Introduction to market microstructure and heterogeneity of investors

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Varenna, July 20-21, 2018

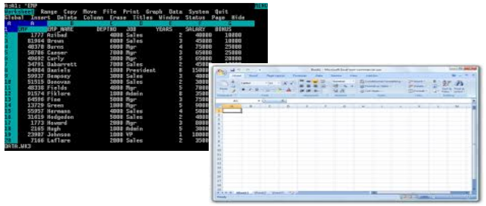
Financial markets

- Financial markets allow two classes of agents to meet:
  - Entrepreneurs: who have industrial projects but need funding
  - Investors: who have money to invest and are ready to share profits and risks of the projects
- Therefore financial markets are systems where a large number of investors interact through trading to determine the best price for a given asset.
- From this point of view financial markets can be seen as a collective evaluation system.

Trading Technology Evolution

Phone

Financial Calculators



Spreadsheets

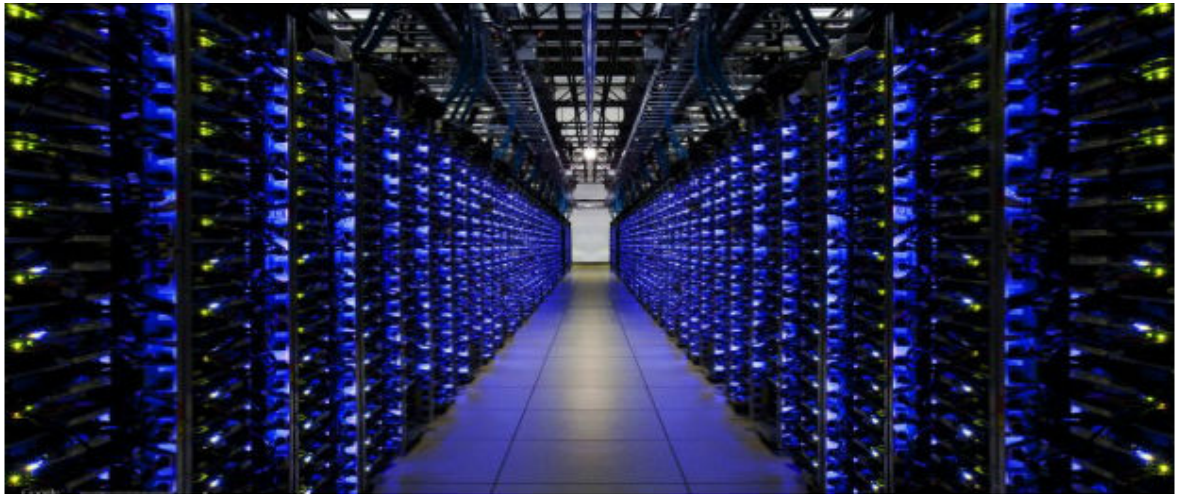
Screen Trading

Algo Trading

Networking, Internet, Cloud Computing

Trading Pit

The New York Stock Exchange today



Financial Data Science

The availability of large datasets is changing our understanding of the financial industry, opening new business opportunities, creating new sources of risk, also at the system level.

New technological, conceptual, methodological challenges

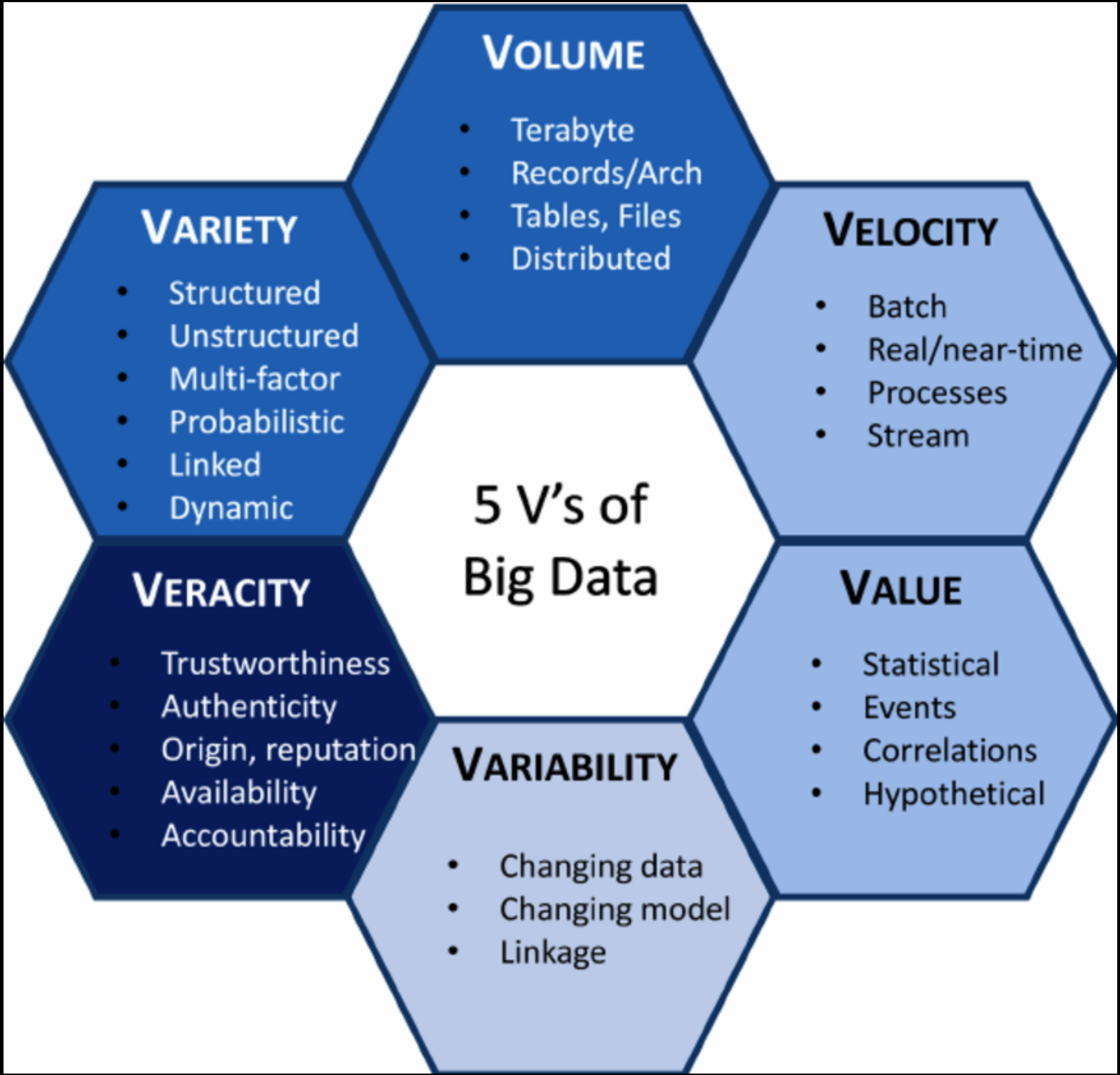
- Huge speed of data production: methods and technology
- Extracting information from complex sources (for example texts or tweets)
- Combining datasets of different origin
- From macro to micro: classification and prediction
- FinTechs (Cryptocurrencies, Blockchain, P2P lending, etc)
- Beyond individuality: the role of interaction among financial entities
- Stakeholders
  - Banks
  - Financial intermediaries
  - Regulators (Central Banks)
  - …..

FINANCIAL DATA

Extract informations and making prediction
Combine different kind of data

Market data	Non public data	Public data
price, volatility, balance-sheet, agency rating, interbank lending	portfolios composition, trading decisions of investors, companies relationship	News, Twitter, Blogs

Extremely fast production of data
Non uniform sampling
Aggregation at different time scales



5 V's of Big Data

VOLUME

- Terabyte
- Records/Arch
- Tables, Files
- Distributed

VARIETY

- Structured
- Unstructured
- Multi-factor
- Probabilistic
- Linked
- Dynamic

VELOCITY

- Batch
- Real/near-time
- Processes
- Stream

VERACITY

- Trustworthiness
- Authenticity
- Origin, reputation
- Availability
- Accountability

VALUE

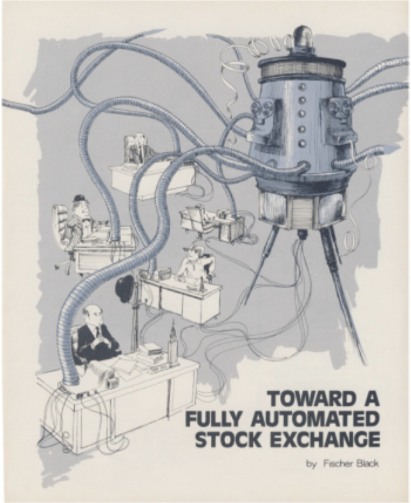
- Statistical
- Events
- Correlations
- Hypothetical

VARIABILITY

- Changing data
- Changing model
- Linkage

Velocity (and Volume)

Automated trading: a precursor



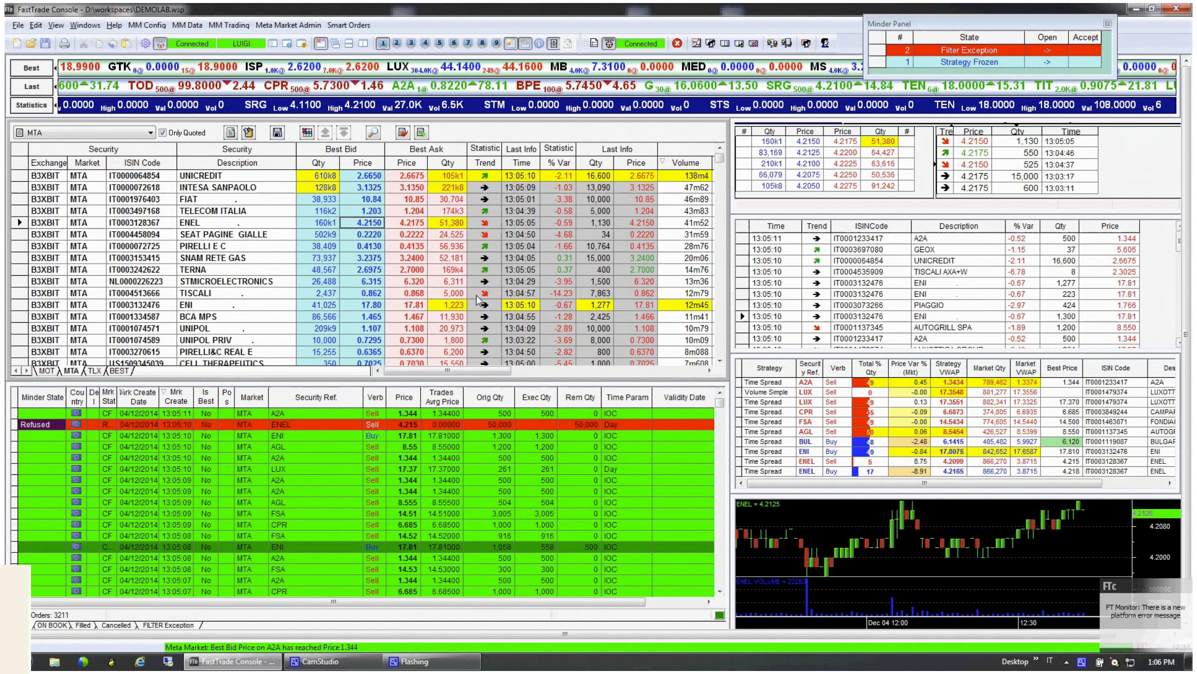
TOWARD A FULLY AUTOMATED STOCK EXCHANGE

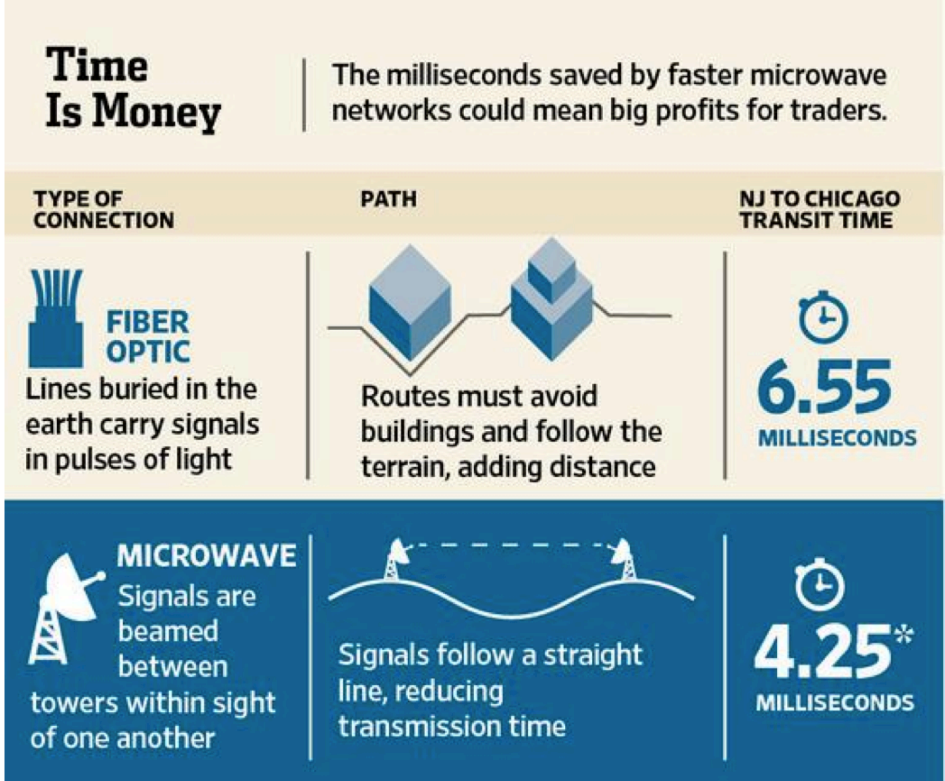
by Fischer Black

Figure: Cover of the 1971 article by Fischer Black on Financial Analyst Journal

Financial Markets Today

- ➢Low Latency
- ➢Co-Location & Proximity
- ➢High Performance Computing
- ➢Systemic Instability





Time Is Money

The milliseconds saved by faster microwave networks could mean big profits for traders.

TYPE OF CONNECTION	PATH	NJ TO CHICAGO TRANSIT TIME
FIBER OPTIC Lines buried in the earth carry signals in pulses of light	Routes must avoid buildings and follow the terrain, adding distance	6.55 MILLISECONDS
MICROWAVE Signals are beamed between towers within sight of one another	Signals follow a straight line, reducing transmission time	4.25* MILLISECONDS

- **Data with nanosecond (!) resolution**
- **10^6 market events per day per stock**

Market microstructure

- Market microstructure “is devoted to theoretical, empirical, and experimental research on the economics of securities markets, including the role of information in the price discovery process, the definition, measurement, control, and determinants of liquidity and transactions costs, and their implications for the efficiency, welfare, and regulation of alternative trading mechanisms and market structures” (NBER Working Group)

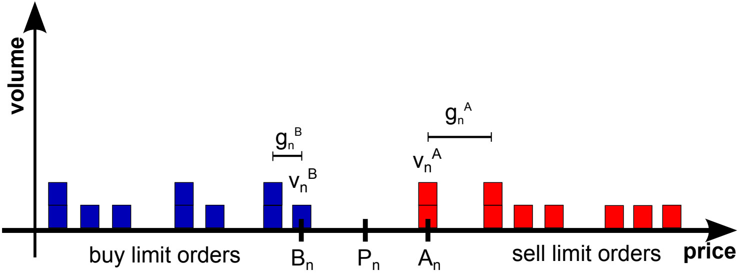
Floor market

- Old market structure
- Now used only in US commodity futures markets (Chicago Board of Trade, New York Mercantile Exchange, Chicago Mercantile Exchange)
- Little transparency on data
- Bund futures at London International Financial Futures Exchange (LIFFE) and Eurex (1997)

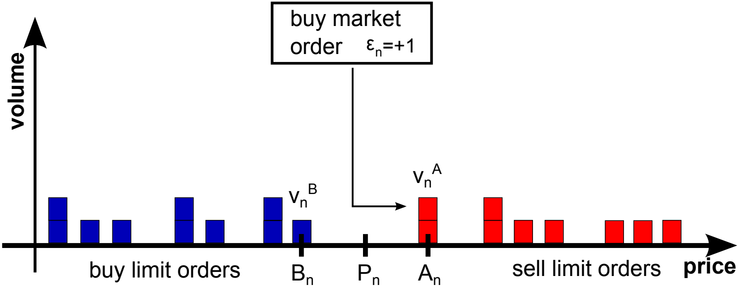
Dealer market

- A dealer is an intermediary who is willing to act as a counterparty for the trades of his customers
- Foreign exchange, corporate bond, swap markets
- Customers cannot typically place limit orders
- A large customer can have relationships with many competing dealers
- Low transparency: quotes in response to customer inquiries and not publicly available
- Interdealer trading is also important (for dealer inventory management). Limit order book for FX
- Dealers facilitate large (block) trades. Upstairs or off book market

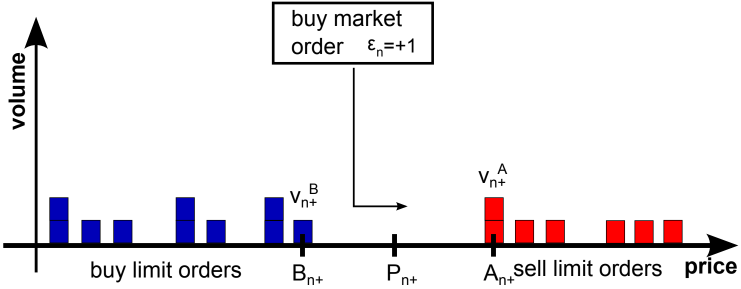
Dynamics of Limit Order Book



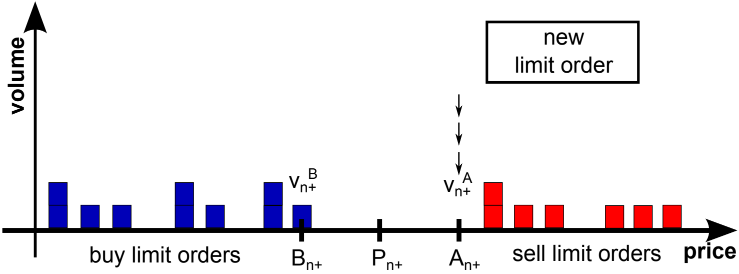
Dynamics of Limit Order Book



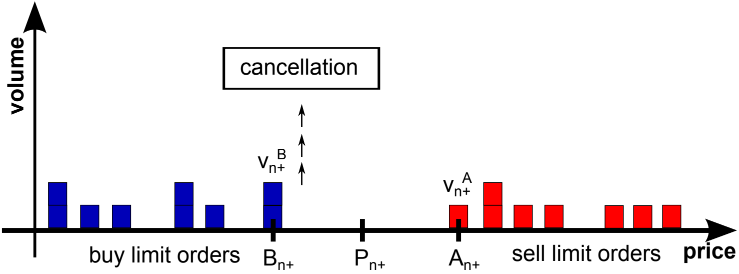
Dynamics of Limit Order Book



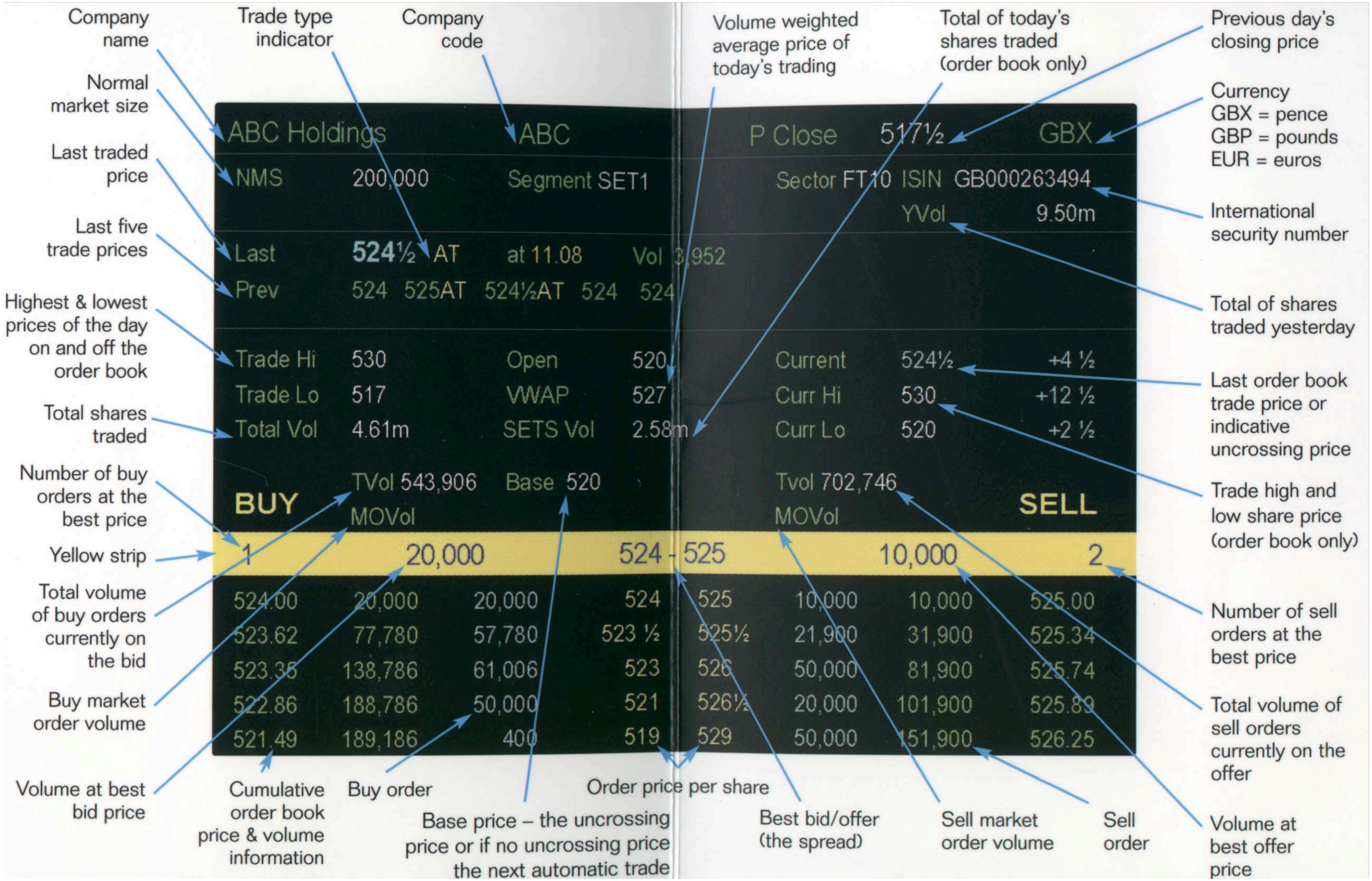
Dynamics of Limit Order Book



Dynamics of Limit Order Book



A snapshot of the book display



ABC Holdings ABC P Close 517½ GBX

NMS 200,000 Segment SET1 Sector FT10 ISIN GB000263494

YVol 9.50m

Last 524½ AT at 11.08 Vol 3,952

Prev 524 525AT 524½AT 524 524

Trade Hi	530	Open	520	Current	524½ +4 ½
Trade Lo	517	VWAP	527	Curr Hi	530 +12 ½
Total Vol	4.61m	SETS Vol	2.58m	Curr Lo	520 +2 ½

BUY TVol 543,906 Base 520 Tvol 702,746 SELL

MOVol MOVol

1 20,000 524 - 525 10,000 2

524.00	20,000	20,000	524	525	10,000	10,000	525.00
523.62	77,780	57,780	523 ½	525½	21,900	31,900	525.34
523.35	138,786	61,006	523	526	50,000	81,900	525.74
522.86	188,786	50,000	521	526½	20,000	101,900	525.89
521.49	189,186	400	519	529	50,000	151,900	526.25

Company name

Normal market size

Last traded price

Last five trade prices

Highest & lowest prices of the day on and off the order book

Total shares traded

Number of buy orders at the best price

Yellow strip

Total volume of buy orders currently on the bid

Buy market order volume

Volume at best bid price

Trade type indicator

Company code

Volume weighted average price of today's trading

Total of today's shares traded (order book only)

Previous day's closing price

Currency
GBX = pence
GBP = pounds
EUR = euros

International security number

Total of shares traded yesterday

Last order book trade price or indicative uncrossing price

Trade high and low share price (order book only)

Number of sell orders at the best price

Total volume of sell orders currently on the offer

Volume at best offer price

Cumulative order book price & volume information

Buy order

Order price per share

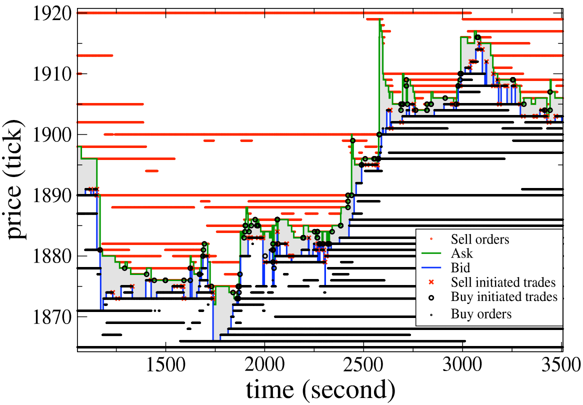
Base price – the uncrossing price or if no uncrossing price the next automatic trade

Best bid/offer (the spread)

Sell market order volume

Sell order

Dynamics of the Limit Order Book

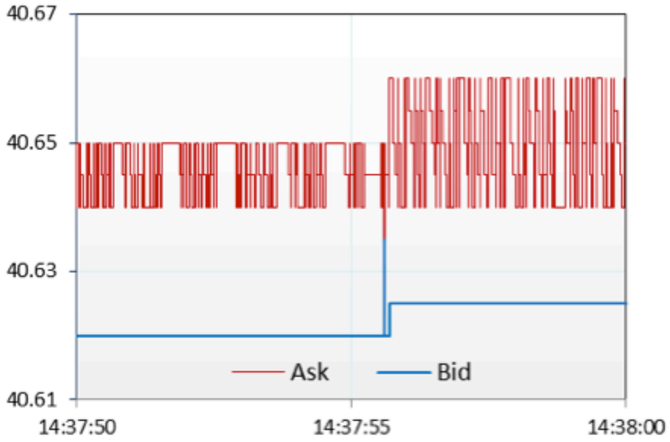


From Ponzi et al. 2009

NOISE OR SIGNAL?

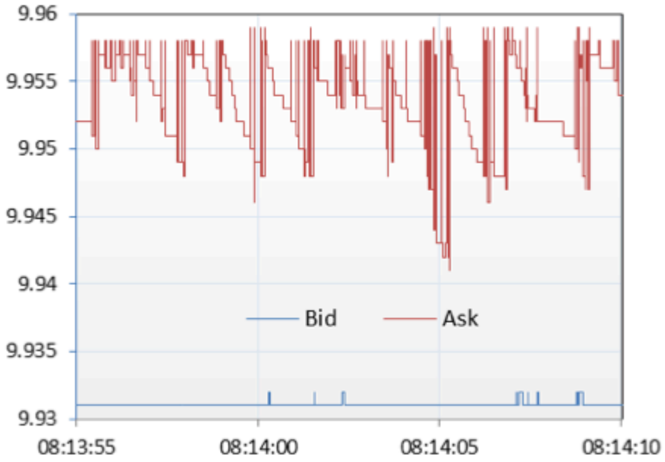
- According to a 2012 study of the AMF, the resting time of orders sent to assets traded at the Euronext-Paris has the following properties:
- 45% of orders stay in the order book less than a second
- 26% of orders stay in the order book less than 100 millisecond
- 11% of orders stay in the order book less than 5 millisecond
- 4% of orders stay in the order book less than 1 millisecond
- What is the informative content of these orders?

Exhibit 1: Quote Stuffing: Heineken, 2nd May, 2011



Source: Credit Suisse AES Analysis

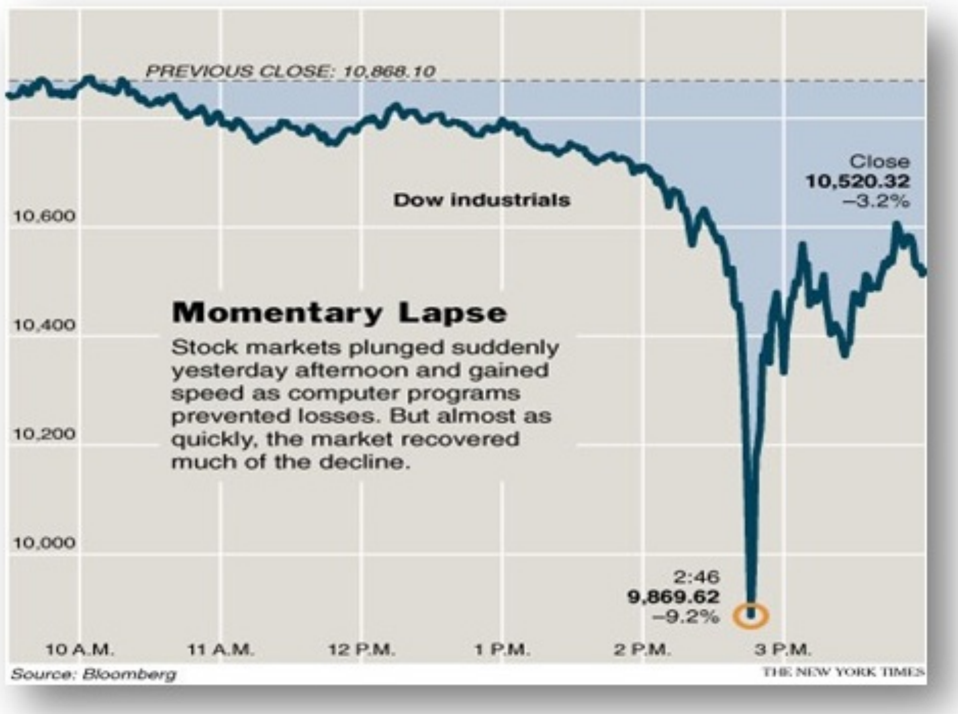
Exhibit 2: Quote Stuffing: Telefonica, 10th August, 2012



Source: Credit Suisse AES Analysis

Endogenous instabilities
the Flash Crash: May 6, 2010

JUST A NORMAL DAY AT THE NATION'S MOST IMPORTANT FINANCIAL INSTITUTION...



Momentary Lapse

Stock markets plunged suddenly yesterday afternoon and gained speed as computer programs prevented losses. But almost as quickly, the market recovered much of the decline.

Source: Bloomberg

THE NEW YORK TIMES

Sometimes liquidity evaporates...

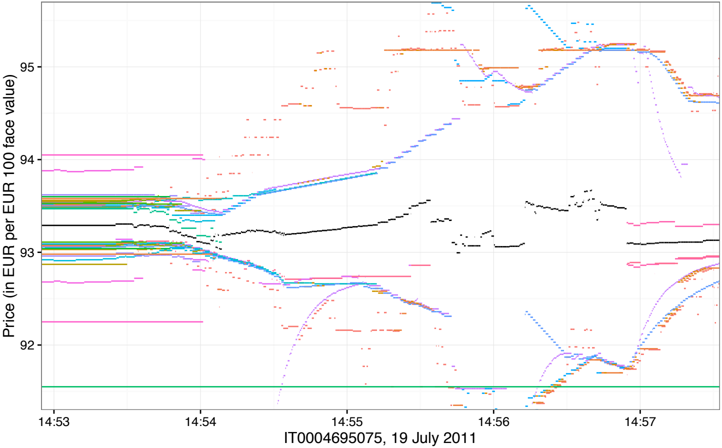
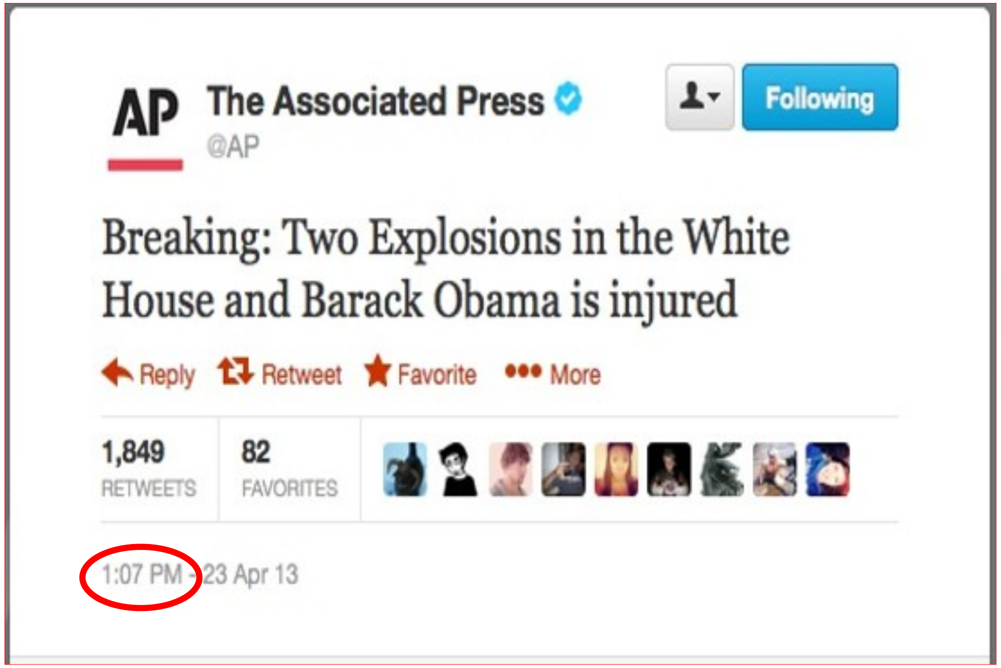


Figure: Limit Order Book dynamics from Mercato Titoli di Stato (MTS. Colored horizontal lines correspond to quotes from different participants. The mid price (black horizontail lines) separates the bid and ask side. No trades reported.

M. Schneider, FL, L. Pelizzon, *How Has Sovereign Bond Market Liquidity Changed? - an Illiquidity Spillover Analysis*

Exogenous instabilities (Twitter Flash Crash, 23rd April 2013)

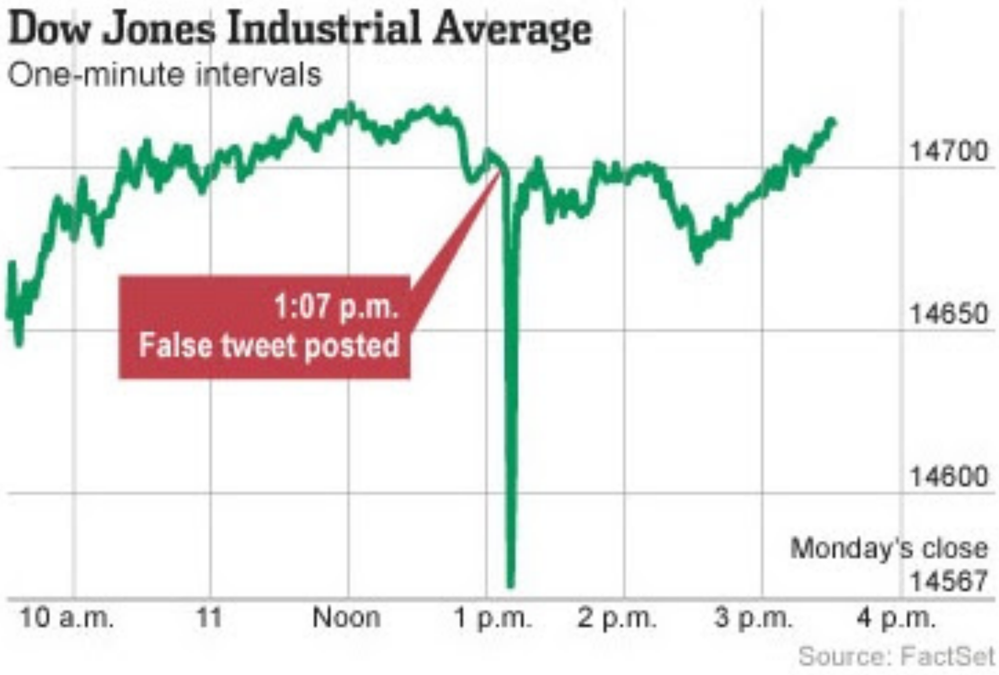


Breaking: Two Explosions in the White House and Barack Obama is injured

1,849 RETWEETS

82 FAVORITES

1:07 PM - 23 Apr 13



The limit order book during the Twitter Flash Crash

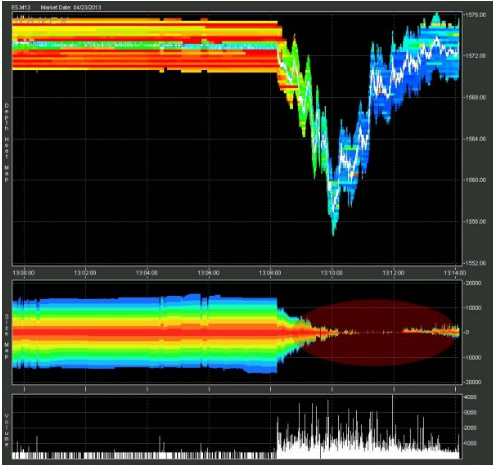
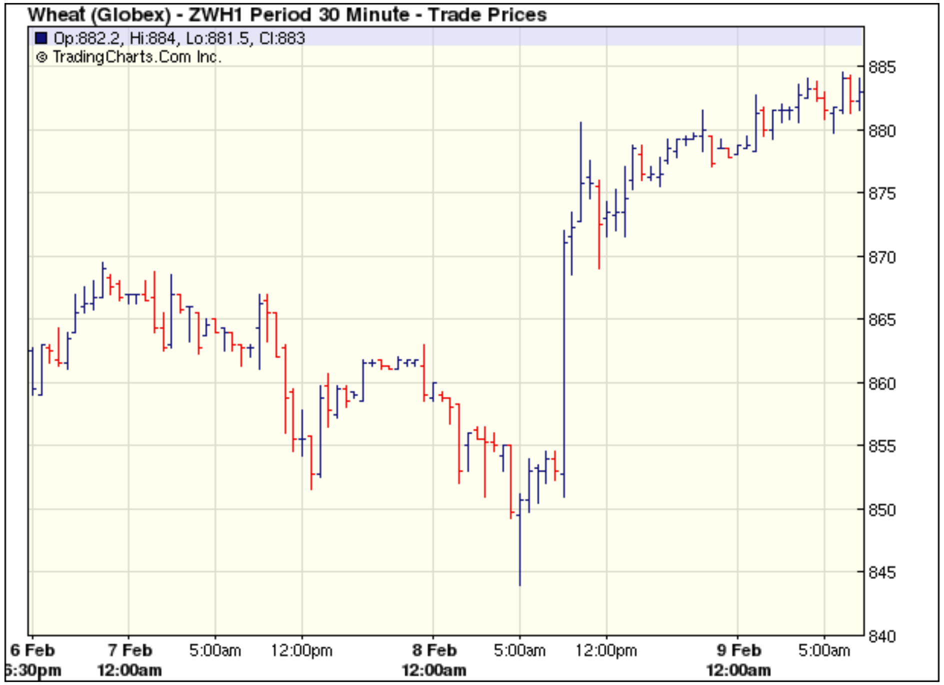


Figure: Source Nanex

Modelling the dynamics of systemic instabilities

- A jump is a price movement which is abnormally large with respect to the statistical properties of prices in the recent past
- 140 highly liquid stocks traded in the US financial markets
- High frequency jumps -> one minute price changes



Focus on

- The self and cross excitation of instabilities (jumps) among stocks
- The role of exogenous drivers (financial news) versus the endogenously generated instabilities
- How the financial markets have changed in the last fifteen years. Role of High Frequency Trading, Algorithmic Trading, and market reforms (RegNMS, MiFid, etc)

Data and jumps identification

- 140 highly liquid stocks in the US equity markets in 2001-2013
- One minute returns
- Jump of **Threshold** θ:

$$\frac{|r|}{\sigma} > \theta$$

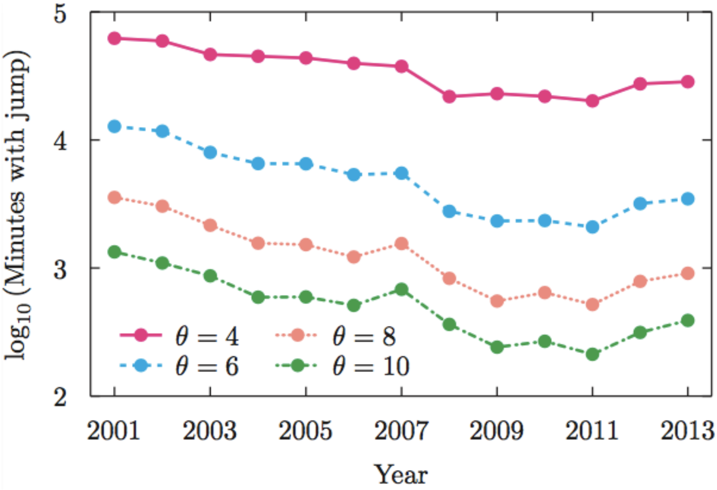
- For volatility estimation we use the realized bipower variation (Barndorff-Nielsen and Shephard (2003, 2004))

$$\hat{\sigma}^2_{\mathrm{bv},t} = \mu_1^{-2}\overline{|r_i||r_{i+1}|} = \mu_1^{-2}\alpha\sum_{i>0}(1-\alpha)^{i-1}|r_{t-i}||r_{t-i-1}|,$$

  with $\mu_1 = \sqrt{\frac{2}{\pi}} \simeq 0.797885$ and $\alpha = 0.032$ (gives 50% of weight to the closest 22 observations).

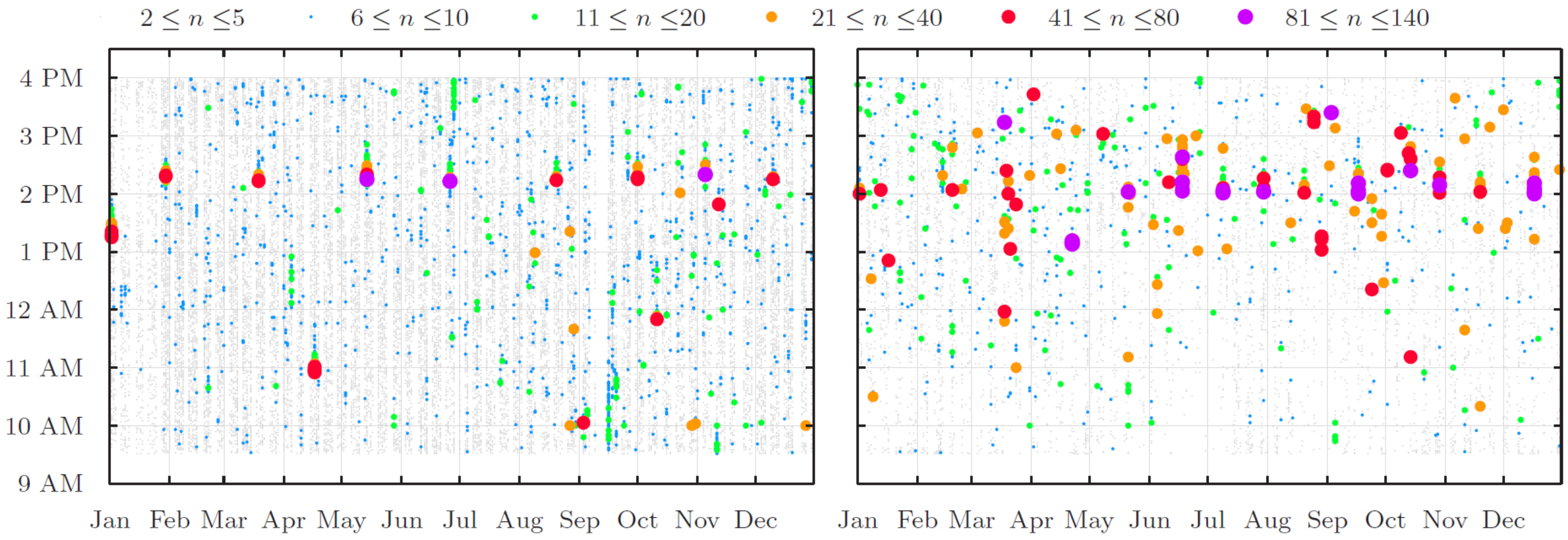
- **Multiplicity** M of a cojump: number of stocks simultaneously jumping (i.e. in the same minute).

Total number of jumps



The total number of jumps and the number of single asset jumps has actually *declined* in recent years

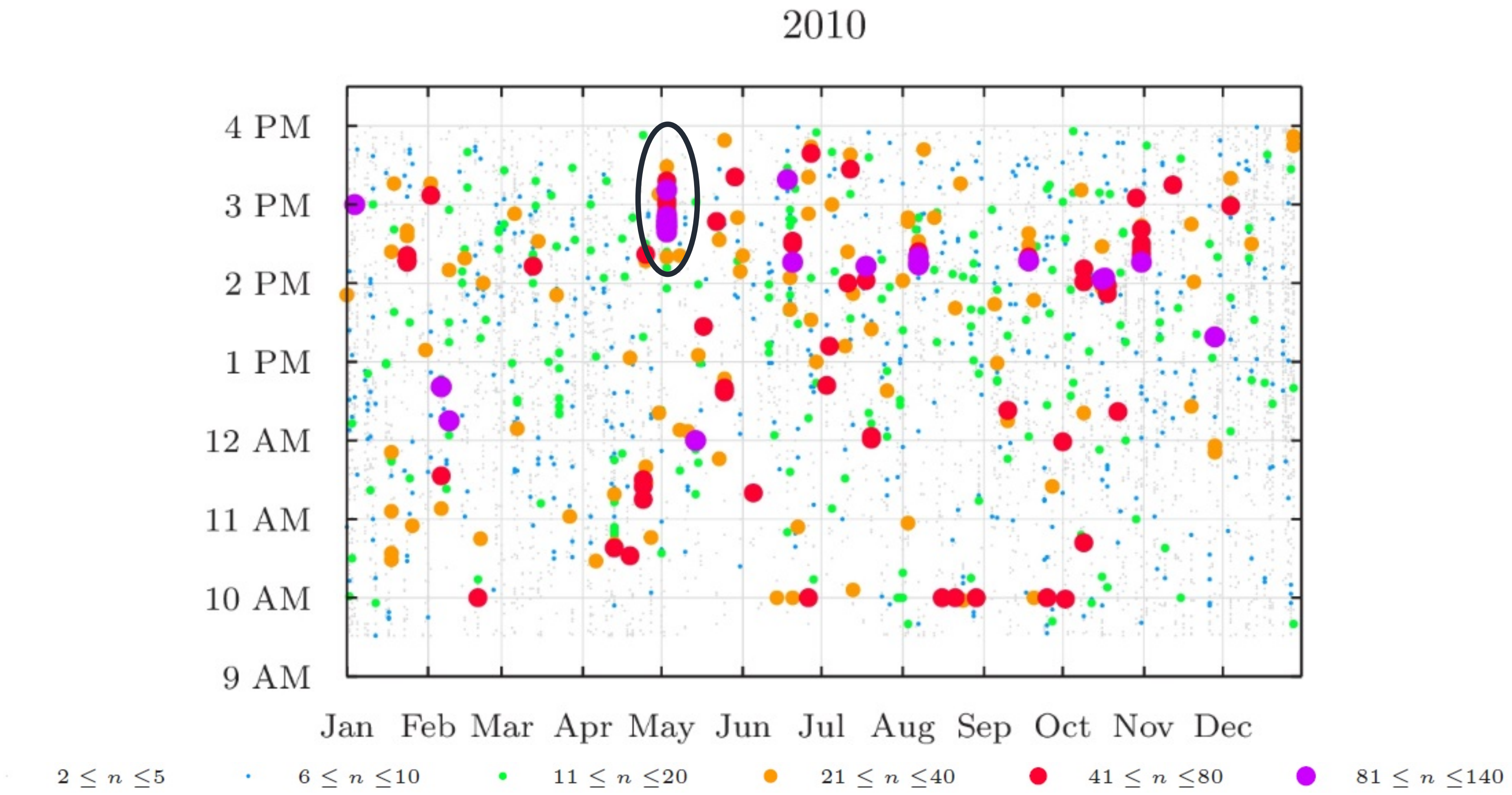
Historical evolution of market instabilities



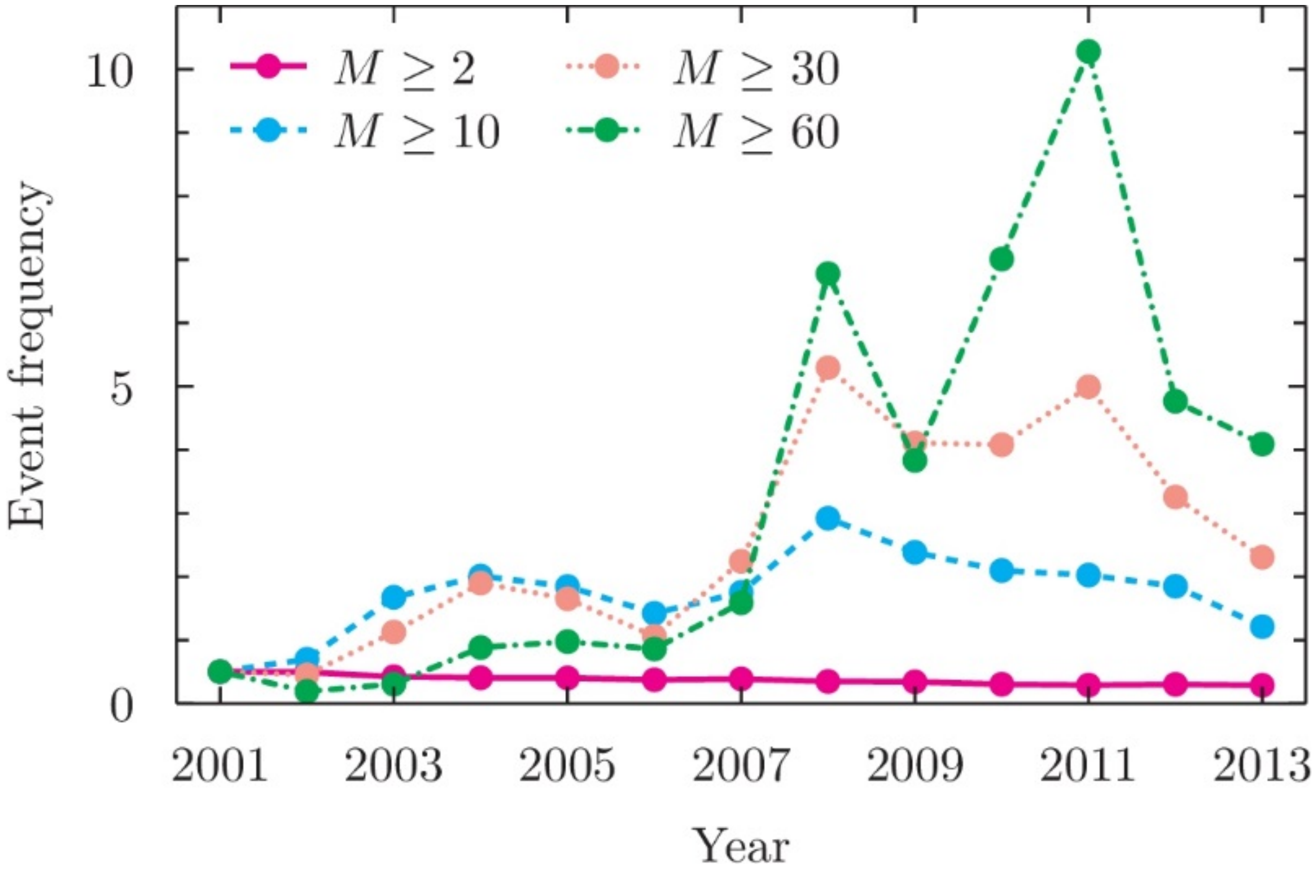
2001

2013

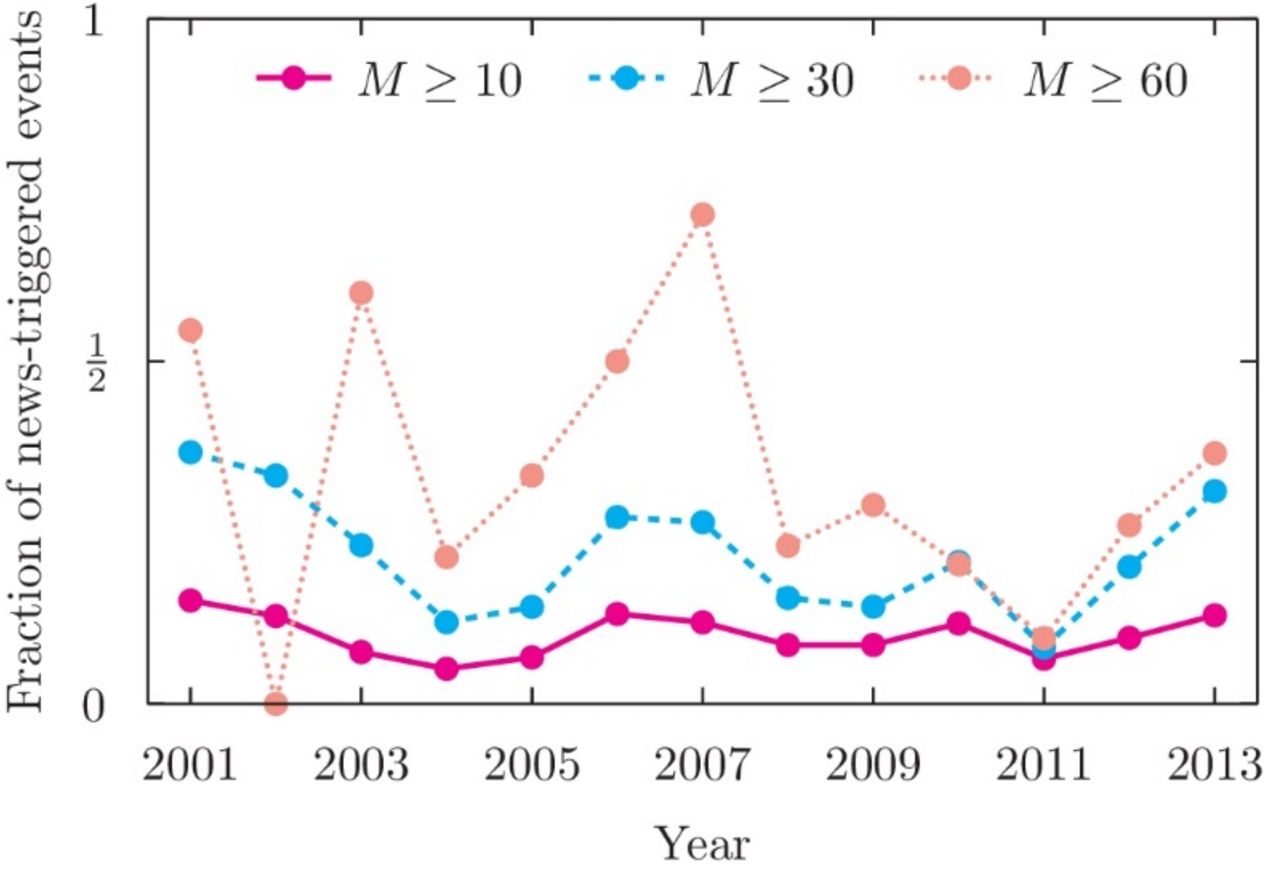
Flash Crash (6th May 2010)



Evolution of systemic instabilities



Exogenous events are less than 50% of all instabilities



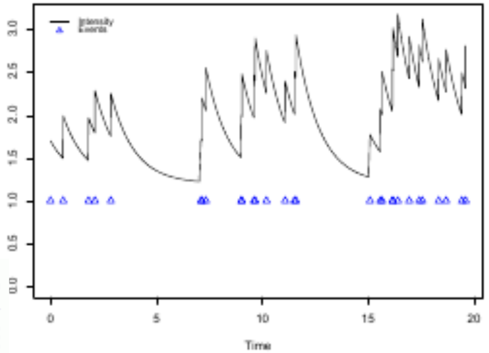
Modelling instabilities with Hawkes processes

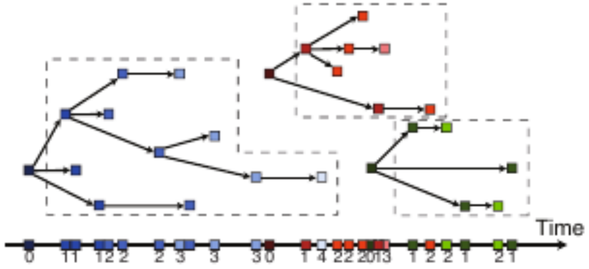
Probability per unit time of an event (jump)

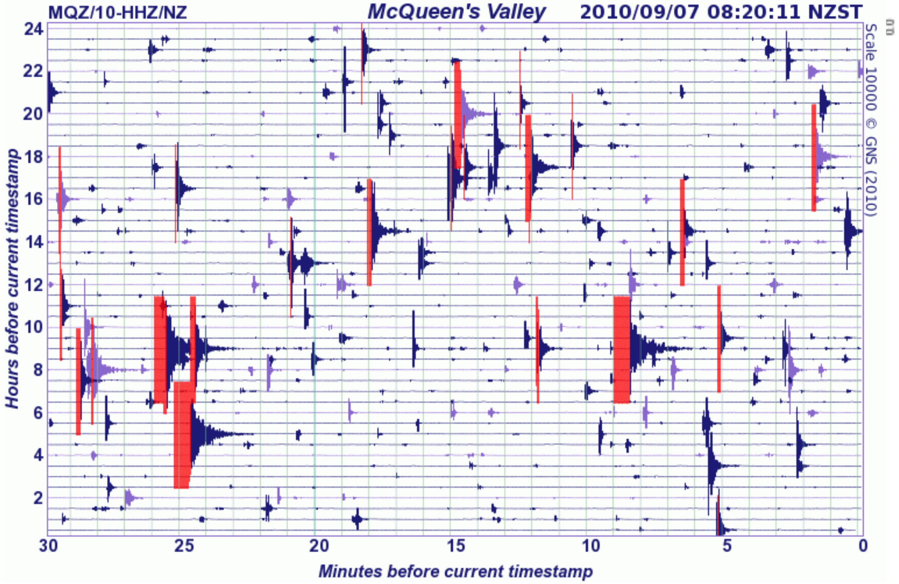
A point process N_t is called a *Hawkes process* if it is a *linear self-exciting process*, defined by the intensity

$$\lambda(t) = \mu + \sum_{t_i < t} \nu(t - t_i) = \mu + \sum_{t_i < t} \alpha e^{-\beta(t - t_i)}$$

where μ is a deterministic function called the *base intensity* and ν is a positive decreasing weight function.







earthquakes

Hawkes process: definition

The counting process $N(t)$ describes the number of events detected until time t.

A family of point processes defined via the intensity function $\lambda(t|\mathcal{F}_t)$

$$\lambda(t|\mathcal{F}_t) = \lim_{\delta\to 0} \mathbb{E}\left[\frac{N(t+\delta)-N(t)}{\delta}|\mathcal{F}_t\right]$$
$$= \mu + \int_{-\infty}^{t} \phi(t-s)\mathrm{d}N(s) = \mu + \sum_{t_i<t} \phi(t-t_i)$$

where

- μ is a positive constant baseline intensity (Poisson component)
- the *kernel* $\phi(t)$ is a *positive* and *causal* function in L_1 (i.e. $\phi(t)=0,\ \forall t<0$)
- stability condition $\|\phi\|_1 \equiv \int_0^\infty \phi(t)dt < 1$
- $n \equiv \|\phi\|_1 =$ *degree of endogeneity*.

Applied to earthquakes, epidemiology, genomics, crime, finance, etc.

Hawkes processes

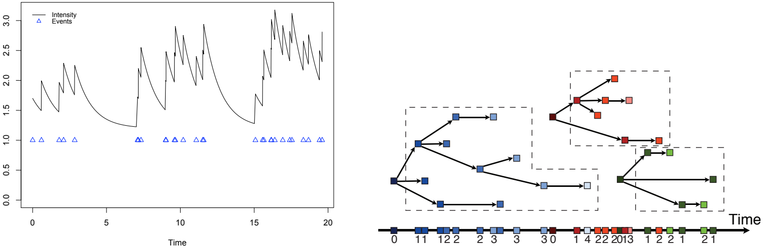


Figure: Left. Example of a simulated univariate Hawkes process. A blue triangle signals the occurrence of a count. A single exponential kernel was employed with $\mu = 1.2$, $\alpha = 0.5$, $\beta = 0.9$. Right. Branching structure of the Hawkes process (top) and events on the time axis (bottom). This picture corresponds to a branching ratio equal to $n = 0.88$. (from Filimonov and Sornette, PRE 2012).

Multivariate Hawkes process

$$\lambda_i(t) = \mu_i + \sum_{j=1}^{D} \int_{-\infty}^{t} \phi_{ij}(t-s)\mathrm{d}N_j(s) = \mu_i + \sum_{i=1}^{D} \sum_{t_j<t} \phi_{ij}(t-t_j)$$

- $\mathrm{d}N_j(s) = \sum_{t_j<s} \delta(s-t_j)\mathrm{d}s$
- μ_i is a positive constant baseline intensity
- the *kernels* $\phi_{ij}(t)$ are *positive* and *causal* functions in L_1

For each component:

$$\Lambda_i = \mu_i + \sum_{j=1}^{D} \Lambda_j \|\phi_{ij}\|$$

Hence:

- μ_i is the immigrant intensity of type i events.
- $\frac{\Lambda_j}{\Lambda_i}\|\phi_{ij}\|$ is the fraction of type i events ”triggered” by type j events.
- $\|\phi_{ij}\|$ is the average number of type i event triggered by a type j event.

The process $N(t)$ is stationary if the spectral radius of the matrix

$$\|\mathbf{\Phi}\| = \{\|\phi_{ij}\|\}$$

is strictly smaller than one.

Estimation of Hawkes processes

- Maximum likelihood estimation
  Given a functional form of the kernel ϕ, the log-likelihood reads:

$$\ln \mathcal{L} = -\int_0^T (\lambda_{\boldsymbol{\theta}}(s))\mathrm{d}s + \int_0^T \ln \lambda_{\boldsymbol{\theta}}(s)\mathrm{d}N(s)$$

- Non parametric estimation
  The second order statistic

$$g(t)dt \equiv \mathbb{E}\left[dN(t)|dN(0)=1\right] - \delta(t) - \mathbb{E}\left[\lambda(t)\right]dt$$

  is sufficient, thanks to the following

Theorem

The kernel ϕ is the only causal solution of the Wiener-Hopf integral equation

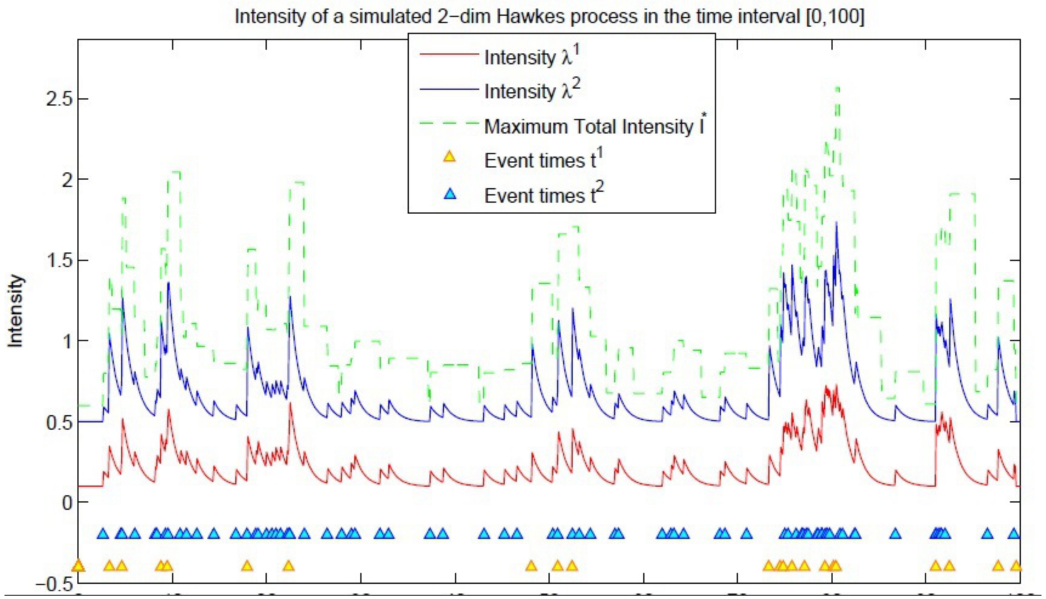
$$g(t) = \phi(t) + g * \phi(t) \qquad \forall t > 0$$

where $*$ indicates convolution.

The challenge: highly dimensional Hawkes processes

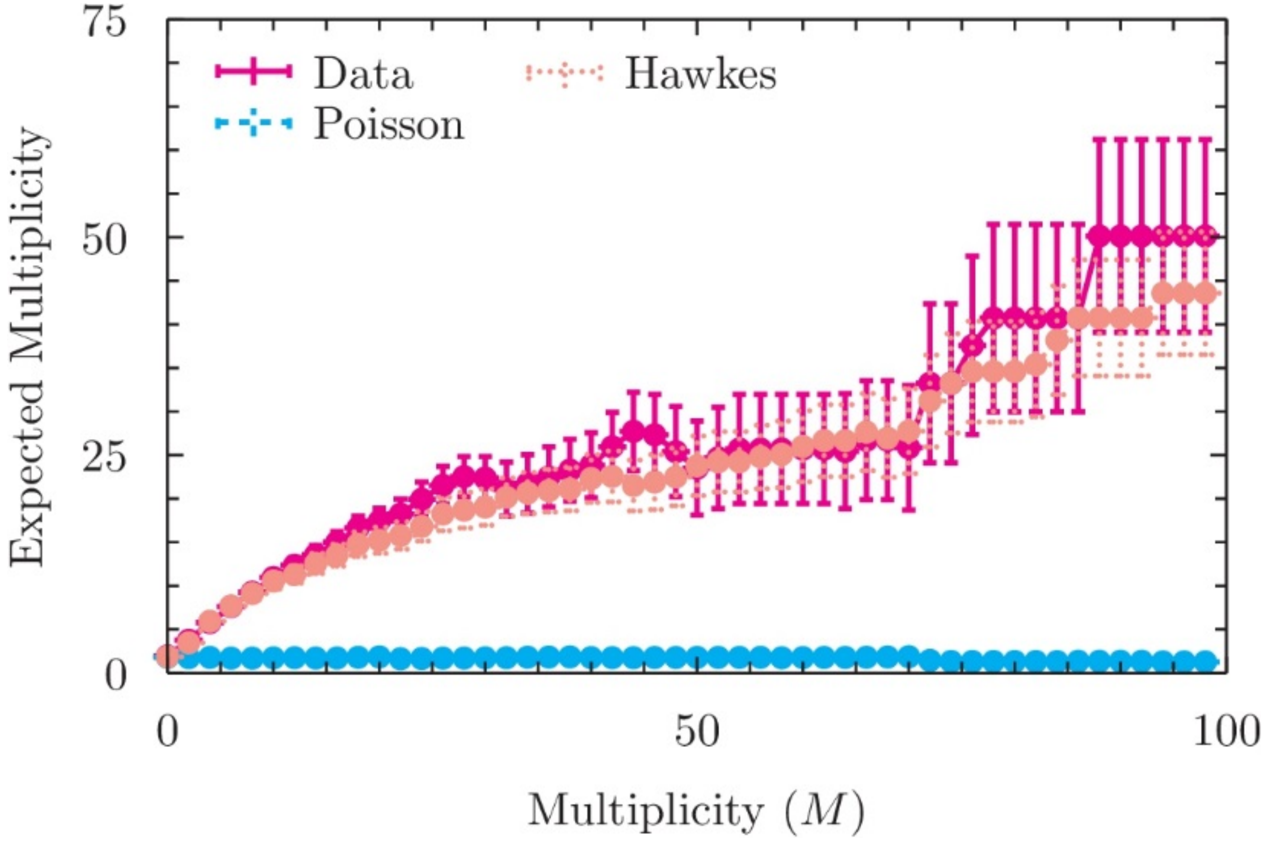
- Multidimensional Hawkes processes are able to describe self and cross excitation between signals, but are difficult to calibrate
- Factor Hawkes models (Bormetti et al 2013)
- Parametric multidimensional Hawkes processes for the multiplicity of events (Calcagnile et al 2015)

$$\lambda_i(t) = \lambda_i^0 + \sum_{j=1}^{M} \sum_{s_j<t} \alpha_{ij} \mathrm{e}^{-\beta_{ij}(t-s_j)}$$

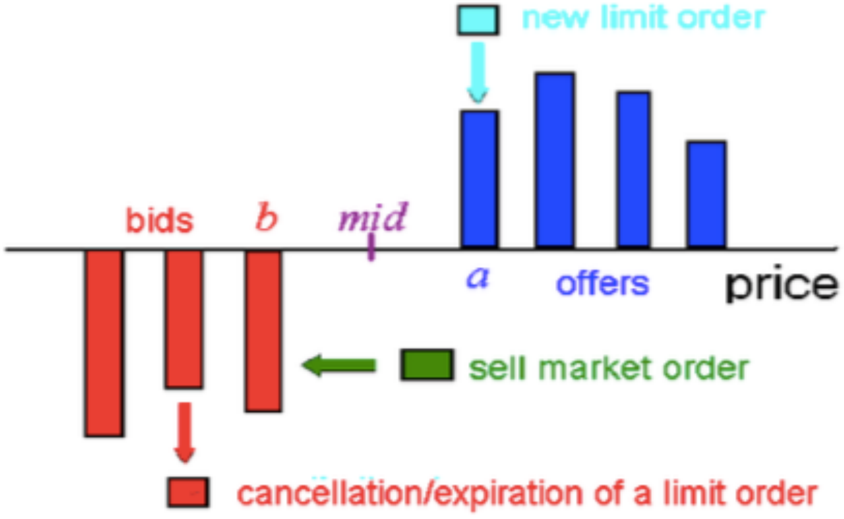


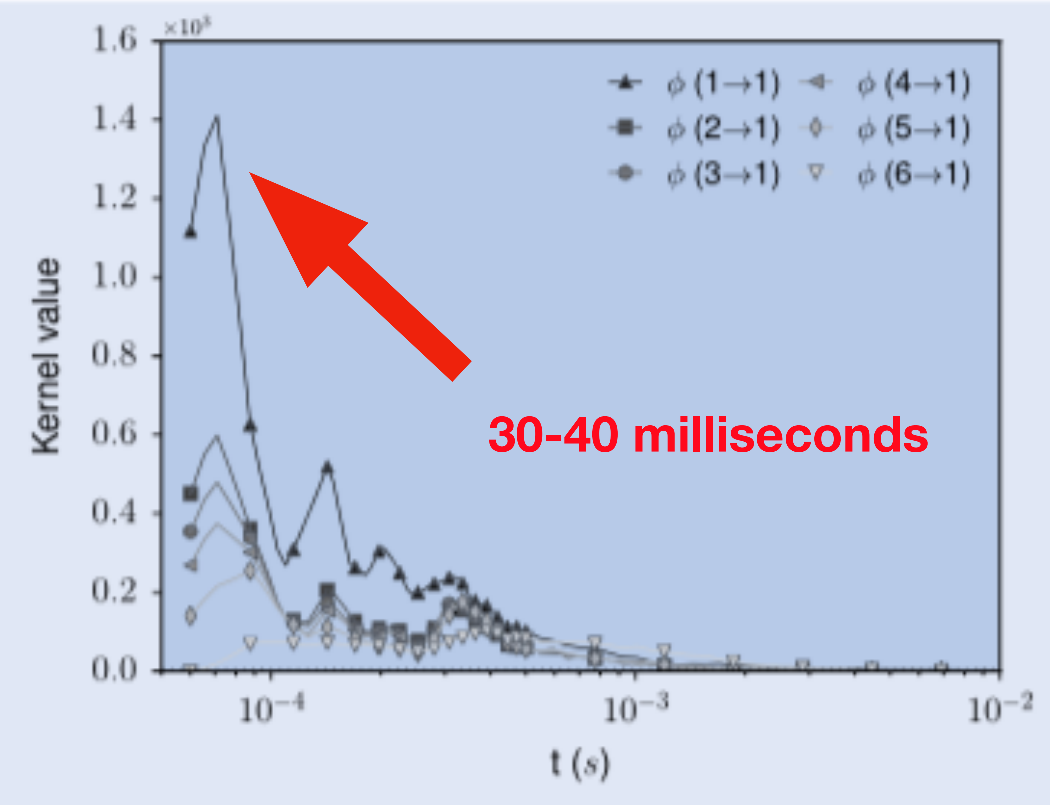
A large fraction of instabilities and of market activity (> 99%) is endogenously generated

High-multiplicity is self-exciting



ULTRA HIGH FREQUENCY: MEASURING FEEDBACK EFFECT ON MICROSECONDS



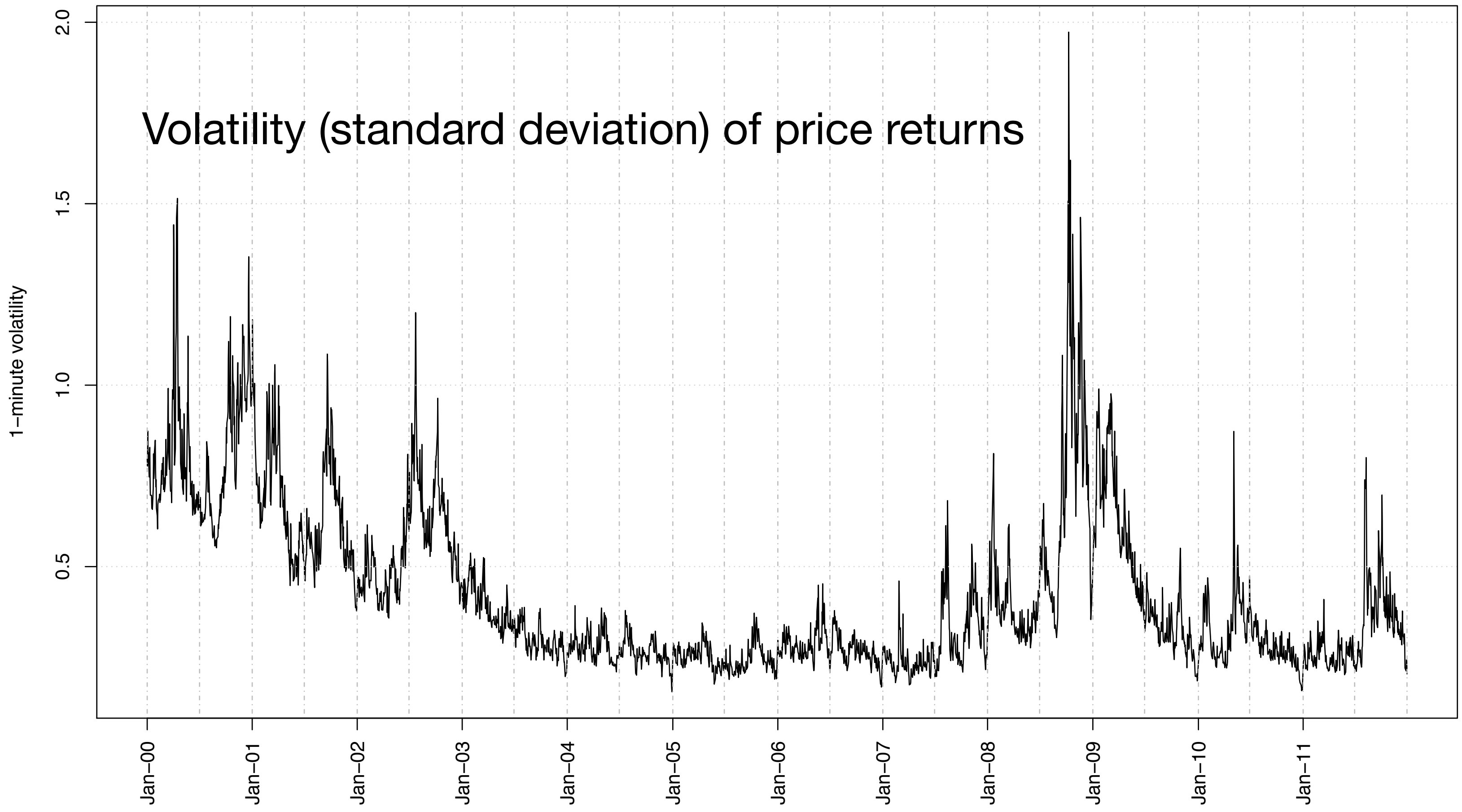


- Inferred kernel of the Hawkes process measuring the endogenous feedback effect on trading in the EUREX market
  - clear evidence of a "market reaction time" at 300μs
  - 300μs is the average co-location roundtrip time!
  - Interaction below market reaction time: HF strategies by same trader (e.g. order splitting)
  - Effect on cancellations ! order re-positioning by market makers

M. Rambaldi, E. Bacry, F. Lillo 2017

Variability

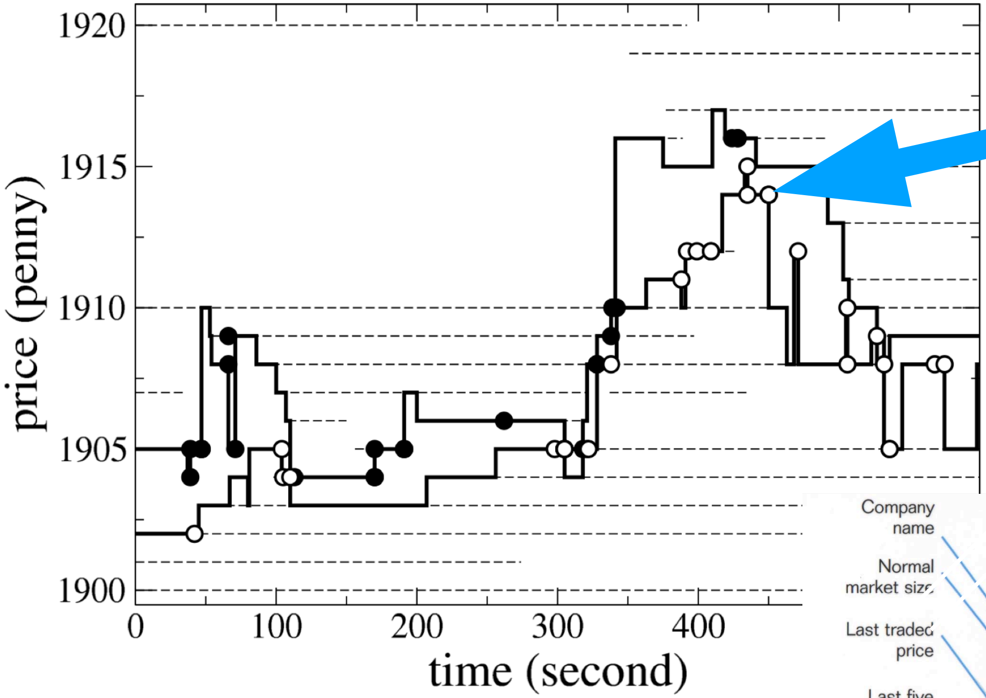
WE LIVE IN A DYNAMICAL WORLD…



Tradeoff between:

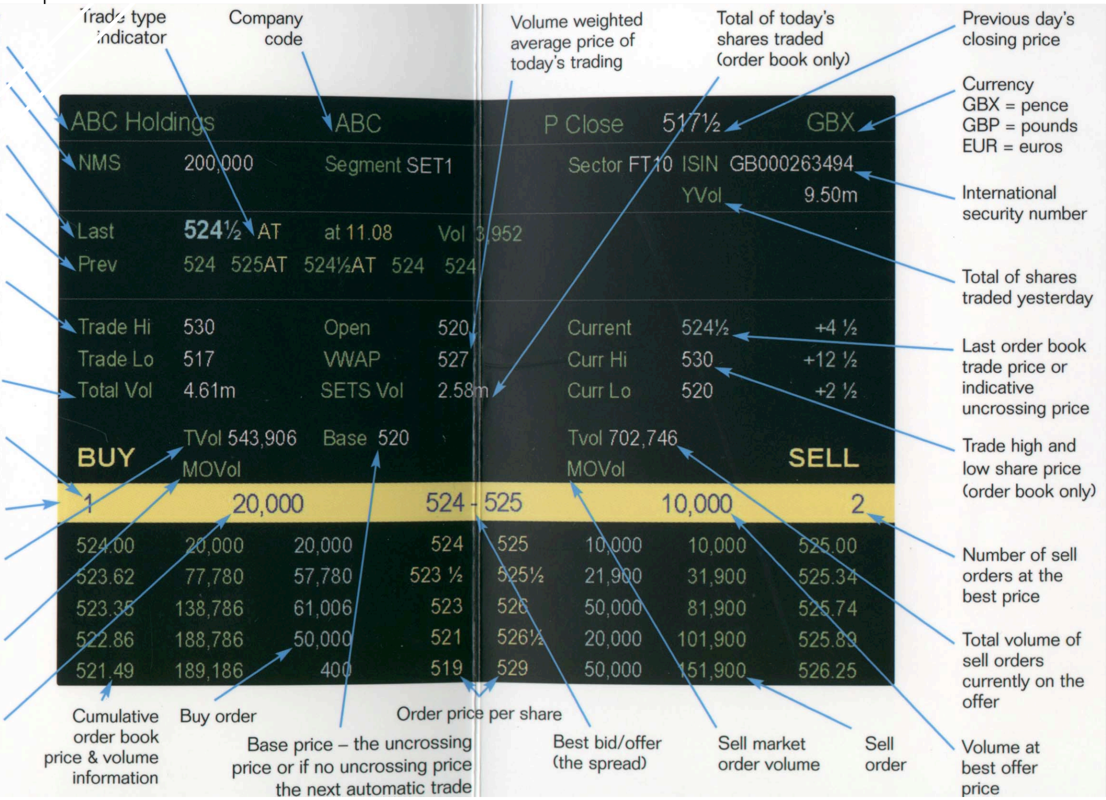
- More accurate estimate (large windows)
- More timely estimate (small windows)
- Error: 1/sqrt(T)

...WHICH IS ALSO NOT ALWAYS OBSERVABLE AND NOISY



trades (old 2000 data)

What is the price now?



ABC Holdings ABC P Close 517½ GBX

NMS 200,000 Segment SET1 Sector FT10 ISIN GB000263494

YVol 9.50m

Last 524½ AT at 11.08 Vol 3,952

Prev 524 525AT 524½AT 524 524

Trade Hi 530 Open 520 Current 524½ +4 ½

Trade Lo 517 VWAP 527 Curr Hi 530 +12 ½

Total Vol 4.61m SETS Vol 2.58m Curr Lo 520 +2 ½

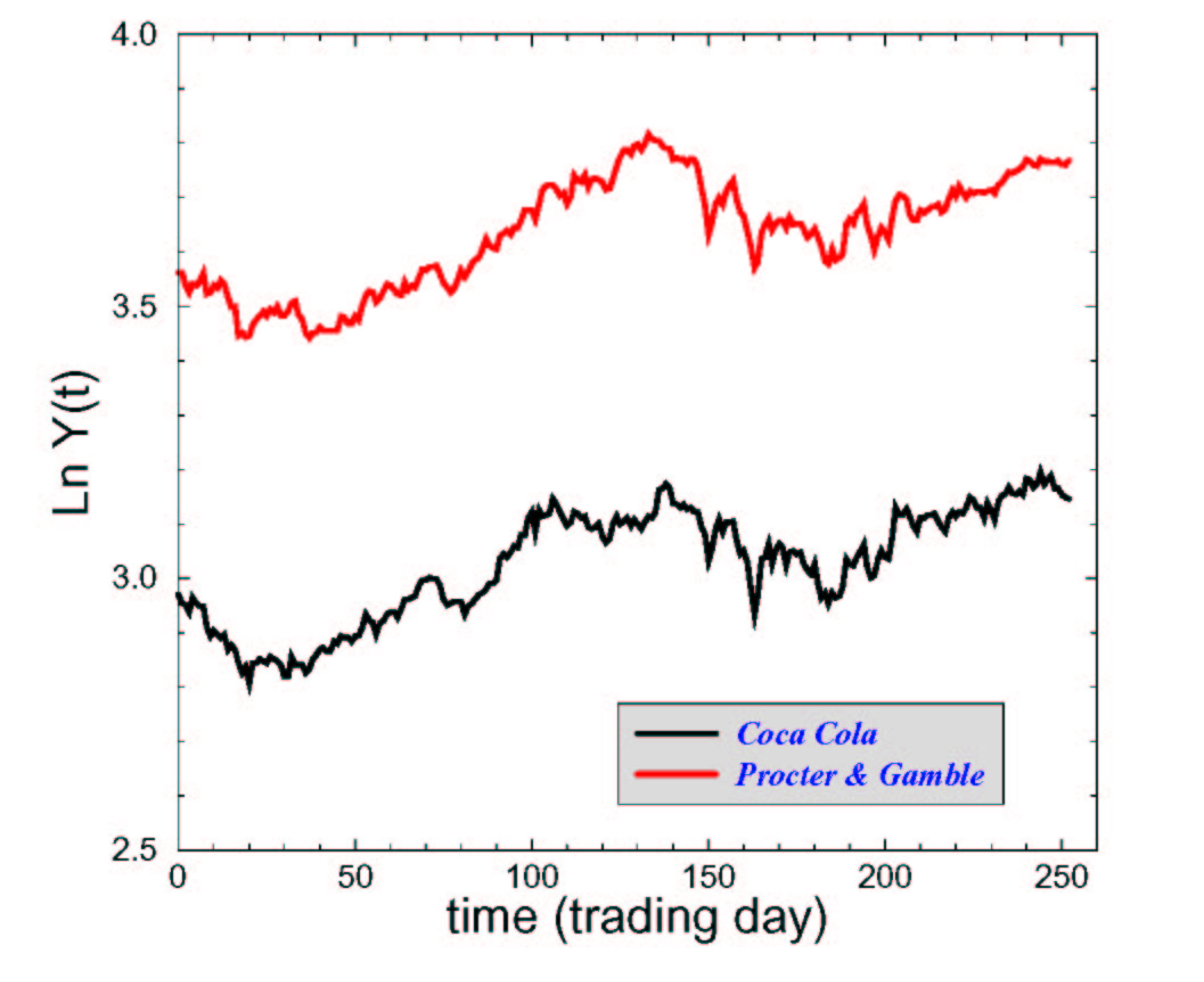
BUY TVol 543,906 Base 520 Tvol 702,746 SELL

MOVol MOVol

1		20,000	524 - 525		10,000		2
524.00	20,000	20,000	524	525	10,000	10,000	525.00
523.62	77,780	57,780	523 ½	525½	21,900	31,900	525.34
523.35	138,786	61,006	523	526	50,000	81,900	525.74
522.86	188,786	50,000	521	526½	20,000	101,900	525.89
521.49	189,186	400	519	529	50,000	151,900	526.25

Company name
Trade type indicator
Company code
Volume weighted average price of today's trading
Total of today's shares traded (order book only)
Previous day's closing price
Normal market size
Currency GBX = pence GBP = pounds EUR = euros
Last traded price
International security number
Last five trade prices
Total of shares traded yesterday
Highest & lowest prices of the day on and off the order book
Last order book trade price or indicative uncrossing price
Total shares traded
Trade high and low share price (order book only)
Number of buy orders at the best price
Yellow strip
Number of sell orders at the best price
Total volume of buy orders currently on the bid
Total volume of sell orders currently on the offer
Buy market order volume
Volume at best bid price
Cumulative order book price & volume information
Buy order
Order price per share
Base price – the uncrossing price or if no uncrossing price the next automatic trade
Best bid/offer (the spread)
Sell market order volume
Sell order
Volume at best offer price

Correlation among stocks is present

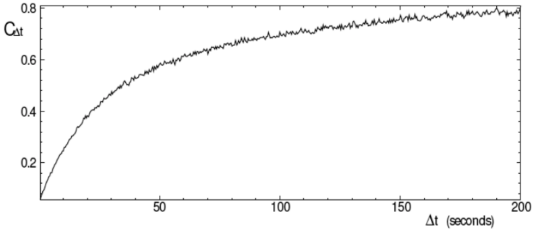


Problem 1: estimating high frequency correlations

Estimating (and forecasting) correlations between asset returns at ultra-high frequency is important but complicated by

- Microstructure noise (e.g. bid-ask bounce)
- Asyncronicity

- Bund 10Y - Bobl 5Y - 40 days - 9-11 am



Epps effect (source Bacry)

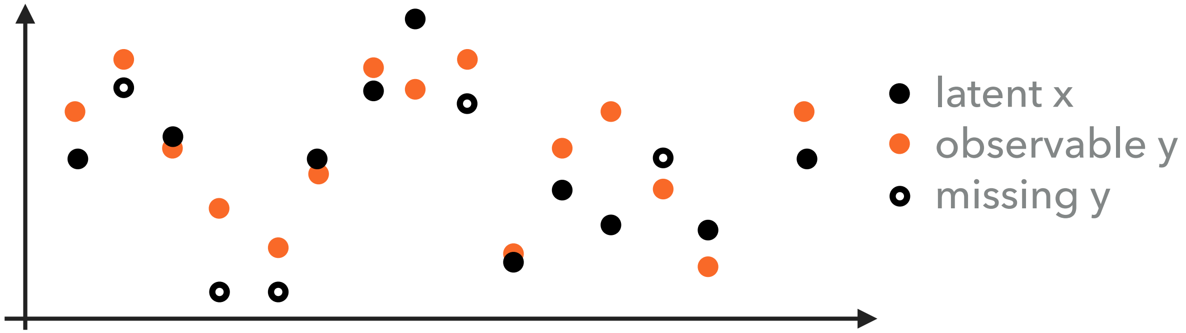
Many estimators robust to these effects have been proposed: Hayashi and Yoshida (2005), Barndorff-Nielsen, Hansen, Lunde, Shephard (2011), Ait-Sahalia, Fan, and Xiu (2010), Corsi, Peluso and Audrino (2014), **and many others**.

AN ECONOMETRIC MODEL FOR DYNAMIC CORRELATIONS

State space representation

$$Y_t = X_t + \epsilon_t, \quad \epsilon_t \sim \mathrm{NID}(0, H_t) \qquad \text{observable}$$

$$X_{t+1} = X_t + \eta_t, \quad \eta_t \sim \mathrm{NID}(0, Q_t) \qquad \text{latent}$$



H_t and Q_t are stochastic but, given observations up to time t – 1, their value at time t is completely known

Kalman filter

missing observations

+

Generalized Autoregressive Score Model

dynamical correlation

Recovering the efficient price

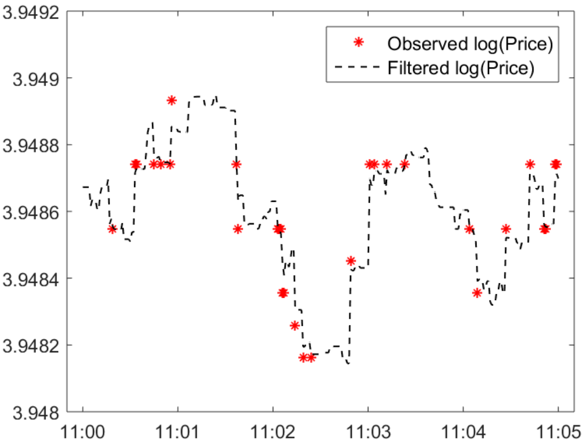
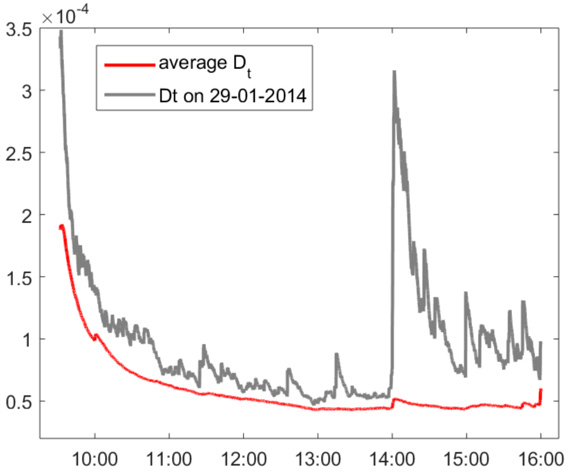


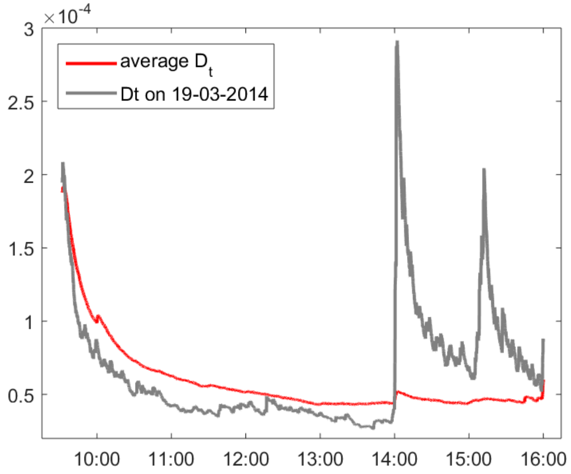
Figure: Observed log-price of Citigroup in a 5 minutes time window on 02/01/2014 and its filtered estimate provided by the LLSD

DYNAMICAL CORRELATION MODEL

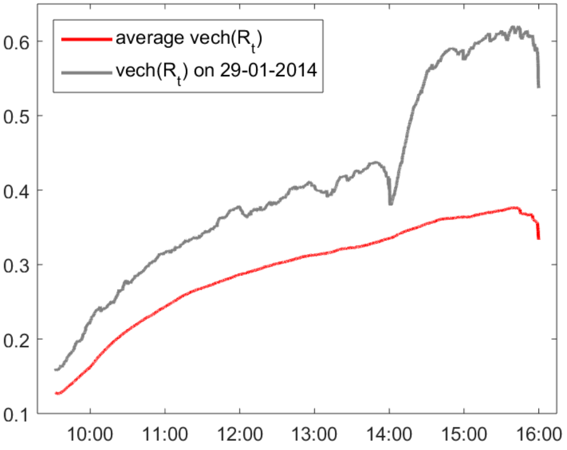
Capture fast, real-time changes of volatilities and correlations: assessing the real-time impact of macro-news announcements

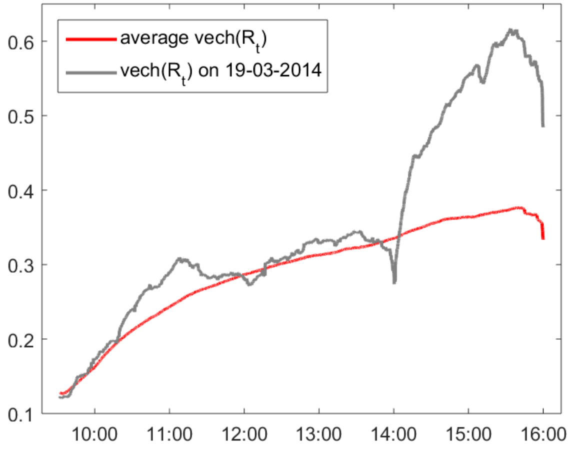
Standard deviations (volatilities)





Cross correlations between stocks





Veracity

How news affect the trading behavior of different categories of investors in a financial market

Research questions

- What is the the relative role of endogenous and exogenous factors affecting trading behavior of agents?
- Endogenous factors: price returns and volatility.
- Exogenous factors: number of news and sentiment via semantic analysis of news.
- Is there a difference in the importance of these factors between different categories of investors (e.g. households, companies, governmental, or financial institutions)?

The Finnish database

- Central register of shareholdings for Finnish stocks and financial assets in the Finnish Central Securities Depository.
- Six main **categories**: non-financial corporations, financial and insurance corporations, general governmental organizations, non-profit institutions, households, and foreign organizations.
- Foreign investors can choose to use nominee registration, giving aggregate results. Our focus is mainly on Finnish investors.
- We consider the stock Nokia in the period Jan. 2, 2003 - Dec. 30, 2008 ($1,510$ trading days).
- The time resolution is one day.

Table: Summary of the number of investors (# ids), the number of transactions (N), and the exchanged volume (V). Volume is given in millions of shares.

Category	# ids	N	V
Companies	8,396	1,009,226	4,825
Financial	392	4,079,174	21,402
Governamental	124	39,278	1,985
Non profit	922	21,778	248
Households	129,952	1,555,096	1,993
Foreign	1,405	789,552	7,685
Total	141,190	7,494,104	38,138

The Thomson Reuters database and the sentiment proxy

- Headlines of the NewsScope archive of news released in English by Thomson Reuters.
- We extract all headlines in English language labeled with at least one Nokia Reuters Instrument Code → $11,484$ unique headlines.
- We consider only the headlines during European trading hours (from 8.00 am to 4.30 pm UTC time).
- We construct a sentiment proxy using the number of positive and negative words present in each headline. Positive and negative words are detected by using the General Inquirer from the Harvard psychosocial dictionary.

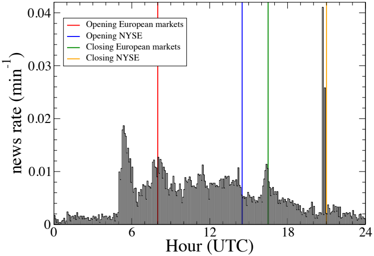


Figure: Average daily pattern of the arrival rate of news on the Nokia company. The rate is measured in number of headlines per minute.

Investigated variables

- Investor variables
  - For each day we classify each agent in buyer (B), seller (S), or buyselling (BS) by using the $q(i,t)$ function defined above.
  - $N_B^K(t)$, $N_S^K(t)$, and $N_{BS}^K(t)$ are the number of investors of category K classified at day t as buyers, sellers or buysellers, respectively.
  - From these variables we obtain

$$\begin{aligned} N^K(t) &= N_B^K(t) + N_S^K(t) + N_{BS}^K(t) & \rightarrow \textit{number of investors of category } K \\ \Delta N_A^K(t) &= N_B^K(t) - N_S^K(t) & \rightarrow \textit{excess of buyers of category } K \\ \Delta N_R^K(t) &= \tfrac{N_B^K(t) - N_S^K(t)}{N^K(t)} & \rightarrow \textit{relative excess of buyers of category } K \end{aligned}$$

- Endogenous variables
  - Daily return
  - Daily volatility (range)
- Exogenous variables
  - Number $H(t)$ of Nokia headlines
  - Absolute and relative sentiment of the news in a given day

$$S_A(t) = G(t) - B(t) \qquad S_R(t) = \frac{G(t) - B(t)}{G(t) + B(t)}$$

where we use the number of positive ($G(t)$) and negative ($B(t)$) words in the headlines.

News, volatility, and agents activity

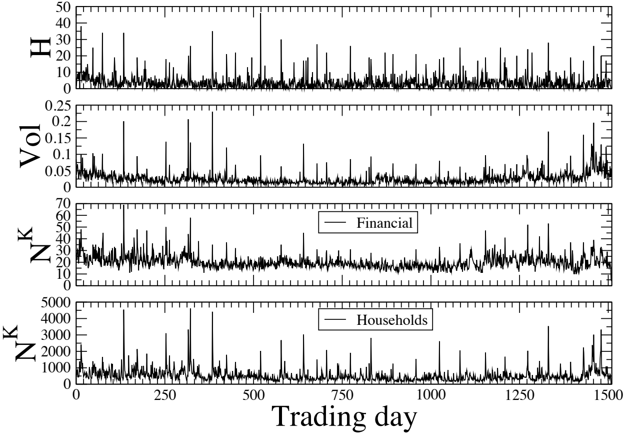


Figure: From top to bottom the figure shows the time series of the number of Nokia headlines $H(t)$, the daily volatility $Vol(t)$ of Nokia stock, and the time series of $N^K(t)$ for the category of Financial investors and for the category of Households investors.

Sentiment, return, and buyers excess

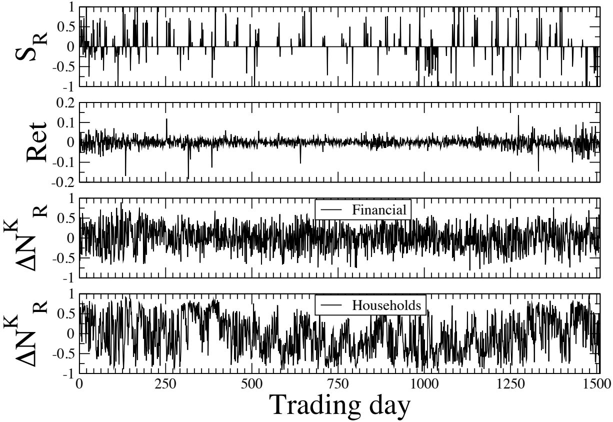


Figure: From top to bottom the figure shows the time series of the relative sentiment indicator $S_R(t)$, the daily return $Ret(t)$ of Nokia stock, and the time series of $\Delta N_R^K(t)$ for the category of Financial investors and of Households investors.

Regression results and partial correlation analysis: news and volatility

- Number of news is correlated with volatility, $\mathrm{Corr}[H, Vol] = 0.501$.
- We fit

$$\widehat{N}^K(t) = \alpha_H \widehat{H}(t) + \alpha_{Vol} \widehat{Vol}(t) + \epsilon(t)$$

where $\widehat{x}$ is the standardized versions with zero mean and unit variance of x.

Table: Summary of the results of the linear regression of the number N^K of trading investors versus the news intensity signal H and the volatility proxy Vol. The number in parentheses are the 5%-95% confidence intervals under Gaussian hypothesis and by using bootstrap analysis. The last two columns show the results of the partial correlation analysis.

Investor category	α_H	α_{Vol}	% variance of residual of N^K	$\rho(N^K, H\|Vol)$	$\rho(N^K, Vol\|H)$
Companies	0.271 (0.229,0.313)	0.517 (0.475,0.559)	51.8 %	0.309	0.534
bootstrap	(0.205,0.335)	(0.437,0.597)			
Financial	0.195 (0.149,0.242)	0.479 (0.433,0.526)	63.8 %	0.207	0.461
bootstrap	(0.125,0.264)	(0.407,0.558)			
Governmental	0.238 (0.183,0.292)	0.192 (0.138,0.246)	86.0 %	0.215	0.180
bootstrap	(0.164,0.303)	(0.119,0.262)			
Non profit	0.319 (0.269,0.369)	0.270 (0.220,0.320)	73.9 %	0.305	0.264
bootstrap	(0.249,0.394)	(0.199,0.344)			
Households	0.226 (0.188,0.263)	0.627 (0.589,0.664)	41.4 %	0.289	0.651
bootstrap	(0.165,0.285)	(0.554,0.697)			
Foreign org.	0.158 (0.109,0.207)	0.442 (0.393,0.492)	70.9 %	0.160	0.416
bootstrap	(0.094,0.224)	(0.374,0.517)			

Regression results and partial correlation analysis: sentiment and returns

- Sentiment is correlated with returns, $\mathrm{Corr}[S_A, Ret] = 0.155$ and $\mathrm{Corr}[S_R, Ret] = 0.118$ (statistically significant).
- We fit
$$\widehat{\Delta} N_R^K(t) = \alpha_{S_R} \widehat{S}_R(t) + \alpha_{Ret} \widehat{R}et(t) + \epsilon(t)$$
where $\widehat{x}$ is the standardized versions with zero mean and unit variance of x.

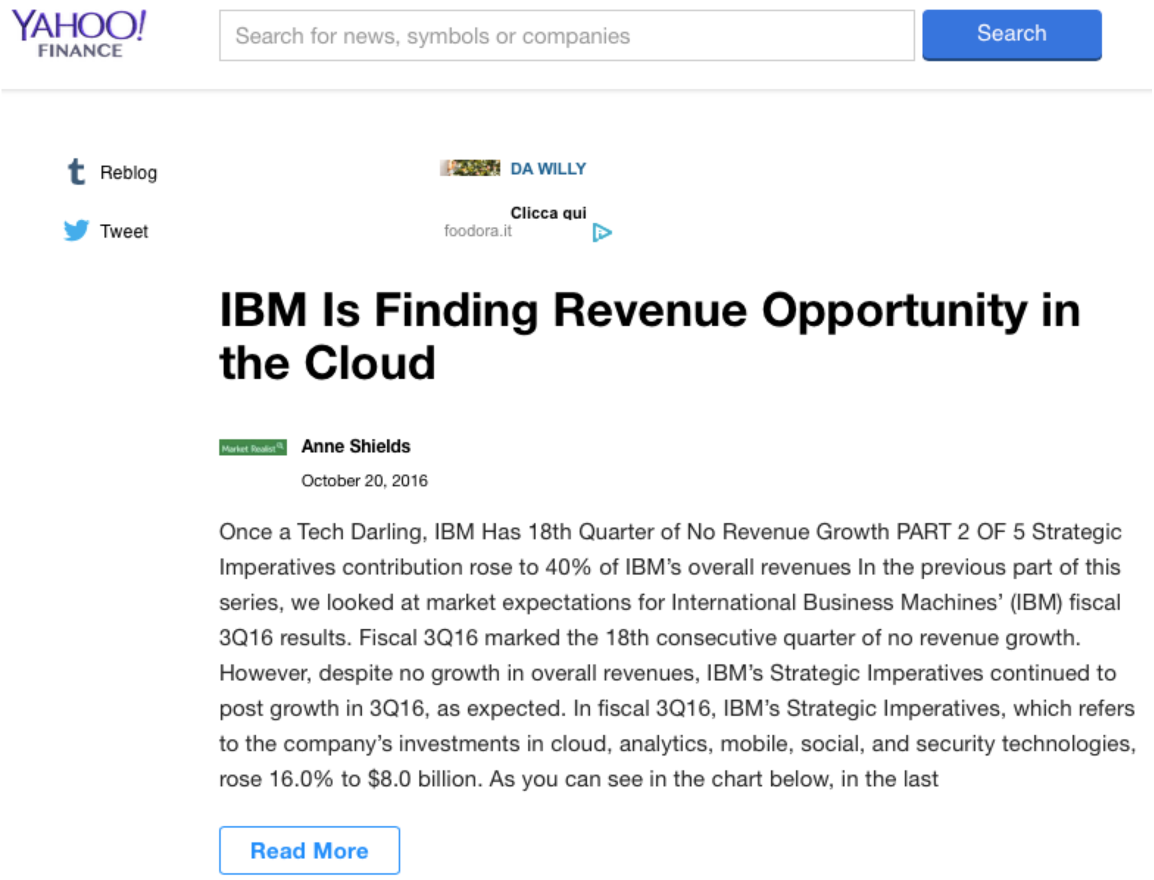
Table: Summary of the results of the linear regression of the relative difference ΔN_R^K between buying and selling investors versus the relative sentiment indicator S_R and the stock return Ret. The number in parentheses are the 5%-95% confidence intervals under Gaussian hypothesis and by using bootstrap analysis. The last two columns show the results of the partial correlation analysis.

Investor category	α_{S_R}	α_{Ret}	% variance of residual of ΔN_R^K	$\rho(N_R^K, S_R \| Ret)$	$\rho(N_R^K, Ret \| S_R)$
Companies bootstrap	0.055 (0.014,0.095) (0.015,0.100)	-0.610 (-0.650,-0.569) (-0.685,-0.548)	63.3 %	0.0685	-0.6056
Financial bootstrap	0.018 (-0.025,0.062) (-0.030,0.064)	-0.520 (-0.564,-0.477) (-0.587,-0.463)	73.1 %	0.0212	-0.5170
Governmental bootstrap	0.021 (-0.029,0.071) (-0.027,0.075)	-0.179 (-0.230,-0.129) (-0.225,-0.136)	96.8 %	0.0215	-0.1782
Non profit bootstrap	0.025 (-0.025,0.075) (-0.028,0.079)	-0.175 (-0.225,-0.125) (-0.227,-0.130)	96.9 %	0.0256	-0.1738
Households bootstrap	0.068 (0.026,0.110) (0.025,0.111)	-0.565 (-0.608,-0.523) (-0.629,-0.512)	68.4 %	0.0811	-0.5615
Foreign org. bootstrap	0.030 (-0.017,0.077) (-0.015,0.076)	-0.400 (-0.446,-0.353) (-0.449,-0.354)	84.2 %	0.0323	-0.3970

Comments

- The activity of governmental and non profit organizations is very poorly explained by return and news sentiment. Of the two factors, return plays clearly a major role.
- Households and companies are those for which sentiment and returns have the best explanatory power of their trading action. Return is clearly more important, but sentiment has also some explanatory power, especially when one consider the relative imbalance between buyers and sellers.
- For financial and foreign organizations the variance explained by the regressions is somewhat intermediate between the two pairs of categories above, but in general returns have a much higher explanatory power and sentiment plays a negligible role.
- For companies, financial institutions, households and foreign organizations $\alpha_{Ret} < 0$ and large indicating that market polarization of trading actions is strongly anticorrelated with the Nokia return. The majority of single investors of these categories are therefore buying when the Nokia price goes down and selling when the price goes up.
- On a daily time scale, news move investors to trade.
- Most of the times the sentiment indicator is not significantly correlated with the imbalance between buyers and sellers.

Algos reading texts



IBM Is Finding Revenue Opportunity in the Cloud

Anne Shields

October 20, 2016

Once a Tech Darling, IBM Has 18th Quarter of No Revenue Growth PART 2 OF 5 Strategic Imperatives contribution rose to 40% of IBM's overall revenues In the previous part of this series, we looked at market expectations for International Business Machines' (IBM) fiscal 3Q16 results. Fiscal 3Q16 marked the 18th consecutive quarter of no revenue growth. However, despite no growth in overall revenues, IBM's Strategic Imperatives continued to post growth in 3Q16, as expected. In fiscal 3Q16, IBM's Strategic Imperatives, which refers to the company's investments in cloud, analytics, mobile, social, and security technologies, rose 16.0% to $8.0 billion. As you can see in the chart below, in the last

- Huge quantity of texts (news, blogs, social networks)
- Extracting in automatic way
  - features
  - meaning
  - sentiment
- Natural Language Processing
- Sentiment extraction
- Are news predicting prices?

NEWS AND CLICKS TO PREDICT RETURNS

- Sentiment of public news have a very weak predictive power on price returns
- Important news (e.g. earning announcements) have a stronger impact; however only when the content of the news was unexpected (see the Efficient Market Hypothesis)

- Is it possible to measure the “surprise” of a news by monitoring the number of clicks it receives in an internet news portal?
- Is the sentiment weighted by the surprise more predictive?

Market data: 100 high capitalization stocks traded in US equity markets, in 2012-2013.

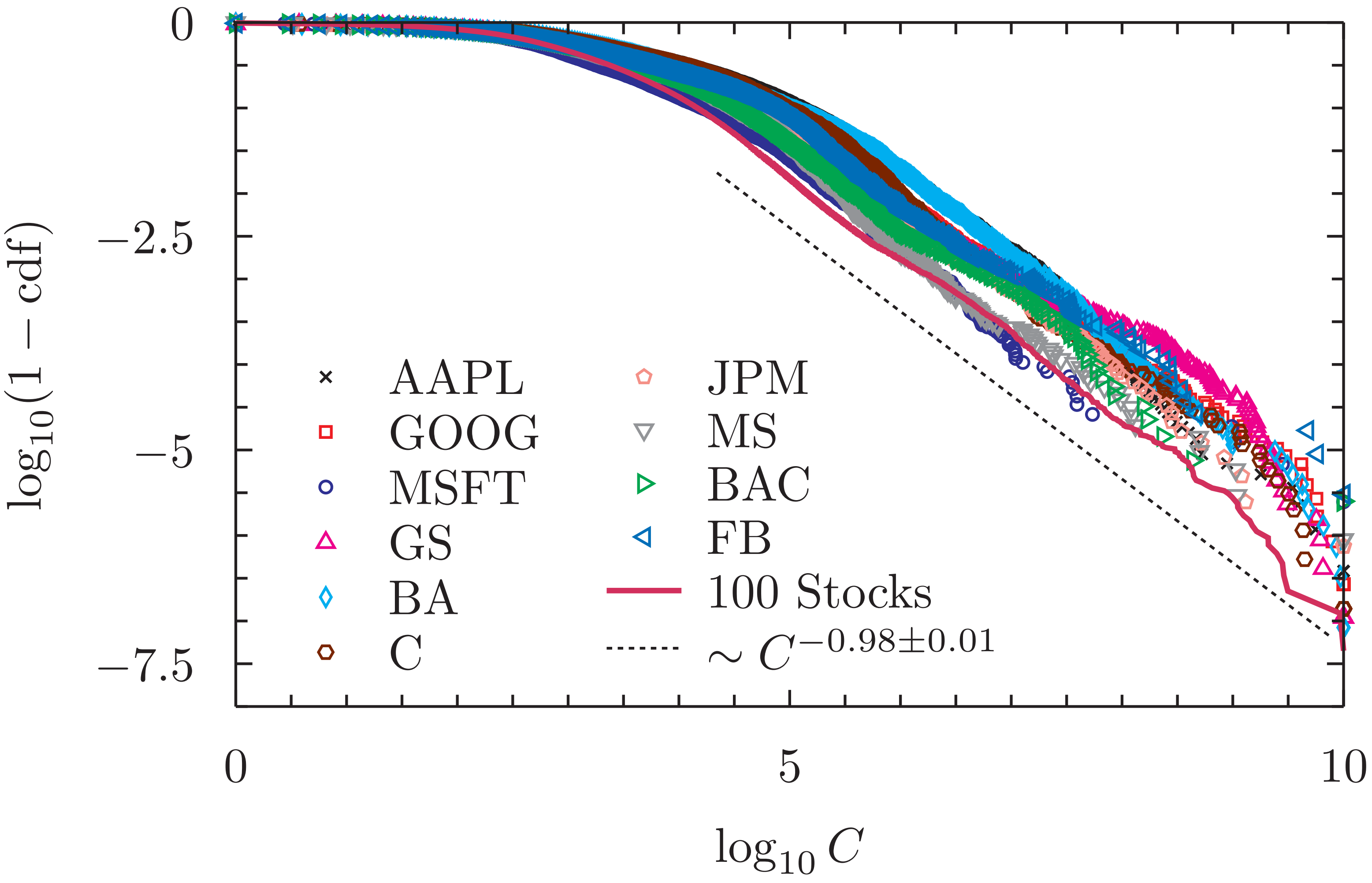
- V , the traded volume in that interval of time,
- R, the logarithmic price return in the time scale,
- σ, the return absolute value, a simple proxy for the stock volatility.

News and click data: news published on **Yahoo! Finance** together with the time series of the aggregated clicks made by the users browsing each page.

- C, the time series of the total number of clicks in a time window,
- S, the sum of the sentiment of all news related to each company,
- **WS, the sum of the sentiment of all news weighted by the number of clicks.**

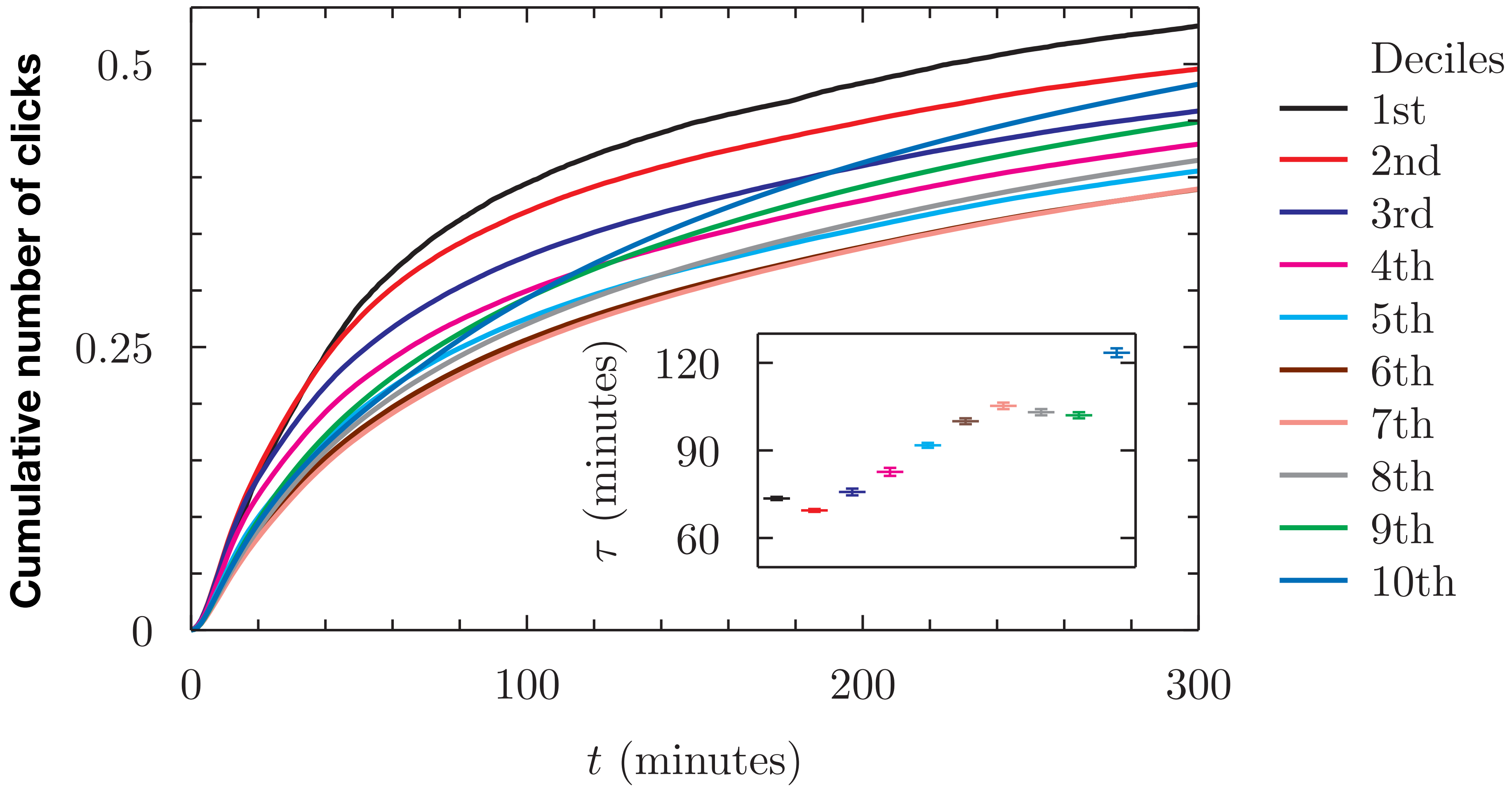
Ranco et al. PlosONE 2016

NOT ALL NEWS TRIGGER THE SAME ATTENTION



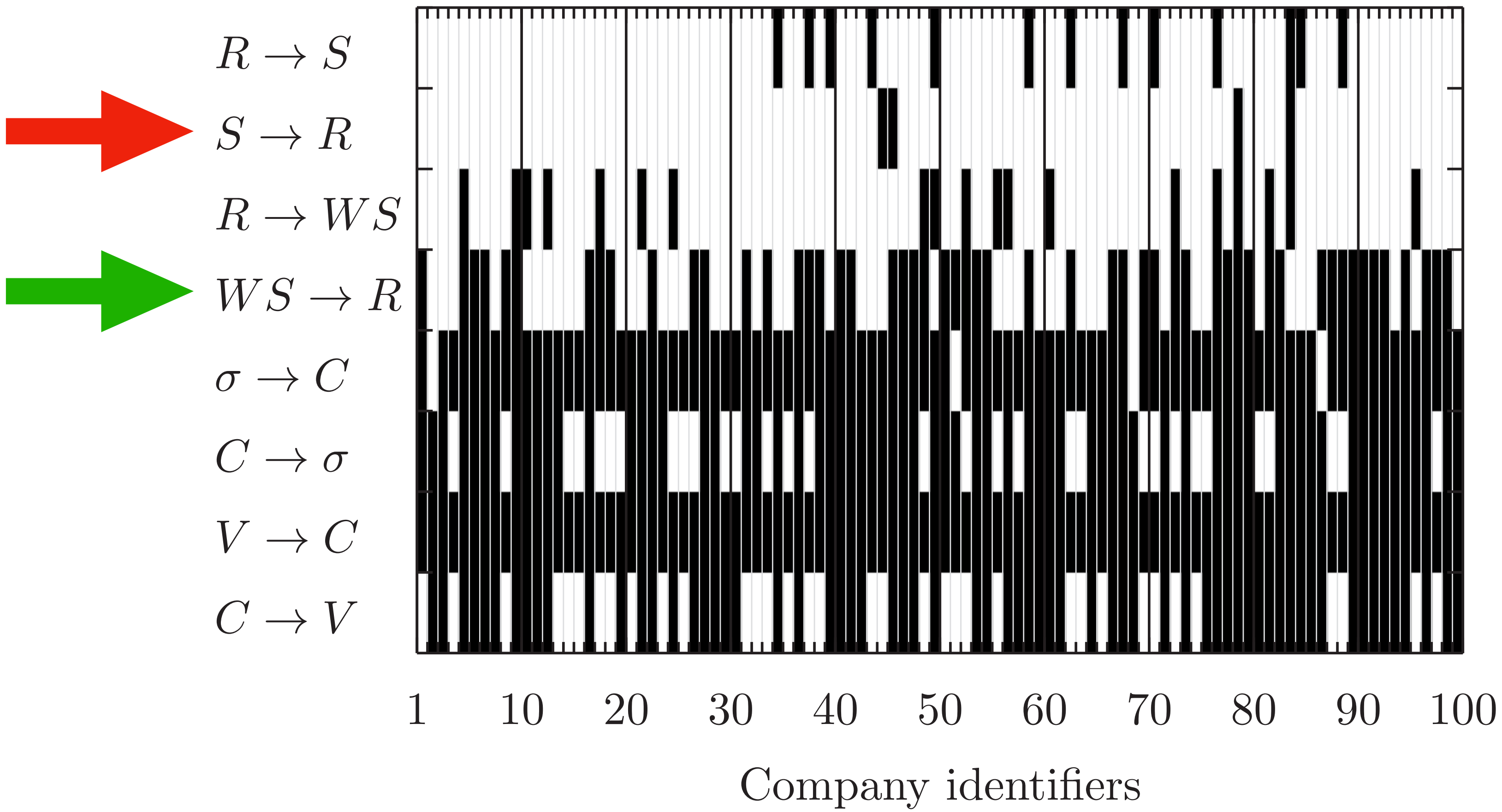
Complementary of the cumulative distribution function of the number of clicks a news receives for the ten assets with the largest number of news and the aggregate portfolio of 100 stocks.

DYNAMICS OF ATTENTION



Time evolution of the cumulative number of clicks per news in a time interval of five hours after the publication. We normalize the cumulated amount by a constant which corresponds to the total number of clicks received by a single news during the first week after publication. The news are grouped in deciles according to the total number of clicks they have received until October 2013 and the curves represent average values. Inset: estimated values and standard errors of the attention time scale obtained by an exponential fit of the decile curves.

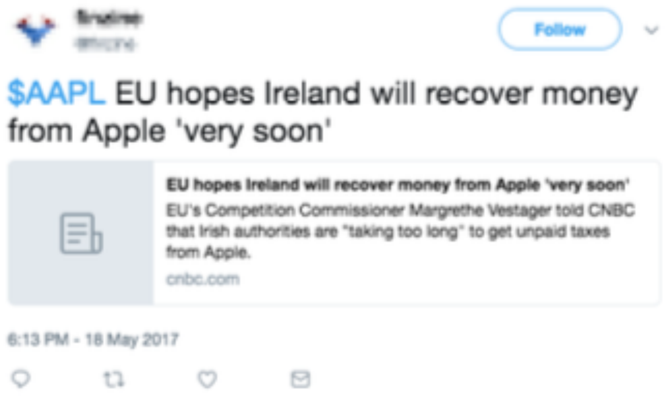
THE IMPORTANCE OF IDENTIFYING THE RELEVANT NEWS



Granger Causality tests at hourly scale between different variables. The white cells correspond to tests for which we do not reject the null hypothesis of no Granger causality at 5% significance level. A black cell corresponds to a statistically significant Granger causality.

Weighting the sentiment of a news with the number of clicks it receives (i.e. the attention of users) highly increases its capability of forecasting price returns

$FAKE: EVIDENCE OF SPAM AND BOT ACTIVITY IN STOCK MICROBLOGS ON TWITTER

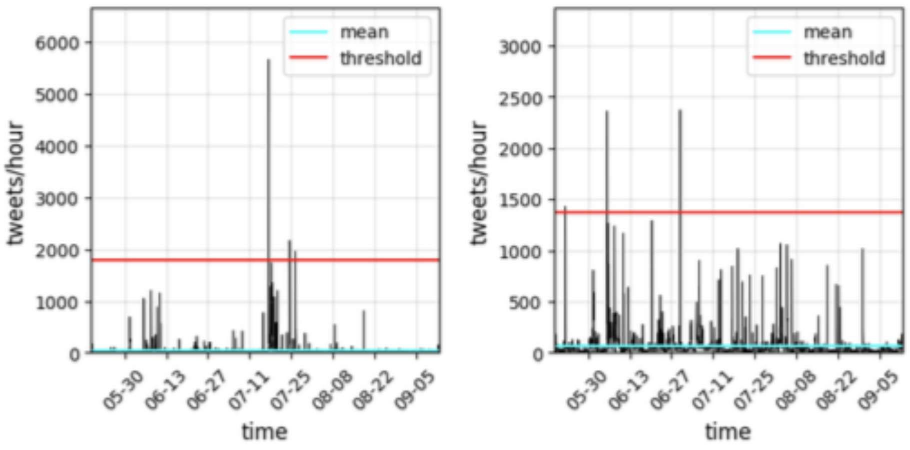


$AAPL EU hopes Ireland will recover money from Apple 'very soon'

EU hopes Ireland will recover money from Apple 'very soon'
EU's Competition Commissioner Margrethe Vestager told CNBC that Irish authorities are "taking too long" to get unpaid taxes from Apple.
cnbc.com

6:13 PM - 18 May 2017

Figure 1: Sample tweet with the $AAPL cashtag.

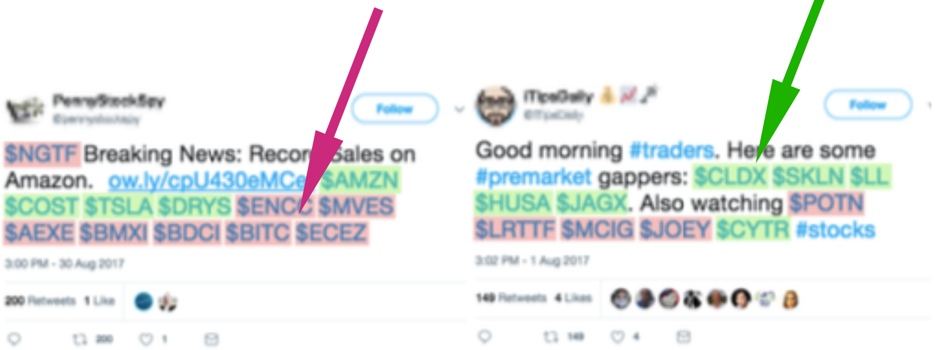


(c) $NFLX (*Netflix, Inc.*).

(d) $TSLA (*Tesla, Inc.*).

high cap stocks

small cap stocks



$NGTF Breaking News: Record Sales on Amazon. ow.ly/cpU430eMCe $AMZN $COST $TSLA $DRYS $ENCC $MVES $AEXE $BMXI $BDCI $BITC $ECEZ

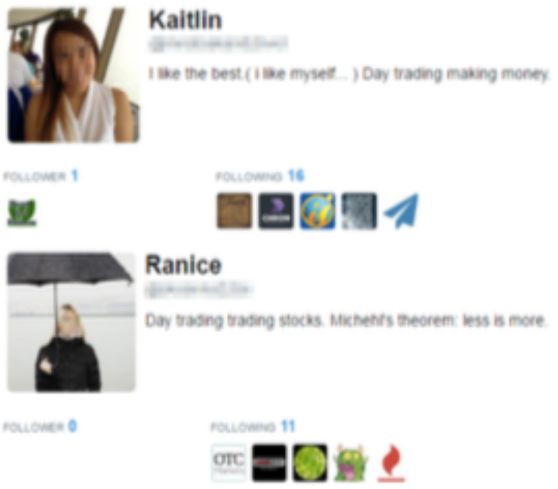
3:00 PM - 30 Aug 2017

200 Retweets 1 Like

Good morning #traders. Here are some #premarket gappers: $CLDX $SKLN $LL $HUSA $JAGX. Also watching $POTN $LRTTF $MCIG $JOEY $CYTR #stocks

3:02 PM - 1 Aug 2017

149 Retweets 4 Likes



Kaitlin

I like the best (i like myself...) Day trading making money

FOLLOWER 1 FOLLOWING 16

Ranice

Day trading trading stocks. Michehl's theorem: less is more

FOLLOWER 0 FOLLOWING 11

Large fraction of tweet peaks on low cap stocks likely due to bots

Cresci et al. 2018