EUR/USD and T-Note

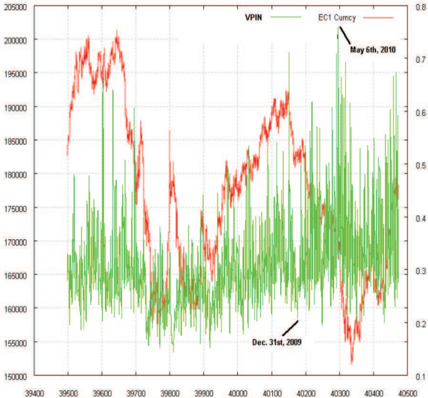

Figure 10 - VPIN for EUR/USD futures

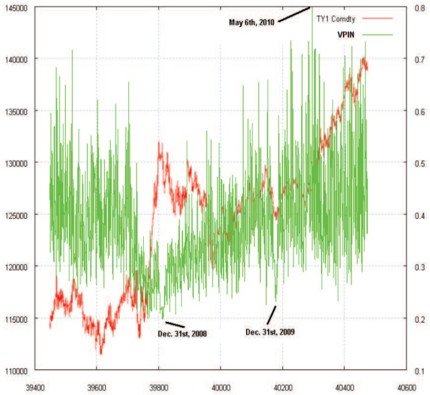

Figure 11 - VPIN for T-Note futures

Conclusions

- Flash Crash causes:
  - When flow toxicity unexpectedly rose (unusually unbalanced order flow as measured by VPIN) HF MMs face large losses.
  - Inventory may grow beyond their risk limits, forcing them to withdraw from the market.
  - If they keep accumulating losses, at some point they may capitulate, dumping their inventory to take the loss.

  Hence, extreme toxicity can transform liquidity providers into liquidity consumers.

- By measuring imbalance in order flow (toxicity) the proposed VPIN metric should predict liquidity crisis (as claimed for the Flash Crash).

- Authors proposed solution to liquidity crisis: Creating an exchange future with the VPIN metric as underlying.