Fast Aggressive Trading

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Motivation I

Recent debate over the merits of high-frequency computer-generated trading and its effects on stock (and other) market quality:

- **Regulators and the buy side:** of the view that action needs to be taken
  - CGT makes markets less robust
    - US Equity Flash Crash: May 2010, DJIA down 9% and then up roughly 9% in minutes.
    - Subsequent flash events in UK stocks, currencies, treasuries .....
  - CGT allows fast traders to exploit and impose costs upon slow traders
- **Academic evidence:** often portrays CGT as helpful to markets
  - CGT leads to higher liquidity
  - CGT brings information to market quicker, improves efficiency.
  - CGT does not lead to greater volatility in markets.

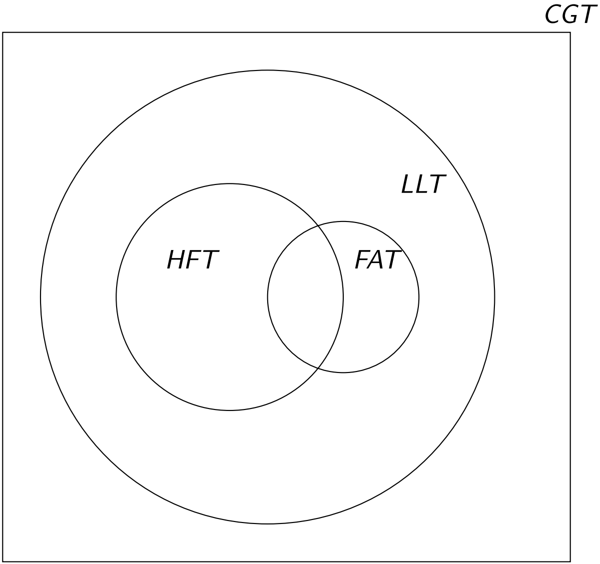
Motivation II

Our goal: to empirically evaluate some of these claims regarding CGT using public data from an exchange (the London Stock Exchange)

The main challenge: to characterise activity as to whether it comes from a fast trading system or not.

- We define a particular form of CGT - fast aggressive trading (FAT)
  - A trade is classified as fast if an aggressive trader hits a standing limit order that is fewer than 50 ms old.
- Our FAT trades are executions which are most likely to have come from an institution with access to a very fast trading system.
- We focus on FAT as:
  - Fast consumers of liquidity are sometimes the bad guys in the policy debate
  - FAT makes up a significant proportion of trading activity in our dataset
  - It's something we can (roughly) measure using publicly available data
- **Empirical work:** compare the features of and market effects of FAT activity versus all other trading activity.

Fast aggressive trading



Our contribution

Fast Aggressive Trading:

- Use data from the London Stock Exchange in 2008/09
- Data driven method to determine trades that are from low latency systems
- Compare high and low latency liquidity consuming trades
  - Describe them: how frequent are they, where do they execute?
  - Measure their execution quality
  - Measure their price impacts
  - Describe average market behaviour around them. Manipulation?

Punchlines: We find that

- FAT appear to look for both depth and bargain prices
- FAT reduces trading costs relative to slower aggressive trades, by 10-15%
- FAT have zero information content, unlike slow trades
- No strong evidence that FAT is manipulative

Regulatory noises I

Martin Wheatley (FCA):
"So, its important to be clear sighted here about the possibilities of HFT. Even if its also an imperative to appreciate the potential risks as we move things forward...there is the inevitable debate around the impact of speed on market fairness, with all those familiar concerns around unfair advantage for the few over the many as well as nervousness around conflicts of interests."

MiFID 2 approach to HFT being thrashed out by ESMA. First, they are attempting to define HFT:
"Three factors would be taken into account: the distance between a trading firm's server and a venue's matching engine; the volume of data capable of being transferred through the firm's connection per second; and a trading frequency of two messages per second over the entire trading day."

This is regulation based on data and processing speed and intensity.

Regulatory noises II

Eric Schneiderman (NY Attorney General):

"We know that high-frequency traders are uniquely able to take advantage of co-location, but there are other services also offered by the exchanges to make it easier for them to take advantage of this very, very slight edge. They supply extra bandwidth, special high-speed switches and ultra-fast connection cables to high-frequency traders, so they can get, and receive, information at the exchanges' data centers even faster. These valuable advantages, once again, give them a leg up on the rest of the market."

"They benefit themselves, clearly, by making billions of dollars per year, and the exchanges make money on the specialized services and co-location they sell to high-frequency traders. But this happens at the expense of the rest of the investing public who truly contribute to our capital markets."

Selective literature review I

Theoretical work, favourable to CGT

- Gerig and Michayluk (2010):
  - Add an automated market-maker that can trade multiple securities and process information from related markets to a standard sequential trade model
  - Leads to greater informational efficiency, larger volumes and lower trading costs for liquidity traders
- Martinez and Rosu (2011):
  - CGT are aggressive traders who exploit a speed advantage
  - Information is then more quickly reflected in prices
- Menkveld and Jovanovic (2012):
  - CGT market makers can reduce adverse selection problems in markets
  - Can improve social welfare in worlds where adverse selection is a problem
  - Can also lower welfare if adverse selection was missing in the first place

Selective literature review II

Theoretical work, unfavourable to CGT

- Cartea and Penalva (2011):
  - Parasitic CGT, trade in between retail traders and professional dealers
  - Retail traders pay higher costs as CGT extract a surplus from trading activity
- Jarrow and Protter (2011):
  - In aggregate, the activity of CGTs trading on correlated signals can create mis-pricings in securities, increase volatility and damage the welfare of non-CGT

Selective literature review III

Applied work (note switch to HFT)

- Hendershott and Riordan (2011):
  - HFT in DAX stocks contributes to price discovery, both through liquidity supply and demand
- Menkveld (2012):
  - Studies the entry of a single HFT player to the Dutch stock market
  - Shows that this new player behaves as a market-maker, with most of its trades passive and so contributing to lower bid-ask spreads
- Brogaard, Hendershott and Riordan (2013):
  - Decompose prices into permanent and transitory components using a state-space framework
  - Show that liquidity-consuming HFT reduce temporary mispricing and contribute to permanent component of price

Selective literature review IV

Data-based identification of computer-generated activity

- Hendershott, Jones and Menkveld (2011):
  - Measure the extent of algo trading using message traffic on the NYSE
  - AT leads to more informative price quotes, increased liquidity and smaller asymmetric information problems
- Hasbrouck and Saar (2013):
  - Define sequences of order events likely to be algo-generated.
  - Times of high algo activity are also those with low spreads, high depth and low volatility.
- Cartea, Payne, Penalva, Tapia (2014):
  - Measure computer-generated activity by order post-cancel pairs (cancel of an order posted less than 100ms before)
  - Times of high computer-generated activity associated with larger spreads and lower depth.

What we do: identifying low latency, liquidity-consuming trades

Our data:

- Full message level data from the LSE on 300+ stocks in 2008H2
- Drop stocks subject to major corporate actions and short-selling bans
- Drop the first and last five minutes of the trading day.

Identifying Fast Aggressive Trades

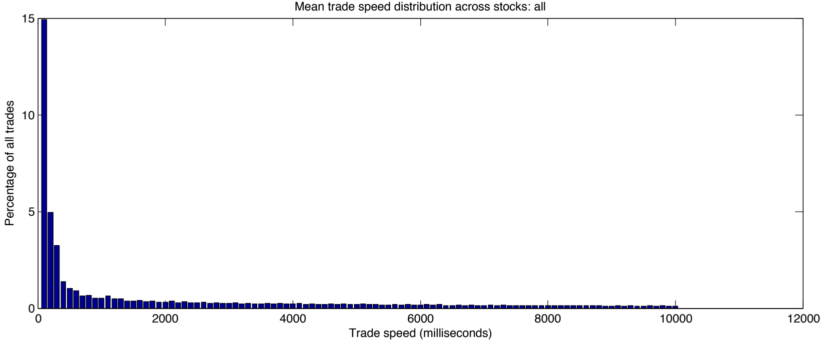
- A marketable order is flagged as Fast if it executes against a standing limit order that is less than Kms old
- We set K to 50ms in results presented
- We have varied K between 100ms and 25ms

Obviously our identification scheme is subject to error

- Two orders from slow traders may enter simultaneously and match by chance
- A fast trader may decide to hit a limit order that is minutes old if other market conditions have changed so that the standing limit order is mis-priced

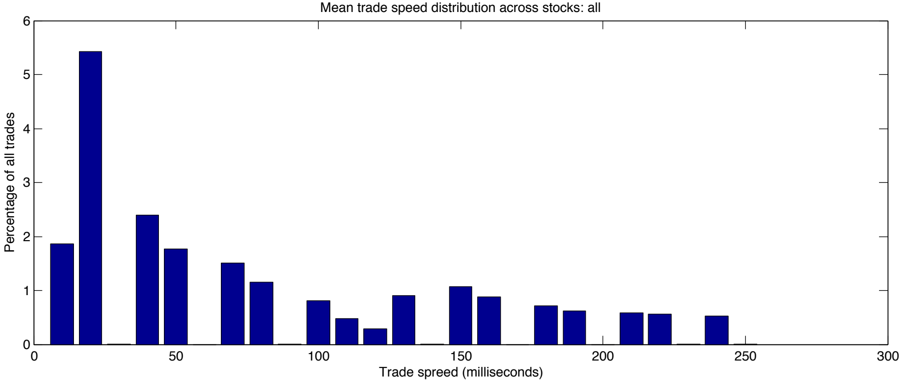
Time to execution by ADV

Figure : Time from order entry to execution: sorted by ADV: 0 - 10,000ms

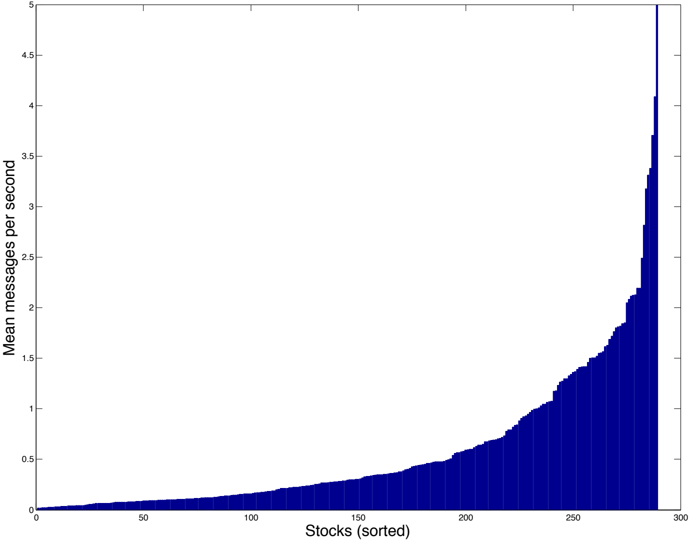


Time to execution by ADV

Figure : Time from order entry to execution: sorted by ADV: 0 - 250ms



Mean message traffic per second (by stock, sorted)



What we don't and can't do

Shortcomings:

- We cannot say anything about the firm submitting orders, as we don't have that data
- We don't say anything about HFT specifically, just FAT
- We do not give any commentary about computer-generated liquidity supply. We do not measure this. We could try to, but that's another paper

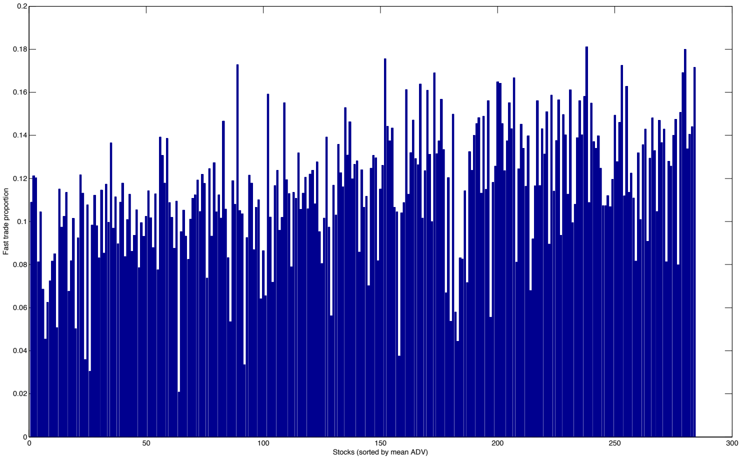
How much FAT?

Table : Summary statistics for market data: stocks grouped into five ADV groups

	Spread	Trade Size	Trades	Volume	FAT25	FAT50	FAT75	FAT100
Q1	48.87	3.18	129.31	493.13	6.05	9.45	10.64	11.96
Q2	36.55	3.87	314.22	1508.81	6.54	10.45	11.88	13.67
Q3	26.45	5.43	569.22	3718.71	7.60	11.91	13.56	15.75
Q4	26.68	7.46	1130.63	10605.02	7.89	12.31	13.95	16.14
Q5	16.56	12.69	2424.54	42530.64	8.38	13.15	14.81	17.15

Notes: each row gives equally weighted trimmed mean values of data for a quintile of stocks, grouped by ADV. Q1 is the lowest and Q5 the highest ADV portfolios.

Cross section FAT proportions (50ms)



Fast activity characteristics

Table : Fast versus slow trade characteristics: fast trade cutoff 50ms

	Fast propn (total)		Trade size		Buy propn		Flow A/C	
	Trades	Volume	Fast	Slow	Fast	Slow	Fast	Slow
Q1	0.095	0.106	3.573	3.144	0.468	0.504	0.311	0.340
Q2	0.105	0.117	4.322	3.817	0.497	0.508	0.279	0.346
Q3	0.119	0.125	5.736	5.394	0.499	0.501	0.251	0.324
Q4	0.123	0.121	7.391	7.478	0.498	0.501	0.230	0.324
Q5	0.132	0.124	12.047	12.804	0.501	0.501	0.215	0.317

Analysis 1: order entry points and execution probabilities

Simple counts of orders, where they enter the order book and how likely they are to execute against fast and slow aggressive traders;

- **Limit order entries:** about 40% behind the BBO, about 40% at the BBO and 20% improve the BBO.
- **Execution probabilities:** around 20% for limit orders submitted at best, rising to close to than 50% for limit orders placed at the midquote.
- **FAT Execution probabilities:** 5% for limit orders submitted at best, and more than 25% for limit orders improving the midquote.
- **FAT frequency:** around 45% of FAT trades hit the best (looking for depth) and 55% hit orders that improved the spread (bargain hunters).

Analysis 2: execution costs of fast and slow traders

How well do fast and slow trades execute? Measure gains generated by speed in being first to exploit favourable trading opportunities as they appear.

Measuring execution quality

1. Execution cost of each trade ($z_{i,t}$) is measured as the difference in basis points, between the trade price and the mid-price just prior to execution i.e. effective spread
2. This is, by construction, positive (negative) for a buy (sell) so the sign is changed for a sell
3. Regress effective spreads on a constant, a Fast trade dummy and controls for trade size, recent stock volume and recent realized stock volatility;

$$z_{i,t} = \beta_{0,i} + \beta_{1,i} Fast_{i,t} + \beta_{2,i} Q_{i,t} + \beta_{3,i} Volume_{i,t} + \beta_{4,i} \sigma_{i,t} + u_{i,t}$$

Estimation: panel FE regressions by ADV quintile. Mean FE gives cost of a slow trade, the Fast coefficient the incremental cost of being FAT

Analysis 2: execution cost results I

Table : Effective spread: fixed effect panel regressions

	Q1	Q2	Q3	Q4	Q5
Fast	-5.382	-3.136	-1.913	-0.955	-0.278
	[-89.522]	[-104.289]	[-103.601]	[-87.083]	[-76.147]
Size	0.555	0.189	0.133	0.065	0.123
	[26.652]	[19.292]	[7.560]	[6.097]	[56.158]
Volatility	0.121	0.117	0.110	0.104	0.074
	[81.072]	[135.404]	[120.347]	[147.970]	[139.998]
Volume	-4.742	-0.772	-487.497	-380.550	-1175.346
	[-2.790]	[-2.703]	[-4.194]	[-3.054]	[-17.082]
Mean FE	26.618	21.510	16.223	17.378	9.612
R^2	0.088	0.106	0.118	0.148	0.125

Analysis 2: execution cost results II

Key result: Being fast saves between 3 and 20% of trading costs compared to a slow trader. Execution cost savings decrease monotonically with the fast trade cutoff time assumed and as stock liquidity increases

Analysis 2: execution costs - conditioning on volume I

Panel A: high volume quartile

	Q1	Q2	Q3	Q4	Q5
Fast	-3.717	-1.938	-0.852	-0.459	-0.126
	[-29.888]	[-32.117]	[-25.062]	[-28.082]	[-23.640]
Mean FE	26.083	20.515	15.201	15.943	9.055
R^2	0.093	0.120	0.124	0.144	0.131

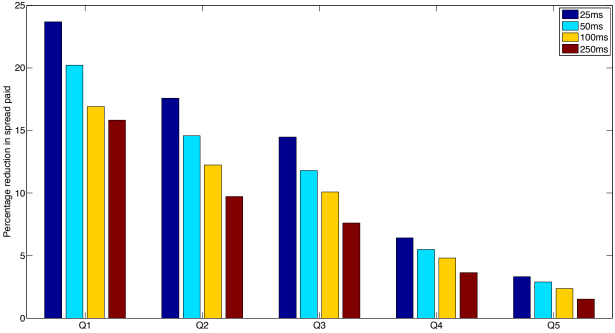
Panel B: low volume quartile

	Q1	Q2	Q3	Q4	Q5
Fast	-6.636	-4.138	-2.778	-1.272	-0.407
	[-63.706]	[-75.511]	[-88.898]	[-59.165]	[-61.514]
Mean FE	27.116	22.381	17.191	18.323	9.843
R^2	0.087	0.093	0.102	0.129	0.085

Analysis 2: execution costs - conditioning on volume II

Key result: Being fast saves more in less active periods. Savings for the least active stocks are 24% in low volume periods, 14% in high volume periods (4% and 1.5% for most active stocks)

Effective spread savings across fast trade cutoffs



Analysis 3: information contents of fast and slow trades

Question: Should counter-parties worry that they're getting adversely selected when they execute against FATs?

Measuring information content: regression analysis

$$r_{t-j,t+k} = \alpha + \beta_1 FAT_t + \beta_2 TradeSize_t + \beta_3 \sigma_t + \beta_4 Volume_t + \epsilon_t$$

- $r_{t-j,t+k}$ is the change in the opposite side quote from j trades before to k trades after the transaction of interest (with sign swapped if the current trade is a sell)
- FAT_t is a dummy for fast aggressive trades
- Controls for trade size, volatility and volume, all de-meaned
- Constant gives the price impact of a non-FAT trade over the relevant horizon and β_1 gives the incremental price impact of a FAT trade.

Note: focus on the opposite side quote so price impacts are not confounded by the effects of new orders that generate our FATs

Analysis 3: information content results

Table : Tick time price impact regressions: 0 to 10 quotes, Opposite side quote returns

	Q1	Q2	Q3	Q4	Q5
Constant	3.299	5.490	5.586	5.283	3.676
	[79.961]	[263.029]	[411.041]	[596.234]	[898.043]
Fast	-0.862	-0.813	-0.459	-0.595	-0.416
	[-8.903]	[-16.044]	[-13.678]	[-31.693]	[-44.968]
Size	1.436	0.891	0.622	0.729	0.479
	[54.022]	[68.989]	[77.909]	[132.169]	[222.630]
Volatility	1.892	1.218	2.201	1.579	3.142
	[6.980]	[5.949]	[6.999]	[11.783]	[14.147]
Volume	0.028	0.013	-0.132	0.197	-0.309
	[3.198]	[1.118]	[-4.887]	[5.389]	[-6.088]
R^2	0.006	0.004	0.005	0.007	0.010

Key Result: If anything, FATs have smaller impacts than other trades

Analysis 3: information content results I

Table : Tick time price impact regressions: -10 to 10 quotes, Opposite side quote returns

	Q1	Q2	Q3	Q4	Q5
Constant	5.791	6.895	6.620	6.559	4.253
	[111.021]	[260.000]	[402.278]	[564.296]	[867.314]
Fast	-8.978	-8.759	-7.346	-6.026	-4.075
	[-73.485]	[-137.543]	[-190.146]	[-245.568]	[-377.971]
Size	1.841	1.371	1.113	1.200	0.822
	[56.904]	[86.891]	[112.631]	[168.990]	[297.800]
Volatility	1.977	1.048	1.367	1.899	2.689
	[8.286]	[6.193]	[7.263]	[11.532]	[12.595]
Volume	-0.038	-0.208	-0.641	-0.509	-1.718
	[-3.224]	[-11.760]	[-19.790]	[-9.777]	[-26.417]
R^2	0.010	0.013	0.016	0.016	0.022

Analysis 3: information content results II

Key Result:

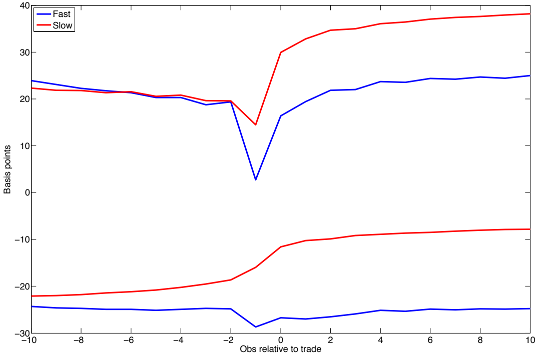
- Slow trades have strong positive impact, FATs have zero impact
- Robustness: this result holds across stocks and across activity subsamples within stocks.

Robustness:

- Confirmed these results using other empirical techniques (e.g. the Kalman Filtering PTD approach).

Analysis 3: graphical summary of key results

Figure : Bid-ask quotes around fast (blue) and slow (red) transactions



Notes: Time (horizontal axis) is measured in quote time. The mid-price is normalized to zero at quote -10. The quotes prevailing at time 0 are those immediately after the trade has executed.

Analysis 3: information content results

This lack of information content is important

- FAT take advantage of very good prices
- But their trades don't move the equilibrium price if you compare the price 10 quotes before to 10 quotes after
- Again, seems like FAT and their counterparties share the bid-ask spread between them
  - I improve the bid, posting at the mid, looking for quick execution and I get it
  - The price moves back to the previous best bid meaning that my execution cost equals the price improvement I gave (i.e. half the spread)
  - My FAT counterparty's execution cost was also half the spread

Of course, one can argue over definitions here. What's the correct horizon over which to measure price impact/information content?

Key result: No great problem of adverse selection here at all

Analysis 4: manipulation

Question: Can we uncover evidence that the fast guys are conning slow traders into offering price improvement and then hitting them?

- Look for evidence of a layering or spoofing strategy:
  - A fast buyer adds a lot of liquidity at or behind the best offer
  - This gives impression of downwards price pressure
  - This induces a price improving limit order (i.e. a limit sell with price lower than the previous best)
  - FAT hits the offer at the improved price ...
  - ... and quickly removes all the fake offers
- **Analysis:**
  - Approach 1: identify a FAT and look for spoofing around this event
  - Approach 2: identify spoofing events and see if probability of FAT rises after them.

Analysis 4: manipulation

Approach 1: Around a manipulative FAT buy we expect to see:

- Increased depth on offer side close to best before the FAT
- FAT executes against a bargain limit order
- Decreased depth on offer after FAT as spoof orders are pulled

We observe:

- Small and insignificant additional depth at top 5 offer prices before the FAT
- Small and insignificant decreases in depth at the best
- FAT executes (by construction)
- More depth at top 5/best after the execution

All inconsistent with spoofing manipulation

Bid depth: increases before FAT buys and decrease afterwards
This result is much stronger, but the opposite of that predicted by manipulation

Analysis 4: manipulation

Approach 2:

- Identify a buy side spoofing event if net quote activity (new limit buys minus new limit sells) in a one second interval is greater than five times its stock-specific standard deviation
- Sell side spoofing identified if net quote activity is minus five times std dev
- Run regressions like

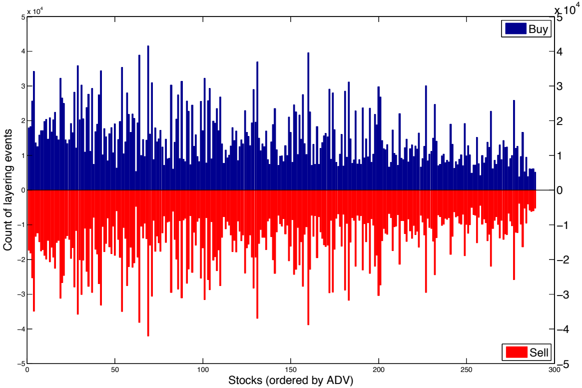
$$\begin{aligned} BuyFast_{it} =& \alpha + \beta_1 BuyFast_{i,t-1} + \beta_2 SellFast_{i,t-1} + \beta_3 BuySlow_{i,t-1} + \beta_4 SellSlow_{i,t-1} \\ &+ \beta_5 ret_{i,t-1} + \beta_6 spread_{i,t-1} + \beta_7 q_{i,t-1} + \beta_8 netq_{i,t-1} \\ &+ \beta_9 BuySpoof_{i,t-1} + \beta_{10} SellSpoof_{i,t-1} + \epsilon_t \end{aligned}$$

We expect:

- Fast Buys should be positively related to sell-side spoofing in $t-1$
- Fast Sells should be positively related to buy-side spoofing in $t-1$

Analysis 4: manipulation

Figure : Spoofing event counts by firms, ordered by increasing ADV



On average, 20,000 spoofing events per stock equivalent to 0.5% of observations

Analysis 4: manipulation

- **For large stocks (Q5):**
  - Fast buys (sells): Sell (buy) spoofing coefficient is larger than buy (sell) coefficient. All are significantly positive
  - The number of FAT observed after spoofing is more than double the number observed in the absence of spoofing
  - But the change in probability of seeing a FAT is small (an increase of 0.5%)
- **For smaller stocks (Q1-Q3):**
  - Fast buys and fast sell coefficients both positive and significant, but small.
  - Thus fast trading occurs slightly more in more unbalanced markets - no spoofing.

Overall: Slightly more FAT after spoofing (in large stocks), but economic magnitude of effect is small. Most FAT occurs without spoofing.

Conclusions: what have we learned?

1. Fast aggressive trading was around 10% of trading activity in London
2. FAT picks off bargain prices but also executes at the best, looking for depth
3. Fast traders execute significantly better than slow traders, on average
    - Effect larger in for faster traders, in less liquid stocks and at less liquid times
4. Fast, computer-based traders bring essentially no information to market
    - This contrasts strongly with the literature looking at US HFTs
    - And suggests they impose no adverse selection costs

An interpretation: FAT is fairly innocuous

- Our fast traders are technologically efficient uninformed traders
- And they may be trading on your behalf (via execution algos at big banks)
- No evidence of FAT being manipulative.
- So should low-latency trading be the focus of regulatory attention?
- Should we be regulating speed or strategy?