

# Financial Markets Microstructure

## Lecture 16

Algo-trading, High-Frequency Trading, and Blockchain

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## Previously on FMM

**Corporate governance** has a lot of connection to company's financial market performance

- access to capital affected by liq-ty
- liq-ty and corporate control are somewhat antithetical
- firm can use stock price as market's feedback on its decisions or as benchmark of CEO performance
- firms have some ways in which they can improve the liquidity of their stocks

# Today on FMM...

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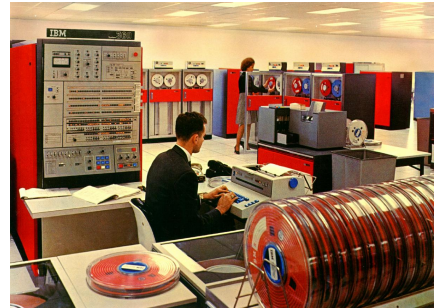
- Algo-trading!
- High-frequency trading!
- Cryptocurrencies!
- and more...

*“...It should come as no surprise then that the financial system exhibits a Moore’s Law of its own – from 1929 to 2009 the total **market capitalization** of the US stock market has **doubled every decade**. The total **trading volume** of stocks in the Dow Jones Industrial Average **doubled every 7.5 years** during this period, but in the most recent decade, the **pace has accelerated**: now the doubling occurs every 2.9 years, growing almost as fast as the semiconductor industry.”*

*Kirilenko and Lo [2013]*

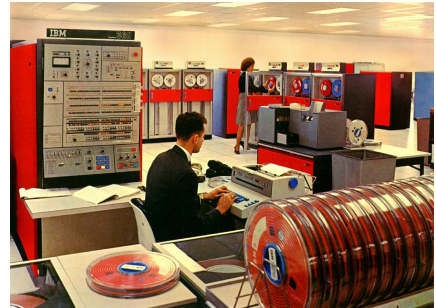
# Digital Markets

- The digital revolution of the past few decades has reshaped financial markets as much as (if not more than) any other aspect of our lives
- The quote above mentions the “extensive margin” akin to the Moore’s Law
- But the “intensive margin” is also at work



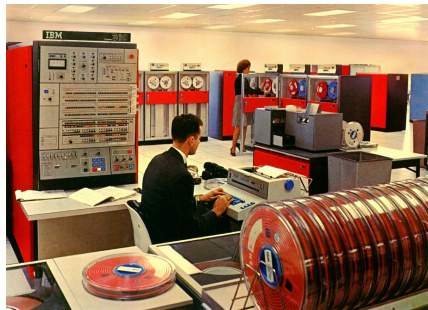
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# Digital Markets

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- But the “intensive margin” is also at work
  - Index funds, automated arbitrage, automated execution & market-making only made possible by computers
- In addition to Moore’s Law, [Murphy’s Law](#) does not fail either
  - If something can go wrong it will, and the scope for failures is as big as ever these days. See Kirilenko and Lo [2013] (pp.60-67) for five [stories](#).



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- 1 Algo-trading: Some numbers
- 2 HFT 1: Investment in speed
- 3 HFT 2: Endogenous liquidity provision
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# More on algo-trading

- Algorithms allow for a lot of stuff:
  - HFT (later today)
  - better hedging though some automated hedges
  - but also for better execution via order-splitting.
- Beason and Wahal [2019] give some (actually a lot of) info on how algorithms work for large institutional investors (a typical counterpart to HFT nowadays)
  - I also put on absalon a 2020 SEC report on algo-trading that gives a bird's-eye overview
- “Parent” orders are split (by algorithms) into many “child” orders that are routed to markets

# Institutional algo-trading

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  - avg: 63.1 runs per parent (avg 10m total duration), 8.8 children per run
- Of the 300 million child orders, less than 0.40 percent are market orders.
  - By comparison, retail investors usage of market orders is over 50 percent
  - $\approx 80\%$  are limit orders,  $\approx 20\%$  are PEG orders – dark limit orders that are dynamically “pegged” to the NBBO
  - Of the limit orders, 24% are marketable, 65% are passive, rest inside the spread
- Many orders are unfilled (even marketable)
  - Conditional on filled, median time-to-trade=5ms
  - Even unfilled orders have price impact

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# High-frequency trading: introduction

- **HFT**: Refers to computerized, algorithmic trading at high pace: fastest participants take advantage of opportunities before others
- **Speed is key**: for instance, in 2010, a USD 300 million cable was laid between Chicago and New Jersey (Nasdaq)
- **Ubiquitous**: estimated to account for more than 50% of volume in the US and more than 25% in Europe
- **Recent phenomenon(?)**: the effect on markets is still not well understood. Few empirical studies and fewer theoretical models
- **Today**: Look at two models of HFT

# Biais, Foucault, and Moinas [2015]

- Simple model of fast trading and investment in speed
- Look at equilibrium behavior and welfare implications
- Endogenize the choice of whether to be fast or slow
  - optimal decision depends on size of trader



# Model: basics

- **Institution:** continuum of profit-maximizing financial institutions indexed by  $i$ , zero endowment, trade one unit
- **Time:**  $\tau \in \{0, 1, 2\}$
- **Asset value:**  $u_i = v + y_i$ , where  $v$  is the fundamental value and  $y$  the institution's private value
  - **Fundamental value:**  $v \in \{\mu - \epsilon, \mu + \epsilon\}$ , equal probability, realized at  $\tau = 2$
  - **Private value:**  $y_i \in \{\delta, -\delta\}$ , equal probability and i.i.d. across investors, observed at  $\tau = 1$
- **Trading:** Occurs at  $\tau = 1$  after private values are learned

# Model: high-frequency trading

- **HFT:** Fraction  $\alpha$  of the institutions invest at  $\tau = 0$  to become HFT
- **Information:** Let's call HFT *fast* institutions (viz. *slow* institutions)
  - Fast institutions have better information: learn  $v$  at  $\tau = 1$  whereas slow institutions learn  $v$  at  $\tau = 2$
  - Fast institutions find a trading opportunity with probability one, slow institutions with probability  $\rho < 1$
- **Timing** (within period  $\tau = 1$ ):
  - 1 Each institution  $i$  observes  $y_i$ , and if fast, observes  $v$
  - 2 Each institution  $i$  finds a trading opportunity or not. If yes, chooses whether to buy/sell/abstain (one-unit trades only):  $d_i \in \{-1, 0, 1\}$ .
  - 3 Liquidity providers execute order  $d_i$  at price  $\mathbb{E}(v|d_i)$  (implicit assumption of market maker competition + no aggregate order flow transparency)

- **Fundamental value:** Good news/bad news:
  - **Good news** refer to high value:  $v = \mu + \epsilon$ .
  - **Bad news** refer to low value:  $v = \mu - \epsilon$ .
- **Fast institutions (FI)** have the following types
  - *GH*: Good news, high private valuation
  - *GL*: Good news, low private valuation
  - *BH*: Bad news, high private valuation
  - *BL*: Bad news, low private valuation
- **Slow institutions (SI)**, on the other hand, are either
  - *H*: high private valuation
  - *L*: low private valuation

# Equilibrium analysis

- **No fast trading:** If  $\alpha = 0$  all orders execute at  $\mu$

- **Active fast trading:** Now suppose  $\alpha > 0$ . Let

$\beta_j^F$  : prob. that fast institution type  $j$  buys

$\beta_j^S$  : prob. that slow institution type  $j$  buys (cond. on trading opp-ty)

- **High value:** Fast  $GH$  types have highest possible valuation:  $\beta_{GH}^F = 1$

- **Low value:** Fast  $BL$  types have lowest possible valuation:  $\beta_{BL}^G = 0$

- **Buy side:** Let  $a = \mathbb{E}[v|buy]$ . Use above observation and Bayes' Rule to get

$$a = \mu + \frac{\alpha \frac{1 + \beta_{GL}^F - \beta_{BH}^F}{4}}{(1 - \alpha) \rho \frac{\beta_H^S + \beta_L^S}{2} + \alpha \frac{1 + \beta_{GL}^F + \beta_{BH}^F}{4}} \epsilon.$$

# Multiple equilibria

- **Multiple equilibria:** Often markets have several equilibria.
- **Self-fulfilling expectations:** This is caused by the endogenous price:
  - If you think buyers will have high valuations  $\rightarrow$  set high  $a$
  - If  $a$  is high, only traders with high valuations will buy
- **Assumption:**  $\frac{\epsilon}{2} < \delta < \epsilon$ : both  $v$  and  $y$  matter;  $v$  more so. Then

$$V_{GH}^F > V_H^S > V_{GL}^F > \mu > V_{BH}^F > V_L^S > V_{BL}^F,$$

where  $V_j^i$  is the value of a type- $i$  institution with type- $j$  information.

- **Equilibrium types:** We focus here on the pure strategy equilibria. There will be three types of equilibria: P1, P2 and P3.

- **P1:**  $\mu \leq a < \mu + \epsilon - \delta$ . Fast institutions with good news always buy, slow institutions buy if private value high:

$$\beta_{GL}^F = \beta_H^S = 1 \text{ and } \beta_{BH}^F = \beta_L^S = 0$$

- **P2:**  $\mu + \epsilon - \delta < a < \mu + \delta$ . Fast institutions with good news and high value buy, but don't trade if information is conflicting. Slow institutions buy if private value high:

$$\beta_{GL}^F = \beta_L^S = \beta_{BH}^F = 0 \text{ and } \beta_H^S = 1$$

- **P3:**  $a = \mu + \epsilon$ . Fast institutions with good news and high value buy, other types of institutions don't trade (*crowding out*):

$$\beta_{GL}^F = \beta_H^S = \beta_{BH}^F = \beta_L^S = 0$$

- Note: as usual, we look on one side of mkt so "sell" same as "abstain" in betas above



# When do we have multiple equilibria?

- **P3 equilibrium:** Always exists. If dealers believe only fast institutions trade  $\rightarrow$  high  $a$ . But then only optimal for fast institutions to trade.
- **Proposition:** **P1 equilibrium** exists if  $\alpha < \alpha_{P1} \equiv \frac{\rho(\epsilon - \delta)}{\rho(\epsilon - \delta) + \delta}$ . Proof.
  - 1 Suppose institutions expect  $a = \mu + \frac{\alpha}{\alpha + (1 - \alpha)\rho}\epsilon$
  - 2 Notice  $\mu - \epsilon + \delta < \mu < a$ : FI never buy with bad news ( $\beta_{BH}^F = 0$  optimal)
  - 3  $\alpha < \alpha_{P1} \Rightarrow a < \mu + \epsilon - \delta$ : good news imply expected FI gains from buying, regardless of private valuation ( $\beta_{GL}^F = 1$  is optimal).
  - 4 Notice  $\mu + \delta > \mu + \epsilon/2 > \mu + \epsilon - \delta > a$ : SI with high valuation always buys ( $\beta_H^S = 1$  is optimal).
  - 5 Conditional on this,  $\mathbb{E}[v|buy] = \mu + \frac{\alpha}{\alpha + (1 - \alpha)\rho}\epsilon$  ( $a$  is optimal price). □
- Similarly, can find values of  $\alpha$  s.t. **P2 equilibrium** exists
- P1 is Pareto dominant for  $\alpha < \alpha_{P1}$ .

# Institution gain (Fast Institutions)

- FI gain in P1 equilibrium is (focus on buy side):

$$\begin{aligned}\mathbb{E}[u - a | \text{buy}, FI] &= \mathbb{E}[u | \text{buy}, FI] - \left[ \mu + \frac{\alpha}{\alpha + (1 - \alpha)\rho} \epsilon \right] \\ &= \mathbb{E}[u | v = \mu + \epsilon] - \left[ \mu + \frac{\alpha}{\alpha + (1 - \alpha)\rho} \epsilon \right] \\ &= \mu + \epsilon - \left[ \mu + \frac{\alpha}{\alpha + (1 - \alpha)\rho} \epsilon \right] \\ &= \frac{(1 - \alpha)\rho}{\alpha + (1 - \alpha)\rho} \epsilon \equiv \pi_F(\alpha)\end{aligned}$$

- Notice  $\pi'_F(\alpha) < 0$ .

# Institution gain (Slow Institutions)

- SI gain in  $P1$  equilibrium is (focus on buy side):

$$\begin{aligned}\rho \mathbb{E}[u - a | buy, SI] &= \rho \left( \mathbb{E}[u | buy, SI] - \left[ \mu + \frac{\alpha}{\alpha + (1 - \alpha)\rho} \epsilon \right] \right) \\ &= \rho \left( \mathbb{E}[u | y_i = \delta] - \left[ \mu + \frac{\alpha}{\alpha + (1 - \alpha)\rho} \epsilon \right] \right) \\ &= \rho \left( \mu + \delta - \left[ \mu + \frac{\alpha}{\alpha + (1 - \alpha)\rho} \epsilon \right] \right) \\ &= \rho \left( \delta - \frac{\alpha}{\alpha + (1 - \alpha)\rho} \epsilon \right) \equiv \pi_S(\alpha)\end{aligned}$$

- Notice  $\pi'_S(\alpha) < 0$ .

# Institution gain

- Both  $\pi_F(\alpha)$  and  $\pi_S(\alpha)$  are decreasing in  $\alpha$ : all trader types lose when proportion of fast traders increases
- This result holds generally (when we focus on the Pareto-dominant equilibria)
  - Fast institutions lose because there is more price impact of trades (more adverse selection)
  - Higher price impact dissuades slow institutions from trading (crowding out)
- So more HFT is always 'bad' for existing traders, but beneficial for institutions that switch to become HFT
  - Note:  $\pi_F(\alpha) - \pi_S(\alpha) > 0$  is independent of  $\alpha$
- Shkilko and Sokolov [2020]: periods when HFT is disrupted are characterized by less adverse selection, lower trading costs

# Endogenous acquisition of technology

- **Cost:** At  $\tau = 0$ , a trader can become a fast institution at cost  $C$
- **Markets:** There is a size- $N$  continuum of markets (this will simplify the maths). An institution of type  $n$  can participate in  $n \leq N$  markets
- **Participation:** Type is distributed according to “pdf”  $h(n)$  on  $[0, N]$  with

$$h(n) = \frac{N}{n}$$

- **Optimal investment:** Invest in becoming fast institution if

$$\begin{aligned} \pi_F(\alpha) \cdot n - C &\geq \pi_S(\alpha) \cdot n \\ \Leftrightarrow n &\geq \frac{C}{\pi_F(\alpha) - \pi_S(\alpha)} \equiv n(\alpha) \end{aligned}$$

## Endogenous acquisition of technology (2)

- Notice that  $n \cdot h(n) = N$ : the total number of investments made by type- $n$  institutions is  $N$  for all  $n$
- Thus: equal amount of  $n$  and  $n'$  investors *within each market*.
- In other words,  $n$  is uniformly distributed within each market:  $n \sim U[0, N]$  such that we get the following fixed-point problem

$$\alpha = \mathbb{P}(n \geq n(\alpha)) = \frac{N - n(\alpha)}{N}$$

## Endogenous acquisition of technology (3)

- Authors find equilibrium with  $\partial\alpha/\partial C < 0$ .
- Welfare result:

If  $\rho > 1/2$  then welfare-maximizing value of  $\alpha$  is 0.

- Hence: in 'well-functioning' markets, equilibrium has too much HFT
- Because HFT effects are:
  - *more trading opportunities* – personal and social benefit
  - *pvt info about  $v$*  – personal benefit, social cost (worse prices for everybody)

# BFM Conclusion

- Fast trading exacerbates adverse selection, but is individually appealing
- If the markets are already reasonably good at matching traders with opportunities, fast trading may be strictly bad for welfare



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- **Claim:** there is an *arms race* in HFT (perpetual wasteful investment in gaining advantage) and this is a result of bad market design
- **Solution:** must go to the root and construct better markets rather than imposing taxes etc.
- **Proposal:** Authors propose to replace the *continuous auction* with *frequent batch auctions*
  - frequent = every 0.1s
- **Paper:** Claims are backed up with a great deal of data and a (very!) simple model

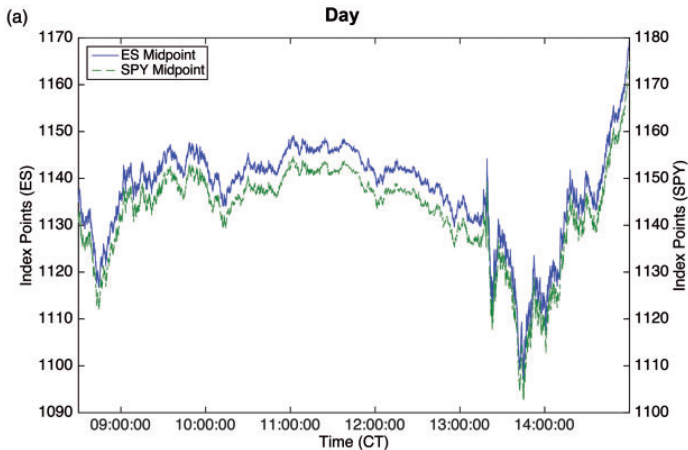
# Correlations and arbitrage

The authors make three points

- 1 **Vanishing correlations:** For short enough latency (time intervals), correlations between almost identical assets break down
- 2 **Arbitrage:** This leads to arbitrage possibilities
- 3 **Perpetual situation:** These arbitrage possibilities do not vanish over time, suggesting that competition does not make them disappear

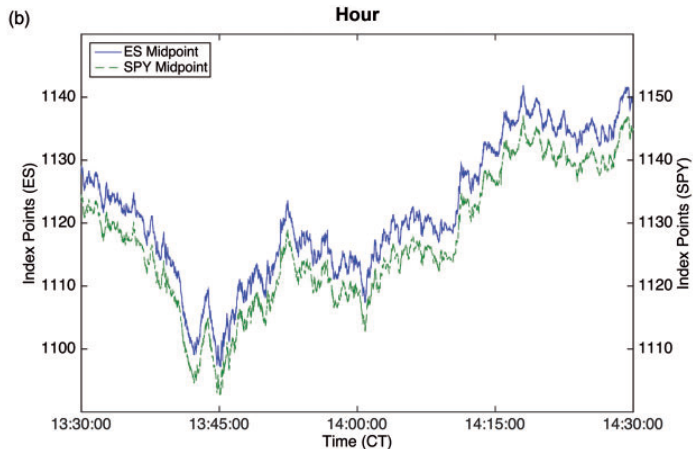
## Budish, Cramton, and Shim [2015]

ES and SPY are the two largest instruments tracking S&P500. In theory perfectly correlated.  
Panel (a) shows a trading day.



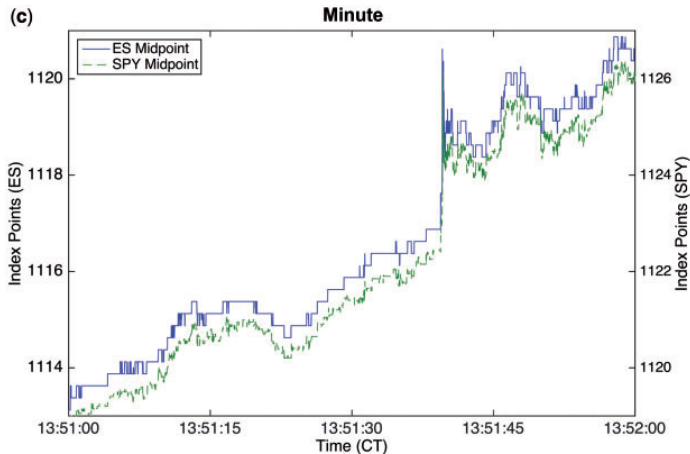
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Panel (b) shows a trading hour.



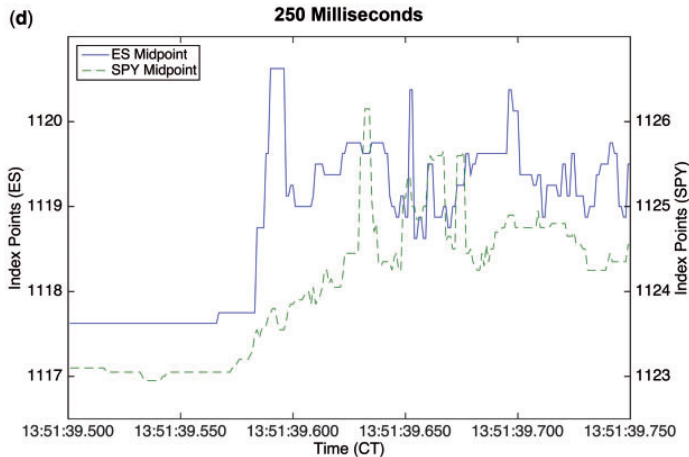
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Panel (c) shows a trading minute.



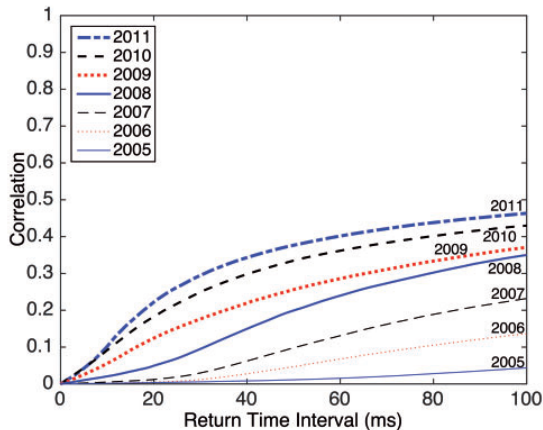
## Budish, Cramton, and Shim [2015]

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Panel (d) shows a high-frequency breakdown.



## Budish, Cramton, and Shim [2015]

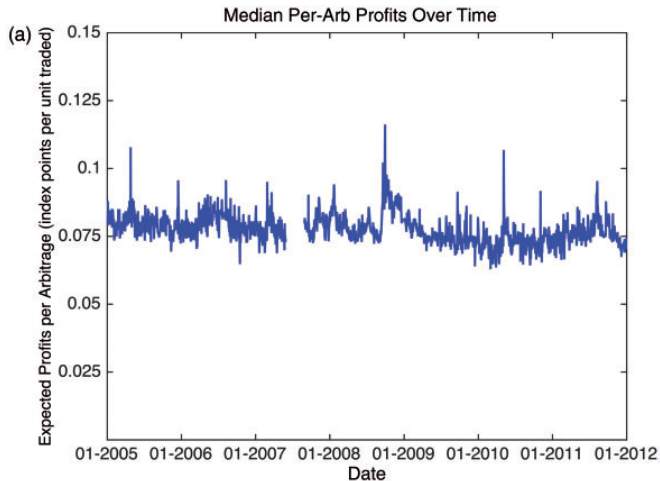
The figure below shows the correlation between ET and SPY by time interval for different years.





## Budish, Cramton, and Shim [2015]

The figure below shows median arbitrage profits over time. Very stable, total  $\sim \$75\text{m}/\text{yr}$



# Model of a continuous market

## Security

- **Value:** There is a signal  $y$ , which is perfectly correlated with the value  $x$ . Signal  $y$  follows compound Poisson distribution.
- **Comp. Poisson:** Jumps arrive at rate  $\lambda_{jump}$  and have size  $J \sim F_{jump}$ .

## Players

- **Noise traders:** arrive according to Poisson process ( $\lambda_{invest}$ )
  - Want to buy/sell one unit
  - Incur cost of delay, so use marketable limit orders  $\simeq$  market orders
- **HFTs:** There are  $N$  HFT firms who use market or limit order

## Order processing

- If multiple orders/messages at same time, uniform random draw to determine first to be processed

# Equilibrium

**Equilibrium properties:** Focus on equilibrium with the following properties

- **Endogenous market maker:** 1 HFT *endogenously* takes the role of liquidity provider. Refer to this as the market maker (MM).
- **Adverse selection:**  $N - 1$  HFTs act as *stale quote snipers*

## Market maker

- **Quotes:** Suppose signal is  $y$ . Set  $a = y + \frac{s}{2}$  and  $b = y - \frac{s}{2}$  where  $s$  is the spread.
- **News:** If news arrive and the new signal is  $y'$ , send message to cancel quotes  $a$  and  $b$  and post new ones:  $a' = y' + \frac{s}{2}$  and  $b' = y' - \frac{s}{2}$ . Noise traders are slower at receiving news.

## Snipers

- Trade if  $|y' - y| > \frac{s}{2}$ .

## Equilibrium (2)

- **Market maker profits:** The MM **flow profits** (per  $dt$  period, normalized by  $dt$ ) are

$$\lambda_{invest} \cdot \frac{s}{2} - \lambda_{jump} \cdot \mathbb{P}\left(J > \frac{s}{2}\right) \cdot \mathbb{E}\left[J - \frac{s}{2} \mid J > \frac{s}{2}\right] \cdot \frac{N-1}{N}.$$

- **Sniper profits:** The profits to stale-quote snipers are

$$\lambda_{jump} \cdot \mathbb{P}\left(J > \frac{s}{2}\right) \cdot \mathbb{E}\left[J - \frac{s}{2} \mid J > \frac{s}{2}\right] \cdot \frac{1}{N}.$$

- **Equilibrium condition:** Make HFT indifferent btw MM and sniper:

$$\lambda_{invest} \cdot \frac{s}{2} = \lambda_{jump} \cdot \mathbb{P}\left(J > \frac{s}{2}\right) \cdot \mathbb{E}\left[J - \frac{s}{2} \mid J > \frac{s}{2}\right].$$

- **Lack of competition:** Spread  $s$  does not depend on  $N$ .

# Continuous auction market versus batch

- **Conclusion:** There will be a **positive bid-ask spread** in continuous market (even as  $N \rightarrow \infty$ ), despite **no asymmetric information** (kind of)
- **Market failure:** Authors argue that this failure is built into the market via processing mechanism
- **Proposed solution:** Frequent batch auction
  - Auction every  $\tau$  moments. Fast institutions have latency  $\delta_{fast}$  and slow institutions latency  $\delta_{slow}$ . Three intervals, depending on when public signal arrives:
    - 1  $[0, \tau - \delta_{slow}]$ : all institutions trade, no AS
    - 2  $[\tau - \delta_{slow}, \tau - \delta_{fast}]$ : only fast institutions trade, AS
    - 3  $[\tau - \delta_{fast}, \tau]$ : no institution trade (inefficient)
- **Outcome:** Before, fast trader always has advantage; now only  $\frac{\delta}{\tau}$  of the time, where  $\delta = \delta_{slow} - \delta_{fast}$ . If  $\delta = 100$  microseconds and  $\tau = 100$  milliseconds. Then  $\frac{\delta}{\tau} = \frac{1}{1000}$ . Large reduction in HFT importance.

# HFT Conclusion

- Effects of speed are similar to those of informed trading
- By design, continuous trading generates arbitrage opportunities
- Firms overinvest in speed in attempts to reap these arbitrage profits
- Risk of being sniped contributes to the spread
- While HFTs can serve as liquidity providers, they do not actually contribute to narrowing the spread
- Use better market design (batch auctions) to improve this

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# Blockchain and cryptocurrencies

- Our discussion would be incomplete without mentioning **blockchain** and **cryptocurrencies**, the biggest trend of 2017
  - blockchain is a “distributed ledger” technology
  - crypto uses blockchain to record transactions in some tokens
- In addition to below, you can find some economic discussion of crypto in Nica, Piotrowska, and Schenk-Hoppé [2017] and Halaburda, Haeringer, Gans, and Gandal [2020]






# How should it work?

- Cryptos (bitcoin, ethereum) are like distributed payment systems
- You can translate that to a financial market:
  - Say coins serve as shares of some company
  - Or there is a decentralized exchange that records stock ownership transactions in a blockchain

# Why the hype?

- **Decentralization**: no exchange to profit from traders  $\Rightarrow$  lower order costs
  - Even when the market is dominated by exchanges, you do not need to use them to trade (in principle)
- **Transparency**: transaction history is visible, order flow is visible, counterparty's trading history visible
  - note: there is very little anonymity, contrary to what some say!
- **Smart contracts**: algotrading by design

# Why not?

- **Limited processing capacity:** block size and frequency is  $\approx$ fixed
  - Visa: 150m tx/day; Bitcoin: 300k tx/day (15.02.21)
- **Order costs** and **execution risk:** you have to bid for your transaction to be accepted into a block.
  - This is on top of execution risk from other sources (for limit orders)
  - Average order costs fluctuate over time 
  - There are concerns that miners inflate fees (Lehar and Parlour [2020])
- **Delay:** blocks are only processed rarely (one per 10 min avg for bitcoin) 
- **Clearing and settlement:** without a trusted mediator, counterparty and security risks intensify 
- **No transparency requirements:** it is more difficult to enforce disclosure of financial info by firms/coin issuers

# Revealed preference

- But in the end, the final users (traders) don't care about the fancy technology in the backend
- They choose whichever is (1) cheaper and (2) more convenient to use
- So web3 converged to the same centralized system we had before:
  - crypto is traded via a few centralized exchanges (Binance, Coinbase, ...)
  - NFTs barely exist(ed?) outside OpenSea and Rarible
- Signal founder has a nice post about it.

## References I

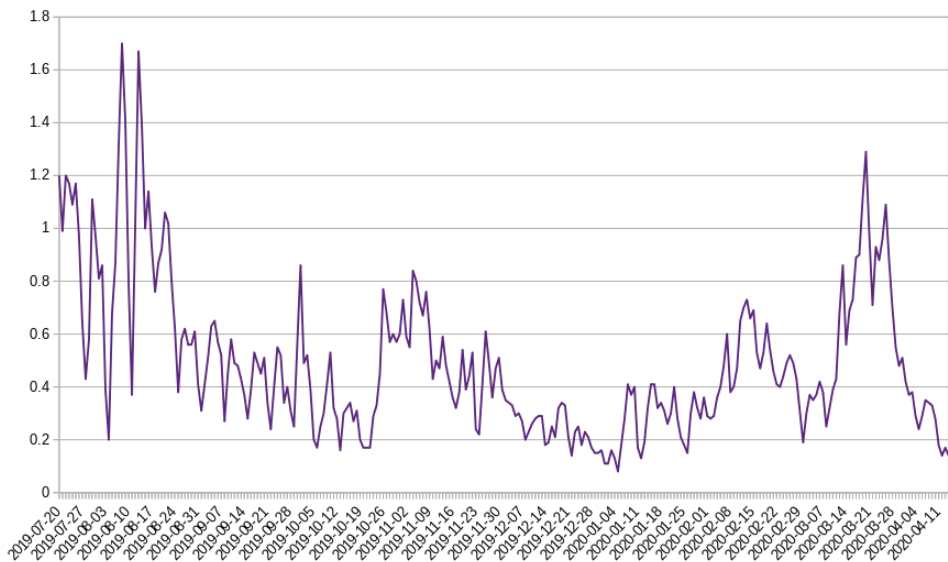
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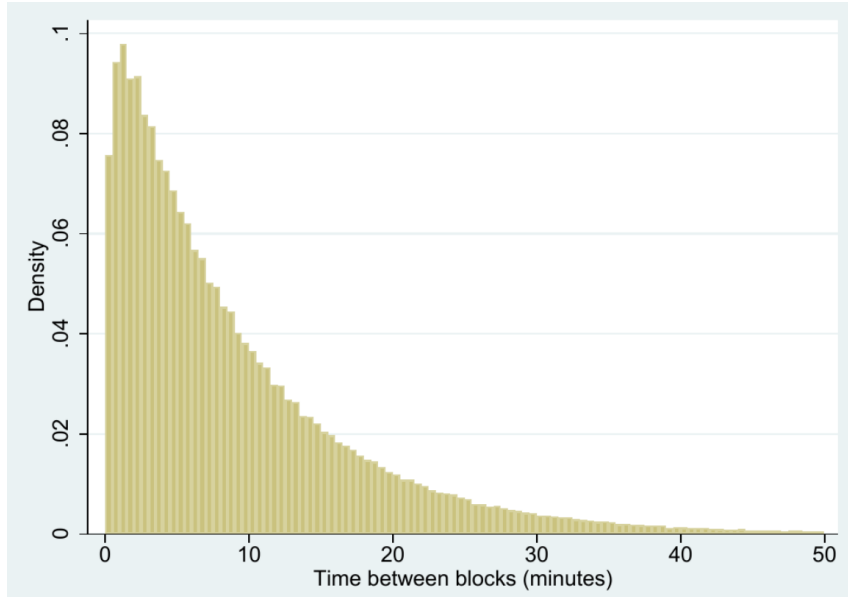
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Bitcoin avg daily order processing fee, USD per transaction

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Histogram of time between blocks (Lehar and Parlour [2020])

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