Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Intermittent criticality in financial markets:
towards predictions of large and flash crashes

Peter Cauwels, Vladimir Filimonov, Didier Sornette, Ryan Woodard
ETH Zurich, D-MTEC, Chair of Entrepreneurial Risks

The concepts of

-Phase transitions

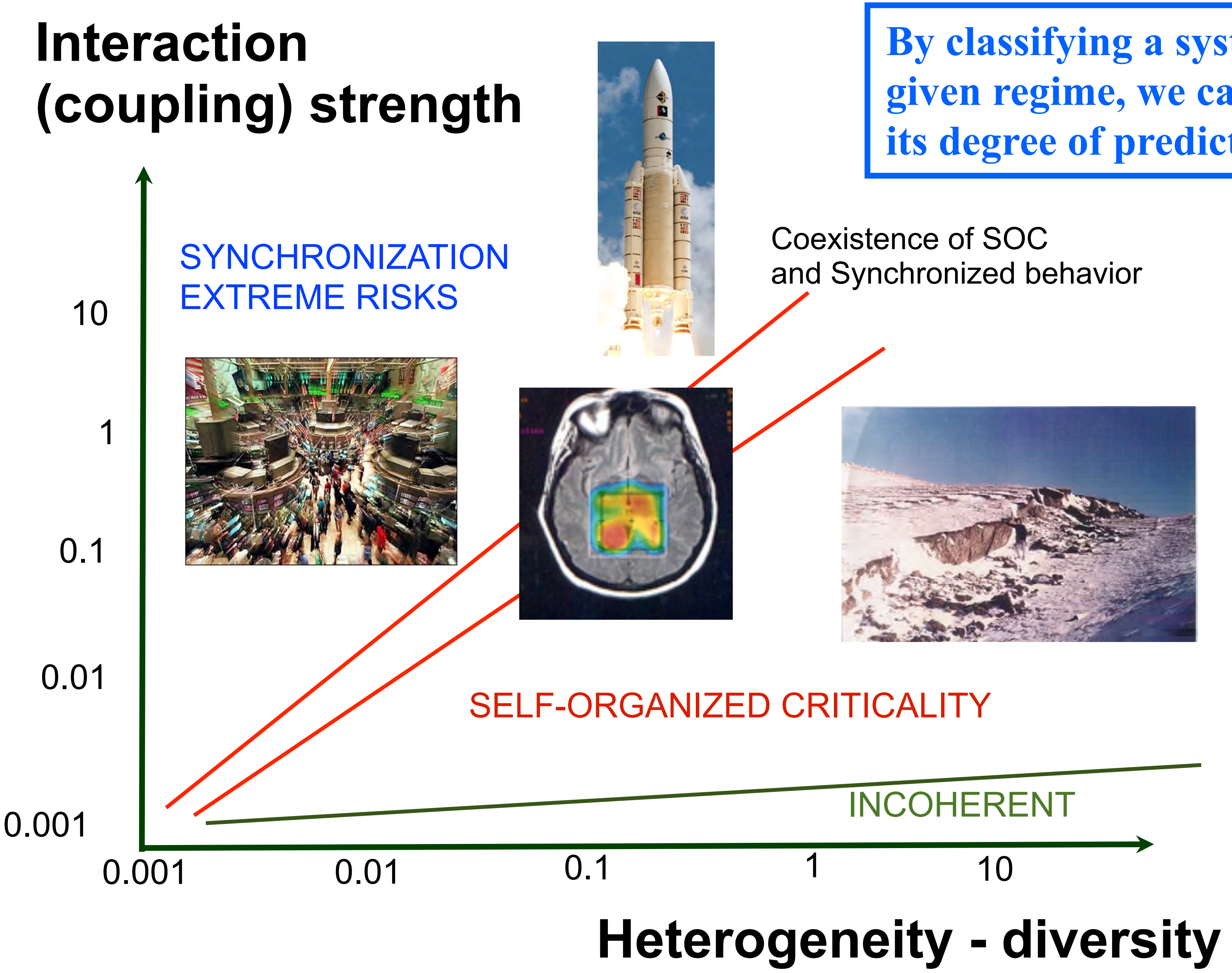
-Bifurcations

-Catastrophes

-Tipping points

Generic Prediction Phase Diagram

By classifying a system in a given regime, we can assert its degree of predictability.



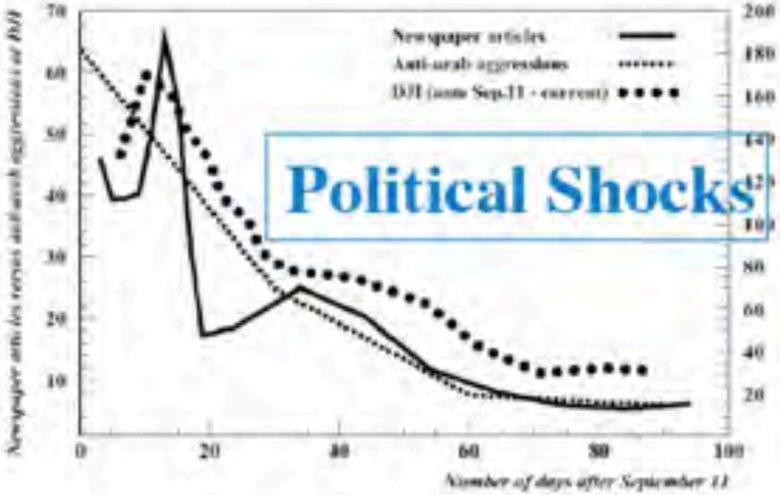
Signs of Upcoming Transition

Early warning signals as predicted from theory

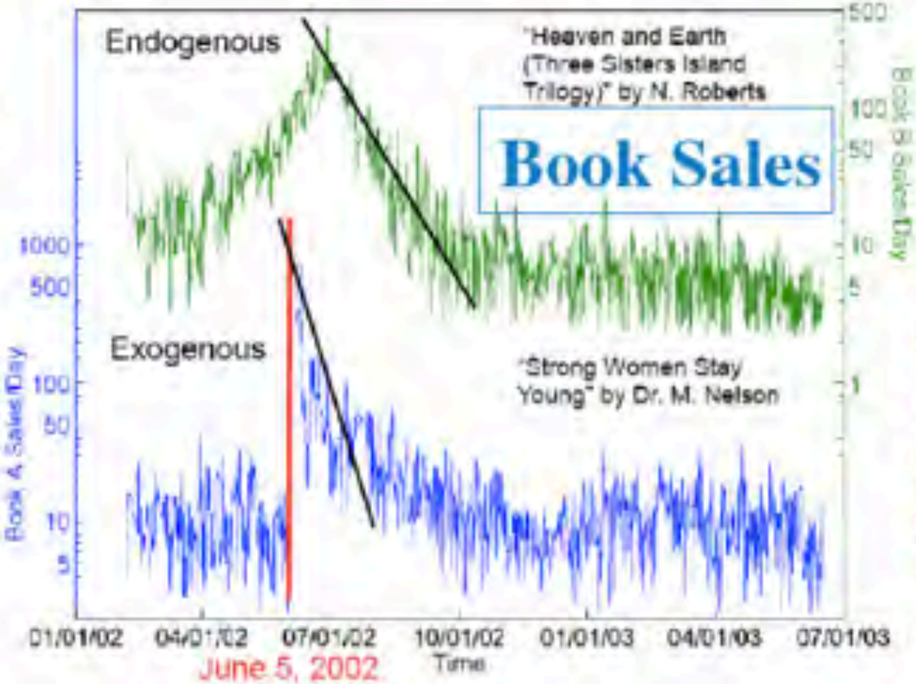
- Slower recovery from perturbations
- Increasing (or decreasing) autocorrelation
- Increasing (or decreasing) cross-correlation with external driving
- Increasing variance
- Flickering and stochastic resonance
- Increased spatial coherence
- **Degree of endogeneity/reflexivity**
- **Finite-time singularities**

Epidemics in Socio-Economic Networks

Roehner, Sornette & Andersen (2004)



Political Shocks



Book Sales

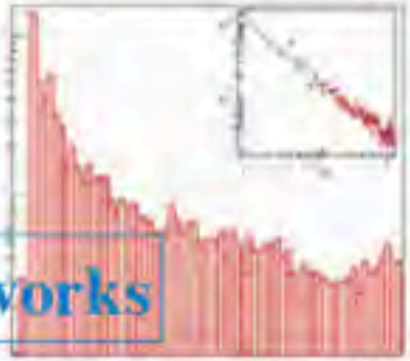
June 4, 2002: New York Times article crediting the "groundbreaking research" of Dr. Nelson

S&P 500

Financial Markets

Sornette etal, PRL (2004)
Sornette etal J.Phys (1996)

YouTube Views

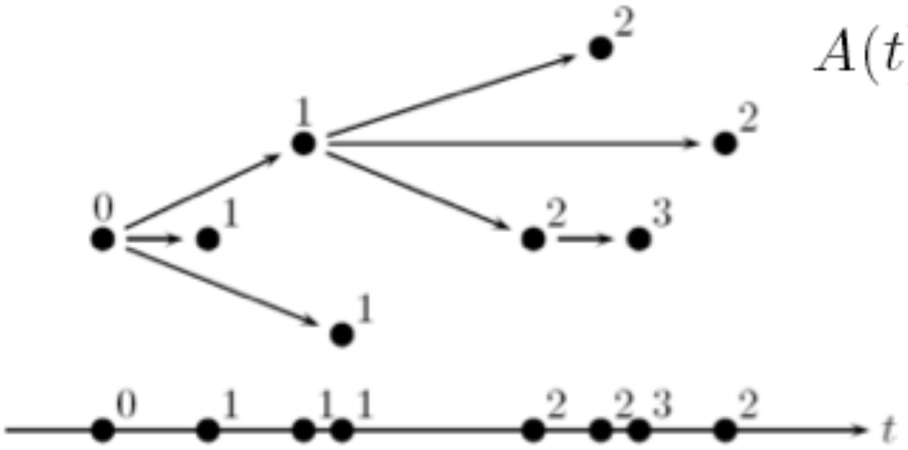


Social Networks

Crane et Sornette (2008)

Epidemic branching process

The activity is modeled as a self-excited Hawkes conditional Poisson branching process



$$A(t) \equiv \langle \lambda(t) \rangle = \eta(t) + n \int_{-\infty}^{t} \phi(t-\tau) A(\tau) d\tau$$

$$A(t) = \eta(t) + \int_0^t \eta(\tau) K(t-\tau)\, d\tau$$

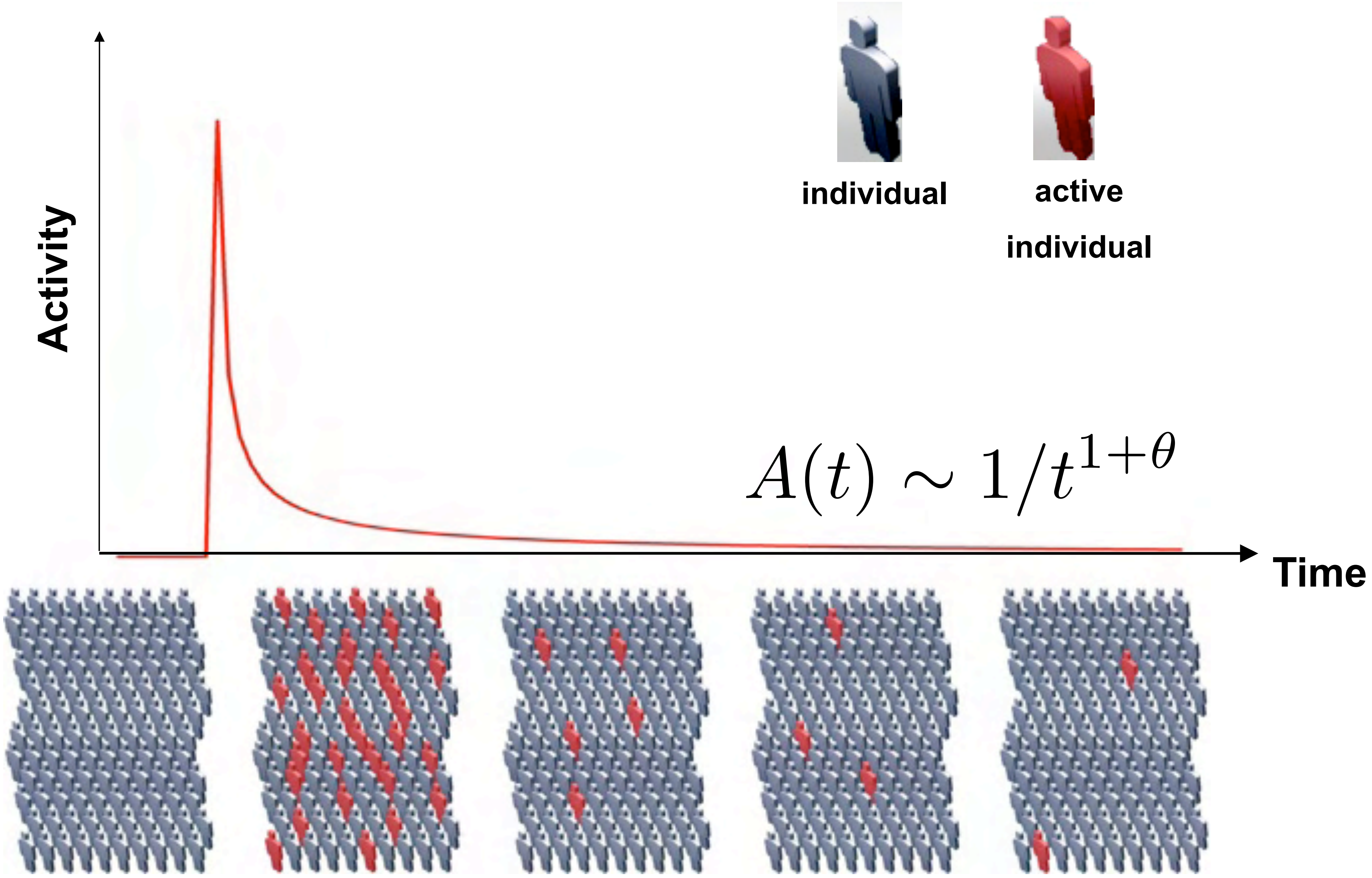
Helmstetter and Sornette,

Physica A (2003)

Key Results:

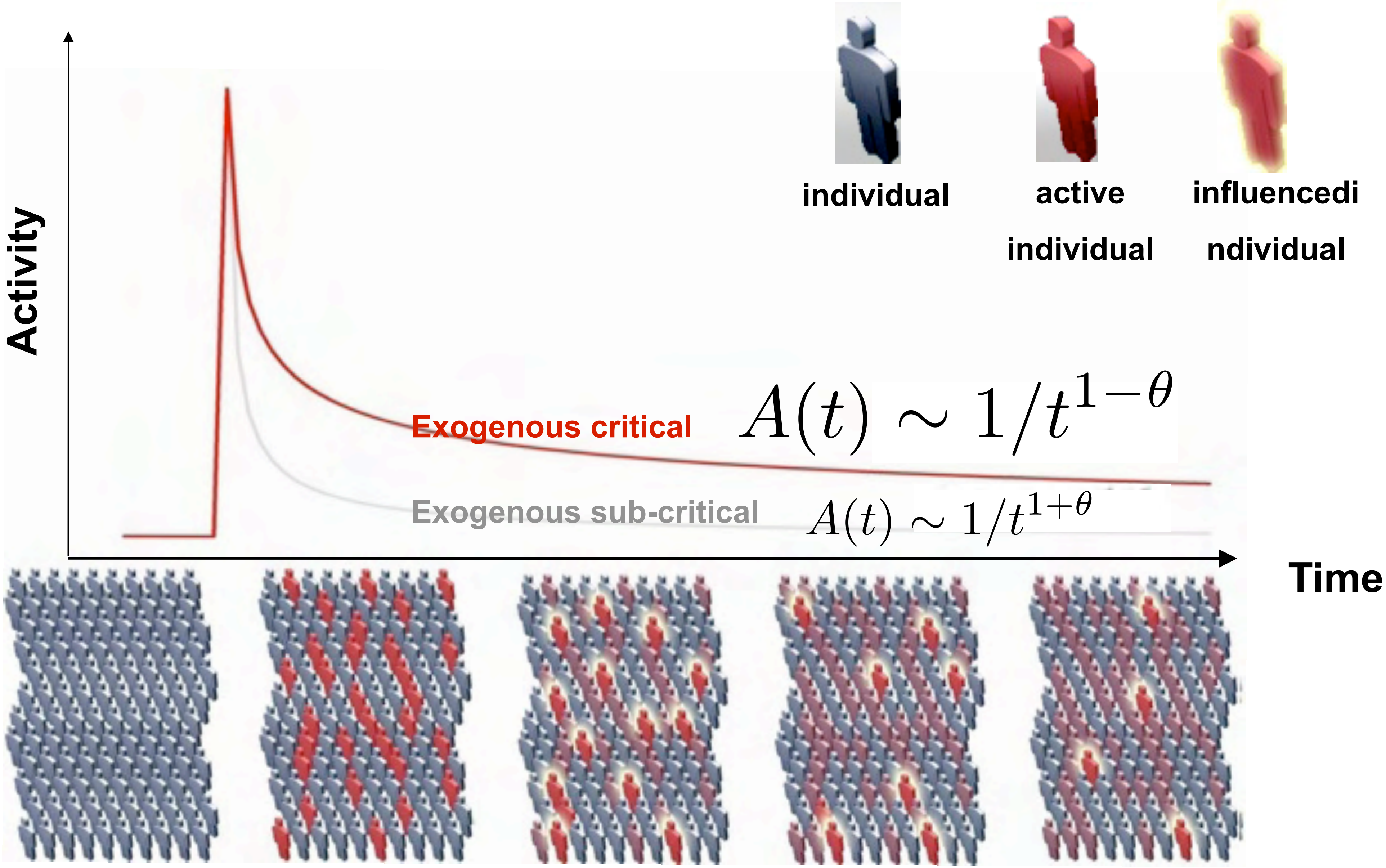
Bare response	$A(t) \sim 1/(t-t_c)^{1+\theta}$
Exo Critical response	$A(t) \sim 1/(t-t_c)^{1-\theta}$
Endo critical response	$A(t) \sim 1/\|t-t_c\|^{1-2\theta}$

Exogenous sub-critical (no spreading)

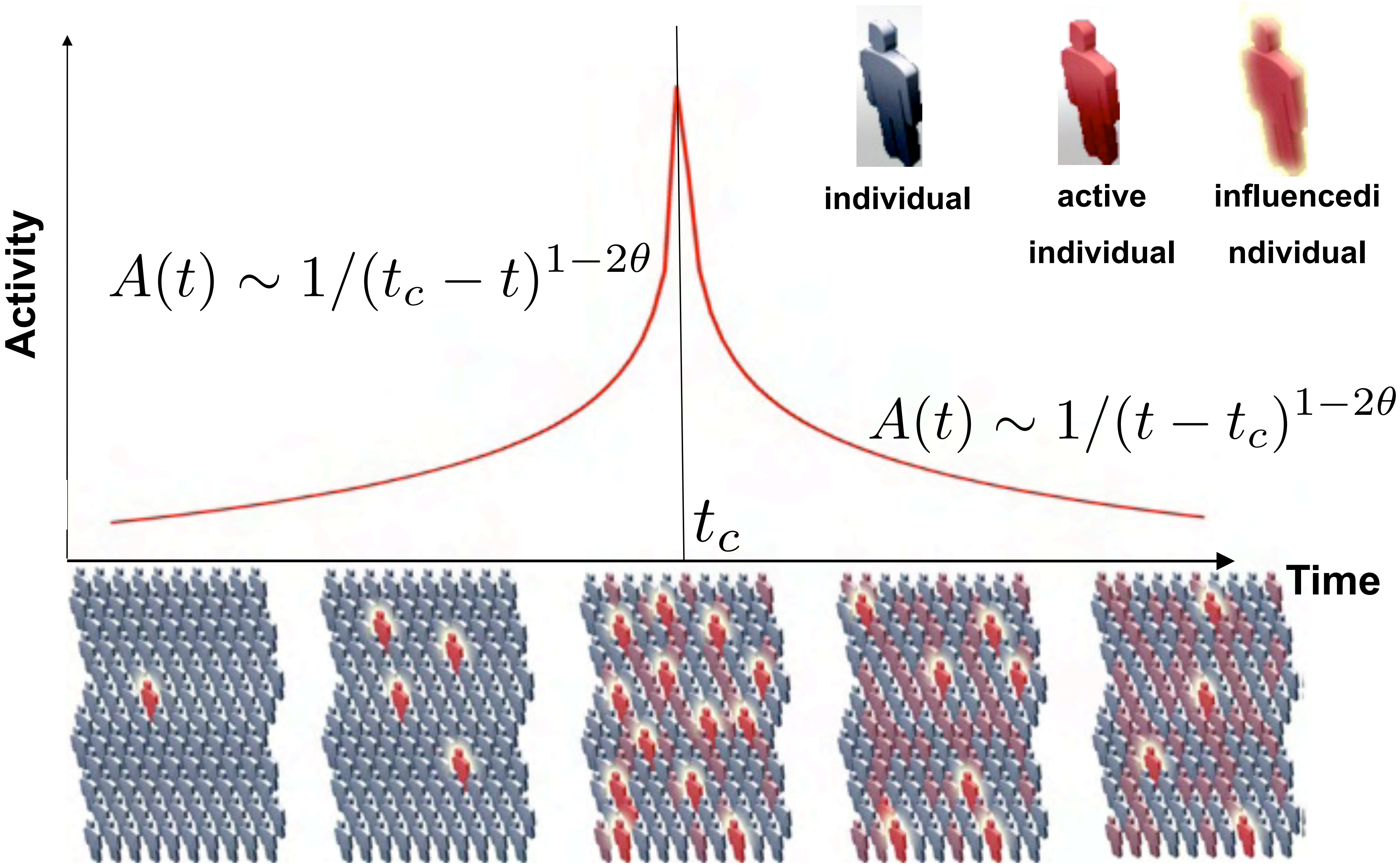


$$A(t) \sim 1/t^{1+\theta}$$

Exogenous critical (spreading)



Endogenous critical (spreading)



Theoretical predictions

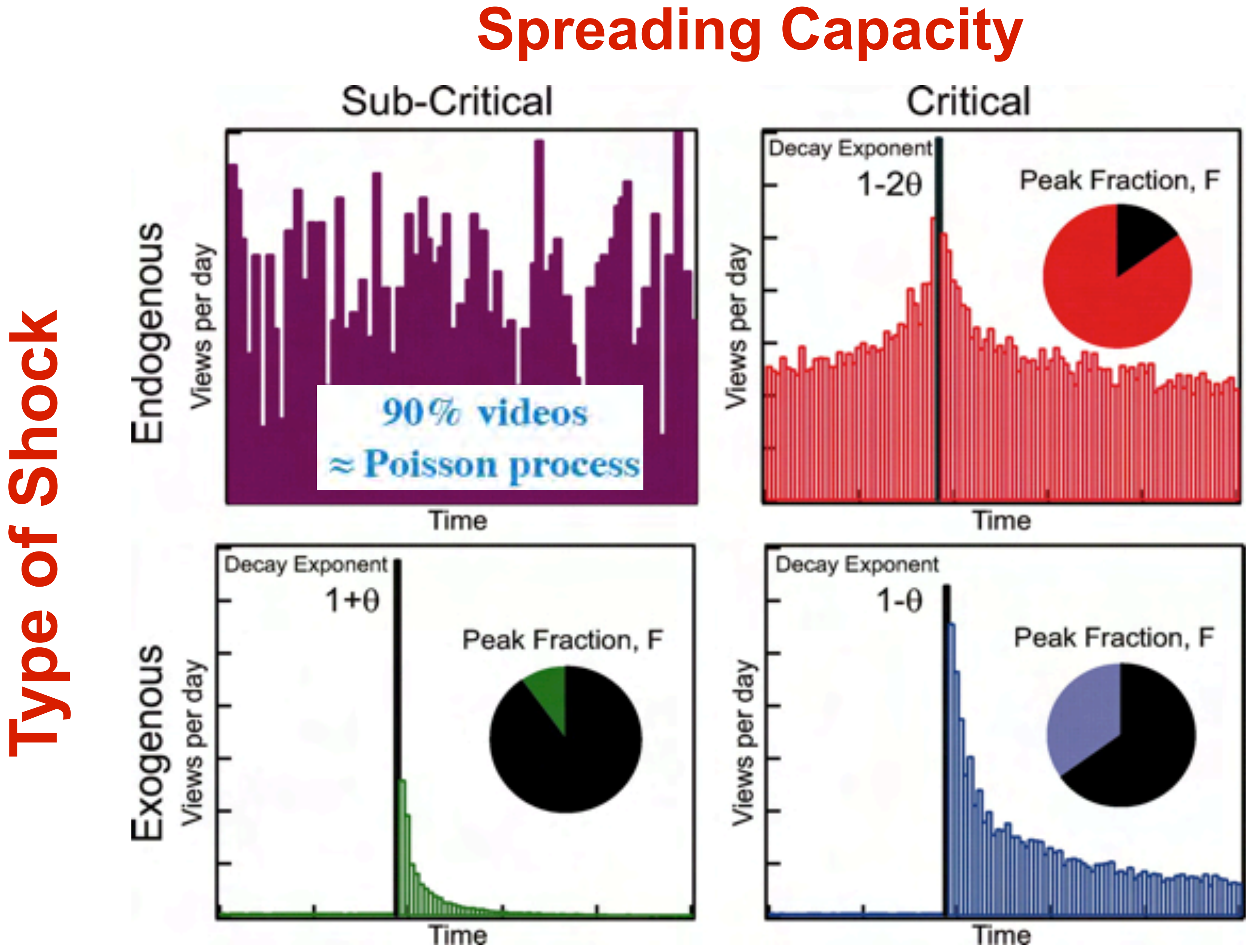
- The power law exponents of the response functions, conditional on the class of peak determined by the slope of the growth reveal distance to CRITICALITY (n=1)

	Endogenous	Exogenous
Foreshock (or growth)	$S(t) \propto \frac{1}{\left\|t\right\|^{1-2\theta}}$	Abrupt peak
Aftershock (or decay)	$S(t) \propto \frac{1}{t^{1-2\theta}}$	$S(t) \propto \frac{1}{t^{1-\theta}}$

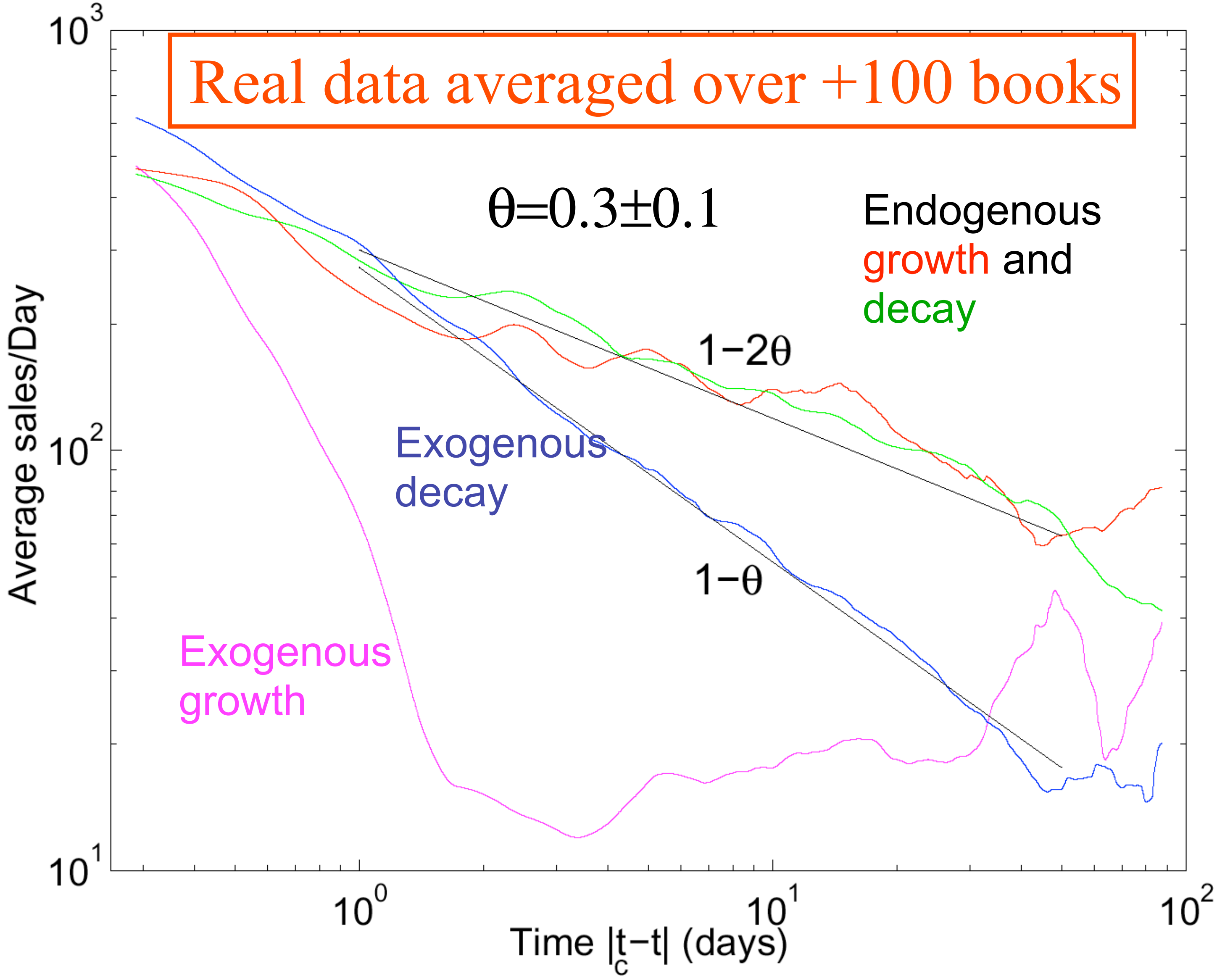
Non-critical: $S(t) \propto \frac{1}{t^{1+\theta}}$

Predicted activity patterns

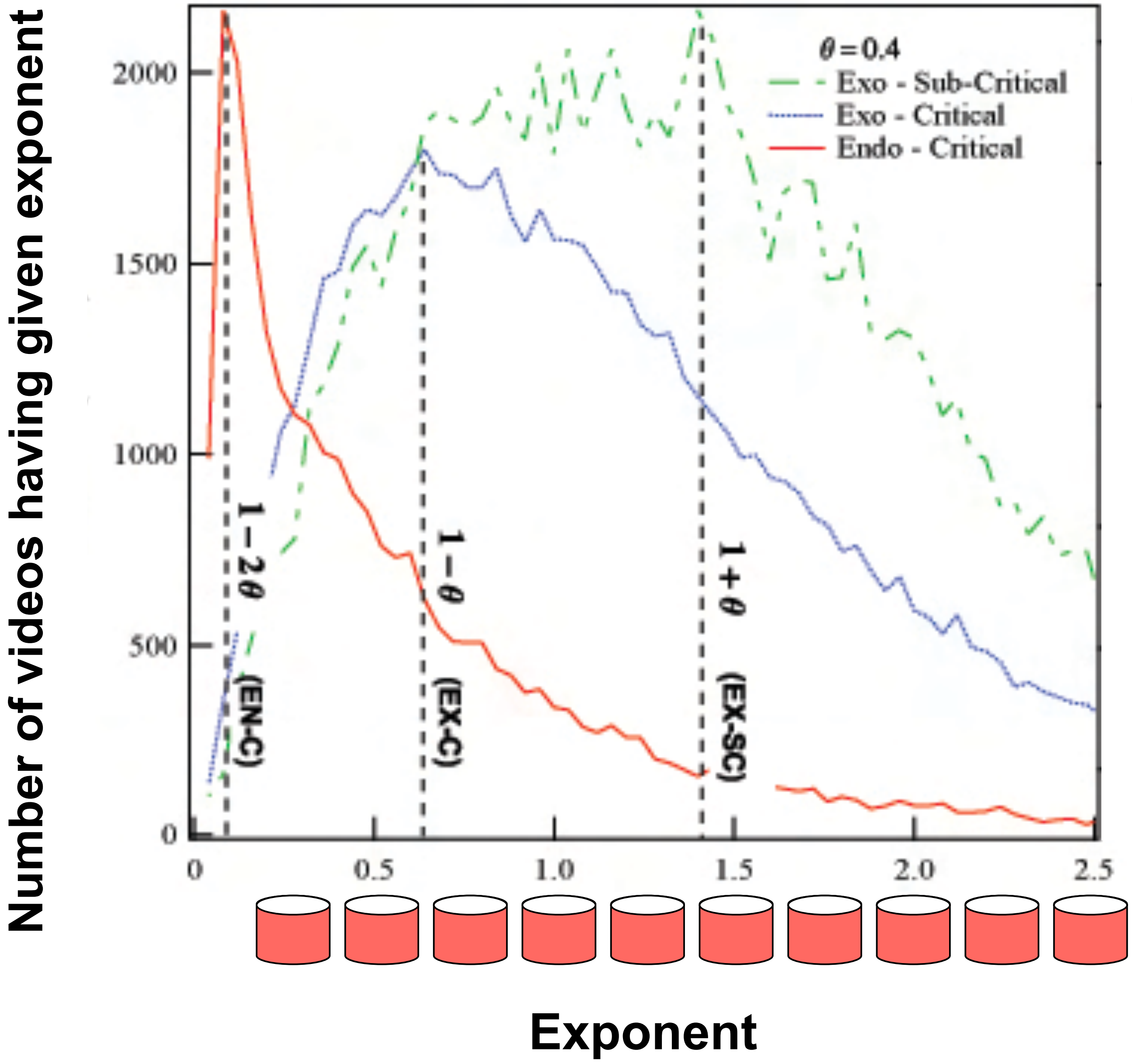
Crane, R and Sornette, D., *PNAS* (2008)



Book sales dynamics

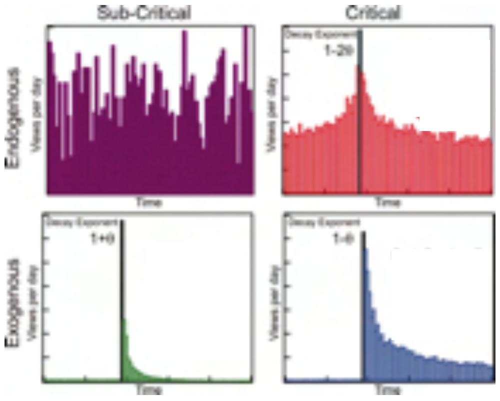


Results: Classifying Relaxation



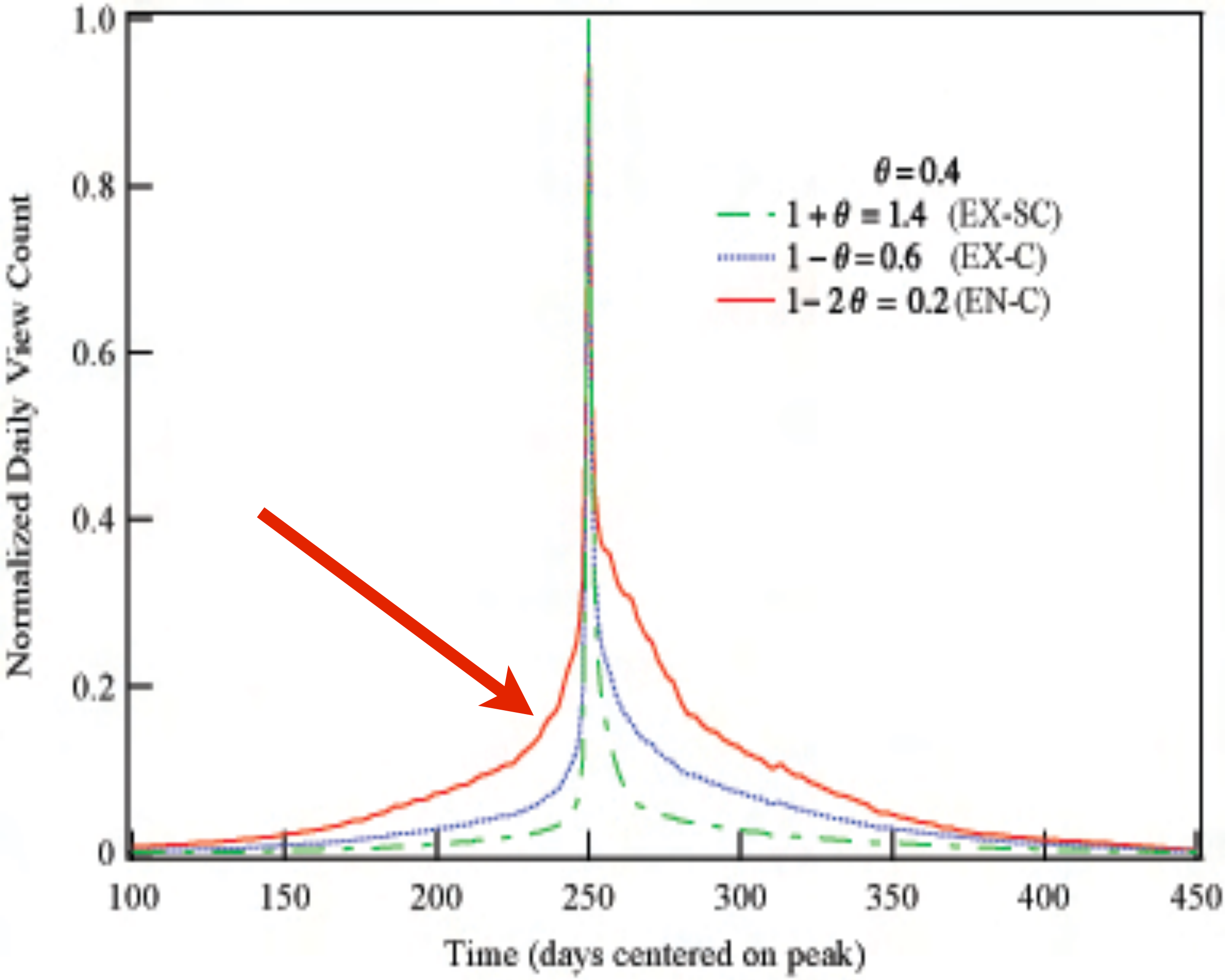
1. Class 1 is defined by $80\% \leq F \leq 100\%$.
2. Class 2 is defined by $20\% < F < 80\%$.
3. Class 3 is defined by $0\% \leq F \leq 20\%$.

Class 1 ⟷ Exogenous subcritical
Class 2 ⟷ Exogenous critical
Class 3 ⟷ Endogenous critical.



Crane et al, PNAS (2008)

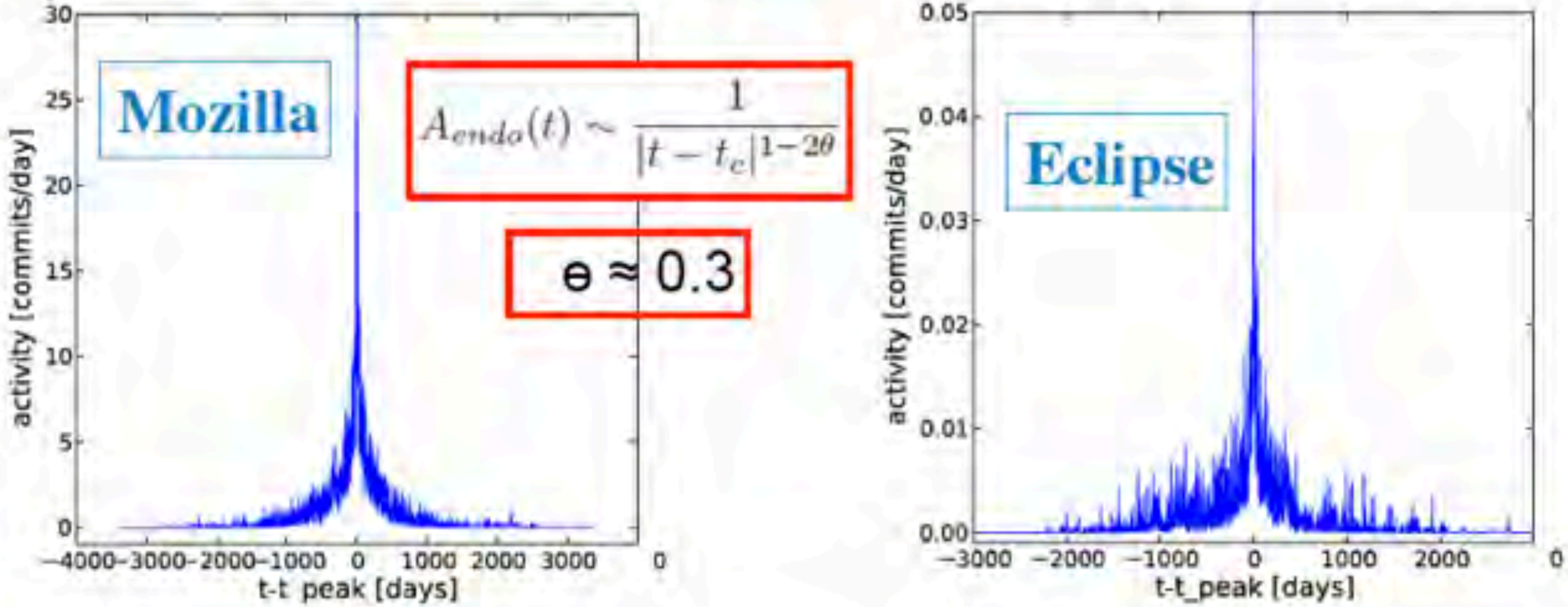
What about precursory information?



Collective Behaviors

in the Software Sphere

- Method
  - Set the “peak activity” to t=0, for all developers
  - Build statistical activity by averaging activity over all coders



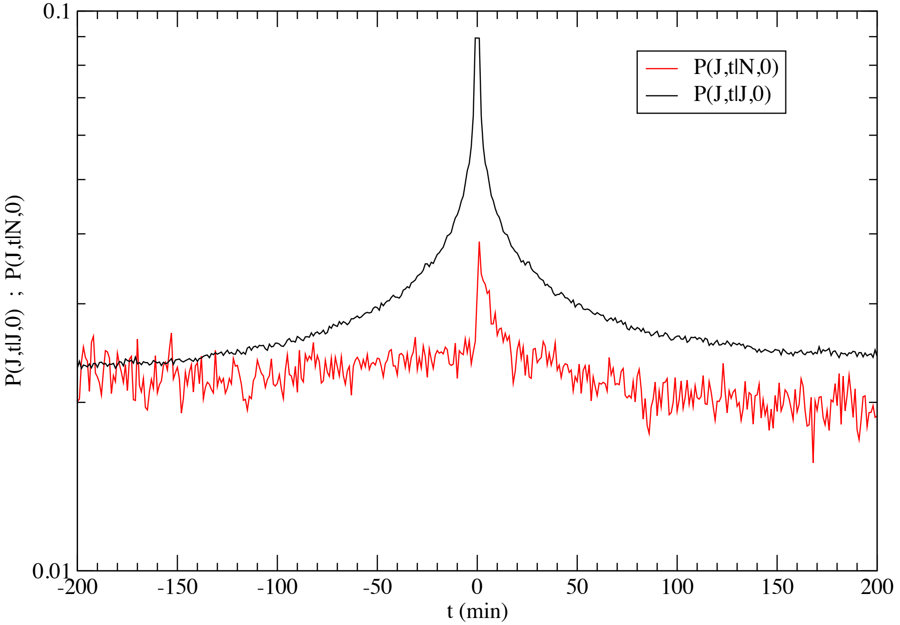
$$A_{endo}(t) \sim \frac{1}{|t-t_c|^{1-2\theta}}$$

$\theta \approx 0.3$

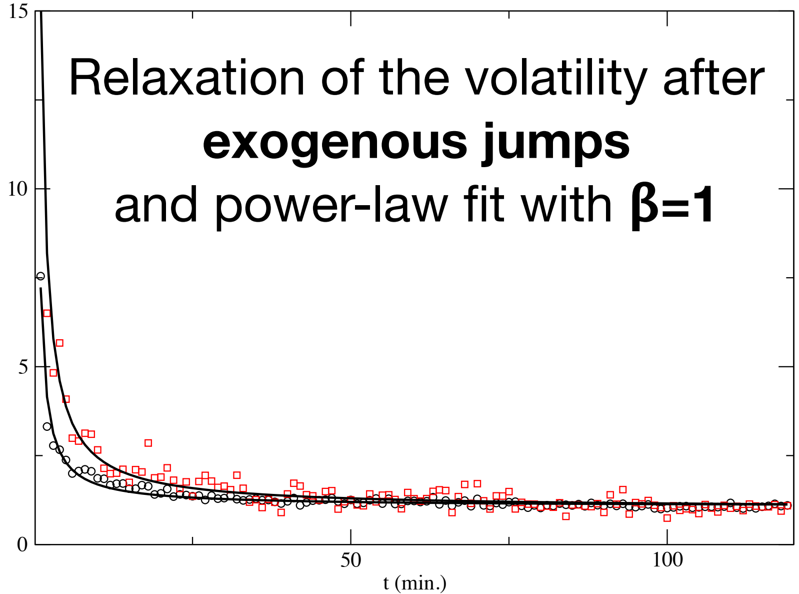
➡ Endogenous regime of developers activity

with Thomas MAILLART (ETH Zurich)

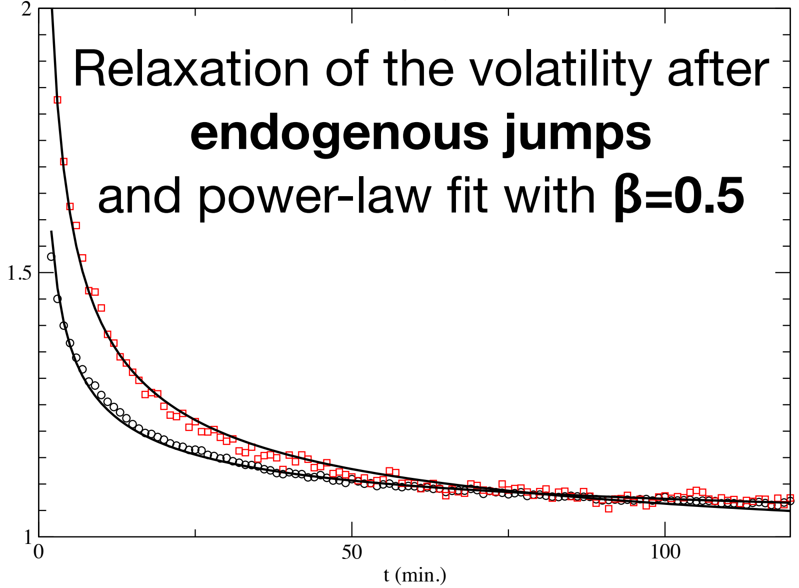
Exogenous versus endogenous jumps in FINANCE



Probability of having **jump** in price
at time *t*, conditional on:
(red) **news** at time *t*=0
(black) **jump** at time *t*=0



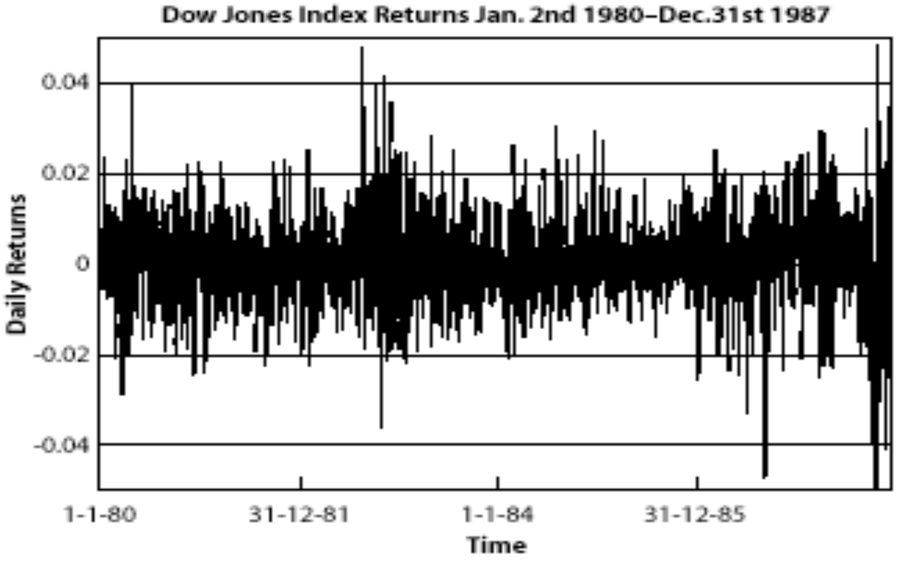
Relaxation of the volatility after
exogenous jumps
and power-law fit with **β=1**



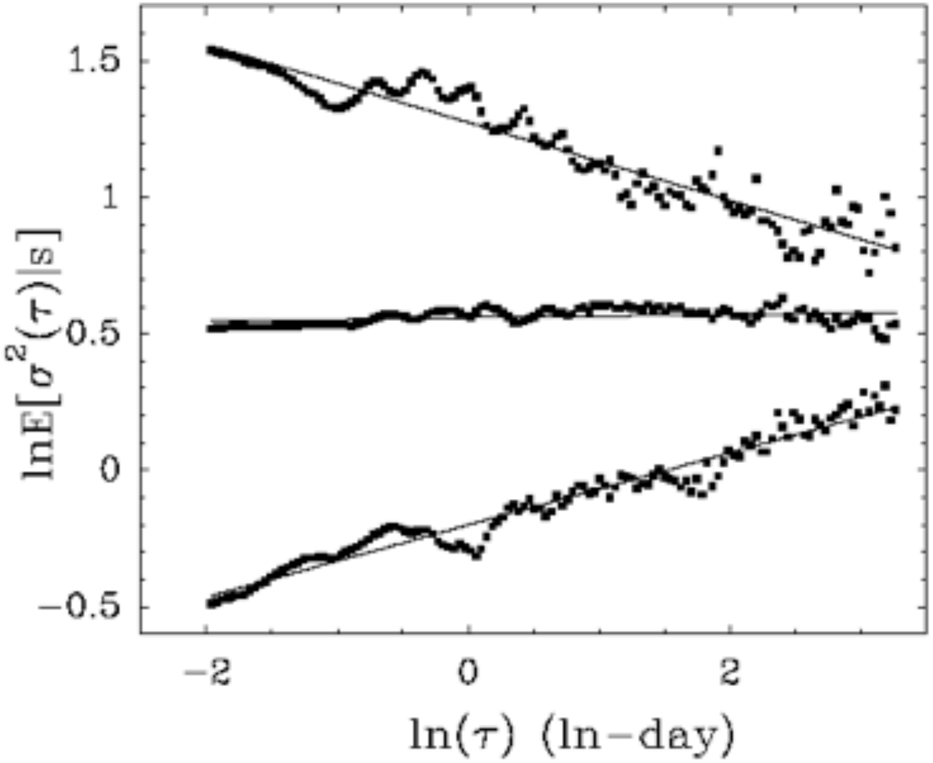
Relaxation of the volatility after
endogenous jumps
and power-law fit with **β=0.5**

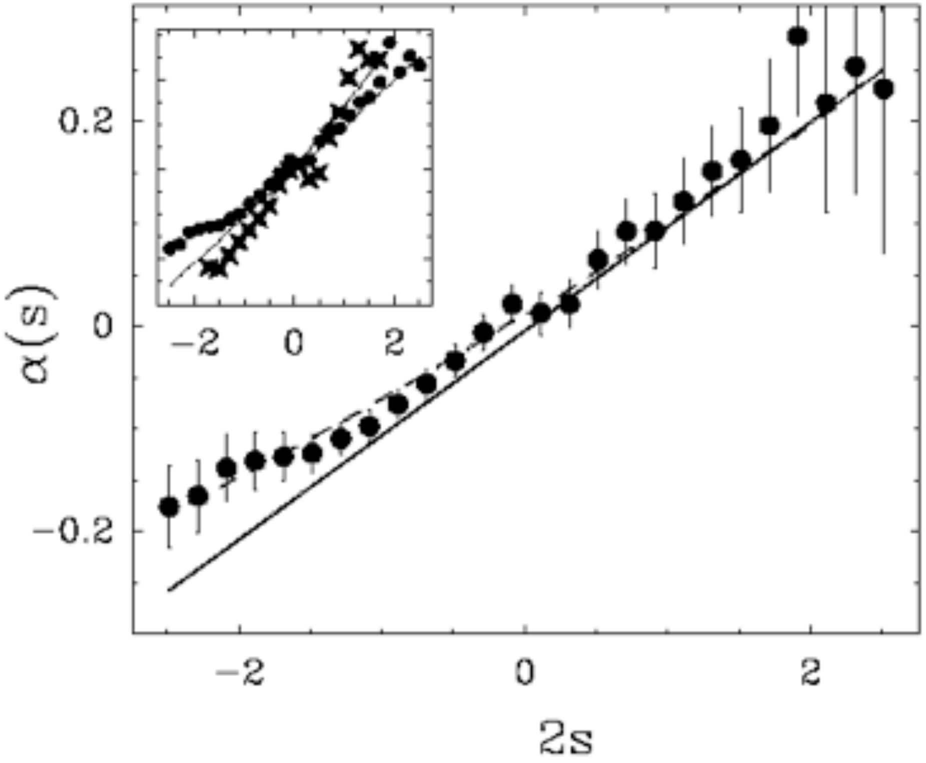
A. Joulin, A. Lefevre, D. Grunberg, J.-P. Bouchaud (2008)
“Stock price jumps: news and volume play a minor role.” Wilmott Magazine, Sep/Oct: 46.

Multifractal power law relaxation of financial volatility


Dow Jones Index Returns Jan. 2nd 1980–Dec.31st 1987

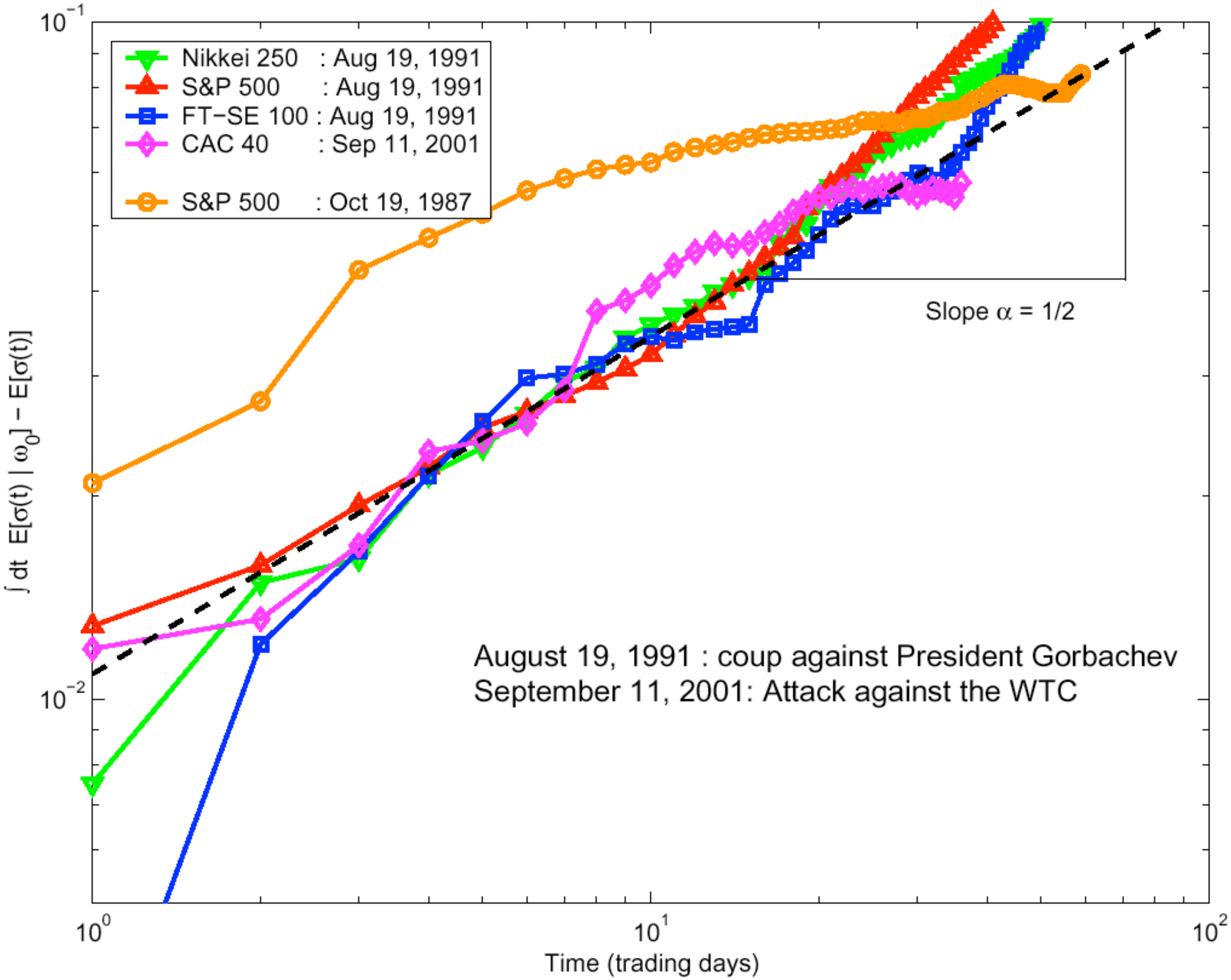
$$\mathrm{E}_{\mathrm{endo}}[\sigma^2(t) \mid \omega_0] \sim t^{-\alpha(s)}$$





Linear response to an external shock

$$\mathrm{E}_{\mathrm{exo}}[\sigma^2(t) \mid \omega_0] - \overline{\sigma^2(t)} \propto e^{2K_0 t^{-1/2}} - 1 \approx \frac{2K_0}{\sqrt{t}}$$



August 19, 1991 : coup against President Gorbachev
September 11, 2001: Attack against the WTC

D. Sornette, Y. Malevergne and J.F. Muzy
Volatility fingerprints of large shocks: Endogeneous versus exogeneous,
Risk Magazine
(http://arXiv.org/abs/cond-mat/0204626)

High frequency trading

We use a class of **self-excited models** that combines (i) external influence on system with (ii) feedback mechanisms to test in a technical way the hypothesis of reflexivity (endogeneity) of the market.

We will show that market is operating close to **criticality**, implying **significant role of endogenous feedback** mechanisms in price formation process and increase of this role over last 10 years due to growth of AT and HFT.

Moreover we will introduce the **metric** that allow one to estimate quantitatively the **relative proportion** between endogenous and exogenous price movements.

We will illustrate the power of this **metric** in distinguishing between **exogenous** (triggered by news) and **endogenous** (resulted from feedback) shocks on market.

Data: E-mini S&P 500 Futures

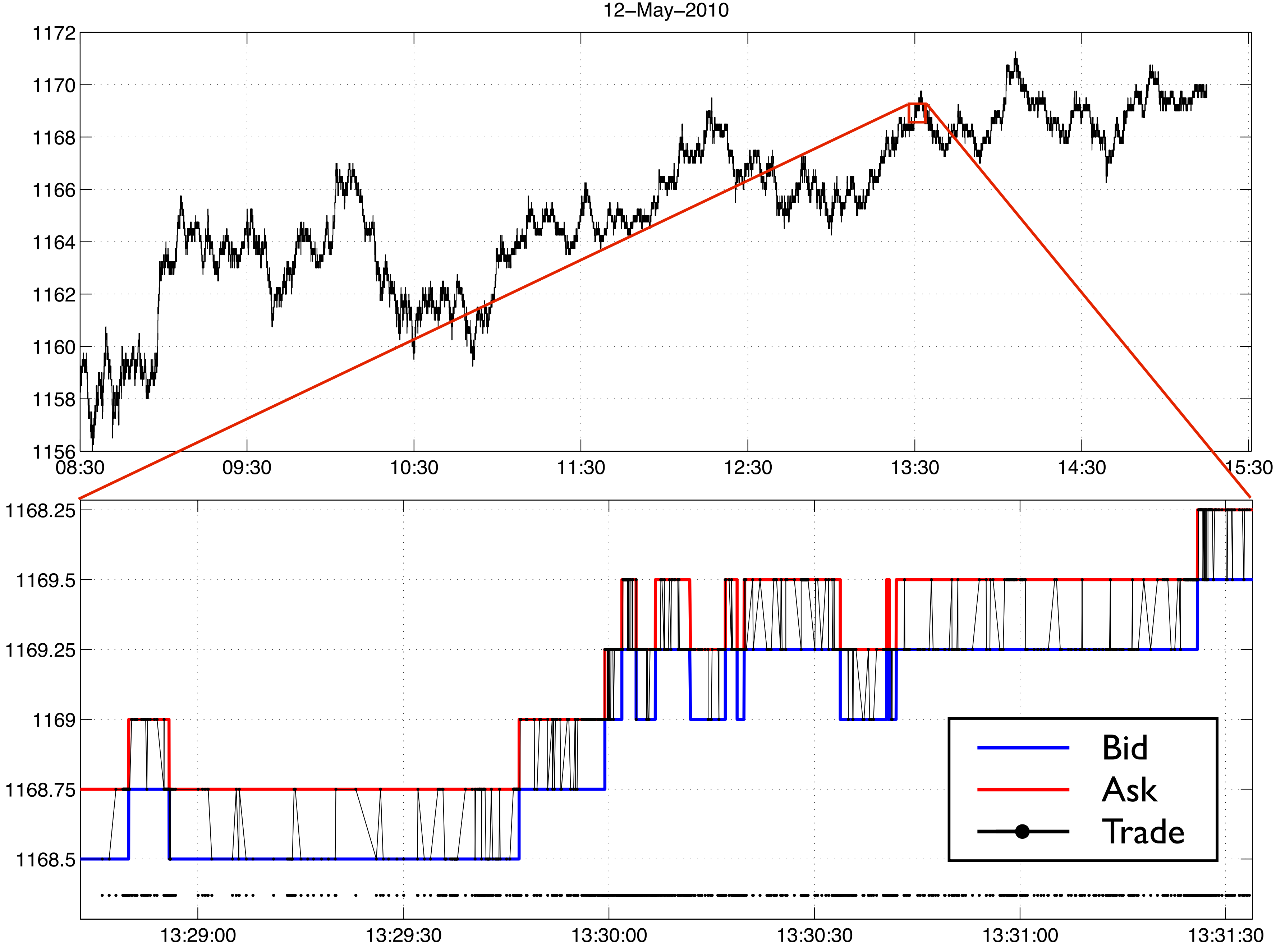
E-mini S&P 500 Futures Contract represents a fraction of the normal S&P 500 futures contract.

Some facts:

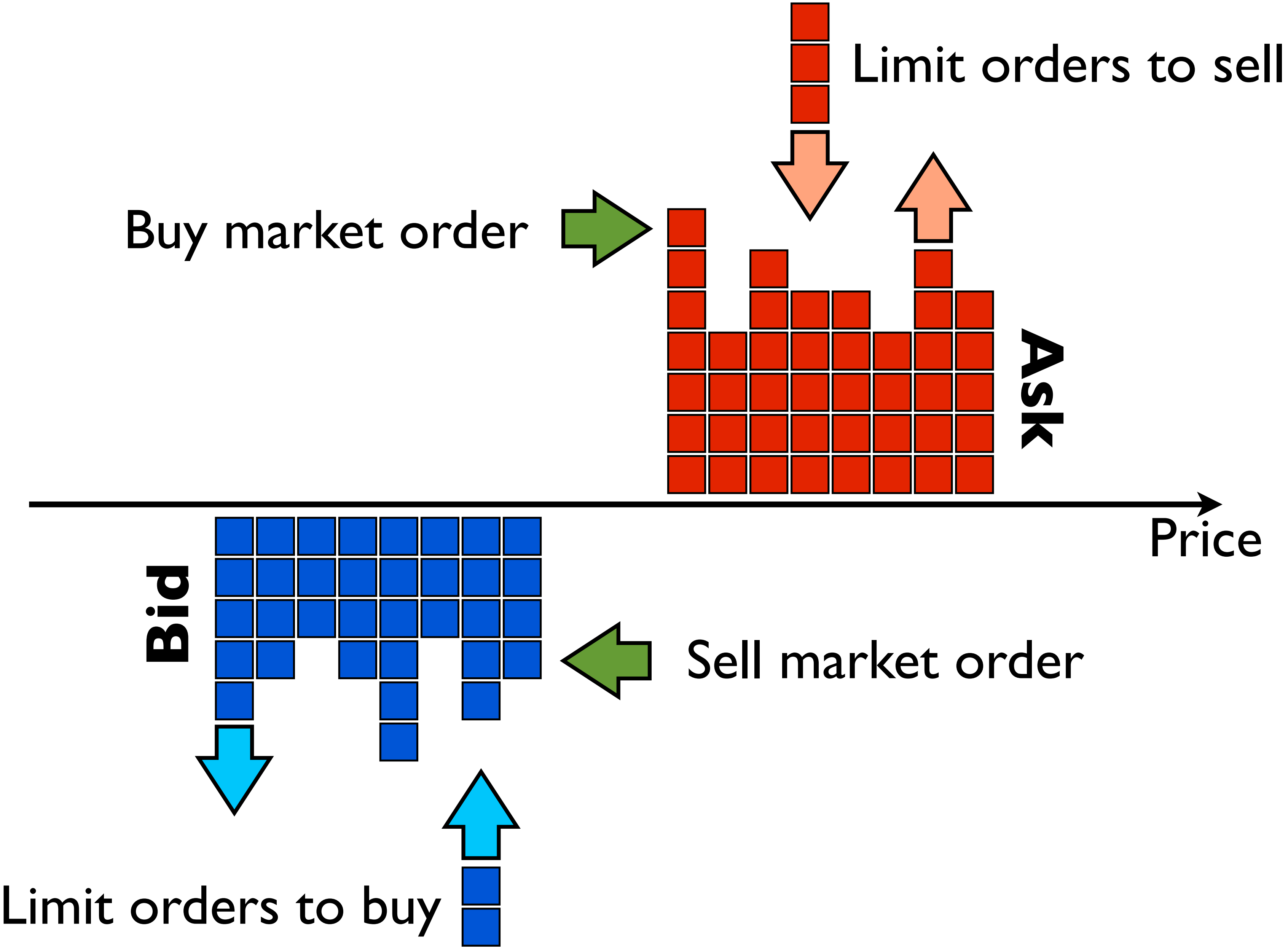
- Ticker symbol: ES
- Exchange: Chicago Mercantile Exchange
- Contract months: Five months in the March Quarterly Cycle (Mar, Jun, Sep, Dec)
- Trading time: 23.25 hours/day (active trading: 6.75 hours)
- Contract size: $50 x E-mini S&P 500 futures price
- Tick size: 0.25 index points=$12.50
- Initial margin: $5,625
- **Average daily volume in 2010: 2,194,975** (for comparison: average daily volume of regular S&P 500 futures: 345,483)

Sample series of E-mini's

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich



Order-book dynamics



Modeling coarse-grained price dynamics

Null hypothesis: **Random Walk** (Bachelier, 1900).

Stylized facts of real price time series:

- *Absence of returns' autocorrelations*
- *Aggregational Gaussianity*
- Fat tails of distributions
- Long memory in volatility
- Intermittency and Volatility clustering
- Multifractal scaling
- Time reversal asymmetry and Leverage effect
- Gain/Loss asymmetry
- Asymmetry in time scales
- Volume-Volatility correlation
- Bubbles and crashes

Reject null

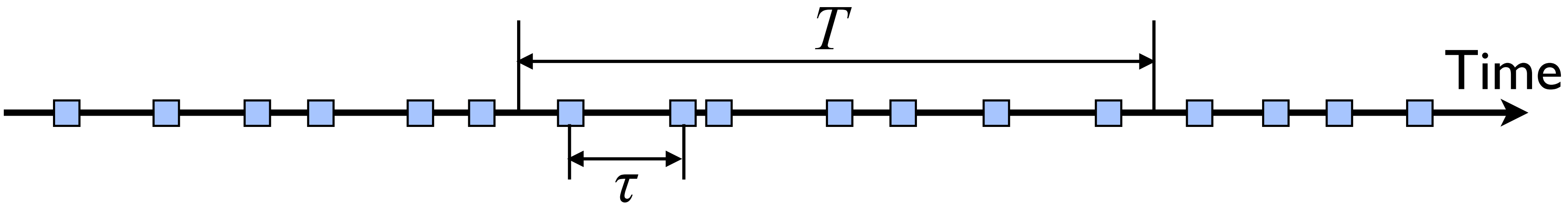
Modeling HF price dynamics

Null hypothesis: **Poisson process**.

Poisson process is a point process for which number of events in a given time interval T is independent from events outside the interval and described with Poisson distribution:

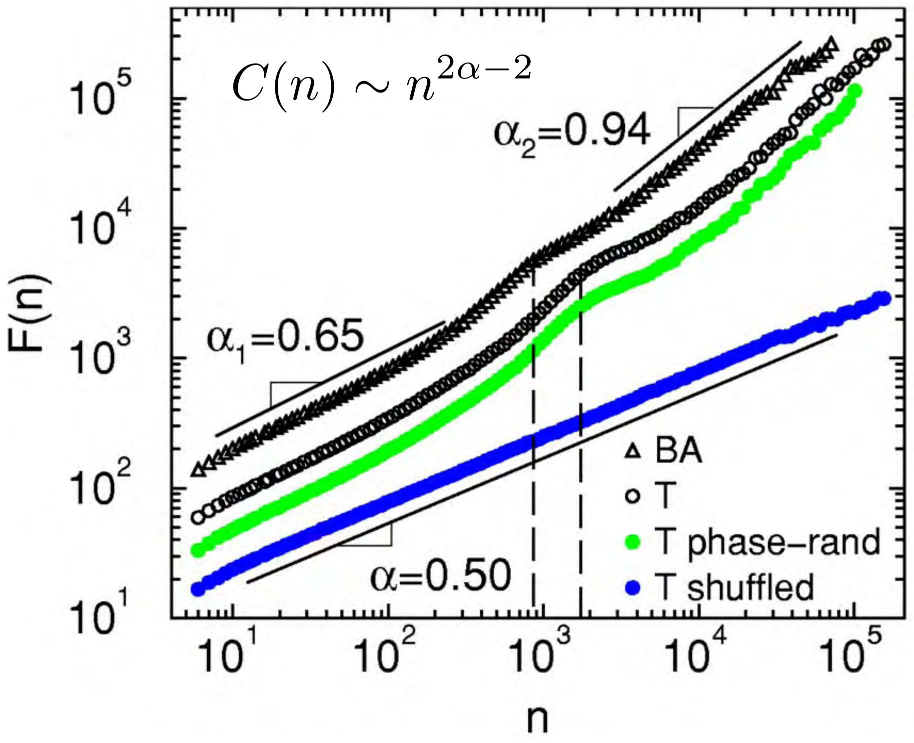
$$P\Big[N(t+T)-N(t)=k\Big]=\frac{(\lambda T)^k}{k!}e^{-\lambda T}$$

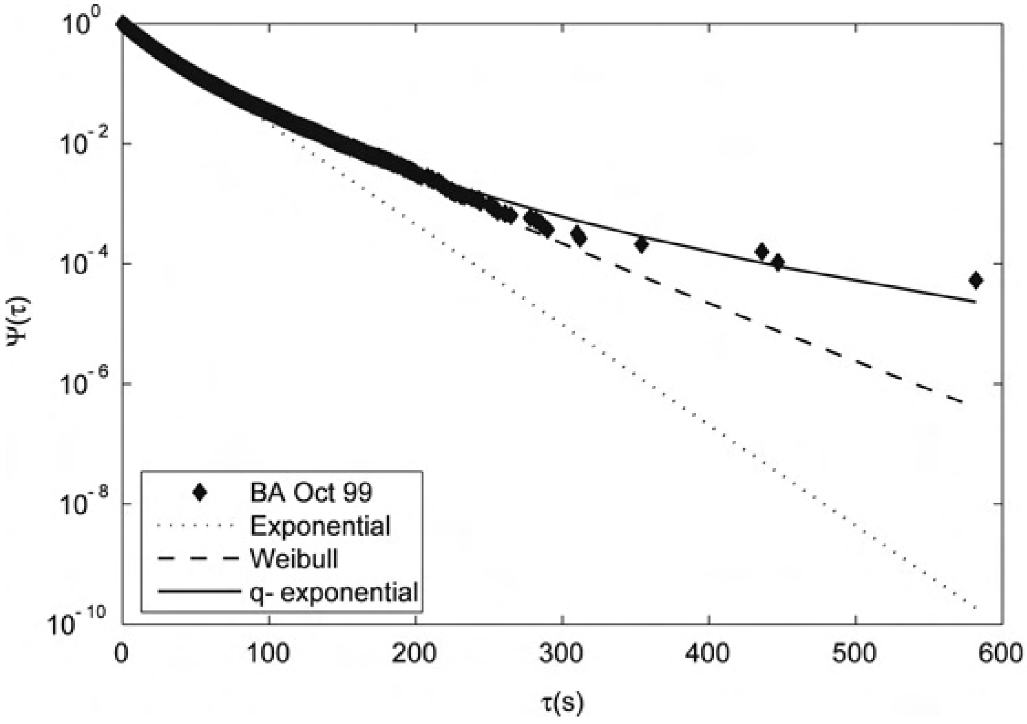
where λ=const is an *intensity* of the process.



Poisson process is characterized by an exponential distribution of inter-event times τ.

“Stylized facts” of real order arrivals





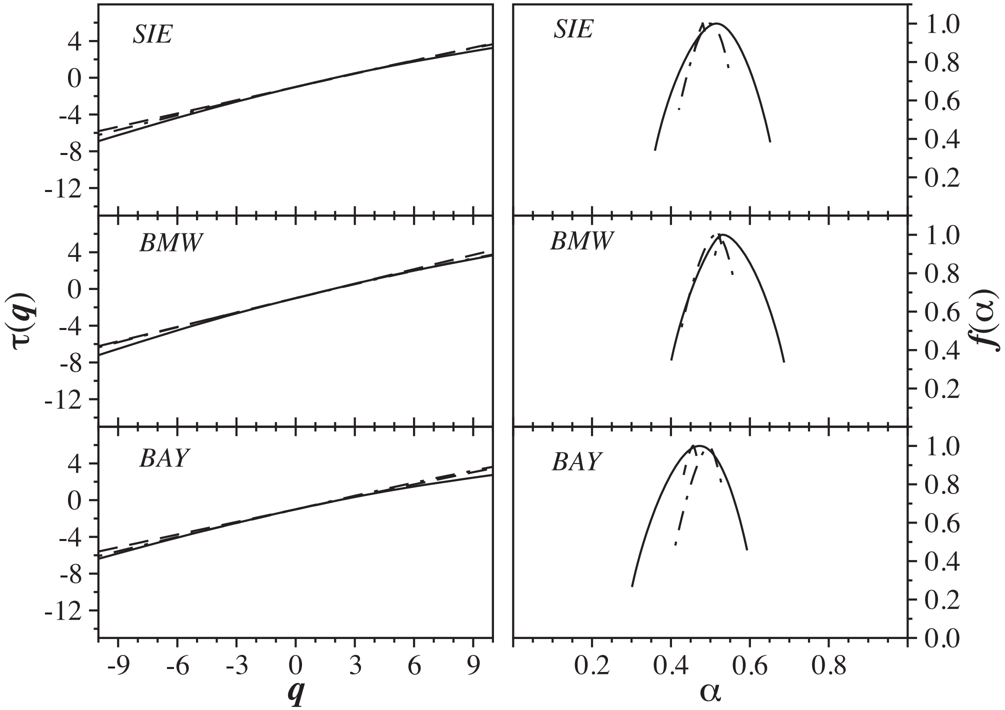
Clustering of order arrivals
Long memory in inter-trade intervals

Slower-than-exponential decay of the distribution of inter-trade intervals

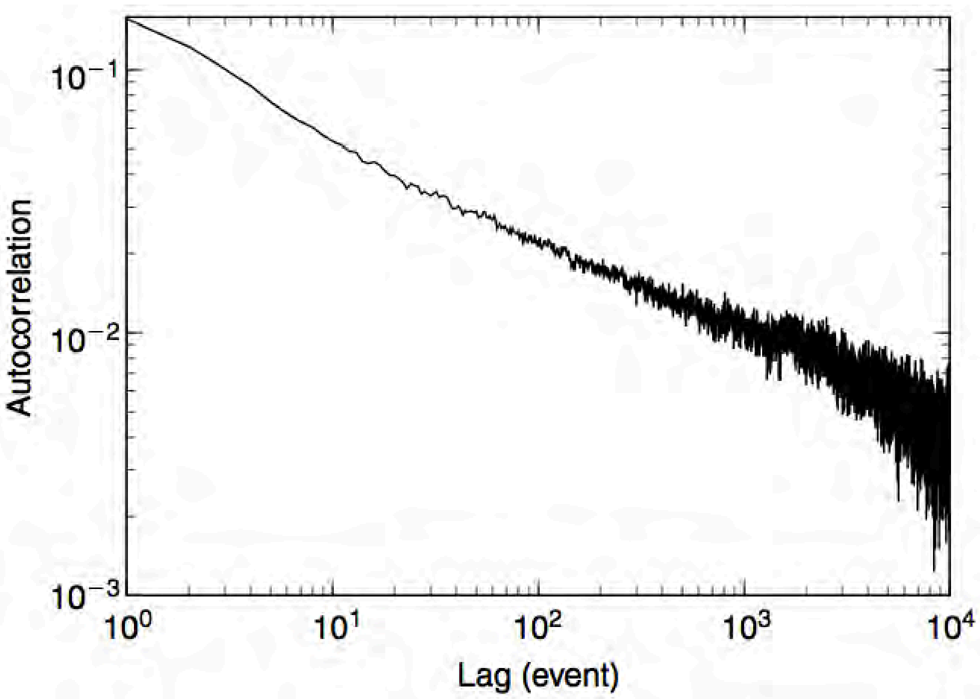
---

- P. Ivanov, A. Yuen, B. Podobnik, Y. Lee (2004) “Common Scaling Patterns in Intertrade Times of U. S. Stocks.” Physical Review E 69 (5): 056107.
- M. Politi, E. Scalas (2008) “Fitting the Empirical Distribution of Intertrade Durations.” Physica A, 387 (8-9): 2025–2034.

“Stylized facts” of real order arrivals



Multifractal scaling of inter-trade intervals



Long memory in the signs of orders

- P. Oswiecimka, J. Kwapien, S. Drozdz (2005) “Multifractality in the Stock Market: Price Increments Versus Waiting Times.” Physica A, 347: 626–638.
- J.-P. Bouchaud, D. Farmer, F. Lillo (2008) “How Markets Slowly Digest Changes in Supply and Demand.” In Handbook of Financial Markets: Dynamics and Evolution (Handbooks in Finance), 57–160.

Modeling HF price dynamics

Extended models:

- **Clustered point processes**
  Poisson process supplemented with artificial clusters around immigrants.
- **Autoregressive Conditional Durations (ACD)**
  GARCH-type model for the inter-trade intervals:

$$\tau_k = \theta_k z_k, \quad z_k > 0, \quad \mathrm{E}[z_k] = 1$$

$$\theta_k = \alpha_0 + \sum_{i=1}^{q} \alpha_i \tau_{k-i} + \sum_{i=1}^{p} \beta_i \theta_{k-i}$$

- **Self-excited point processes**:
  - Linear: **Hawkes process**
  - Nonlinear, e.g. **Multifractal Stress Activation (MSA)**

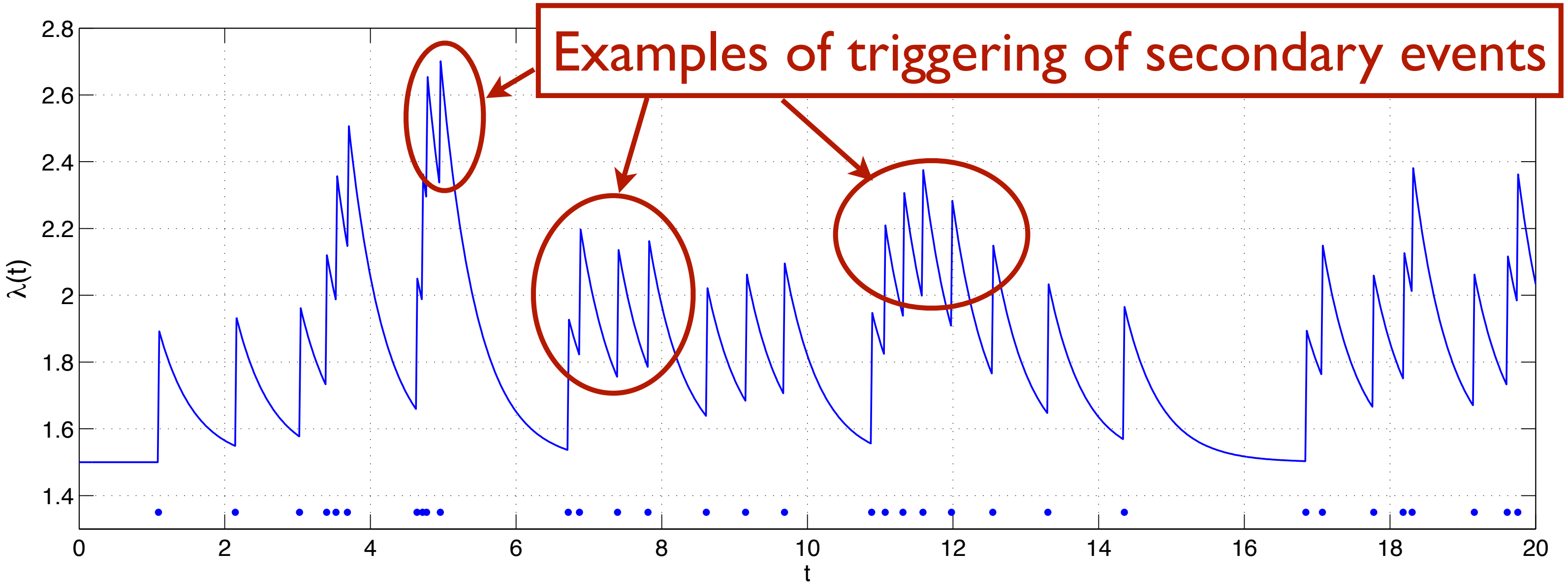
- R. Engle, J. Russell (1998) “Autoregressive Conditional Duration: A New Model for Irregularly Spaced Transaction Data.” Econometrica: Journal of the Econometric Society, 66 (5): 1127–1162.
- A. Hawkes (1971) “Point Spectra of Some Mutually Exciting Point Processes.” Journal of the Royal Statistical Society. Series B (Methodological) 33 (3): 438–443.
- D. Sornette, G. Ouillon (2005) “Multifractal Scaling of Thermally Activated Rupture Processes.” PRL 94(3): 038501
- V.A. Filimonov and D. Sornette, Self-Excited Multifractal Dynamics, Europhysics Letters 94, 46003 (2011)

Self-excited Hawkes process

Self-excited Hawkes process is the point process whose intensity $\lambda_t(t)$ is conditional on its history:

$$\lambda(t) = \underbrace{\mu}_{\text{Background intensity}} + \sum_{t_i<t} \underbrace{\varphi(t-t_i)}_{\text{Self-excitation part}}$$

Traditionally the exponential memory kernel is used: $\varphi(t) = \alpha e^{-\beta t}$



Examples of triggering of secondary events

Sample realization of the Hawkes process with μ=1.5, α=0.4, β=2

Branching representation of the Hawkes process

Recall that sum of N independent Poisson processes with intensities $\lambda_1, \lambda_2, ..., \lambda_N$ is a Poisson process with intensity $\lambda = \lambda_1 + \lambda_2 + ... + \lambda_N$.

Thus self-excited Hawkes process

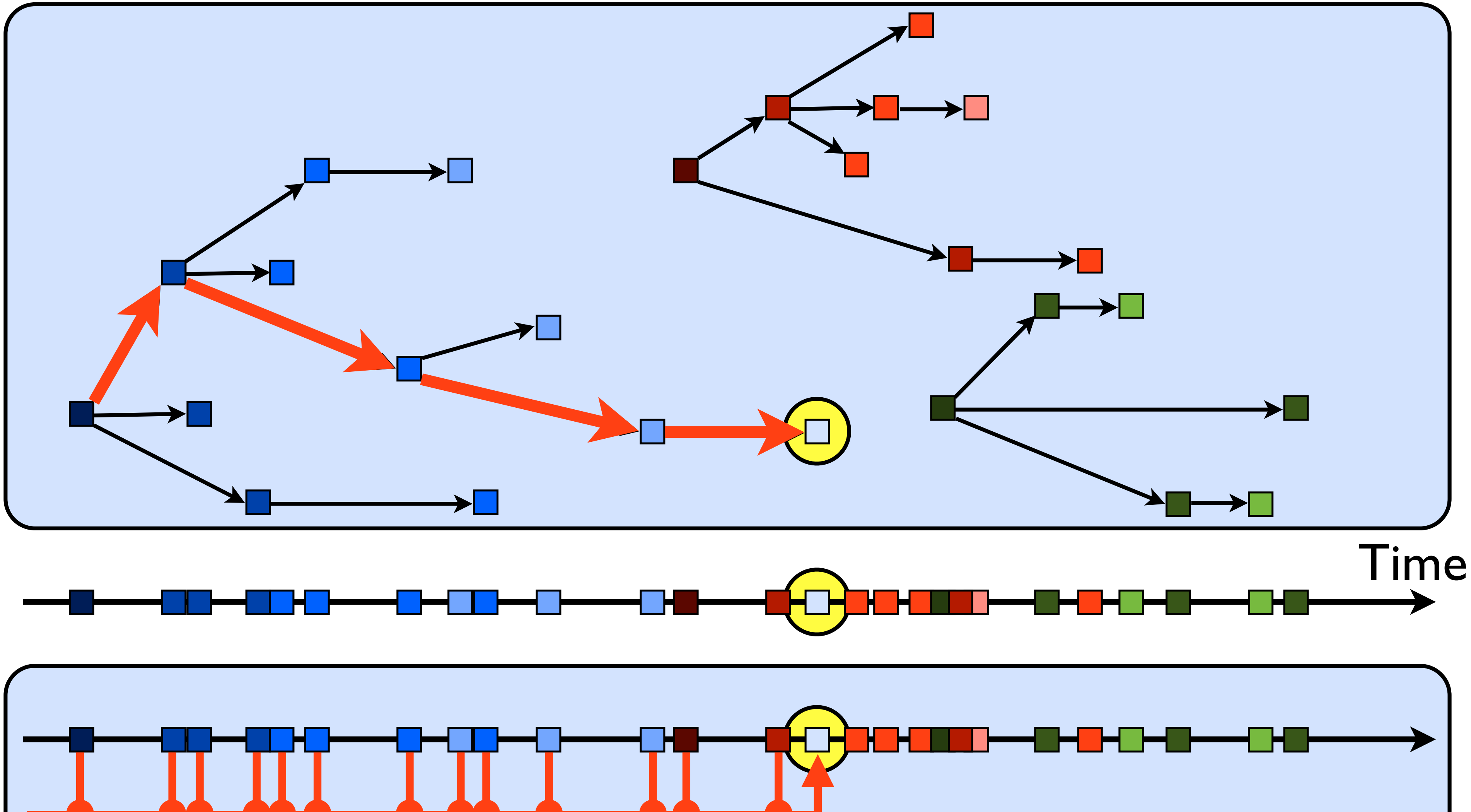
$$\lambda(t) = \mu + \sum_{t_i < t} \varphi(t - t_i)$$

could be regarded as a sum of independent non-homogeneous Poisson processes with intensities:

$$\lambda_0 = \mu, \quad \lambda_1 = \varphi(t - t_1), \quad \ldots, \quad \lambda_n = \varphi(t - t_n)$$

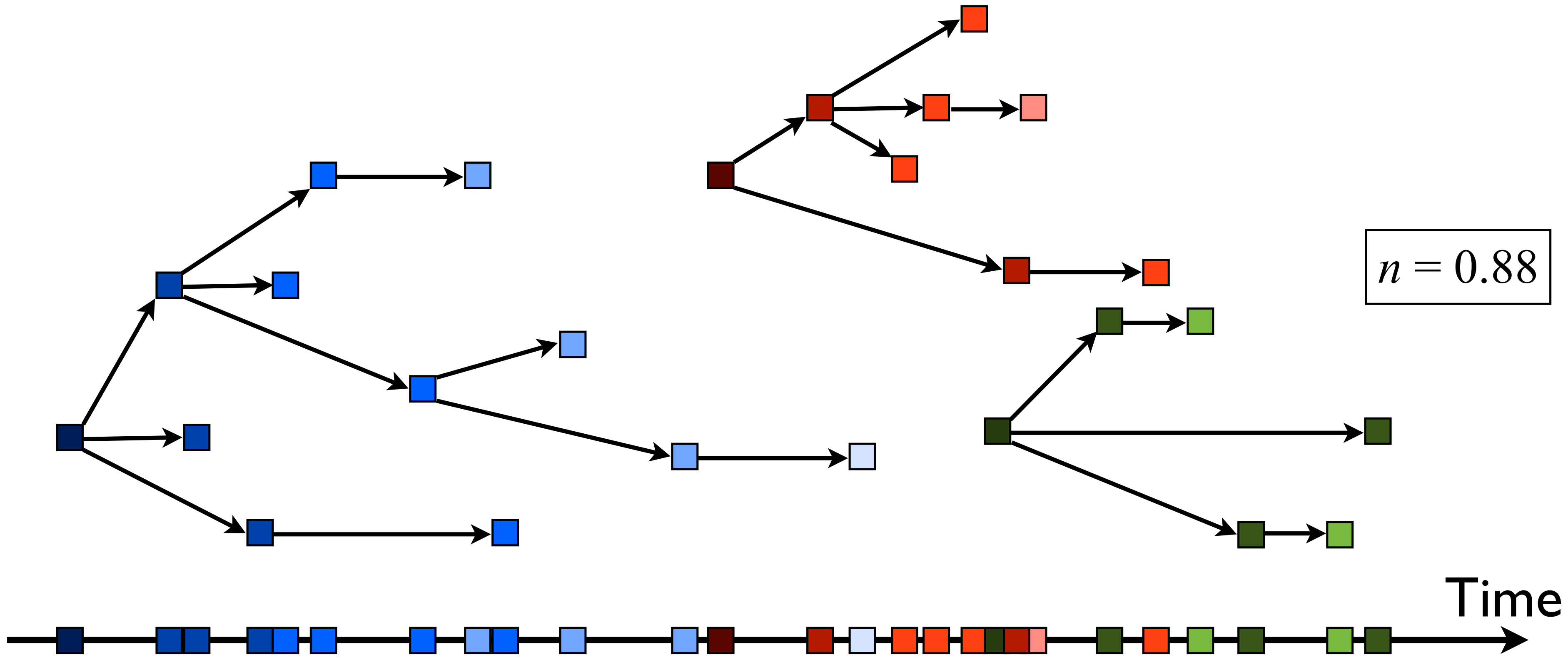
Each of them represent decaying intensity after a single shock and they altogether form a **branching process**.

Branching processes



$$\lambda(t) = \mu + \sum_{t_i<t} \varphi(t - t_i)$$

Branching processes



Crucial parameter of the branching process is the **“branching ratio” (*n*)**
- average number of “daughters” per one “mother”

For $\boldsymbol{n} < 1$ system is **subcritical** (stationary evolution)

For $\boldsymbol{n} = 1$ system is **critical** (tipping point)

For $\boldsymbol{n} > 1$ system is **supercritical** (with $p>0$ will explode to infinity)

The branching ratio

In the *sub-critical regime* ($n < 1$), in the case of a constant background intensity ($\mu(t)=\mu=\mathrm{const}$) the average rate of all endogenous events (“aftershocks”) is equal to:

$$R_{\mathrm{endo}} = \mu \cdot \left(n + n^2 + n^3 + \dots\right) = \mu \sum_{i=1}^{\infty} n^i = \frac{\mu n}{1-n}$$

The average rate of exogenous events is equal to $R_{\mathrm{exo}}=\mu$.

Total average rate of all events is:

$$R = R_{\mathrm{exo}} + R_{\mathrm{endo}} = \mu + \frac{\mu n}{1-n} = \frac{\mu}{1-n}$$

Thus:

$$\boxed{n = R_{\mathrm{endo}}/R}$$

In other words, **the branching ratio (n) is equal to the proportion of the average number of *endogenously* generated events among all events.**

Estimation of the branching ratio

For the Hawkes process the branching ratio is given by expression:

$$n = \int_0^\infty \varphi(t) dt$$

In particular, for the exponential kernel: $n = \alpha/\beta$

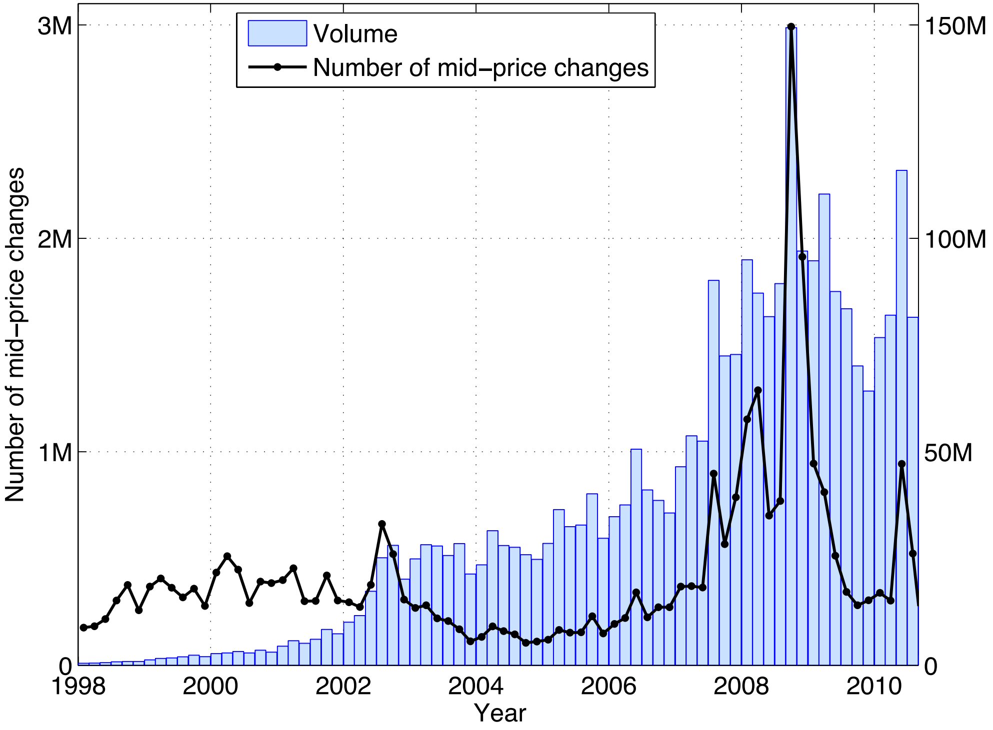
The Maximum Likelihood estimator:

$$\log L(\theta | t_1, \dots, t_n) = - \int_0^T \lambda_t(t) dt + \int_0^T \log \lambda_t(t) dN(t)$$

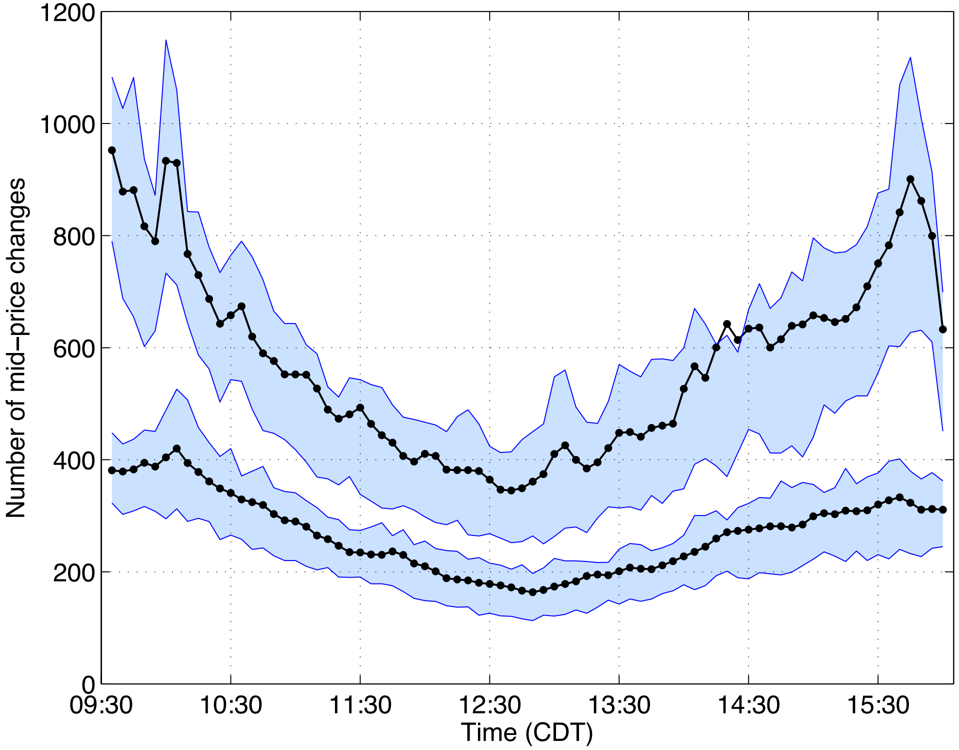
In particular, for the exponential kernel:

$$\log L = -\mu T + n \sum_{t_i < T} \left(e^{-\beta(T - t_i)} - 1 \right) + \sum_{t_i < T} \log \left(\mu + n\alpha \sum_{t_j < t_i} e^{-\beta(t_i - t_j)} \right)$$

Seasonality profiles



Average numbers of mid-price changes per day and average daily volume in 1998-2010



Average number of mid-price changes in 10 minutes interval during Regular Trading Hours in 2001 and 2009

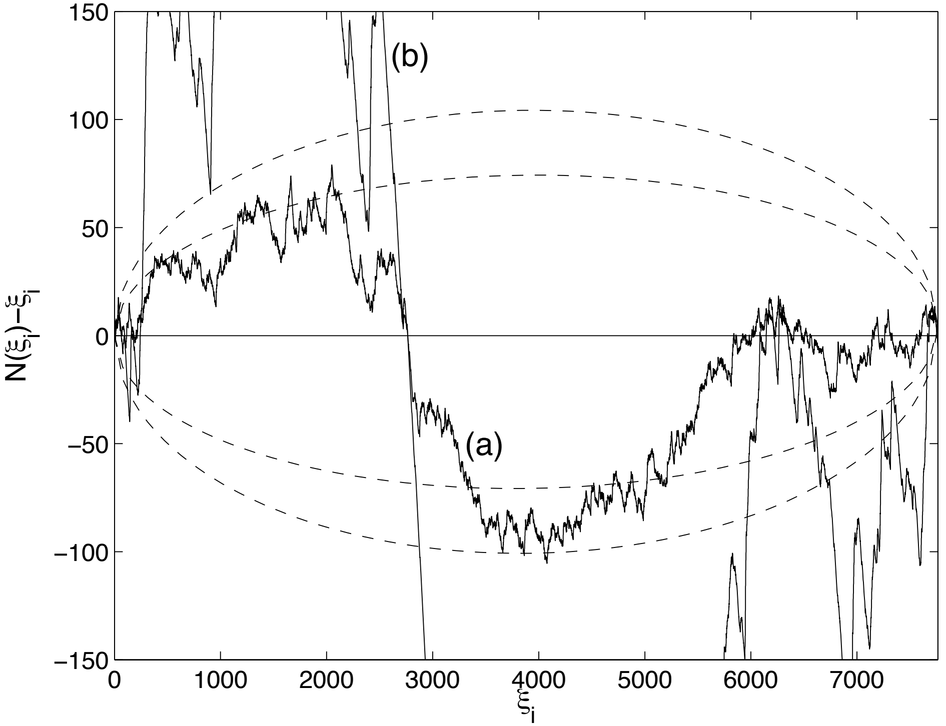
Residual analysis

An important step of estimation procedure is **quality-of-fit** test.

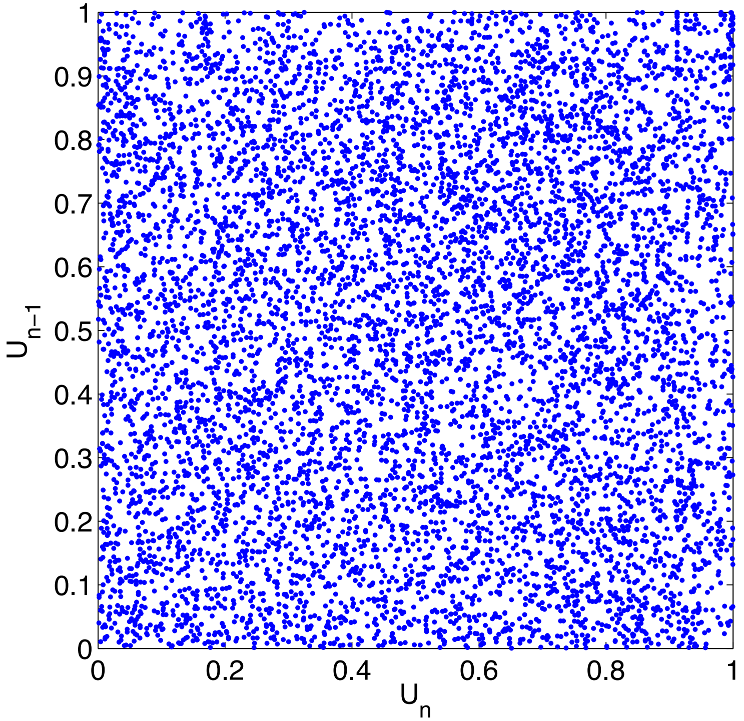
For the Hawkes process it could be done with the residual analysis.

Residual process: $\tau_k = \int_0^{t_k} \lambda_t(t)dt$

Eg. estimation within the period March 11, 2010 14:30-14:40:

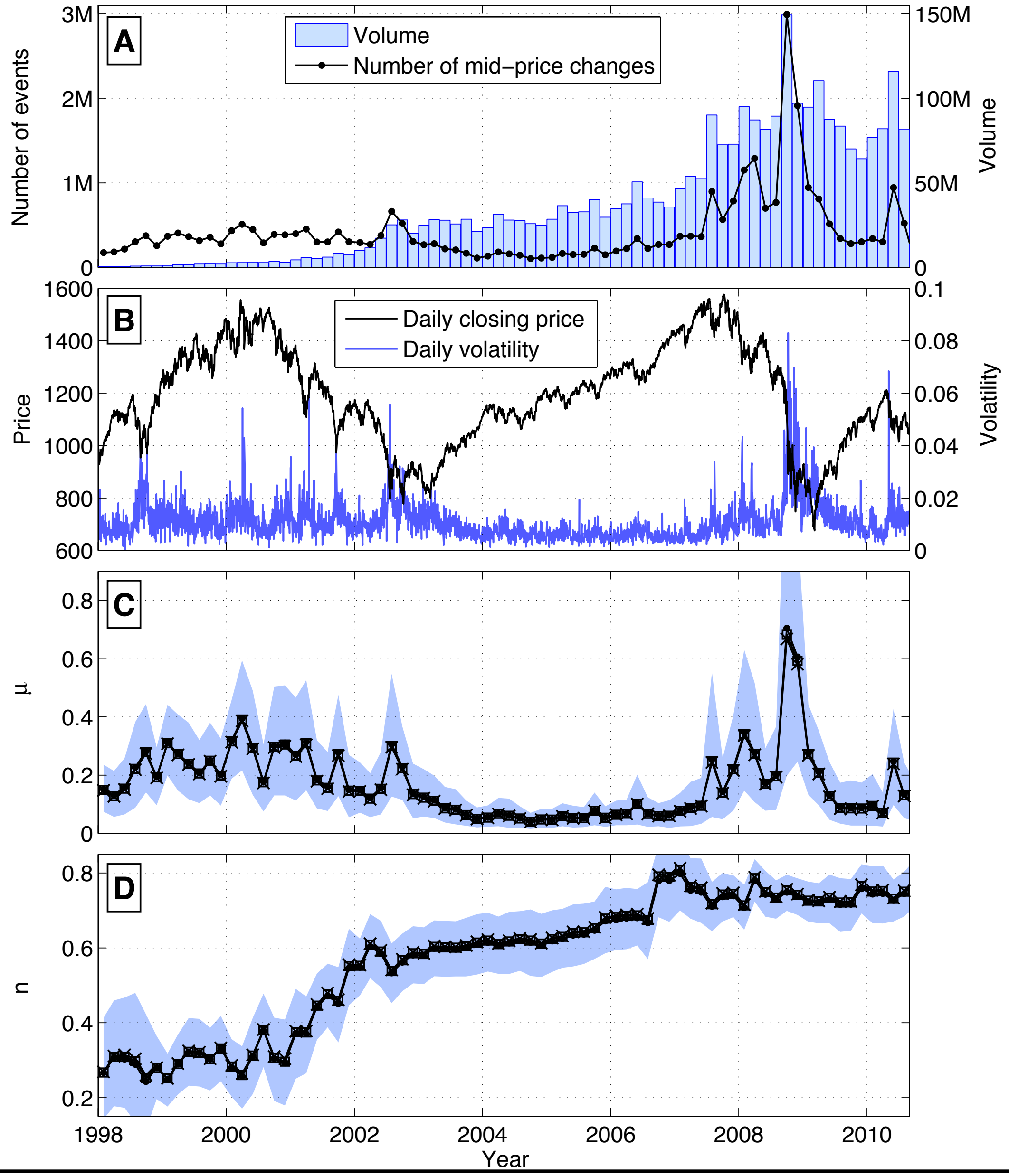


(a) Self-excited Hawkes model
(b) Poisson model



$$U_k = 1 - \exp(\tau_{k-1} - \tau_k)$$

Estimation of reflexivity



- V. Filimonov, D. Sornette (2012) “Quantifying reflexivity in financial markets: towards a prediction of flash crashes”, submitted to PRE, http://arxiv.org/abs/1201.3572

Imitation and informational cascades

Imitation

Imitation (observation and replication of someone's behavior) is among the most complex forms of learning.
It is found in highly socially living species which show, from a human observer point of view, "intelligent" behavior and signs for the evolution of traditions and culture.

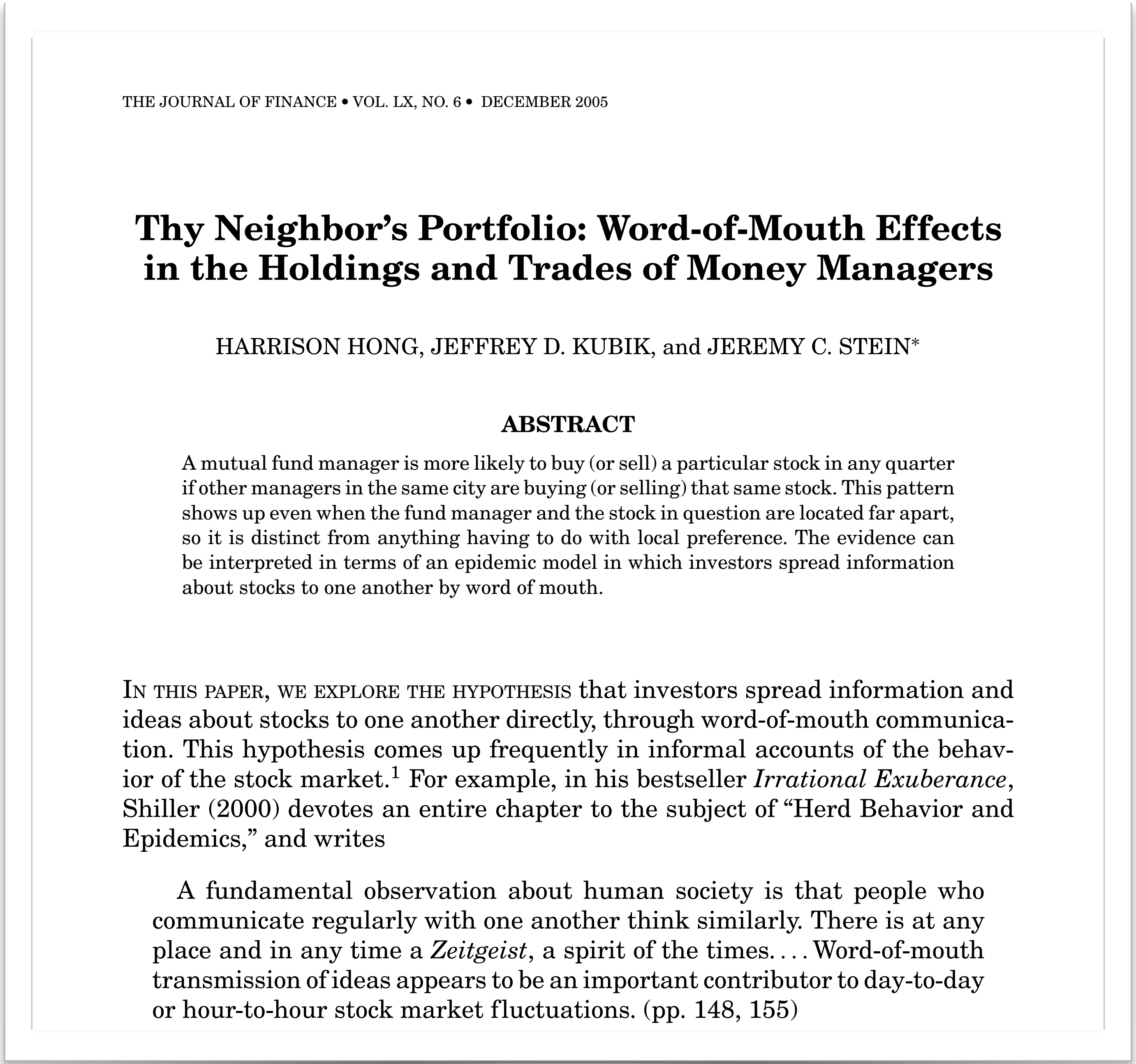
Informational cascades

Being in the crowd infer information and limits rationality. People observe actions of others and then make the same choice that the others have made, independently of their own private information signals.

"Well, heck! If all you smart cookies agree, who am I to dissent?"

- S. Bikhchandani, D. Hirshleifer, I. Welch (2008) "Information cascades" The New Palgrave Dictionary of Economics, 2nd ed.

Imitation in the Financial World



THE JOURNAL OF FINANCE • VOL. LX, NO. 6 • DECEMBER 2005

Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers

HARRISON HONG, JEFFREY D. KUBIK, and JEREMY C. STEIN*

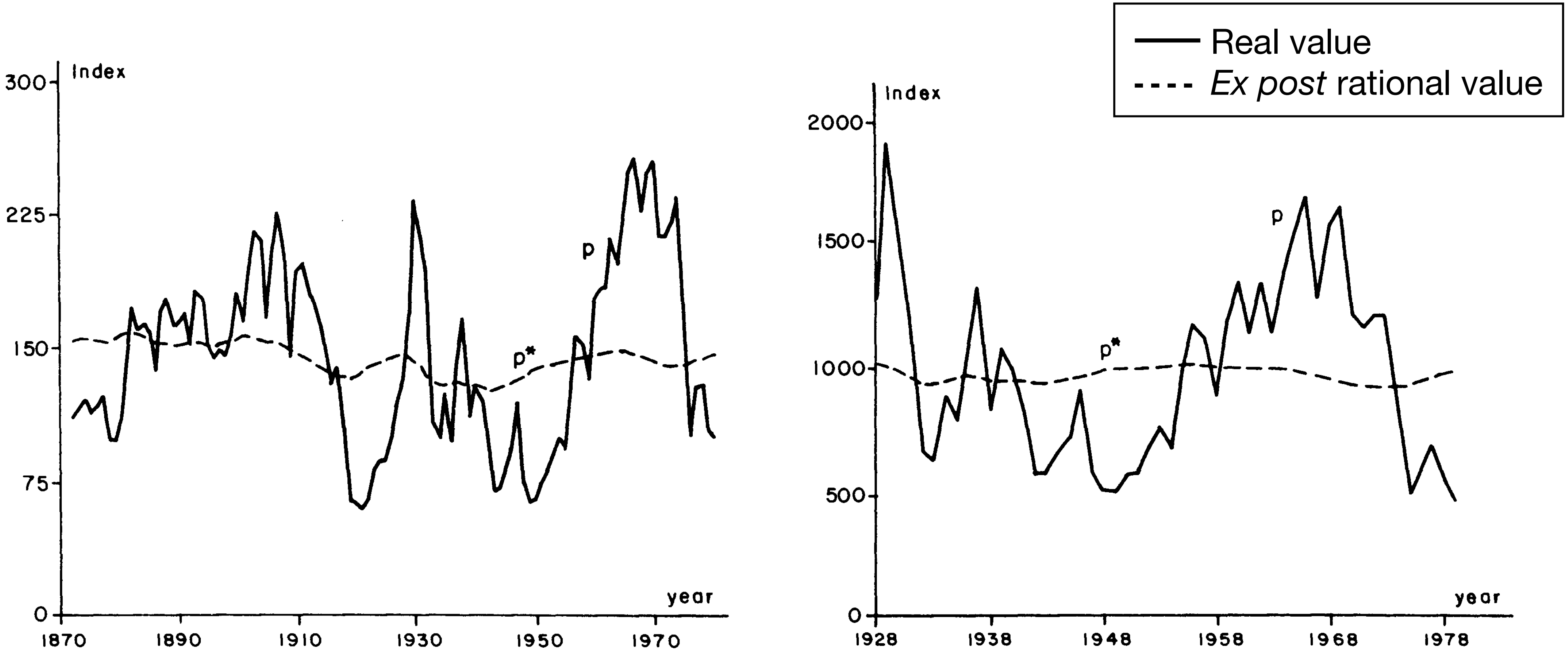
ABSTRACT

A mutual fund manager is more likely to buy (or sell) a particular stock in any quarter if other managers in the same city are buying (or selling) that same stock. This pattern shows up even when the fund manager and the stock in question are located far apart, so it is distinct from anything having to do with local preference. The evidence can be interpreted in terms of an epidemic model in which investors spread information about stocks to one another by word of mouth.

IN THIS PAPER, WE EXPLORE THE HYPOTHESIS that investors spread information and ideas about stocks to one another directly, through word-of-mouth communication. This hypothesis comes up frequently in informal accounts of the behavior of the stock market.[1] For example, in his bestseller *Irrational Exuberance*, Shiller (2000) devotes an entire chapter to the subject of "Herd Behavior and Epidemics," and writes

> A fundamental observation about human society is that people who communicate regularly with one another think similarly. There is at any place and in any time a *Zeitgeist*, a spirit of the times. . . . Word-of-mouth transmission of ideas appears to be an important contributor to day-to-day or hour-to-hour stock market fluctuations. (pp. 148, 155)

“Excess volatility” puzzle



S&P 500 **Dow Jones Industrial Average**

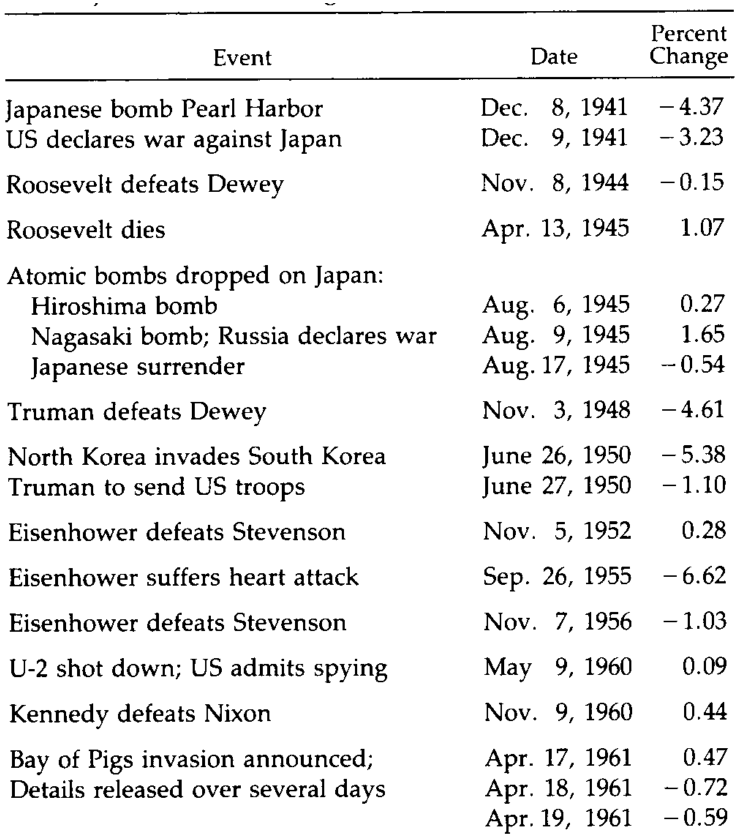
R. Shiller (1981) “Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends?” The American Economic Review 71 (3): 421–436

See also:

- S. F. LeRoy and R.D. Porter (1981) “The Present-Value Relation: Tests Based on Implied Variance Bounds.” Econometrica: Journal of the Econometric Society: 555–574
- S. F. LeRoy (2008) “Excess Volatility Tests.” The New Palgrave Dictionary of Economics, 2nd ed.

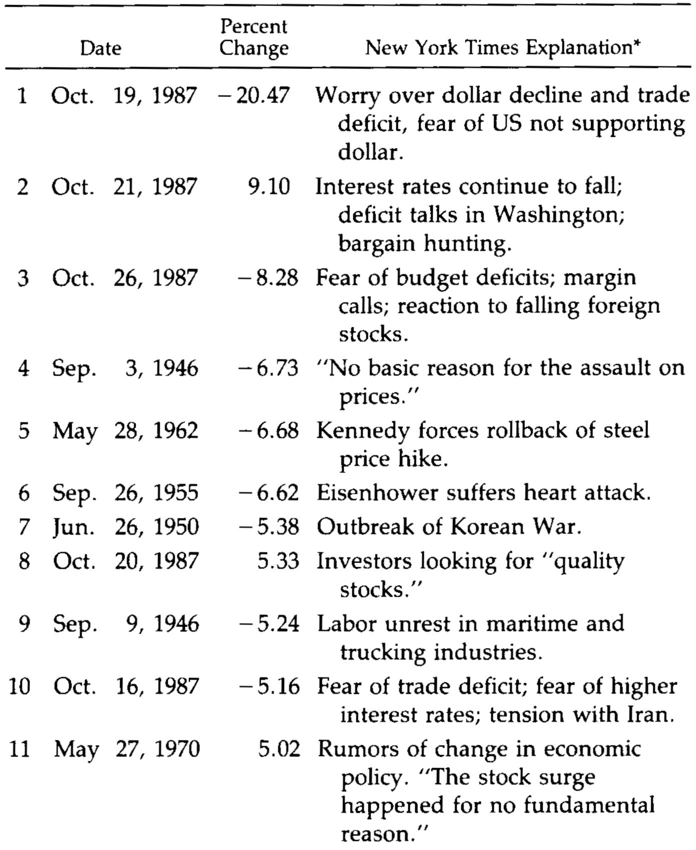
“What moves stock prices?”

Major events and changes in S&P500 Index, 1941-1987



Event	Date	Percent Change
Japanese bomb Pearl Harbor	Dec. 8, 1941	−4.37
US declares war against Japan	Dec. 9, 1941	−3.23
Roosevelt defeats Dewey	Nov. 8, 1944	−0.15
Roosevelt dies	Apr. 13, 1945	1.07
Atomic bombs dropped on Japan:		
Hiroshima bomb	Aug. 6, 1945	0.27
Nagasaki bomb; Russia declares war	Aug. 9, 1945	1.65
Japanese surrender	Aug. 17, 1945	−0.54
Truman defeats Dewey	Nov. 3, 1948	−4.61
North Korea invades South Korea	June 26, 1950	−5.38
Truman to send US troops	June 27, 1950	−1.10
Eisenhower defeats Stevenson	Nov. 5, 1952	0.28
Eisenhower suffers heart attack	Sep. 26, 1955	−6.62
Eisenhower defeats Stevenson	Nov. 7, 1956	−1.03
U-2 shot down; US admits spying	May 9, 1960	0.09
Kennedy defeats Nixon	Nov. 9, 1960	0.44
Bay of Pigs invasion announced;	Apr. 17, 1961	0.47
Details released over several days	Apr. 18, 1961	−0.72
	Apr. 19, 1961	−0.59

Largest post-war movements in S&P 500 Index and their “causes”



	Date	Percent Change	New York Times Explanation*
1	Oct. 19, 1987	−20.47	Worry over dollar decline and trade deficit, fear of US not supporting dollar.
2	Oct. 21, 1987	9.10	Interest rates continue to fall; deficit talks in Washington; bargain hunting.
3	Oct. 26, 1987	−8.28	Fear of budget deficits; margin calls; reaction to falling foreign stocks.
4	Sep. 3, 1946	−6.73	“No basic reason for the assault on prices.”
5	May 28, 1962	−6.68	Kennedy forces rollback of steel price hike.
6	Sep. 26, 1955	−6.62	Eisenhower suffers heart attack.
7	Jun. 26, 1950	−5.38	Outbreak of Korean War.
8	Oct. 20, 1987	5.33	Investors looking for “quality stocks.”
9	Sep. 9, 1946	−5.24	Labor unrest in maritime and trucking industries.
10	Oct. 16, 1987	−5.16	Fear of trade deficit; fear of higher interest rates; tension with Iran.
11	May 27, 1970	5.02	Rumors of change in economic policy. “The stock surge happened for no fundamental reason.”

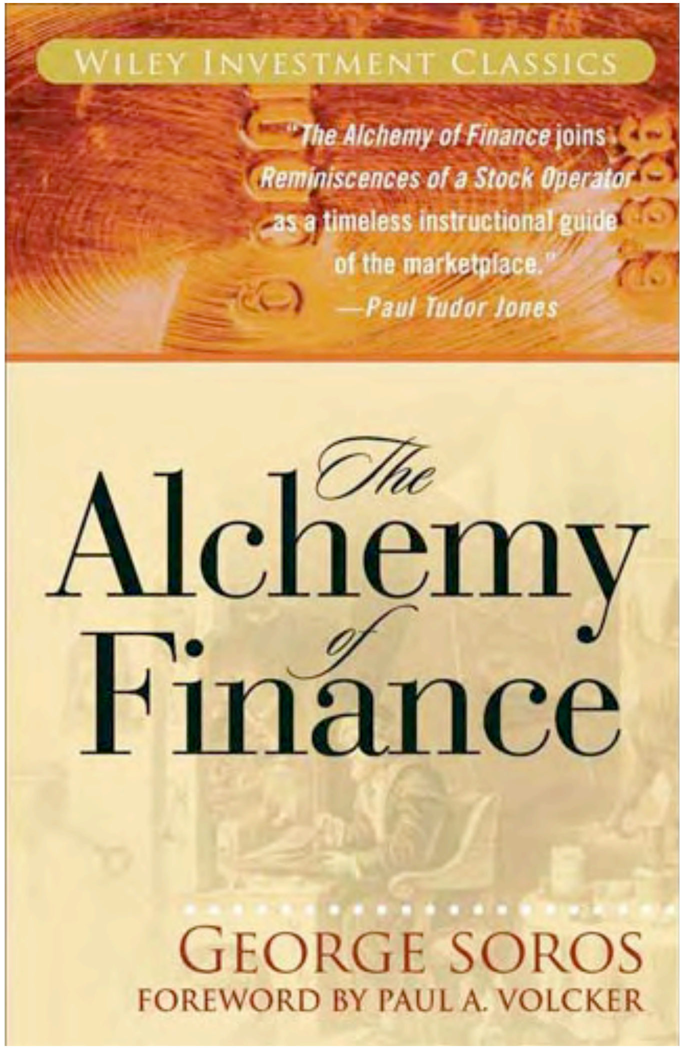
D. Cutler, J. Poterba, L. Summers (1987) “What moves stock prices?”
Journal of Portfolio Management 15 (3): 4–12

See also:

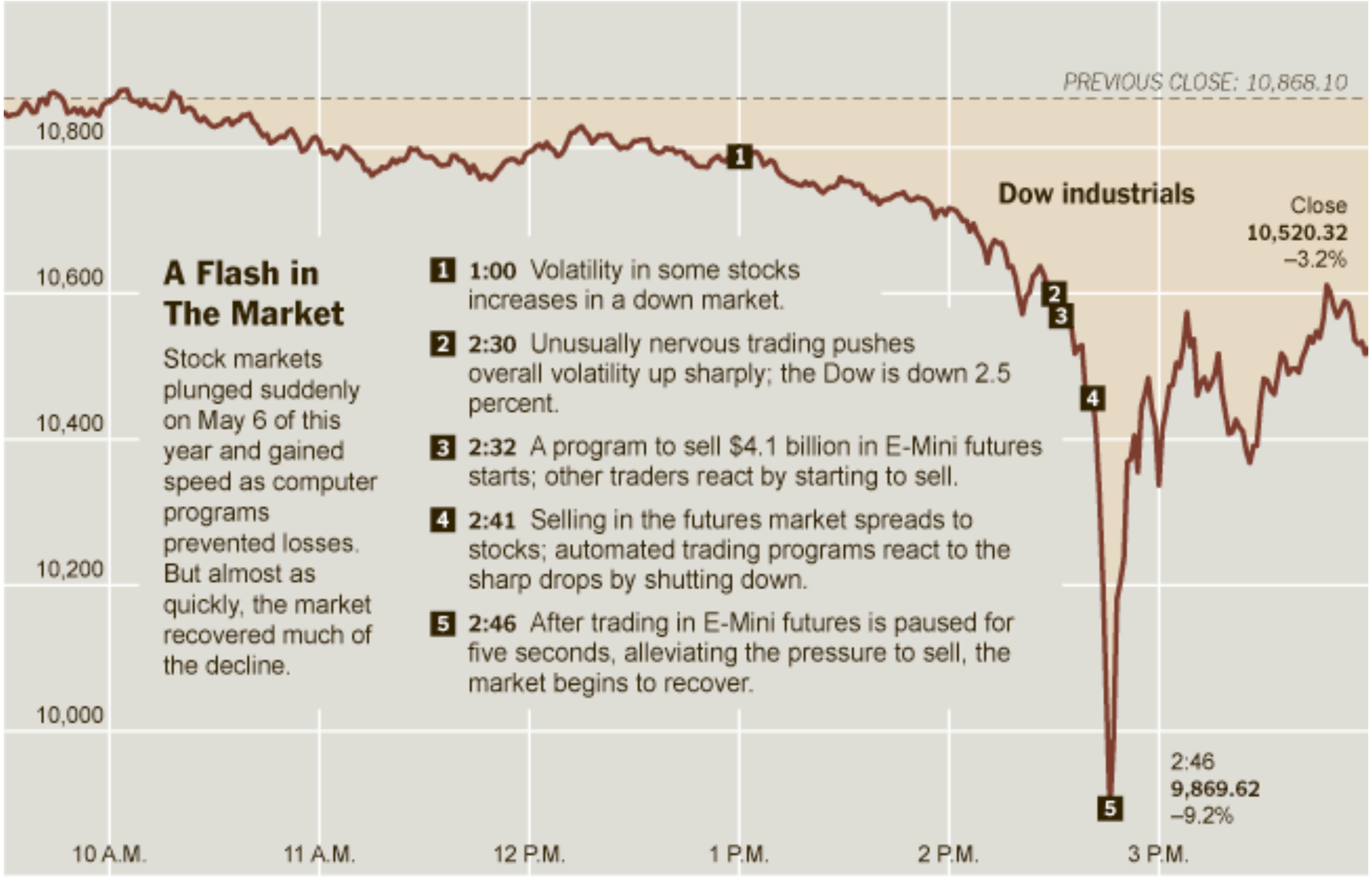
- G. McQueen, V. Roley (1993) “Stock prices, news, and business conditions.” Review of Fin. Studies 6 (3): 683–707
- O. Erdogan, A. Yezegel (2009) “The news of no news in stock markets”, Quantitative Finance 9 (8): 897–909
- M. Fleming, E. Remolona (1997) “What Moves the Bond Market?” FRBNY Economic Policy Review 3 (4): 31–50
- R. C. Fair (2002) “Events That Shook the Market.” Journal of Business 75 (4): 713–731

Idea of the “reflexivity” of market

- George Soros adapted ideas of Orlean (1980x) and others and proposed the concept of “***reflexivity***”, where the biases of individuals enter into market transactions, potentially changing the perception of fundamentals of the economy.
- When markets are rising or falling rapidly, they are typically in the state of ***disequilibrium*** rather than *equilibrium*, and that the conventional economic theory of the market (EMH) is not valid in these situations.
- Reflexivity asserts that ***prices do in fact influence the fundamentals*** and that these newly-influenced set of fundamentals then proceed to change expectations, thus influencing prices; the process continues in a self-reinforcing pattern.
- In other words, the underlying market mechanisms create ***positive feedback loops*** that



Flash-crash event: 6 May 2010



A Flash in The Market

Stock markets plunged suddenly on May 6 of this year and gained speed as computer programs prevented losses. But almost as quickly, the market recovered much of the decline.

1 **1:00** Volatility in some stocks increases in a down market.

2 **2:30** Unusually nervous trading pushes overall volatility up sharply; the Dow is down 2.5 percent.

3 **2:32** A program to sell $4.1 billion in E-Mini futures starts; other traders react by starting to sell.

4 **2:41** Selling in the futures market spreads to stocks; automated trading programs react to the sharp drops by shutting down.

5 **2:46** After trading in E-Mini futures is paused for five seconds, alleviating the pressure to sell, the market begins to recover.

Sources: Bloomberg (Dow industrials); Securities and Exchange Commission

THE NEW YORK TIMES

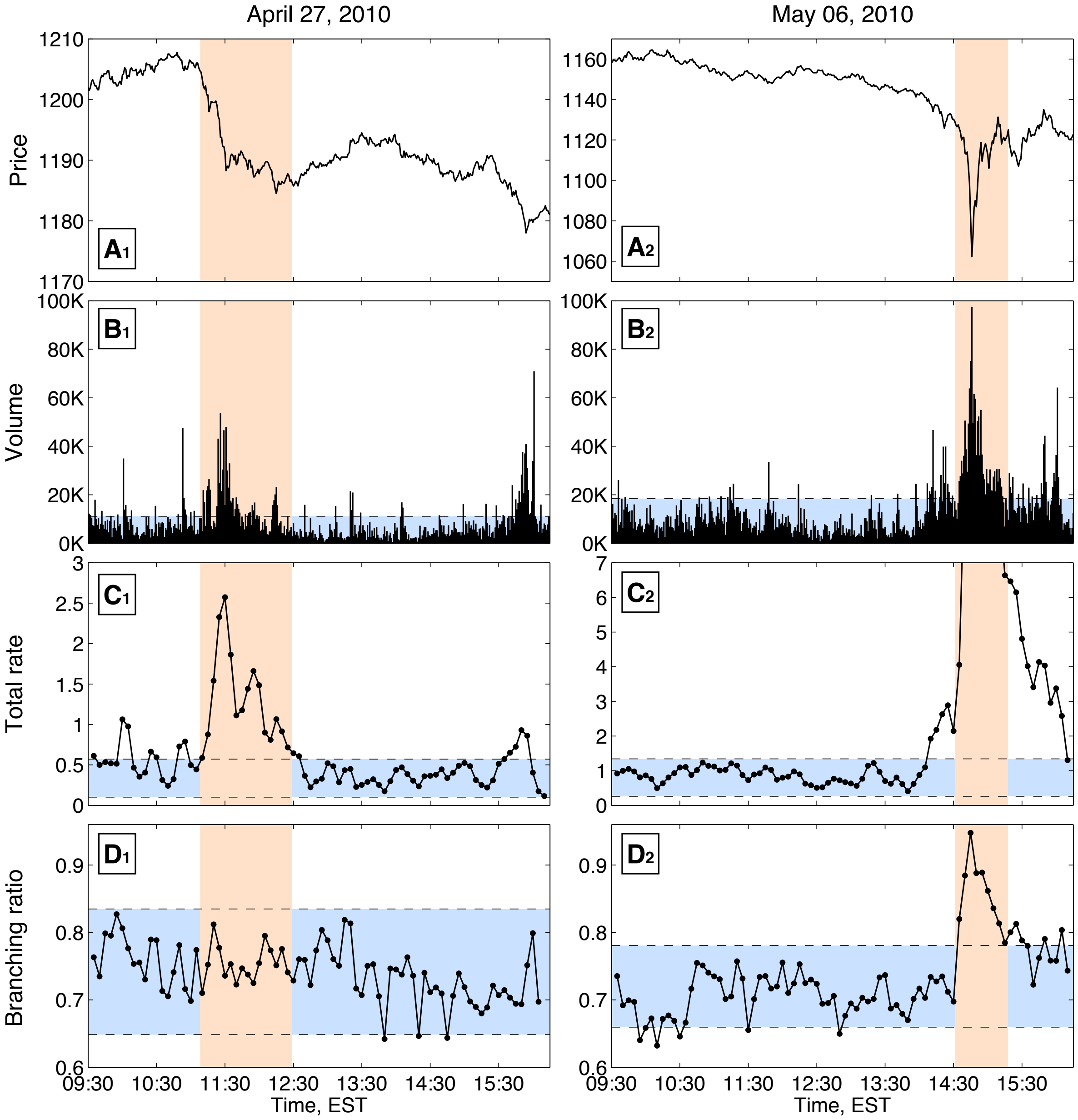
- “Findings Regarding the Market Events of May 6, 2010”: Report of the Staffs of the CFTC and SEC to the Joint Advisory Committee on Emerging Regulatory Issues (September 30, 2010).
- *Source of picture*: G. Bowley “Lone $4.1 Billion Sale Led to ‘Flash Crash’ in May”, New York Times (Oct. 2, 2010)

Exogenous vs endogenous shocks in HF

Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

April 27, 2010:

almost all US markets fell significantly following the dramatic decrease of the credit rating of Greece and Portugal



May 6, 2010:

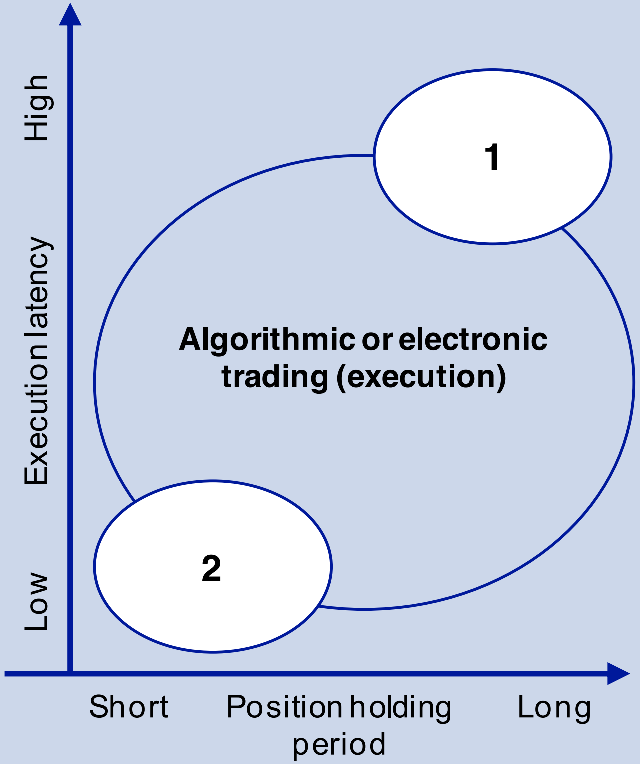
the so-called "flash-crash" event, when the activity of high-frequency traders of the S&P 500 E-mini futures contracts leaded to a dramatic fall in other markets

---

- V. Filimonov, D. Sornette (2012) "Quantifying reflexivity in financial markets: towards a prediction of flash crashes", submitted to PRE, http://arxiv.org/abs/1201.3572

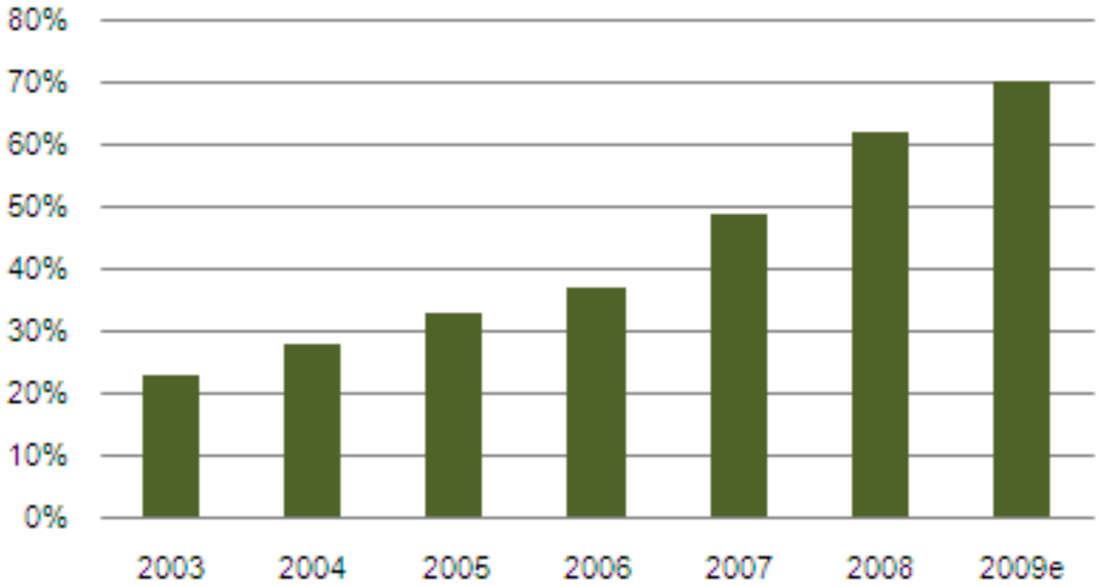
Algorithmic and High-Frequency Trading

HFT vs. AT and traditional long-term investing



1) Traditional long-term investing
2) High-frequency trading

Source: Aldridge 2010



Growth of High Frequency Trading Firms
(Percentage of Average Daily Trade Volume)
(Source: Aite Group)

- “New World Order: the High Frequency Trading Community and Its Impact on Market Structure.” The Aite Group Report (2009) http://www.aitegroup.com/Reports/ReportDetail.aspx?recordItemID=531
- I. Aldridge (2010) “High-Frequency Trading: A Practical Guide to Algorithmic Strategies and Trading Systems.” John Wiley & Sons.
- D. Sornette and S. von der Becke, Crashes and High Frequency Trading (2011), report for the UK Government project entitled ``The Future of Computer Trading in Financial Markets'', Foresight Driver Review - DR7, (http://ssrn.com/abstract=1976249)

Have we seen any real-life examples?

Financial bubbles, which we have been observing for over 400 years:

Tulip mania

South Sea bubble

IT bubble

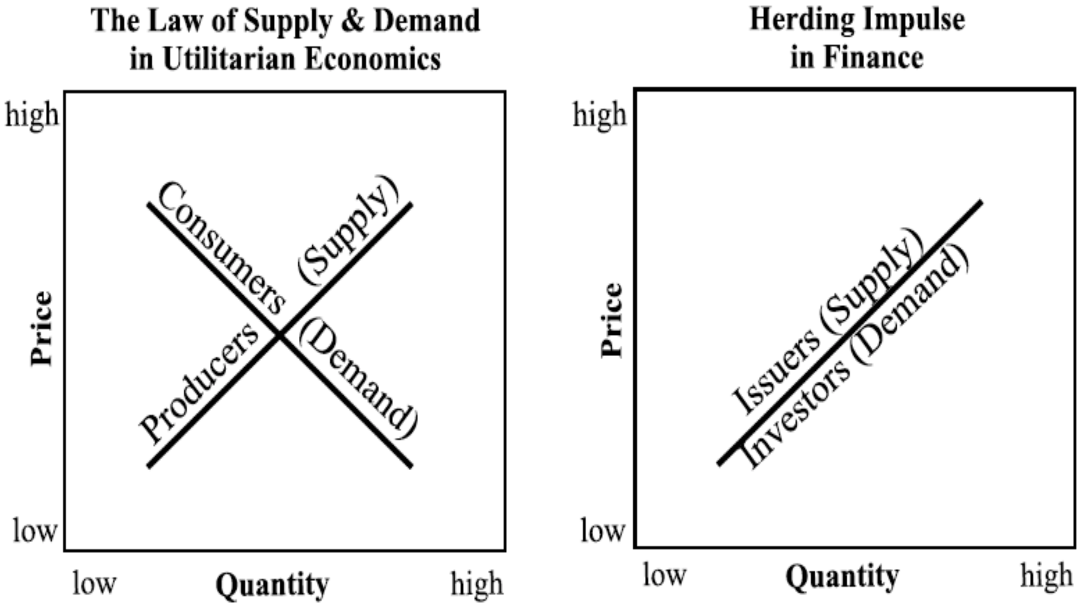
Housing bubble

Signs of Upcoming Transition

Early warning signals as predicted from theory

- Slower recovery from perturbations
- Increasing (or decreasing) autocorrelation
- Increasing (or decreasing) cross-correlation with external driving
- Increasing variance
- Flickering and stochastic resonance
- Increased spatial coherence
- Degree of endogeneity/reflexivity
- **Finite-time singularities**

Positive feedbacks



© 2003 Robert R. Prechter, The Socionomics Institute

-bubble phase
-crash phase

$$\boxed{\frac{dp}{dt} = cp^d}$$

$$p(t) = \left(\frac{c}{m}\right)^{-m} (t_c - t)^{-m}$$

$$m = 1/(d-1) > 0 \text{ and } t_c = t_0 + m p_0^{1-d}/c.$$

Faster than exponential transient unsustainable growth

=> transition to another regime

Super-exponential growth (positive feedbacks)

$$\frac{dp}{dt} = rp(t)[K - p(t)].$$

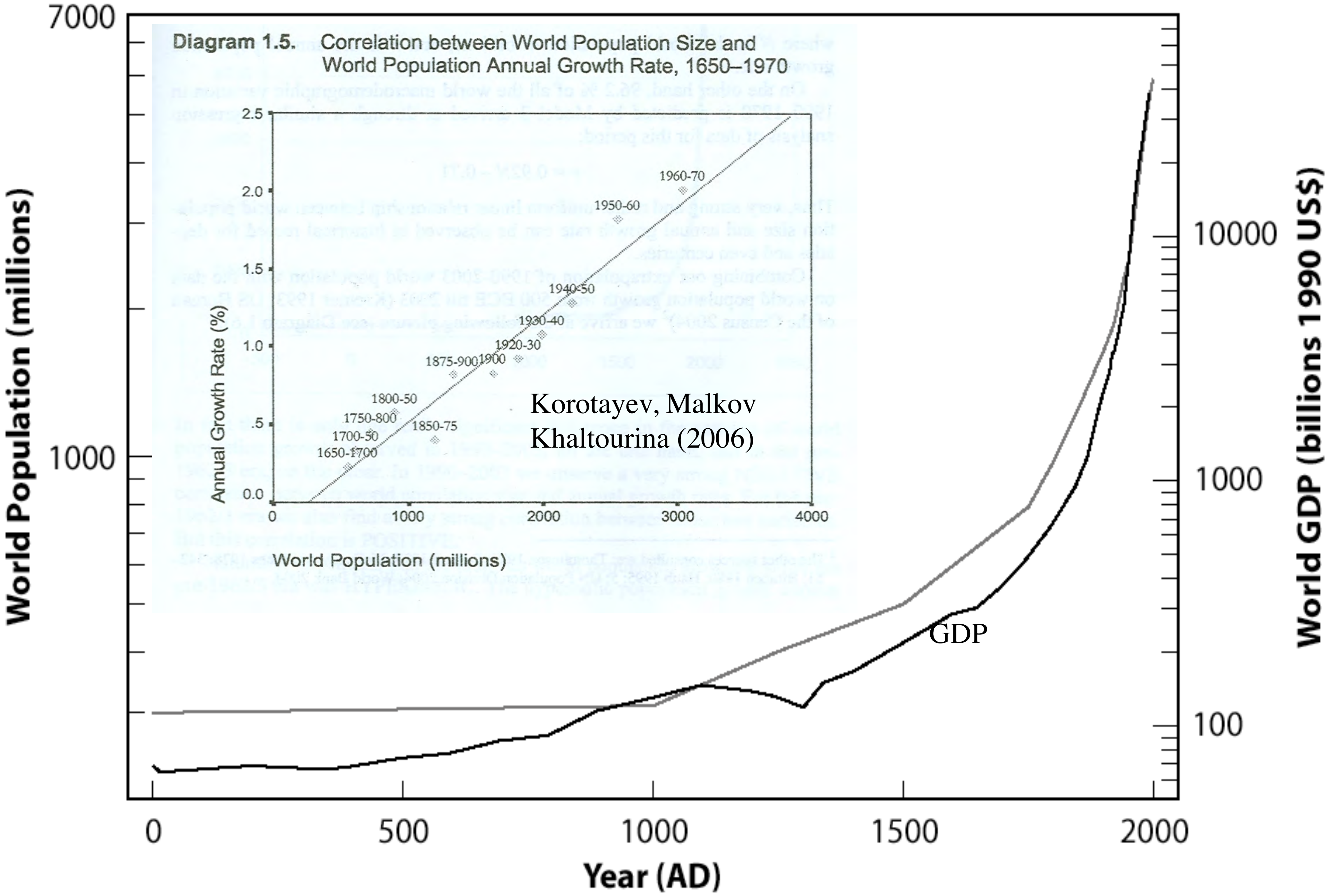
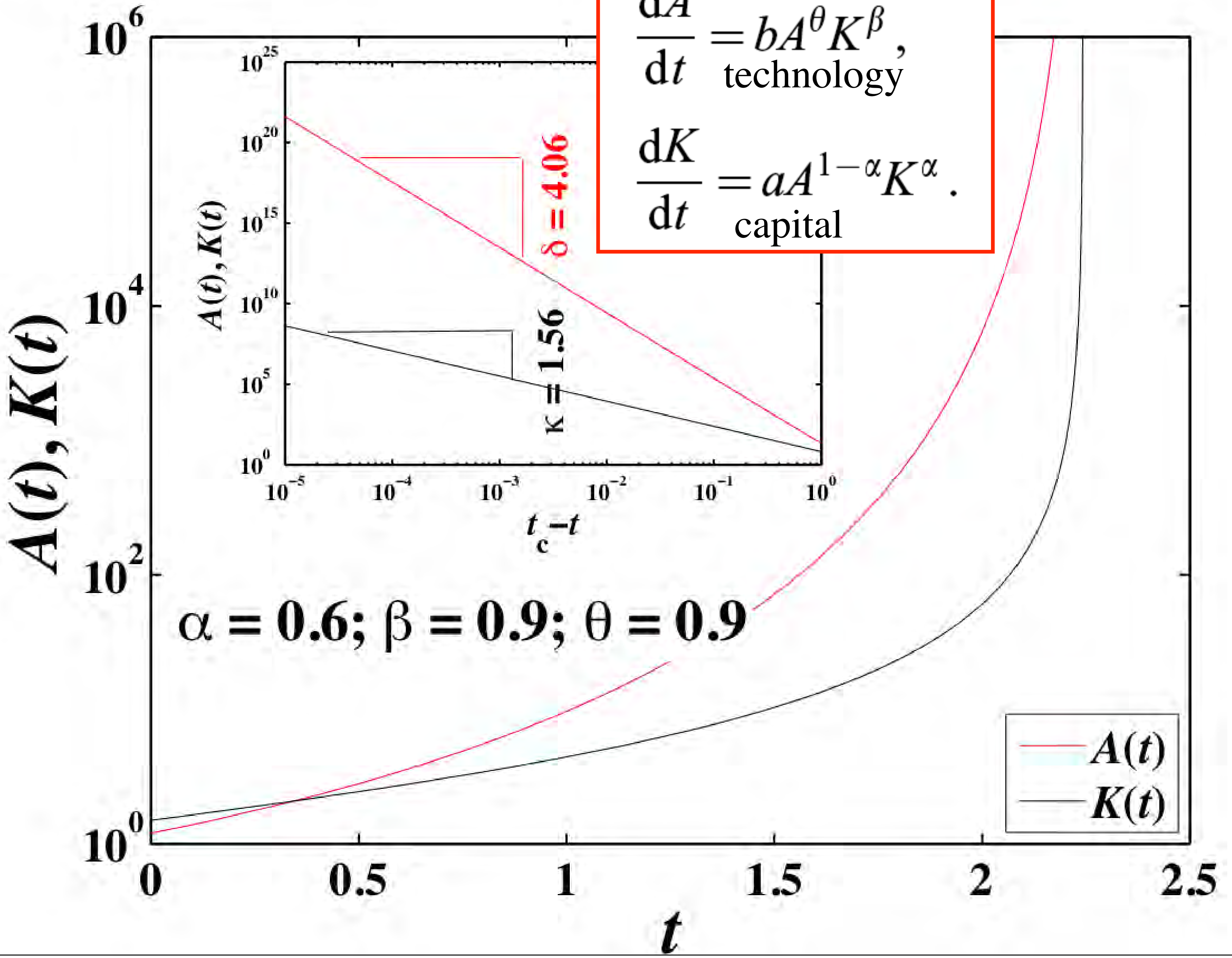


Diagram 1.5. Correlation between World Population Size and World Population Annual Growth Rate, 1650–1970

Korotayev, Malkov Khaltourina (2006)

Multivariate endogeneous growth models and FTS

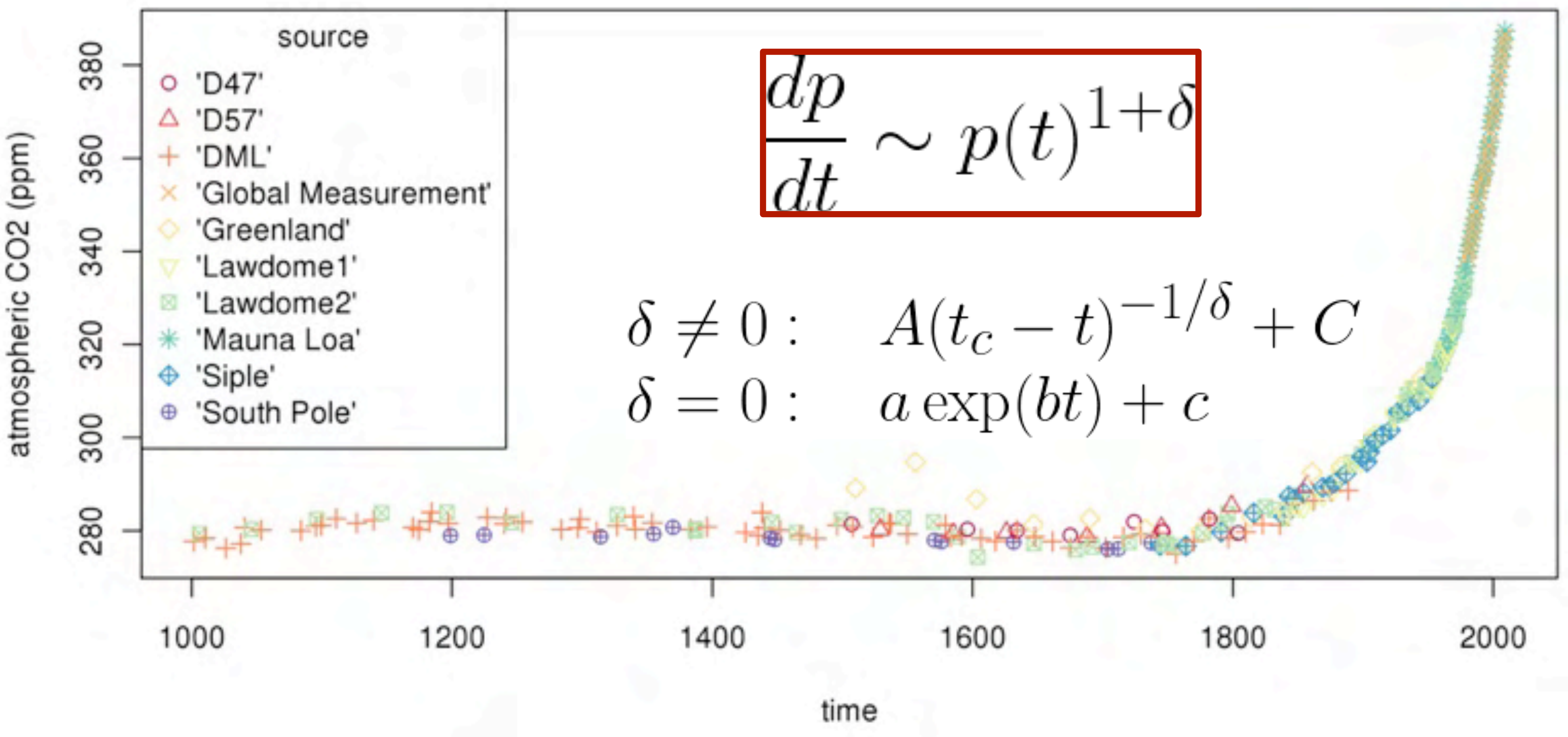
Case θ+β>1 : FTS



$$\frac{\mathrm{d}A}{\mathrm{d}t} = \underbrace{bA^{\theta}K^{\beta}}_{\text{technology}},$$

$$\frac{\mathrm{d}K}{\mathrm{d}t} = \underbrace{aA^{1-\alpha}K^{\alpha}}_{\text{capital}}.$$

CO2 measurements from different sources



$$\boxed{\frac{dp}{dt} \sim p(t)^{1+\delta}}$$

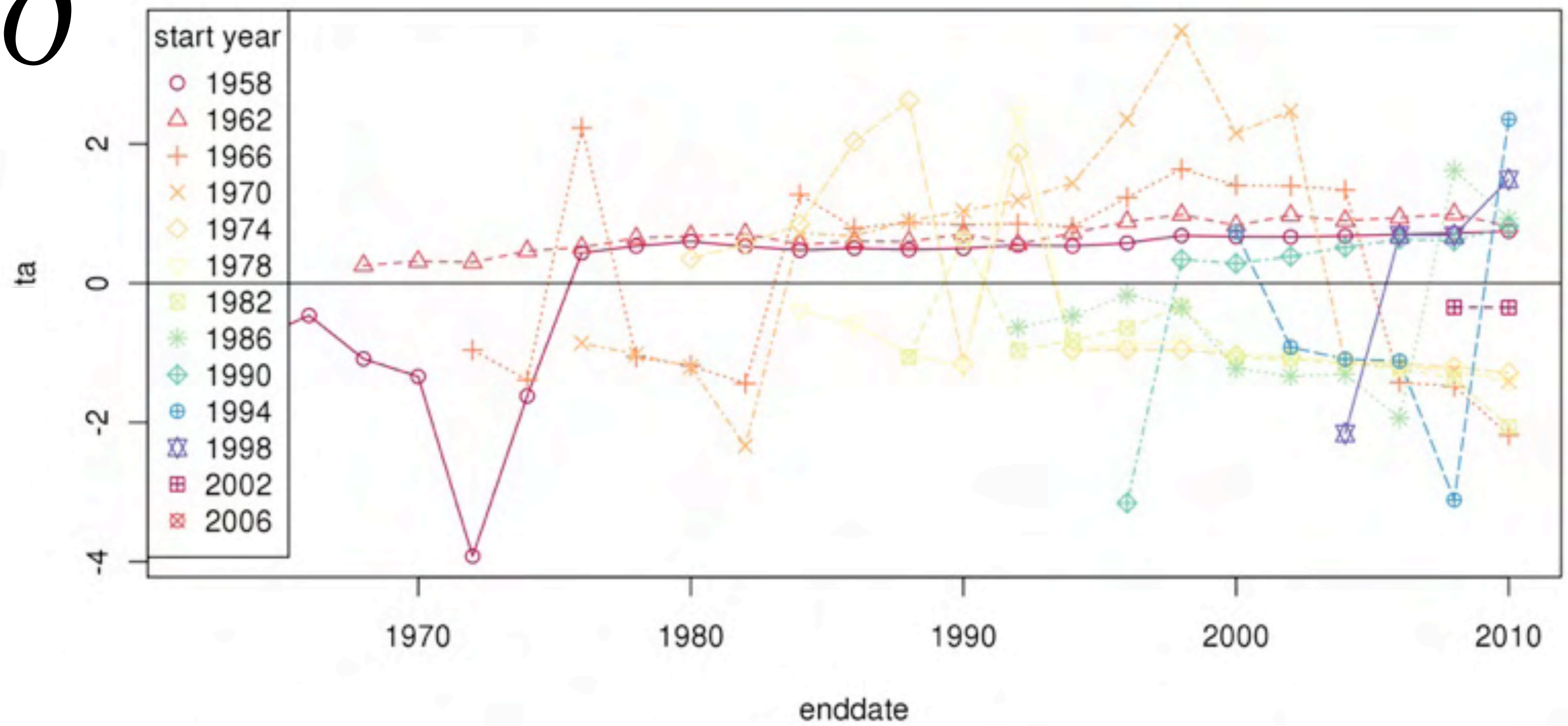
$$\delta \neq 0 : \quad A(t_c - t)^{-1/\delta} + C$$

$$\delta = 0 : \quad a \exp(bt) + c$$

Exponential and Super-Exponential Population and atmospheric CO2 Dynamics

No Improvements on the Horizon

δ



=> significant evidence for positive => growth $\geq$ exponential

A. Huesler and D. Sornette (http://arxiv.org/abs/1101.2832)

Finite-time Singularity

as a result of positive feedbacks

- Planet formation in solar system by run-away accretion of planetesimals
- PDE's: Euler equations of inviscid fluids and relationship with turbulence
- PDE's of General Relativity coupled to a mass field leading to the formation of black holes
- Zakharov-equation of beam-driven Langmuir turbulence in plasma
- rupture and material failure
- Earthquakes (ex: slip-velocity Ruina-Dieterich friction law and accelerating creep)
- Models of micro-organisms chemotaxis, aggregating to form fruiting bodies
- Surface instability spikes (Mullins-Sekerka), jets from a singular surface, fluid drop snap-off
- Euler's disk (rotating coin)
- Stock market crashes...

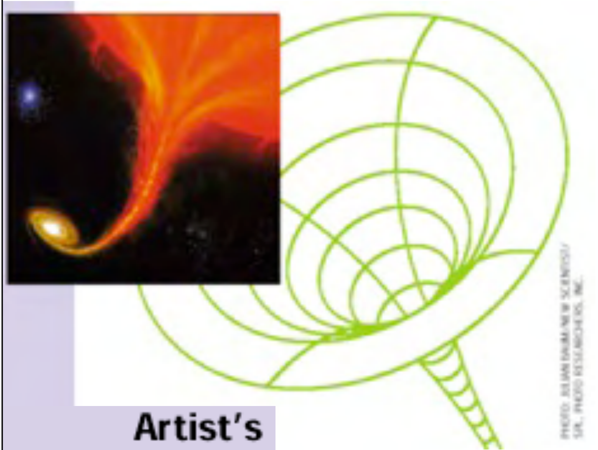
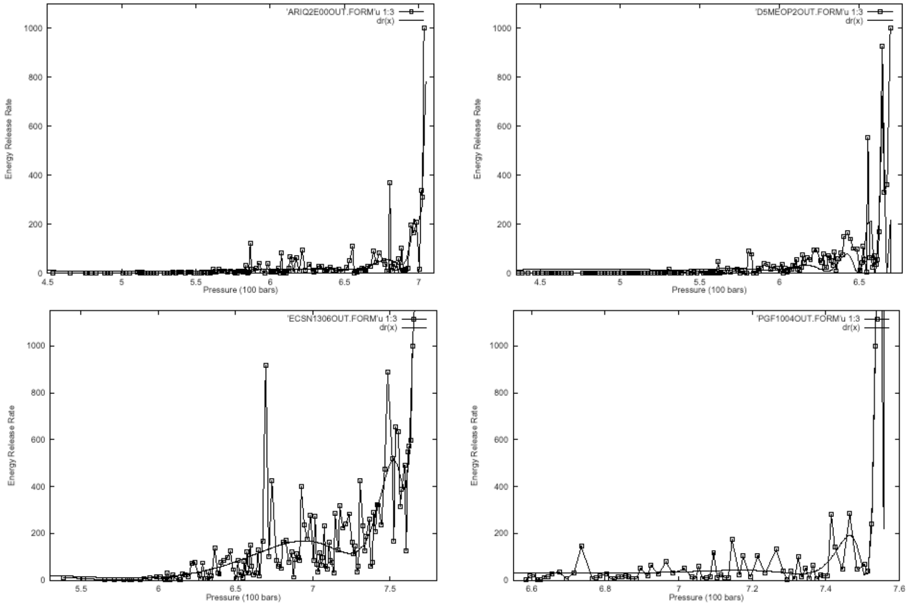


PHOTO: JULIAN BAUM/NEW SCIENTIST/
SPL, PHOTO RESEARCHERS, INC.

Artist's illustration of matter from a red giant star being pulled toward a black hole.



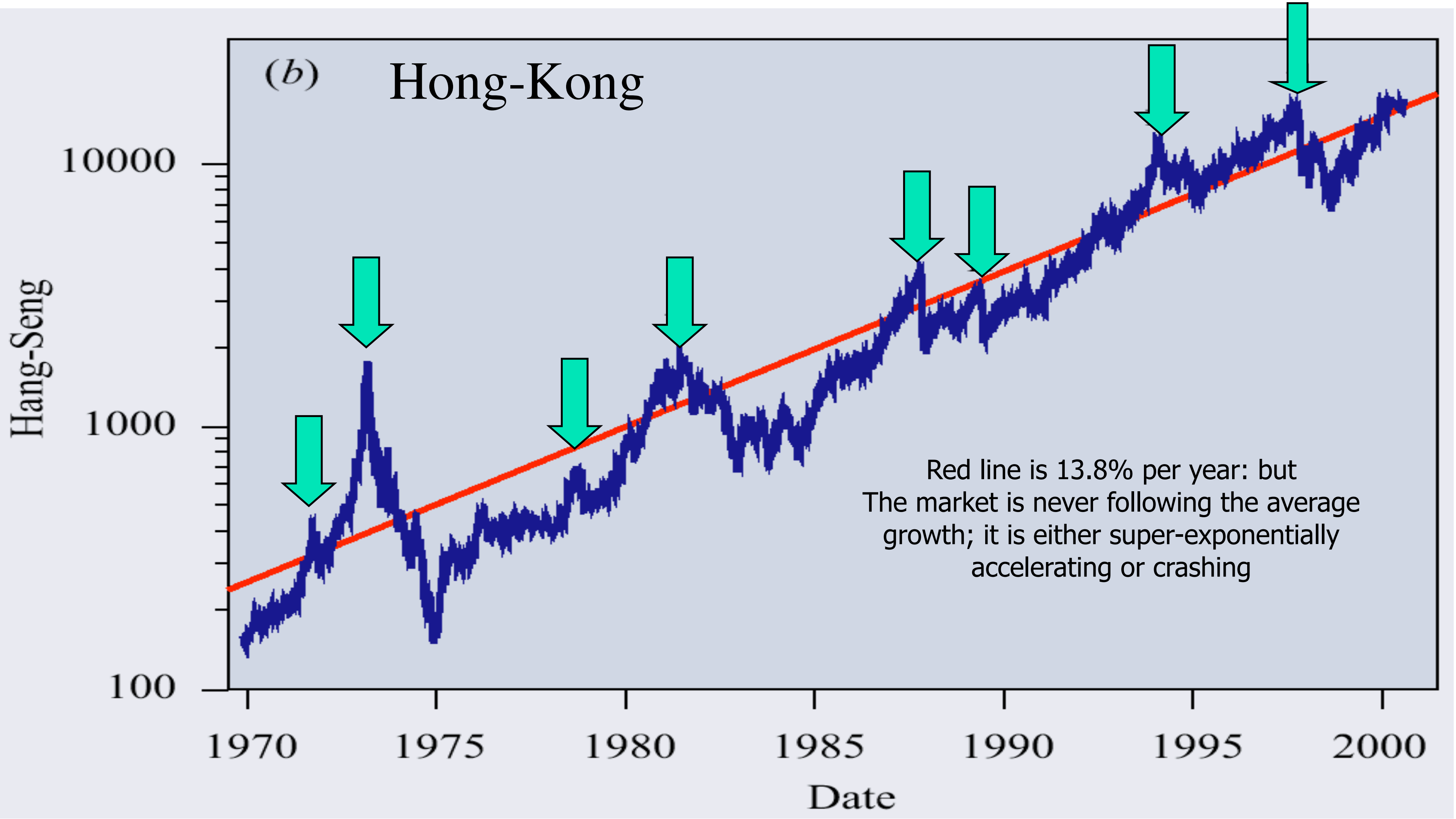
- Increasing variance
- Increased spatial coherence
- **Finite-time singularity**

Our prediction system is now used in the industrial phase as the standard testing procedure.

EADS
LAUNCH
VEHICLES

J.-C. Anifrani, C. Le Floc'h, D. Sornette and B. Souillard
"Universal Log-periodic correction to renormalization group scaling for rupture stress prediction from acoustic emissions", J.Phys.I France 5, n°6, 631-638 (1995)

Financial Instability Hypothesis (Minsky)



Red line is 13.8% per year: but
The market is never following the average
growth; it is either super-exponentially
accelerating or crashing

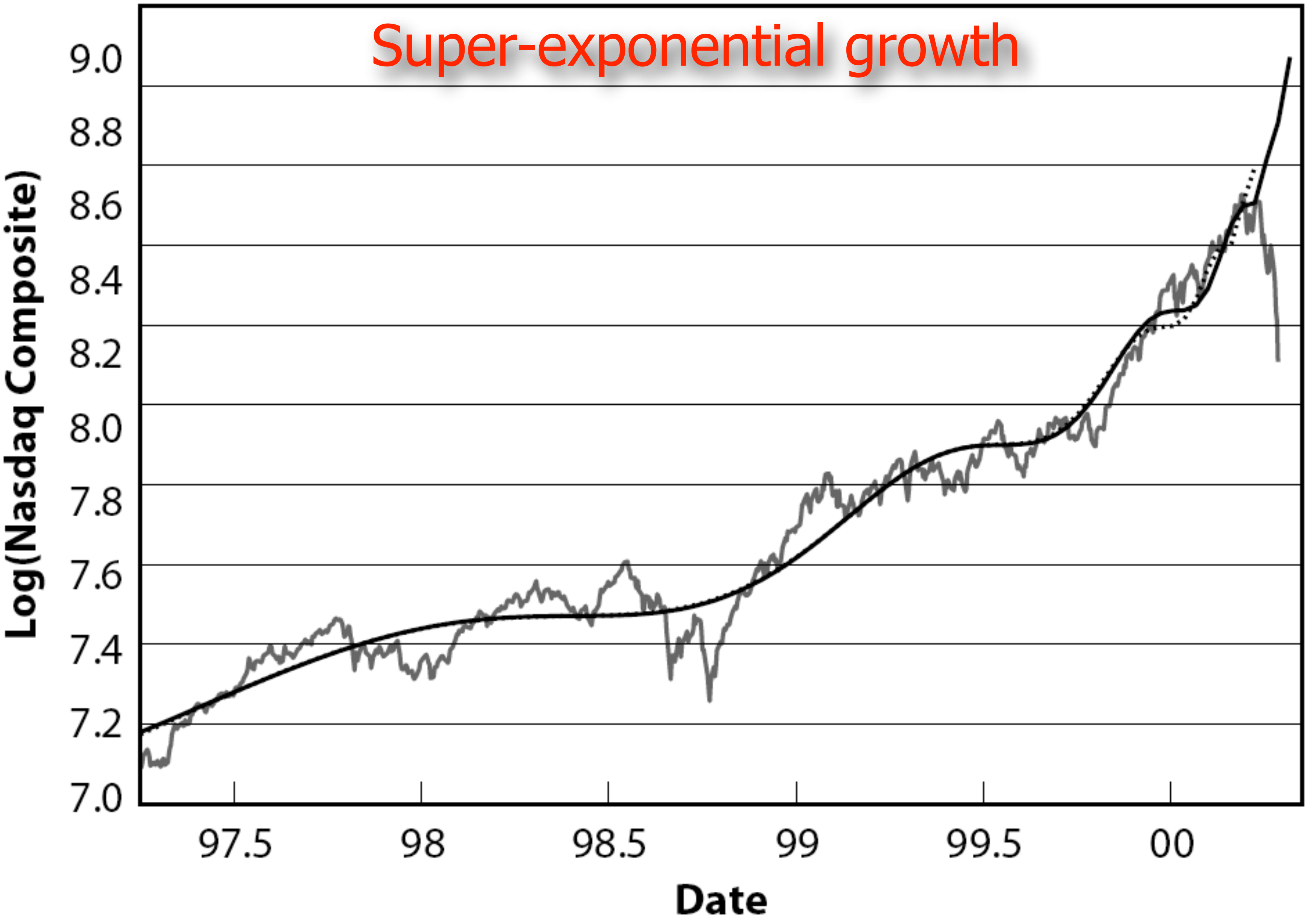
Patterns of price trajectory during 0.5-1 year before each peak: Log-periodic power law

Predictability of the 2007-XXXX crisis: 15y History of bubbles and Dragon-kings

- The ITC “new economy” bubble (1995-2000)
- Slaving of the Fed monetary policy to the stock market descent (2000-2003)
- Real-estate bubbles (2003-2006)
- MBS, CDOs bubble (2004-2007) and stock market bubble (2004-2007)
- Commodities and Oil bubbles (2006-2008)

Didier Sornette and Ryan Woodard
Financial Bubbles, Real Estate bubbles, Derivative Bubbles, and the Financial and Economic Crisis (2009)
(http://arxiv.org/abs/0905.0220)

THE NASDAQ CRASH OF APRIL 2000



Real-estate in the UK

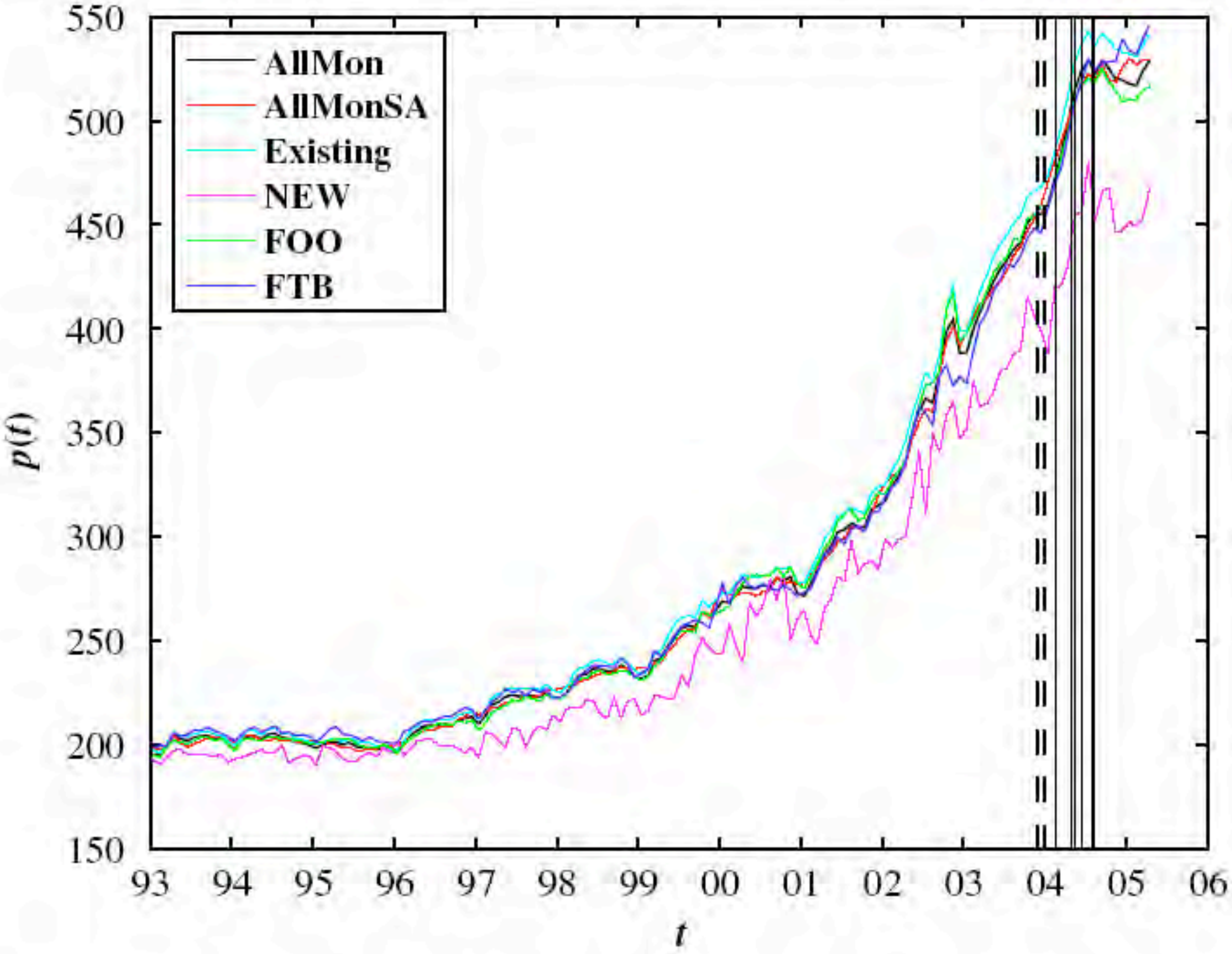


Fig. 1. (Color online) Plot of the UK Halifax house price indices from 1993 to April 2005 (the latest available quote at the time of writing). The two groups of vertical lines correspond to the two predicted turning points reported in Tables 2 and 3 of [1]: end of 2003 and mid-2004. The former (resp. later) was based on the use of formula (2) (resp. (3)). These predictions were performed in February 2003.

W.-X. Zhou, D. Sornette, 2000–2003 real estate bubble in the UK but not in the USA, Physica A 329 (2003) 249–263.

Real-estate in the USA

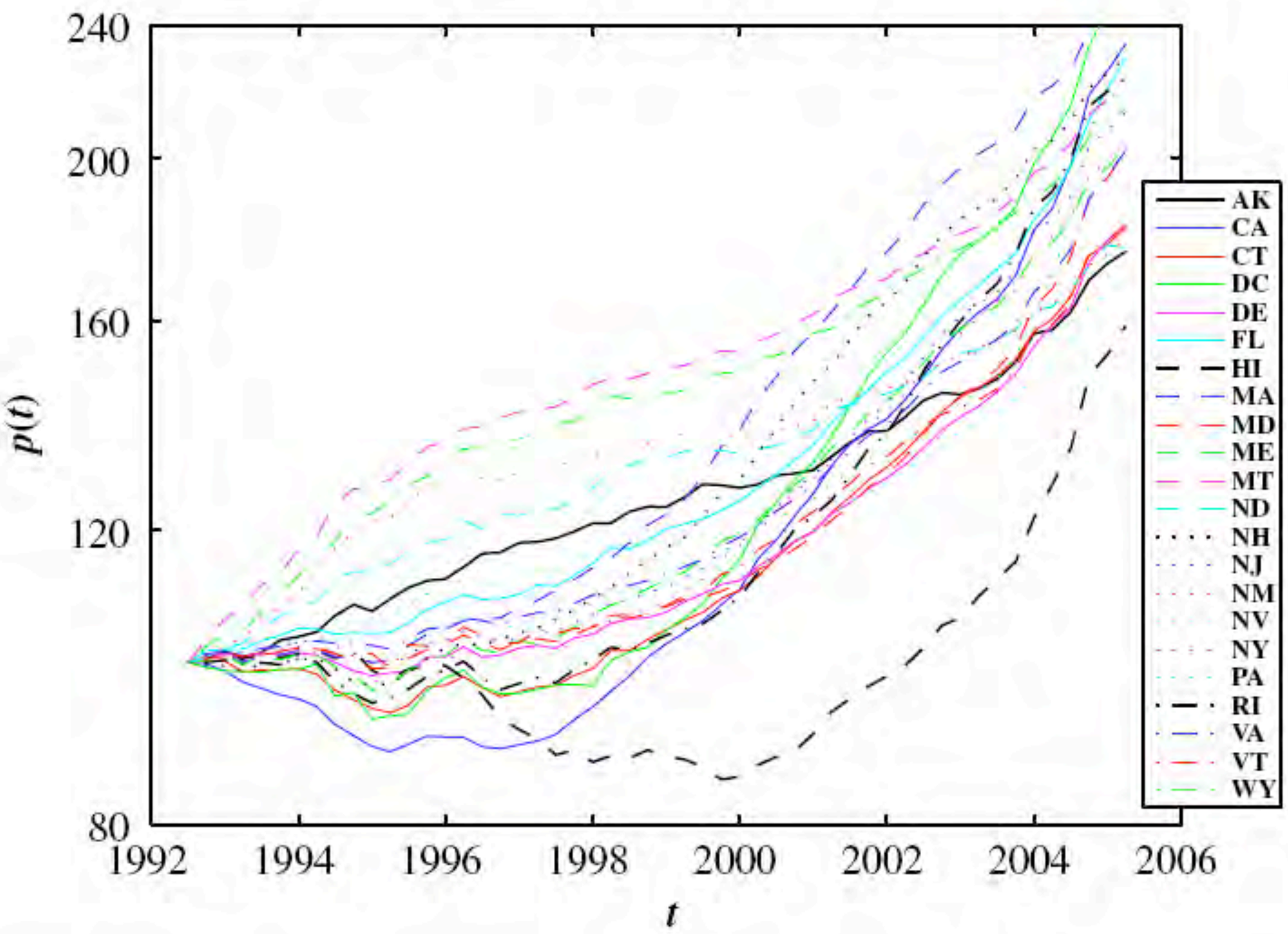
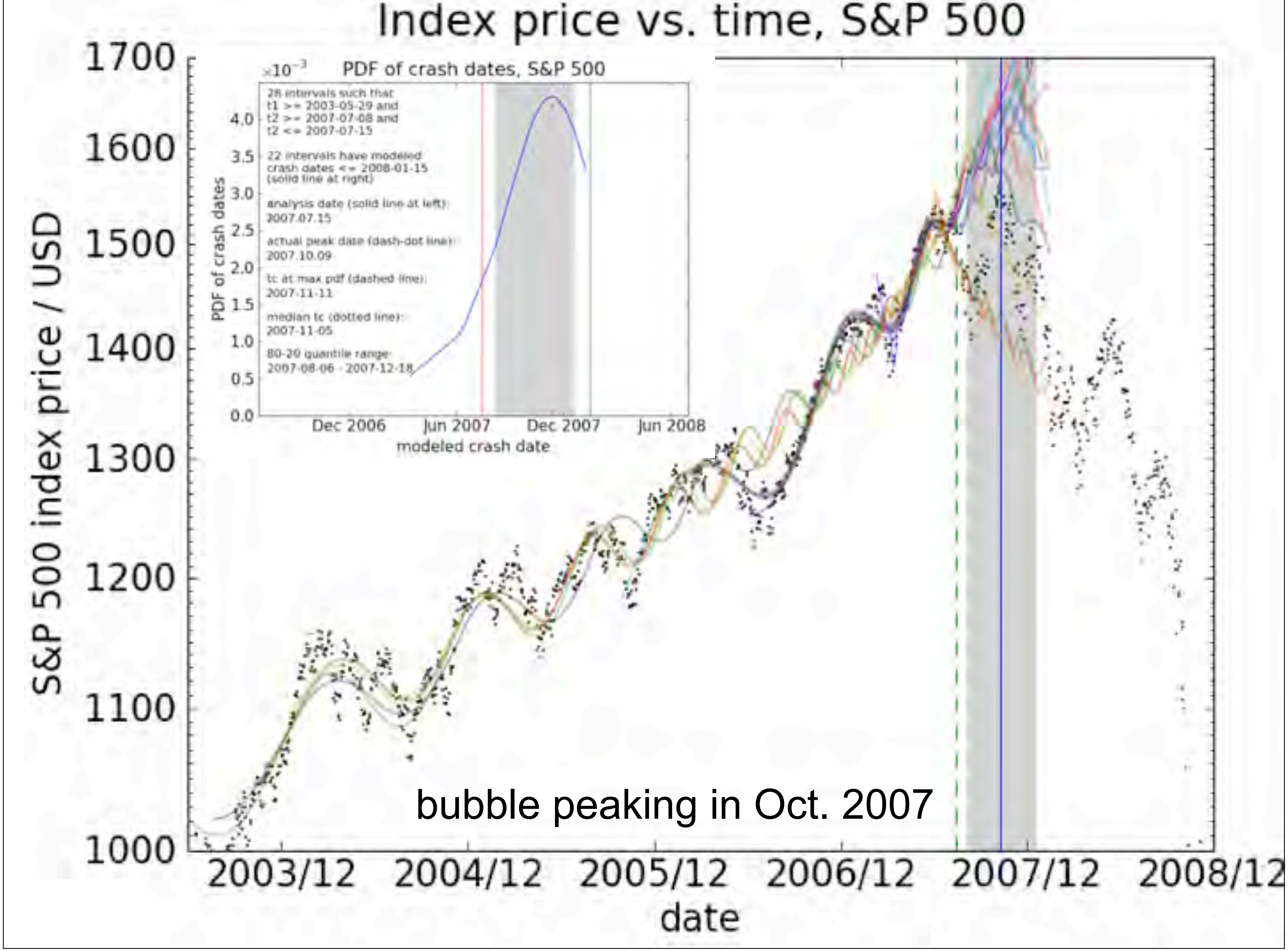


Fig. 5. (Color online) Quarterly average HPI in the 21 states and in the District of Columbia (DC) exhibiting a clear upward faster-than-exponential growth. For better representation, we have normalized the house price indices for the second quarter of 1992 to 100 in all 22 cases. The corresponding states are given in the legend.

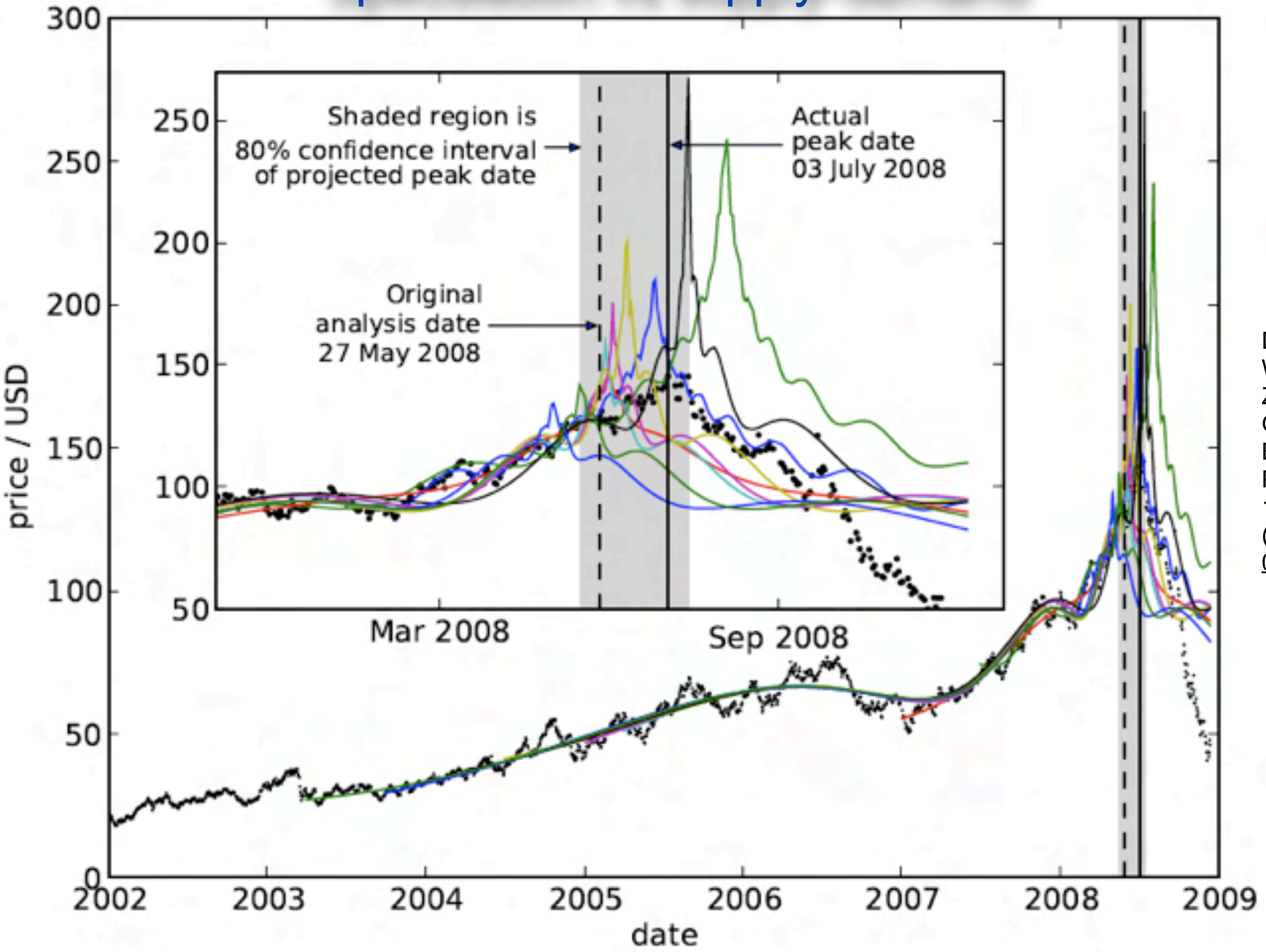
W.-X. Zhou, D. Sornette / Physica A 361 (2006) 297–308



bubble peaking in Oct. 2007

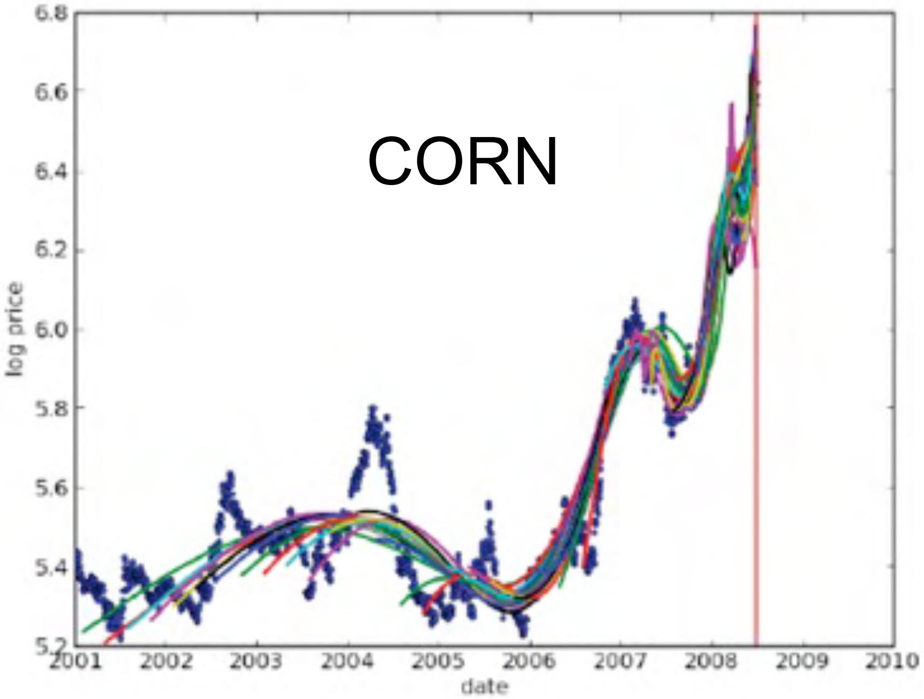
2006-2008 Oil bubble

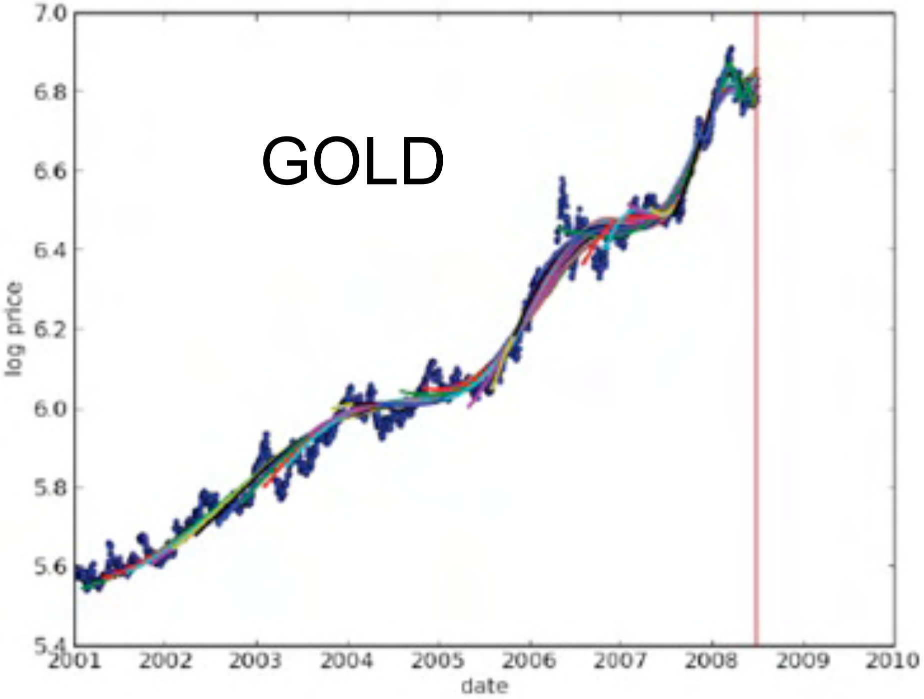
Speculation vs supply-demand



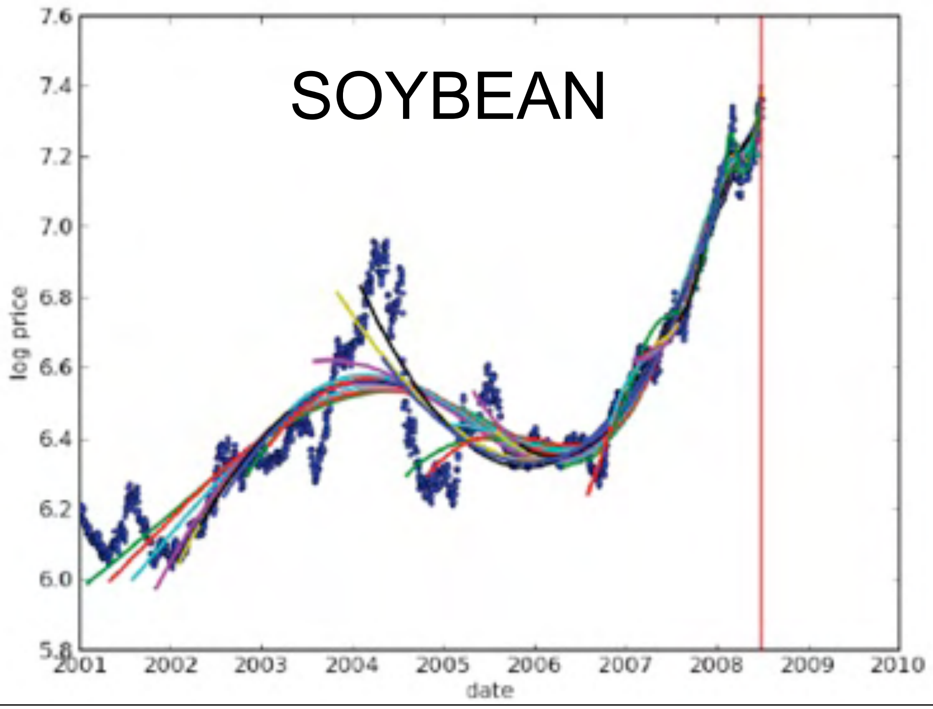
D. Sornette, R. Woodard and W.-X. Zhou, The 2006-2008 Oil Bubble and Beyond,
Physica A 388, 1571-1576 (2009)
(arXiv.org/abs/0806.1170)

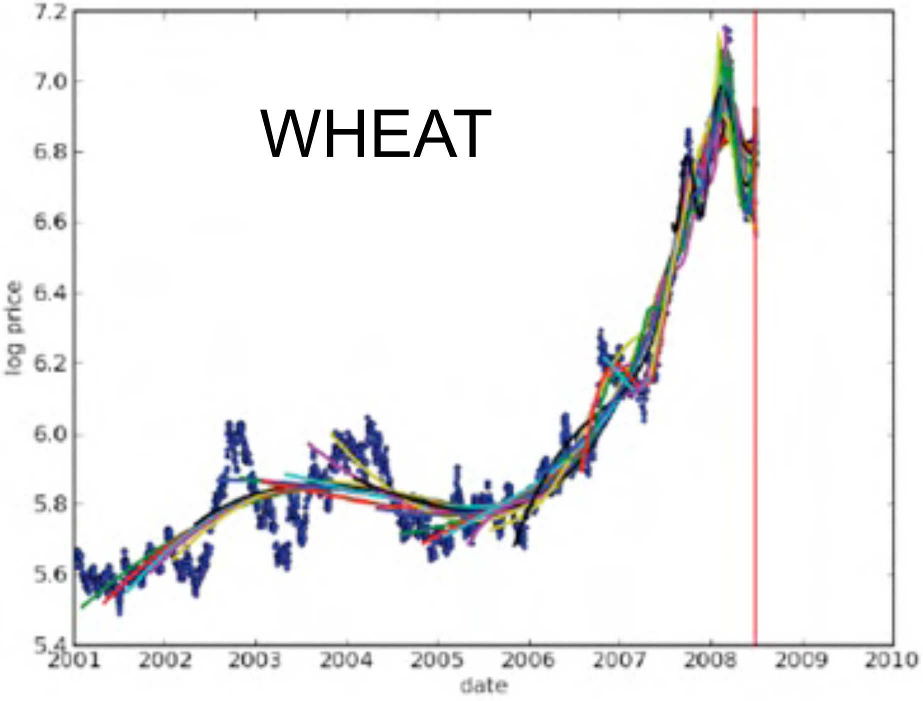
Typical result of the calibration of the simple LPPL model to the oil price in US$ in shrinking windows with starting dates t_{start} moving up towards the common last date t_{last} = May 27, 2008.



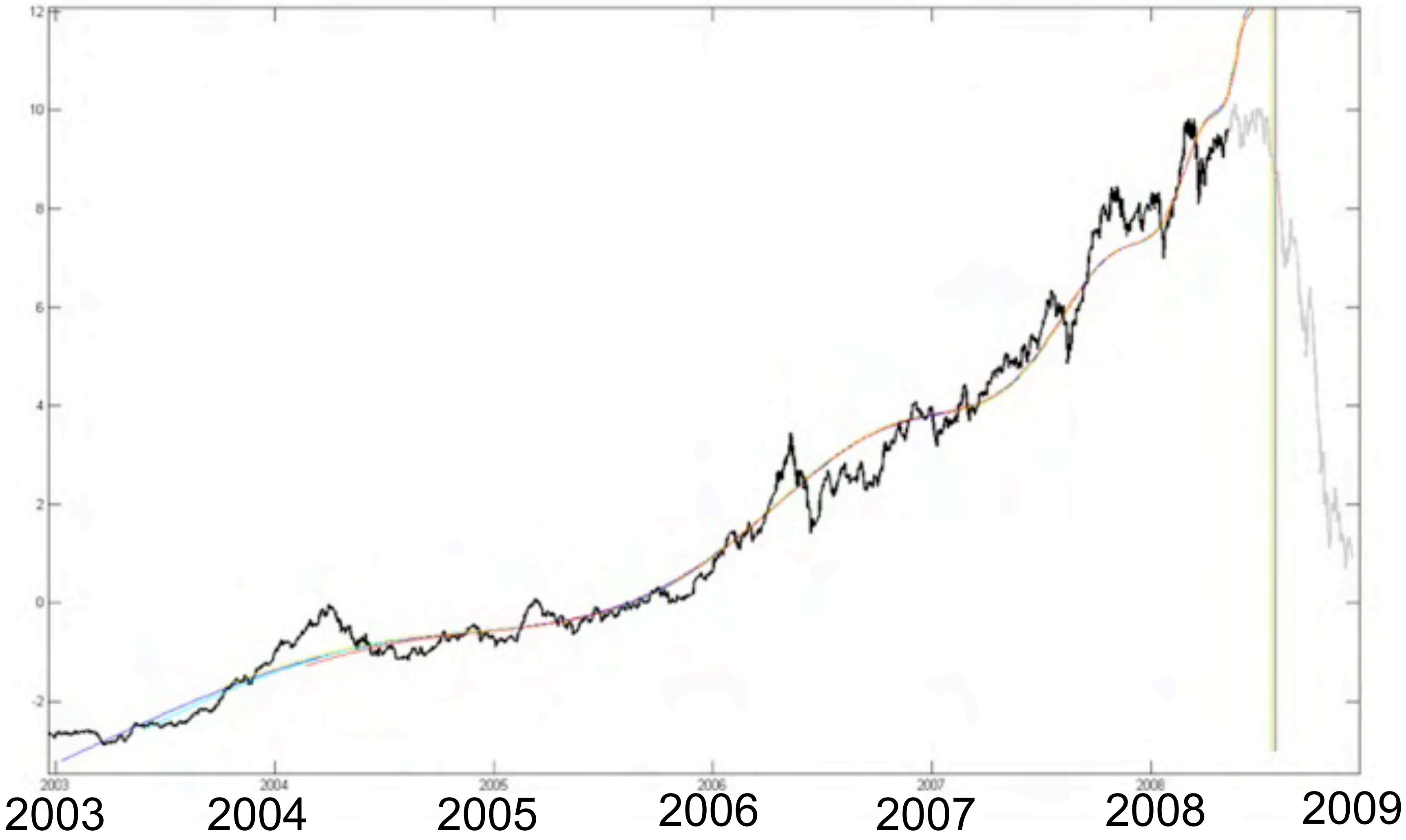


R.Woodard and D.Sornette (2008)



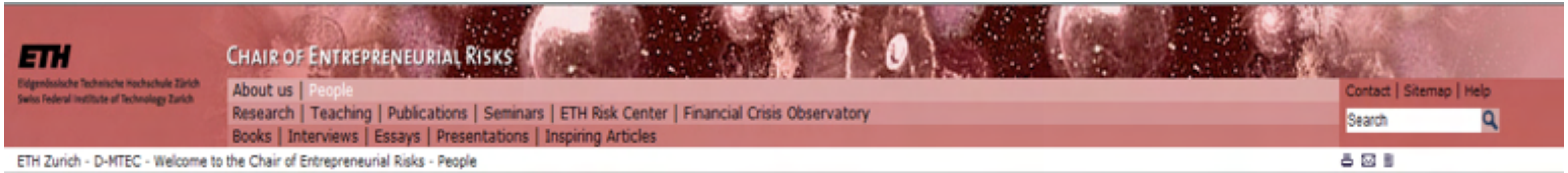


The Global BUBBLE



PCA first component on a data set containing, emerging markets equity indices, freight indices, soft commodities, base and precious metals, energy, currencies...

(Peter Cauwels FORTIS BANK - Global Markets)



What we do

Financial Crisis Observatory (FCO)

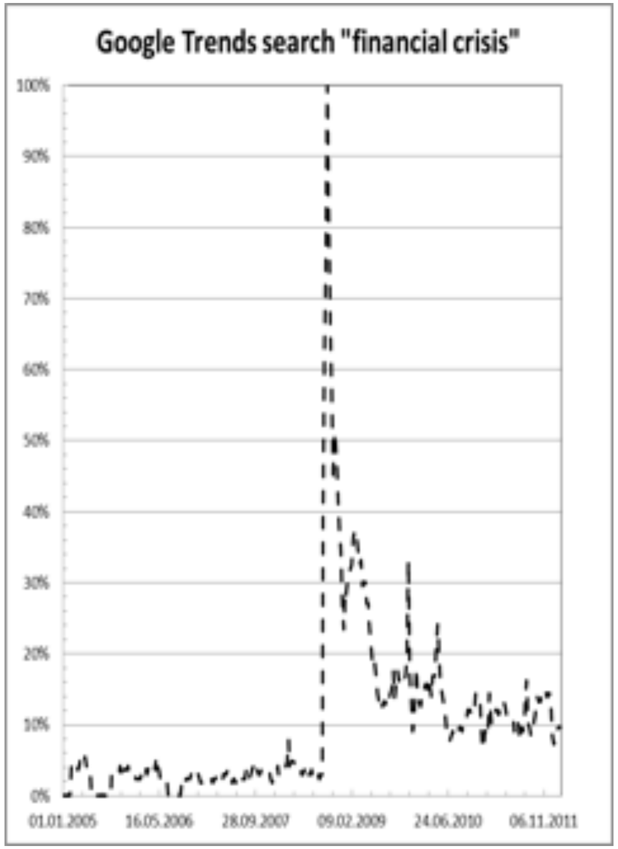
A platform aimed at testing and quantifying, in a systematic way and on a large scale, the hypothesis that financial markets have a degree of predictability, especially during regimes when bubbles develop.

A number of proprietary models and algorithms have been developed to scan the market for inefficiencies, pockets of predictability, early warning signals.

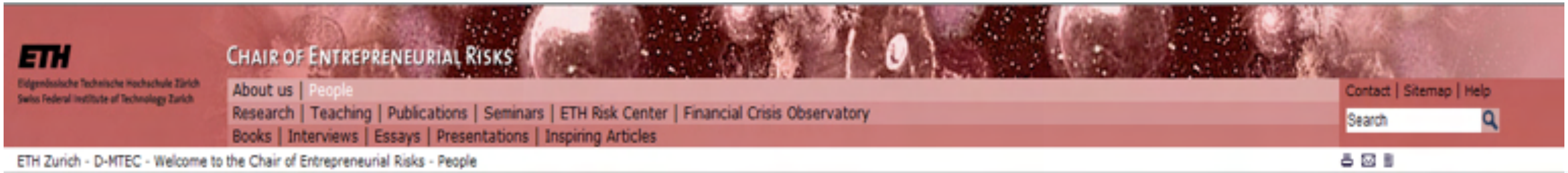
Currently, we analyze on a daily basis:

- +- 2000 Equities, Indices and ETFs;
- +- 80 Currency pairs;
- +- 30 Commodities (base metals, precious metals and soft commodities);
- +- 10 Rates Futures and Generic Bond Indices;
- The major market sentiment indices (e.g. VIX).

We have an Infrastructure for 30k assets and are a major shareholder of the Brutus Cluster with 14000+ cores (http://en.wikipedia.org/wiki/Brutus_cluster)



http://www.er.ethz.ch/fco/index



What we do

http://www.er.ethz.ch/fco/index

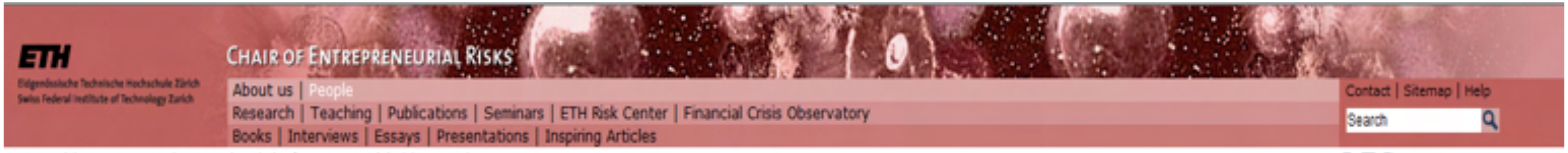
Financial Bubble Experiment (FBE)

To complement the FCO (which has a risk management angle), the FBE was set up. Where the FCO is about monitoring and analyzing, the FBE is a live trading experiment. The markets are our laboratory, positions are taken and financial structures are set up with the rigor of a scientific experiment. The final goal is to test and/or to falsify our hypotheses in real life:

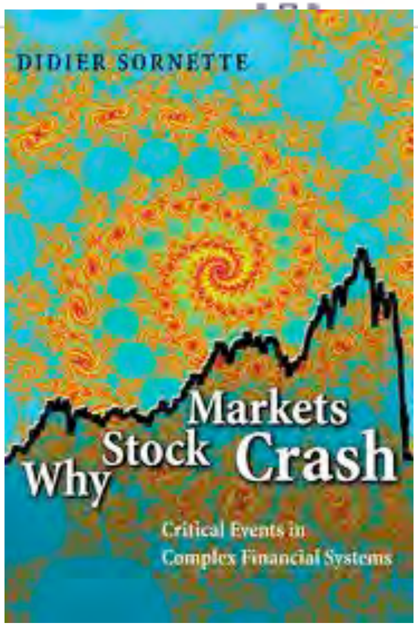
- Hypothesis H1: Financial (and other) bubbles can be diagnosed in real-time before they end;

- Hypothesis H2: The termination of financial (and other) bubbles can be bracketed using probabilistic forecasts, with a reliability better than chance.

http://www.er.ethz.ch/fco/index



http://www.er.ethz.ch/fco/index



Evolution of the project

The methodology has been developed and tested in the past fifteen years following different phases.

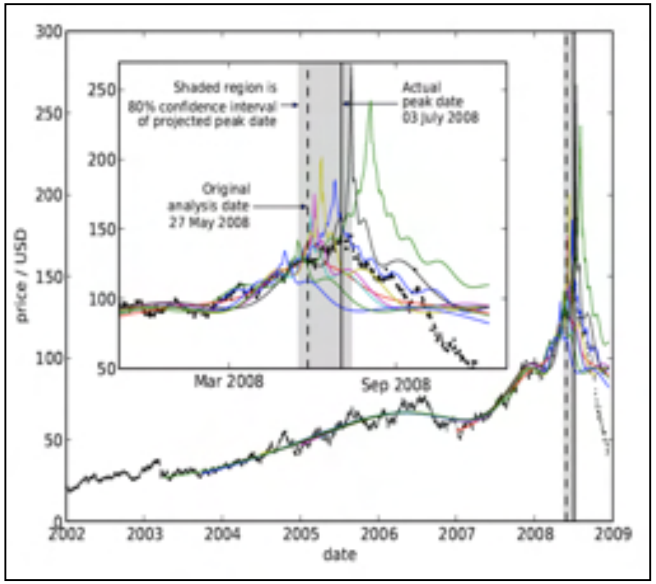
Phase 1: Ex-post analysis of bubbles and crashes

Development and testing of the methodology based on ex-post analysis of historical bubbles and crashes. A review can be found in the book "Why Stock Markets Crash", or in the overview of publications on our website: http://www.er.ethz.ch/publications/finance

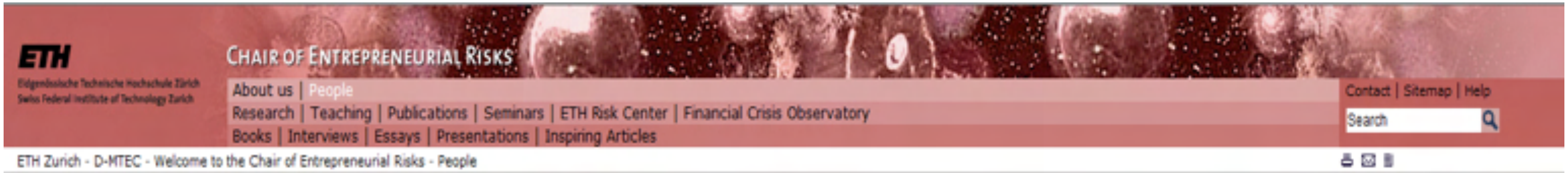
Phase 2: Ex-ante prediction of bubbles and crashes

Prediction and publication, on an ad-hoc basis, of the risk of bubbles and crashes before the actual occurrence, examples:

- The US Real Estate Bubble (See: http://arxiv.org/abs/physics/0506027 - Submitted June 2005)
- The Oil Bubble (See http://arxiv.org/abs/physics/0506027 - Submitted June 2008)
- The Chinese Stock Market bubbles (See: http://arxiv.org/pdf/0909.1007.pdf and http://arxiv.org/ftp/arxiv/papers/0907/0907.1827.pdf - Submitted July 2009)



Oil Bubble



http://www.er.ethz.ch/fco/index

Phase 3: Ex-ante prediction in the FBE experiment

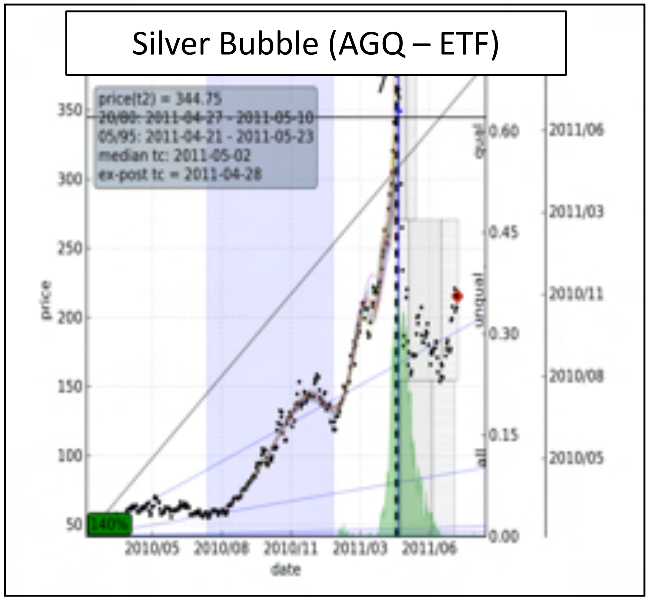
The digital authentication key of a document with the forecasts is published on the internet. The contents of the document is only published after the event has passed to avoid any possible impact of the publication of the ex-ante prediction on the final outcome.
The results are published on http://www.er.ethz.ch/fco/index

Phase 4: Manual Trading

Getting out of the ivory tower of platonic modeling, testing, analyzing and publication. This is a real-money trading experiment with the purpose to thoroughly test and try to falsify our hypotheses in the Financial Markets Laboratory. This is the phase we are currently in. We trade equities, indices, ETFs, commodities and currencies. We use different strategies (hedged/ unhedged, Long/Short, Spreads, Options, Gamma, Vol). The models are calibrated based on daily data series.

Phase 5: Algorithmic Trading

We are currently working on extending our manual trading into an automatic algorithmic trading process. This includes expanding our time resolution from daily data to intraday minute data. We want to apply this in liquid contracts like: equity index futures, EMINI, Bund Futures, Currencies, …



Silver Bubble (AGQ – ETF)

CHF Bubble (FXF – ETF)

Final remarks

- In contrast to “neo-classical” theories, feedback mechanisms (reflexivity) play exceptionally important role in price dynamics.
- News plays a minor role in market volatility; most of price changes are result of internal feedback mechanisms.
  Due to the development of AT (and in particular HFT) endogeneity of price movements increased dramatically.
- The estimation of the **branching ratio** provides a novel powerful metric of endogeneity, which is much richer than standard direct measures of activity such as volume and trading rates.
- Finite-time singular dynamics of log-prices
- Real-time diagnostics of the market and distinguishing of exogenous (triggered by news) and endogenous (self-excited) events.