Order Flow Toxicity Under the Microscope

David Abad
(goliat@ua.es, UA, Spain)

Magdalena Massot
(m.massot@uib.es, UIB, Spain)

Samarpan Nawn
(samarpan.nawn@iimu.ac.in, IIMU, India)

Roberto Pascual
(rpascual@uib.es, UIB, Spain)

Jose Yagüe
(ppyague@um.es, UM, Spain)

Toxic order flow

- “Order flow is toxic when it adversely selects liquidity providers, who may be unaware they are providing liquidity at a loss”
  (Easley, López de Prado, and O’Hara, 2012, abstract)
- Fancy way to talk about **information-motivated trading**.
- Traders could be “informed” because
  a) they have **private signals about fundamentals** (traditional view)
  (e.g., O’Hara, 1995)
  b) they are **faster than others in processing public signals** (hard information)
  (e.g., O’Hara, 2015)

This study's driving question

- What components of the order flow should we look at to:
  a) infer about underlying information?
  b) build effective advanced indicators of order flow toxicity?
- … in the context of modern high-frequency markets dominated by algorithmic trading strategies

Traditional view: the trade initiator

- In seminal MM models of adverse selection informed traders trade aggressively
  (e.g., Glosten and Milgrom, 1985; Kyle, 1985;
  Easley and O'Hara, 1987 …)
- They always take liquidity (initiate trades)
- **The trade initiator** …
  ["1" (-1) if the liquidity taker is a buyer (seller)]

  … and, by extension, the **order imbalance (OI)**
  [buyer – seller-initiated volume]

  … play a pivotal role in the MM tool kit to signal toxic order flow (Hasbrouck, 1991; Easley et al., 1996).

More recent research

- In US markets, OIs do not correlate with toxicity (e.g., Kim and Stoll, 2014; Collin-Dufresne and Fos, 2015; Easley et al., 2016; Barardehi, Bernhardt, and Davies, 2019).
- Informed traders often use limit orders (e.g., Goettler, Parlour, and Rajan, 2009; Annand, Chakrabarty, and Martell, 2005; Bloomfield, O'Hara, and Saar, 2005)
- In high-frequency markets:
    - Price discovery occurs predominantly through limit orders (Brogaard, Hendershott, and Riordan, 2019)
- Our reading: **we cannot ignore non-marketable orders** (submissions and updates) in evaluating toxicity

Why do we pay special attention to HFT?

- Main contributors to the order flow
  (SEC, 2014; Angel, Harris, and Spatt, 2015)

- Their orders and trades convey information
  (e.g., Brogaard et al., 2019; Chakrabarty et al., 2019)

- Trades-initiated by HFTs are inherently toxic
  - "HF-bandits" or "stale-quote snipers" generate adverse-selection costs in slow traders
    (e.g., Benos and Sagade, 2016; Baldauf and Mollner, 2019)
  - A higher presence of HF-bandits correlates with lower liquidity (e.g., van Kervel, 2015; Foucault, Kozhan, and Tham, 2017; Menkveld and Zoican, 2017)

Why do we pay special attention to HFT?

- HFT's flickering quotes may signal toxicity
  - Active risk management: HFTs actively update quotes in response to incoming news or upon detecting informed trading
    (e.g., Jovanovic and Menkveld, 2016)
  - They face lower adverse-selection costs
    (e.g., Hoffmann, 2014; Brogaard et al., 2015)
  - Their quotes incorporate information faster
    (e.g., Riordan and Storkenmaier, 2012)

The setting

❑ **The market:** NSE of India

- Fully electronic order-driven market (no DMM)
- 1300 listed companies
- Scarcely fragmented / no dark pools

	2018 WFE's rankings
Market Cap. ($US)	10th
Volume traded ($US)	14th
Number of trades	3rd
Speed of turnover	10th
Capital raised (IPOs)	5th
New listings	11th

The setting

- **AT/HFT:**
  - Prominent presence of ATs
  - Allowed since April 2008, widespread since January 2010 (colocation)
  - 95% of all messages, 43% of trading volume in 2013 (Nawn and Banerjee, 2019)

- **The sample:**

  NIFTY-50 index constituents (April 30, 2015) (60% of the total market value)

- **The sample period:**

  May to July 2015

The database

- Detailed trade and message files
- We can track each individual order's history overtime (each order has a unique code)
- **We can rebuild the whole LOB at any instant.**
- **Useful flags:**
  - "Order entry mode" or "AT" flag
  - "Client" flag (proprietary/agency)

Trader type identification

	“Client”	
“Order entry mode”	Proprietary	Agency
AT	High-frequency traders (**HFTs**)	Agency Algo. Traders (**AATs**)
Non-AT	Non-algorithmic traders (**NATs**)	

- HFTs are “professional traders acting in a proprietary capacity […]” characterized by “the use of extraordinarily high-speed and sophisticated computer programs for generating, routing, and executing orders […]” (SEC, 2010)

○ Important: message by message classification!

- Traders can switch their type

The Net Order Flow (NOF)

- **Summary metric:**
  - Computed over regular time intervals (or bars) (from 1-sec. to 300-sec.)

$$NOF_{i,b} = \frac{\text{Buying Pressure}_{\text{i,b}} - \text{Selling pressure}_{\text{i,b}}}{\text{Total pressure}_{\text{i,b}}}$$

  - The metric considers all sort of messages (submissions, cancellations, and revisions)
  - Why do we time-aggregate? We follow seminal work on MM, like the PIN or VPIN literature (Easley et al., 1996; Easley et al. 2012).

How do we compute the NOF

❑ Buying pressure

$$BP_{i,b} = V_{i,b}^{MB} + V_{i,b}^{LB} + V_{i,b}^{CS}$$

V^{MB}: volume of all marketable orders to buy submitted

V^{LB}: volume of non-marketable orders to buy submitted

V^{CS}: volume of standing limit orders **to sell** cancelled

❑ Selling pressure

$$SP_{i,b} = V_{i,b}^{MS} + V_{i,b}^{LS} + V_{i,b}^{CB}$$

** Order size revisions are treated as new submissions (cancellations) if increasing (decreasing).

How do we compute the NOF

❑ The metric

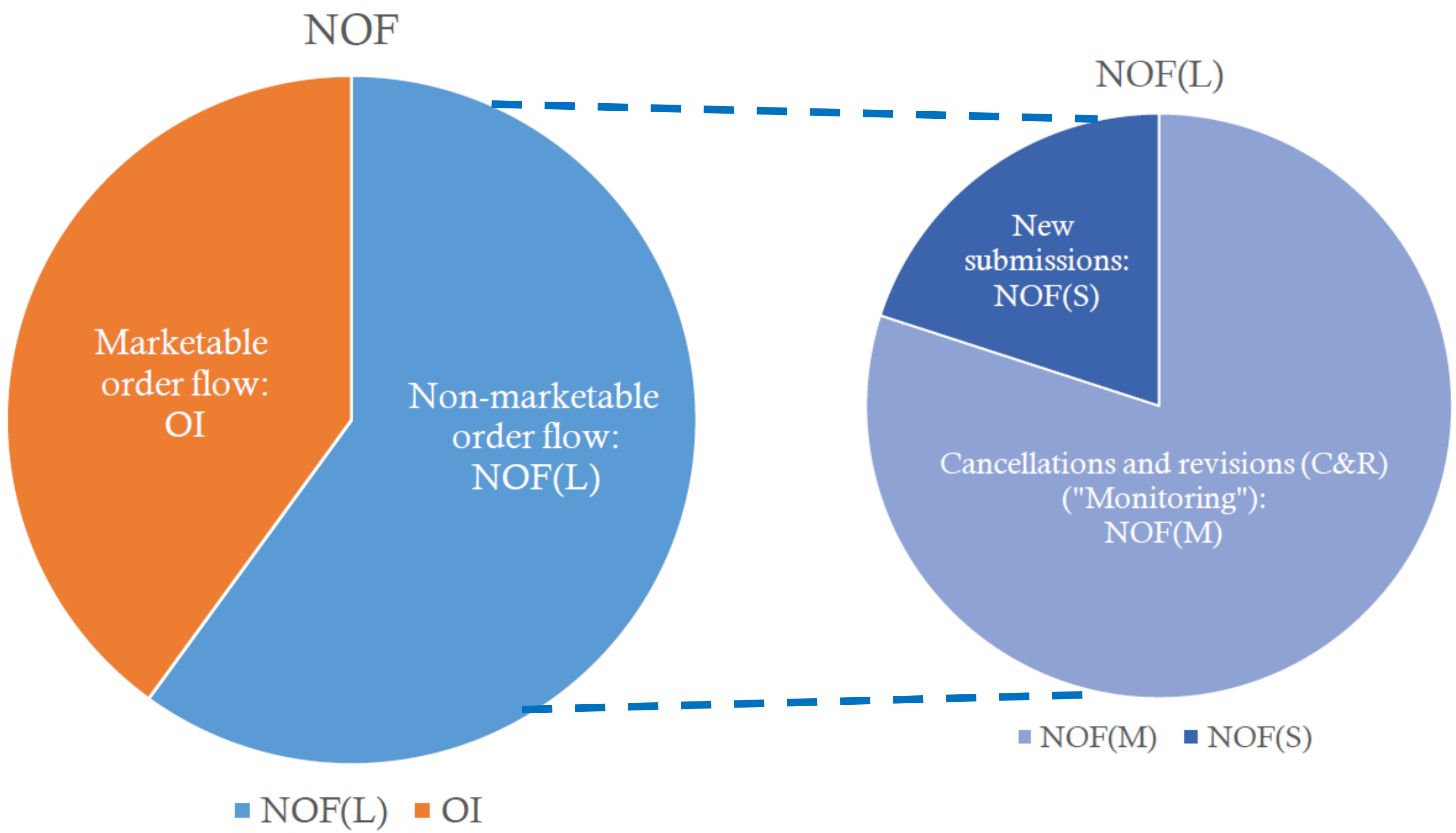
$$\boxed{NOF_{i,b} = \frac{BP_{i,b} - SP_{i,b}}{V_{i,b}^{OF}}}$$

$$V_{i,b}^{OF} = BP_{i,b} + SP_{i,b}$$

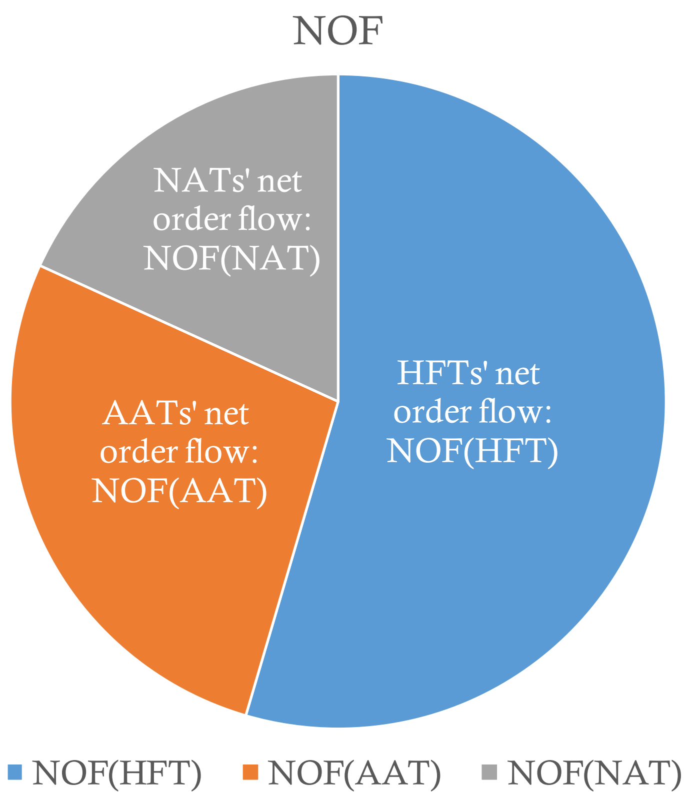
❑ Order imbalance (trade-initiator based)

$$OI_{i,b} = \frac{V_{i,b}^{TB} - V_{i,b}^{TS}}{V_{i,b}^{T}}$$

Message-type-based decomposition



Trader-type-based decomposition



The same for OI, NOF(L), NOF(M), and NOF(S)

General notation

❑ Parameters:

$$\boxed{NOF_{i,b}^{l}\left(tr,m\right)}$$

$$tr=\{a,HFT,AAT,NAT\}$$
$$m=\{a,L,S,M\}$$
$$l=\{a,1,5\}$$
$$b=\{1\text{s},\ 5\text{s},\ 60\text{s},\ 300\text{s}\}$$

"a" is the default case; to simplify notation,

$$NOF_{i,b}=NOF_{i,b}^{a}\left(a,a\right)$$

Informativeness (I)

The NOF-return relationship

- For the NOF to convey information, shocks to the NOF should …
  a) move prices in the same direction (e.g., Glosten and Milgrom, 1985)
  b) have a non-transient price impact (e.g., Hasbrouck, 1988, 1991)

- **First step:**
  - What is the relationship between stock returns and contemporaneous and lagged NOF (**<u>standardized per stock</u>**)?

Informativeness (I)

The NOF-return relationship

- **Approach:**
  - Pooled regression with standard errors clustered by stock.
  - Continuously-compound quote midpoint returns (*r*) (in bsp) and NOF computed over intraday bars of length *b* seconds

$$r_{i,b} = \alpha + \sum_{k=0}^{n} \beta_k' IM_{i,b-k} + \sum_{k=1}^{n} \gamma_k r_{i,b-k} + \alpha_O OP_{i,b} + \alpha_C CP_{i,b} + e_{i,b}$$

$$IM_{i,b} = \begin{cases} NOF_{i,b}^{l} \\ \left\{ NOF_{i,b}^{l}(L), OI_{i,b} \right\} \end{cases}$$

  - As Chordia and Subrahmanyam (2004) but with intraday intervals and all messages.

Informativeness (I)

The NOF-return relationship

Coef.	Time bar length (seconds) 1	5	60	300
Panel A: NOF[1]				
NOF(t)	0.52 ***	0.96 ***	4.16 ***	9.19 ***
NOF(t-1)	0.05 ***	0.16 ***	0.06	-0.69 ***
NOF(t-2)	0.01 ***	0.02 ***	-0.20 ***	-0.81 ***
NOF(t-3)	0.00 **	-0.02 ***	-0.18 ***	-0.53 ***
Adj-R^2	0.09	0.12	0.27	0.31
Panel B: NOF[5]				
NOF(t)	0.37 ***	0.76 ***	4.10 ***	9.53 ***
NOF(t-1)	0.07 ***	0.22 ***	0.38 ***	-0.14
NOF(t-2)	0.03 ***	0.08 ***	-0.09 ***	-0.50 ***
NOF(t-3)	0.01 ***	0.03 ***	-0.10 ***	-0.33 ***
Adj-R^2	0.05	0.08	0.26	0.35
Panel C: NOF				
NOF(t)	0.08 ***	0.28 ***	2.45 ***	5.98 ***
NOF(t-1)	0.07 ***	0.22 ***	0.65 ***	0.71 ***
NOF(t-2)	0.04 ***	0.10 ***	0.14 ***	-0.03
NOF(t-3)	0.02 ***	0.05 ***	0.06 ***	-0.10 **
Adj-R^2	0.01	0.02	0.10	0.14

***, **, * means statistically significant at the 1%, 5%, and 10% level

Findings:

- *NOF* is strongly contemporaneously correlated with returns for all *b* and all *l*.
- Noisier *NOF* metrics as *b* decreases and *l* increases.

Informativeness (I)

The NOF-return relationship

Coef.	Time bar length (seconds) 1	5	60	300
Panel A: NOF[1](L) and OI				
NOF(L)(b)	0.41 ***	0.73 ***	3.08 ***	7.11 ***
NOF(L)(b-1)	0.03 ***	0.11 ***	0.12 ***	-0.40 ***
NOF(L)(b-2)	0.00 **	0.01 ***	-0.13 ***	-0.60 ***
NOF(L)(b-3)	0.00 ***	-0.01 ***	-0.12 ***	-0.40 ***
OI(b)	0.45 ***	0.73 ***	2.85 ***	6.55 ***
OI(b-1)	0.02 ***	0.06 ***	-0.18 ***	-1.00 ***
OI(b-2)	0.00 ***	-0.02 ***	-0.21 ***	-0.62 ***
OI(b-3)	-0.01 ***	-0.03 ***	-0.18 ***	-0.36 ***
Adj-R^2	0.13	0.16	0.29	0.33
Panel B: NOF[5](L) and OI				
NOF(L)(b)	0.25 ***	0.54 ***	3.13 ***	7.63 ***
NOF(L)(b-1)	0.05 ***	0.17 ***	0.34 ***	-0.03
NOF(L)(b-2)	0.02 ***	0.06 ***	-0.04 **	-0.38 ***
NOF(L)(b-3)	0.01 ***	0.02 ***	-0.05 ***	-0.29 ***
OI(b)	0.47 ***	0.75 ***	2.75 ***	6.21 ***
OI(b-1)	0.02 ***	0.07 ***	-0.13 ***	-0.83 ***
OI(b-2)	0.00 *	-0.01 ***	-0.20 ***	-0.52 ***
OI(b-3)	-0.01 ***	-0.03 ***	-0.17 ***	-0.30 ***
Adj-R^2	0.10	0.13	0.30	0.37

***, **, * means statistically significant at the 1%, 5%, and 10% level

Findings:

- ***NOF(L)* is positively correlated with returns**, even after we control for the *OI*.
- As *b* increases, returns become more responsive to the *NOF(L)* than to the *OI*.

Informativeness (II)

Quote midpoint impact

- **2nd step:** Do shocks to NOF cause permanent of transient impacts on prices?
- **SVAR model** approach (e.g., Hasbrouck, 1991; O'Hara, Yao, and Ye, 2011)
- Simplest case: *NOF*

$$\begin{bmatrix} 1 & -\phi_0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} r_{i,b} \\ NOF^{l}_{i,b} \end{bmatrix} = \Psi\left(L\right) \begin{bmatrix} r_{i,b} \\ NOF^{l}_{i,b} \end{bmatrix} + \Lambda G_t + \begin{bmatrix} \varepsilon^{r}_{i,b} \\ \varepsilon^{NOF}_{i,b} \end{bmatrix}$$

- Estimated per stock-*b* case, # of lags by AIC
- The cumulative structural **IRF** of the SVAR provides is our estimate of the permanent price impact (in bsp) to a shock (1% increase) in *NOF*

Informativeness (II)

Quote midpoint impact

	Time bar length (seconds)			
Panel A: NOF[1]	1	5	60	300
IRF/σ(R)	**0.41**	**0.47** ***	**0.52** ***	**0.54**
(IQR)	(0.05)	(0.07)	(0.11)	(0.15)
Sig. IRF>0 (# stocks)	50	50	50	50
Panel B: NOF[5]				
IRF/σ(R)	**0.33**	**0.39** ***	**0.52** ***	**0.57** **
(IQR)	(0.06)	(0.09)	(0.13)	(0.10)
Sig. IRF>0 (# stocks)	50	50	50	50
Panel C: NOF				
IRF/σ(R)	**0.15**	**0.22** ***	**0.35** ***	**0.39**
(IQR)	(0.05)	(0.08)	(0.14)	(0.12)
Sig. IRF>0 (# stocks)	50	50	50	50

Bold format means statistically significant (at least) at the 5% level

***, **, * means statistically different than the preceding bar-size's statistic

Findings:

- **The *NOF* conveys information**: significant cross-sectional permanent price impact (also per stock)
- The impact increases with the bar size (b)
- Little gain in adding order flow beyond $l = 5$

Informativeness (II)

Quote midpoint impact

- Second case: *NOF(L)* and *OI*

$$\begin{bmatrix} 1 & -\phi_0^r & -\pi_0^r \\ 0 & 1 & -\pi_0^{NOF} \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{i,b} \\ NOF_{i,b}^l(L) \\ OI_{i,b} \end{bmatrix} = \Phi(L) \begin{bmatrix} r_{i,b} \\ NOF_{i,b}^l(L) \\ OI_{i,b} \end{bmatrix} + \Lambda G_t + \begin{bmatrix} \varepsilon_{i,b}^r \\ \varepsilon_{i,b}^{NOF} \\ \varepsilon_{i,b}^{OI} \end{bmatrix}$$

- The causality assumption between *NOF(L)* and *OI* is later reversed to obtain upper and lower bounds for each cumulative structural IRF

Informativeness (II)

Quote midpoint impact

	Time bar length (seconds)			
	1	5	60	300
	Shock to NOF(L)			
IRF/σ(R)	**0.29** ***	**0.35** ***	**0.42** ***	**0.46** ***
(IQR)	(0.04)	(0.04)	(0.10)	(0.14)
Sig. IRF>0 (# stocks)	50	50	50	50
	Shock to OI			
IRF/σ(R)	**0.23**	**0.32**	**0.30**	**0.33**
(IQR)	(0.06)	(0.07)	(0.05)	(0.08)
Sig. IRF>0 (# stocks)	50	50	50	50

Bold format means statistically significant (at least) at the 5% level
***, **, * means statistically different from the OI statistic

Findings (case *l=1*):

- Shocks to *NOF(L)* have a larger price impact than shocks to *OI*
- **Non-aggressive orders convey information beyond aggressive orders**
- Consistent with Brogaard et al. (2019).

Informativeness (III)

Conditional test I: Trader types

- **Trader types:** Are there differences in the informativeness of the NOF across trader types?
- The SVAR now looks like this:

$$\begin{bmatrix} 1 & -\phi_{h0}^{r} & -\phi_{a0}^{r} & -\phi_{n0}^{r} \\ 0 & 1 & -\phi_{a0}^{HFT} & -\phi_{n0}^{HFT} \\ 0 & 0 & 1 & -\phi_{n0}^{AAT} \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{i,b} \\ IM_{i,b}^{HFT} \\ IM_{i,b}^{AAT} \\ IM_{i,b}^{NAT} \end{bmatrix} = \Phi(L) \begin{bmatrix} r_{i,b} \\ IM_{i,b}^{HFT} \\ IM_{i,b}^{AAT} \\ IM_{i,b}^{NAT} \end{bmatrix} + \Lambda G_t + \begin{bmatrix} \varepsilon_{i,b}^{r} \\ \varepsilon_{i,b}^{HFT} \\ \varepsilon_{i,b}^{AAT} \\ \varepsilon_{i,b}^{NAT} \end{bmatrix}$$

- Same estimation procedure as in previous models.

Informativeness (III)

Conditional test I: Trader types

	Shock to NOF			
Bar length (seconds)	1	5	60	300
	HFTs			
IRF/σ(R)	**0.35**	**0.30**	**0.13**	**0.18**
(IQR)	(0.04)	(0.05)	(0.08)	(0.09)
Sig. IRF>0 (# stocks)	50	50	45	30
	AATs			
IRF/σ(R)	**0.24** ***	**0.27** ***	**0.43** ***	**0.50** ***
(IQR)	(0.04)	(0.04)	(0.14)	(0.17)
Sig. IRF>0 (# stocks)	50	50	50	50
	NATs			
IRF/σ(R)	**0.21** ***	**0.24** ***	**0.28** ***	**0.29** ***
(IQR)	(0.03)	(0.04)	(0.04)	(0.09)
Sig. IRF>0 (# stocks)	50	50	50	45

Bold format means statistically significant (at least) at the 5% level

***, **, * means statistically different than the HFTs' statistic

Findings (case *l*=*1*):

- The NOF conveys information for all trader types
- **For *b*≤5, the HFTs' NOF is more informative**, but loses information content vis-à-vis non-HFTs for larger bars.

Informativeness (III)

Conditional test I: Trader types

Bar length (seconds)	*Shock to OI* 1	5	60	300
	HFTs			
IRF/σ(R)	**0.31**	**0.29**	0.07	0.01
(IQR)	(0.06)	(0.06)	(0.04)	(0.05)
Sig. IRF>0 (# stocks)	50	50	23	0
	AATs			
IRF/σ(R)	**0.23** ***	**0.23** ***	**0.25** ***	**0.30** ***
(IQR)	(0.04)	(0.02)	(0.05)	(0.06)
Sig. IRF>0 (# stocks)	50	50	50	43
	NATs			
IRF/σ(R)	**0.17** ***	**0.15** ***	**0.14** ***	0.16 ***
(IQR)	(0.03)	(0.02)	(0.03)	(0.06)
Sig. IRF>0 (# stocks)	50	50	50	13

Bold format means statistically significant (at least) at the 5% level

***, **, * means statistically different than the HFTs' statistic

Findings (case *l*=1):

- For $b \leq 5$ (>5), the HFTs' *OI* is more informative than non-HFTs' *OI* (quickly loses information content).
- Consistent with HF-bandits trading on extremely short-lived informative signals (Hirschey, 2018).

Informativeness (III)

Conditional test I: Trader types

	Shock to NOF(L)			
Bar length (seconds)	1	5	60	300
	HFTs			
IRF/σ(R)	**0.16**	**0.15**	**0.12**	0.14
(IQR)	(0.02)	(0.03)	(0.08)	(0.10)
Sig. IRF>0 (# stocks)	50	50	39	13
	AATs			
IRF/σ(R)	**0.16**	**0.19**	**0.31** ***	**0.41** ***
(IQR)	(0.04)	(0.04)	(0.10)	(0.21)
Sig. IRF>0 (# stocks)	50	50	50	47
	NATs			
IRF/σ(R)	**0.18** ***	**0.22** ***	**0.22** ***	**0.26** ***
(IQR)	(0.02)	(0.03)	(0.04)	(0.07)
Sig. IRF>0 (# stocks)	50	50	50	44

Bold format means statistically significant (at least) at the 5% level
***, **, * means statistically different than the HFTs' statistic

Findings (case *l*=1):

- We do not find the HFTs' *NOF(L)* to be the most informative.
- Like their *OI*, the HFTs' *NOF(L)* losses information content quickly with time aggregation.

Informativeness (III)

Conditional test II: Message type

- **Message types:** Are cancellations and revisions (C&R) of limit orders informative?
- The SVAR has four equations in this case:

$$r_{i,t} \qquad \underset{\substack{\text{marketable}\\\text{orders}\\\text{(trades)}}}{OI_{i,t}} \qquad \underbrace{NOF_{i,t}(S)}_{\substack{\text{non-marketable}\\\text{limit order}\\\text{submissions}}} \qquad \underbrace{NOF_{i,t}(M)}_{\substack{\text{cancellations and revisions}\\\text{(C\&R)}}}$$

- Two conflicting views in the literature:

  H_0: [Net C&R convey information] C&R reflect HFTs refreshing quotes quickly on hard information (Jovanovic and Menkveld, 2016; Dahlström et al., 2018).

  H_1: [Net C&R imbalances are noisy] C&R reflect gaming and fraudulent practices by HFTs (Angel and McCabe, 2013; Eggington et al., 2016).

Informativeness (III)

Conditional test II: Message type

OI	Time bar length (seconds) 1	5	60	300
IRF/σ(R)	**0.32**	**0.33**	**0.32**	**0.35**
(IQR)	(0.05)	(0.07)	(0.05)	(0.09)
Sig. IRF>0 (# stocks)	50	50	50	50
NOF(S)				
IRF/σ(R)	**0.31** *	**0.34**	**0.39** ***	**0.43** ***
(IQR)	(0.06)	(0.05)	(0.07)	(0.15)
Sig. IRF>0 (# stocks)	50	50	50	50
NOF(M)				
IRF/σ(R)	**0.21** ***	**0.20** ***	**0.23** ***	**0.28** ***
(IQR)	(0.03)	(0.03)	(0.12)	(0.16)
Sig. IRF>0 (# stocks)	50	50	50	40

Bold format means statistically significant (at least) at the 5% level

***, **, * means statistically different than the OI statistic

Findings:

- Not as informative as other components but, still, C&R convey information beyond submissions.
- Flickering quotes are more likely to reflect active monitoring than manipulative practices.

Order flow toxicity

- Which NOF components can work as ***advanced*** indicators of order flow toxicity?
- Toxicity is inversely related to liquidity, so …
  (e.g., Glosten and Milgrom, 1985; Kyle, 1985)
- … we use high-frequency metrics of liquidity computed over regular time bars to evaluate which components of NOF can ***anticipate*** liquidity shortfalls.

- Liquidity metrics:
  - <u>Immediacy costs:</u>
    - ***RQS***: Time-weighted average relative bid-ask spread

$$RQS_{i,b}=\sum_{k=1}^{n_b}\left[\frac{a_{i,k}-b_{i,k}}{0.5\left(a_{i,k}+b_{i,k}\right)}\right]\times\frac{t_{k,k+1}}{\sum_{k=1}^{n_b}t_{k,k+1}}$$

    - ***RES***: Volume-weighted average relative effective spread

$$RES_{i,b}=\sum_{j=1}^{z_b}\left[2\frac{\left(p_{i,j}-q_{i,j}\right)}{q_{i,j}}x_{i,j}\right]\times\frac{v_j}{\sum_{j=1}^{z_b}v_j}$$

- Liquidity metrics:
  - Depth / price impact:
    - ***AIR***: Amihud's (2002) illiquidity ratio (x10^6) – inverse metric of liquidity

$$AIR_{i,b} = \frac{\left| \ln\left(q_{i,b}^{last}\right) - \ln\left(q_{i,b}^{first}\right) \right|}{\sum_{j=1}^{z_b} v_j}$$

- Control variables:
  - Log of the volume in shares (V); standard deviation of the quote midpoint return (σ); dummies for the first and last trading hours (OP, CP)

Order flow toxicity
Methodological approach

$$ILLIQ_{i,b} = \alpha_0 + \alpha_1 ILLIQ_{i,b-1} + \beta' \left| IM_{i,b-1} \right| +$$
$$+\delta_1 V_{i,b-1} + \delta_2 \sigma(\Delta q)_{i,b-1} + \lambda_O OP_{i,b} + \lambda_C CP_{i,b} + e_{i,b}$$

- **H_0: $\boldsymbol{\beta}$>0**
- We estimate the model per stock and bar size (*b*) and report average estimated coefficient and aggregated t-statistics.
  (as Chordia, Roll, and Subrahmanyam, 2005)

Order flow toxicity

Aggregated NOF (case *l*=*l*)

Dependent variable	First model NOF[1](b) 1s		First model NOF[1](b) 5s		Second model NOF[1](L)(b) 1s		Second model NOF[1](L)(b) 5s		Second model OI(b) 1s		Second model OI(b) 5s	
(a) RQS (b+1)												
coef*100	-7.29	***	-4.32	***	-13.77	***	-7.60	***	-0.47		0.35	
t-test	-14.39		-6.59		-24.83		-12.55		-1.26		1.17	
Sig.>0 at 1% (5%)	0 (0)		3 (5)		0 (0)		0 (0)		9 (11)		18 (22)	
(b) RES (b+1)												
coef*100	-26.61	***	-17.00	***	-31.83	***	-20.52	***	-5.73	***	-4.08	***
t-test	-40.33		-21.74		-43.59		-26.21		-5.82		-3.49	
Sig.>0 at 1% (5%)	0 (0)		0 (0)		0 (0)		0 (0)		4 (5)		4 (5)	
(c) AIR (b+1)												
coef*100	-26.45	***	-17.88	***	-36.72	***	-25.85	***	14.65	***	17.68	***
t-test	-15.51		-12.67		-20.68		-19.42		7.47		11.93	
Sig.>0 at 1% (5%)	0 (0)		0 (0)		0 (0)		0 (0)		39 (41)		49 (49)	

***, **, * means statistically significant at the 1%, 5%, and 10% level, respectively

Findings:

- NOF cannot be used to build effective advanced indicators of order flow toxicity.
- OI alone does not work either (as in Easley et al., 2012).

Order flow toxicity

NOF by trader type (case l=1)

Dependent variable	HFTs' NOF[1] 1s bars	HFTs' NOF[1] 5s bars	AATs' NOF[1] 1s bars	AATs' NOF[1] 5s bars	NATs' NOF[1] 1s bars	NATs' NOF[1] 5s bars
(a) RQS (b+1)						
coef*100	7.44 ***	5.24 ***	-3.04 ***	-3.43 ***	-8.58 ***	-4.28 ***
t-test	25.79	13.75	-7.28	-5.68	-19.05	-5.84
Sig.>0 at 1% (5%)	49 (49)	45 (46)	1 (1)	1 (2)	0 (0)	2 (3)
(b) RES (b+1)						
coef*100	13.23 ***	8.35 ***	-7.13 ***	-10.26 ***	-13.33 ***	-9.98 ***
t-test	34.04	15.88	-12.84	-13.14	-21.47	-11.01
Sig.>0 at 1% (5%)	49 (49)	44 (44)	3 (3)	0 (0)	0 (0)	0 (0)
(c) AIR (b+1)						
coef*100	24.10 ***	14.72 ***	-8.21 ***	-10.93 ***	-12.14 ***	-2.09
t-test	20.90	12.93	-5.89	-7.75	-5.66	0.58
Sig.>0 at 1% (5%)	49 (49)	46 (47)	2 (2)	0 (0)	2 (2)	14 (15)

***, **, * means statistically significant at the 1%, 5%, and 10% level, respectively

Findings:

- **Only the HFTs' NOF signals toxicity**
- With l=5, only true for b=1 →Toxicity is better captured by updates in the market quotes due to the HFTs' order flow.

Order flow toxicity

NOF components by trader type (case *l*=*1*, *b*=1)

Dependent variable	HFTs' NOF[1](L)		HFTs' OI		AATs' NOF[1](L)		AATs' OI		NATs' NOF[1](L)		NATs' OI	
(a) RQS (b+1)												
coef*100	4.57	***	9.18	***	-7.60	***	4.18	***	-13.89	***	1.60	***
t-test	16.97		29.27		-19.75		8.96		-40.27		3.56	
Sig.>0 at 1% (5%)	46 (46)		50 (50)		0 (0)		49 (49)		0 (0)		32 (36)	
(b) RES (b+1)												
coef*100	8.51	***	19.64	***	-11.55	***	5.83	***	-9.24	***	-8.93	***
t-test	22.63		46.03		-22.19		8.69		-18.93		-14.04	
Sig.>0 at 1% (5%)	44 (44)		50 (50)		0 (0)		46 (47)		0 (0)		0 (0)	
(c) AIR (b+1)												
coef*100	19.48	***	19.13	***	-12.82	***	6.31		-25.30	***	4.63	
t-test	18.43		12.26		-11.80		1.34		-19.94		0.10	
Sig.>0 at 1% (5%)	44 (46)		49 (50)		2 (2)		18 (21)		1 (1)		11 (13)	

***, **, * means statistically significant at the 1%, 5%, and 10% level, respectively

Findings:

- **Only the HFTs' NOF(L) signals toxicity**
- Adding non-marketable limit orders beyond the best quotes (*l*=*5*), weakens the findings.

Order flow toxicity

NOF by trader type and message type (case *l*=*1*, *b*=1)

Panel A: HFTs	HFTs'			AATs'			NATs'		
Dependent variable	NOF(S)	NOF(M)	OI	NOF(S)	NOF(M)	OI	NOF(S)	NOF(M)	OI
(a) RQS (b+1)									
coef*100	4.10 ***	6.33 ***	8.52 ***	-5.23 ***	0.87	4.14 ***	-13.01 ***	-2.08 ***	1.81 ***
t-test	14.77	21.12	26.66	-16.42	1.48	8.96	-38.23	-9.43	3.90
Sig.>0 at 1% (5%)	47(48)	50 (50)	50 (50)	3 (4)	24 (30)	49 (49)	0 (0)	1 (1)	33 (36)
(b) RES (b+1)									
coef*100	5.51 ***	12.33 ***	18.24 ***	-6.20 ***	4.32 ***	5.35 ***	-8.12 ***	0.32	-8.61 ***
t-test	14.67	30.12	42.23	-14.51	9.17	8.03	-16.91	0.84	-13.70
Sig.>0 at 1% (5%)	43 (43)	50 (50)	50 (50)	6 (6)	42 (44)	44 (47)	0 (0)	16 (19)	0 (0)
(c) AIR (b+1)									
coef*100	19.40 ***	19.54 ***	16.21 ***	-6.45 ***	3.91	5.76	-22.26 ***	-3.70 ***	4.93
t-test	16.34	19.29	9.77	-8.47	0.93	1.16	-18.34	-5.70	0.20
Sig.>0 at 1% (5%)	48 (49)	48 (48)	46 (46)	4 (4)	17 (18)	18 (20)	1 (1)	1 (2)	12 (12)

***, **, * means statistically significant at the 1%, 5%, and 10% level, respectively

Finding:

- Rather than impairing the signaling capacity of the HFTs' NOF, their C&R contribute to it.
- Again, high rates of C&R are consistent with active risk management by HFTs.

To take away

At the intraday level:

- The net flow of non-marketable limit orders conveys information, often more than the net flow of marketable orders (OI)
  (in line with Brogaard et al., 2019)
- The informativeness of the HFTs' NOF declines with time aggregation
  (HFTs trading on short-lived signals – e.g., Hirschey, 2018)
- C&R of orders (mostly attributable to HFTs) convey information beyond new submissions
  (HFTs active risk management, refreshing their quotes quickly on hard information – e.g., Jovanovic and Menkveld, 2016)
- Only the HFTs' NOF (at or near the best quotes) works as a leading indicator of order flow toxicity
  (the overall NOF/OI fails – as Easley et al., 2016)

Implications

- Practical implications:
  - "We" should track the HFTs' NOF to develop effective leading indicators of toxicity.
  - Market authorities could then use such indicators to design forward-looking circuit breaker mechanisms that could effectively prevent short-term liquidity drops (e.g., Abad, Massot, and Pascual, 2018)
  - Existing toxicity metrics such as PIN (Easley et al., 1996) and VPIN (Easley et al., 2012) could improve their performance by using the proper input.

More to come

Work in progress:

Ex-ante Highly toxic periods:
earnings announcements
(e.g., Bhattacharya et al. 2018)

Thank you!