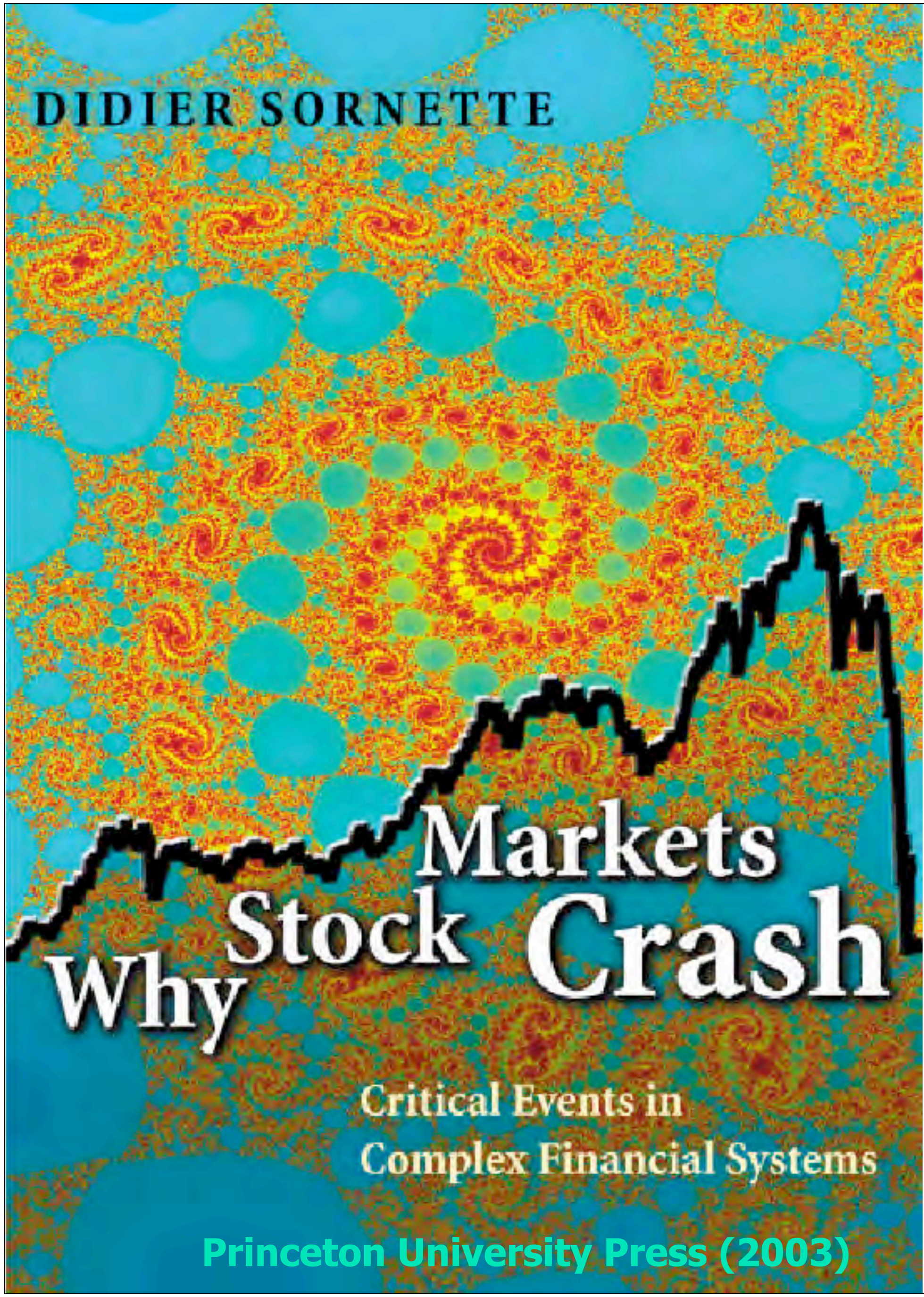

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Swiss Federal Institute of Technology Zurich

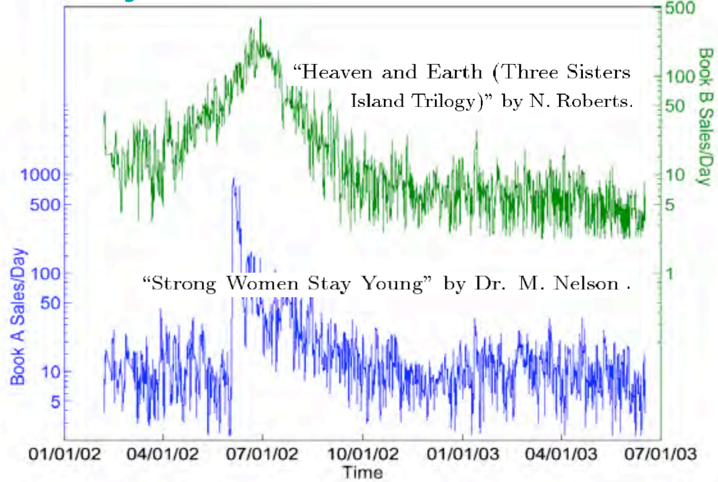
CHAIR OF ENTREPRENEURIAL RISKS

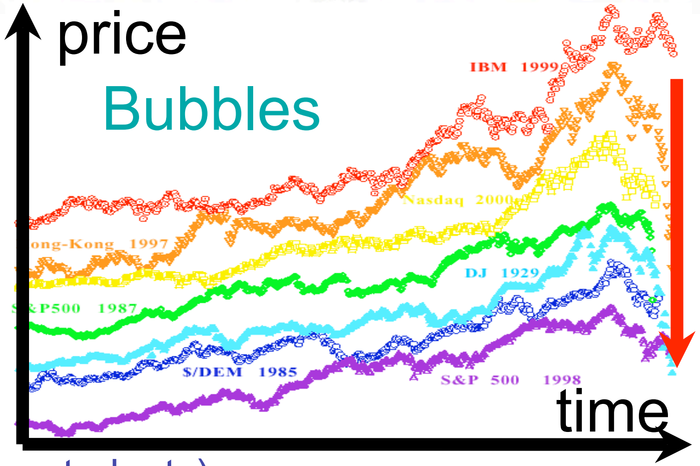
News | About us | People
Research | Teaching | Publications
Predictions | Books | Interviews | Essays | Presentations

- Collective dynamics and organization of social agents (Commercial sales,YouTube, Open source softwares, Cyber risks)
- Agent-based models of bubbles and crashes, credit risks, systemic risks
- Prediction of complex systems, stock markets, social systems
- Asset pricing, hedge-funds, risk factors…
- Human cooperation for sustainability
- Natural and biological hazards (earthquakes, landslides, epidemics, critical illnesses…)

(2-3 guest-professors, 5 foreign associate professors, 1 post-docs, 1 senior researcher, 9 PhD students, 4-6 Master students)

Dynamics of success





MOTIVATIONS

- What are financial bubbles?
- Do they exist really?
- Why do we care?
- Can they be detected?
- Different models (social interactions, herding, news, value vs noise trading...)
- Can their end (the CRASH) be predicted?
- Systemic risks? Sub-prime mess...
- What is ahead of us?

What are bubbles?
How do detect them?
How to predict them?

Academic Literature:

No consensus on what is a bubble...

Ex:
Refet S. Gürkaynak, Econometric Tests of Asset Price Bubbles: Taking Stock.

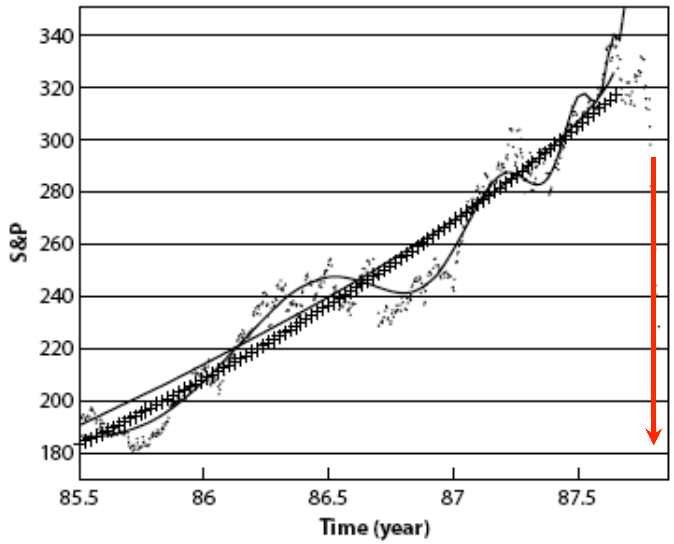
Can asset price bubbles be detected? This survey of econometric tests of asset price bubbles shows that, despite recent advances, econometric detection of asset price bubbles cannot be achieved with a satisfactory degree of certainty. For each paper that finds evidence of bubbles, there is another one that fits the data equally well without allowing for a bubble. We are still unable to distinguish bubbles from time-varying or regime-switching fundamentals, while many small sample econometrics problems of bubble tests remain unresolved.

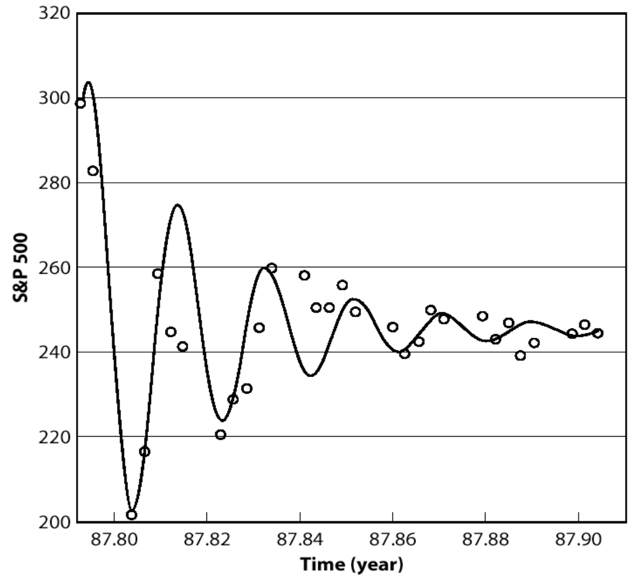
The Fed: A. Greenspan (Aug., 30, 2002):
"We, at the Federal Reserve…recognized that, despite our suspicions, it was very difficult to definitively identify a bubble until after the fact, that is, when its bursting confirmed its existence… Moreover, it was far from obvious that bubbles, even if identified early, could be preempted short of the Central Bank inducing a substantial contraction in economic activity, the very outcome we would be seeking to avoid."

THE CRASH OF OCTOBER 1987

Proximate explanations after the fact!

- ❑ Computer trading
- ❑ Derivatives
- ❑ Illiquidity
- ❑ Trade and budget deficits
- ❑ Over-valuation
- ❑ The auction system
- ❑ Off-market and off-hours trading
- ❑ Floor brokers
- ❑ Forward market effect
- ❑ Different investor styles

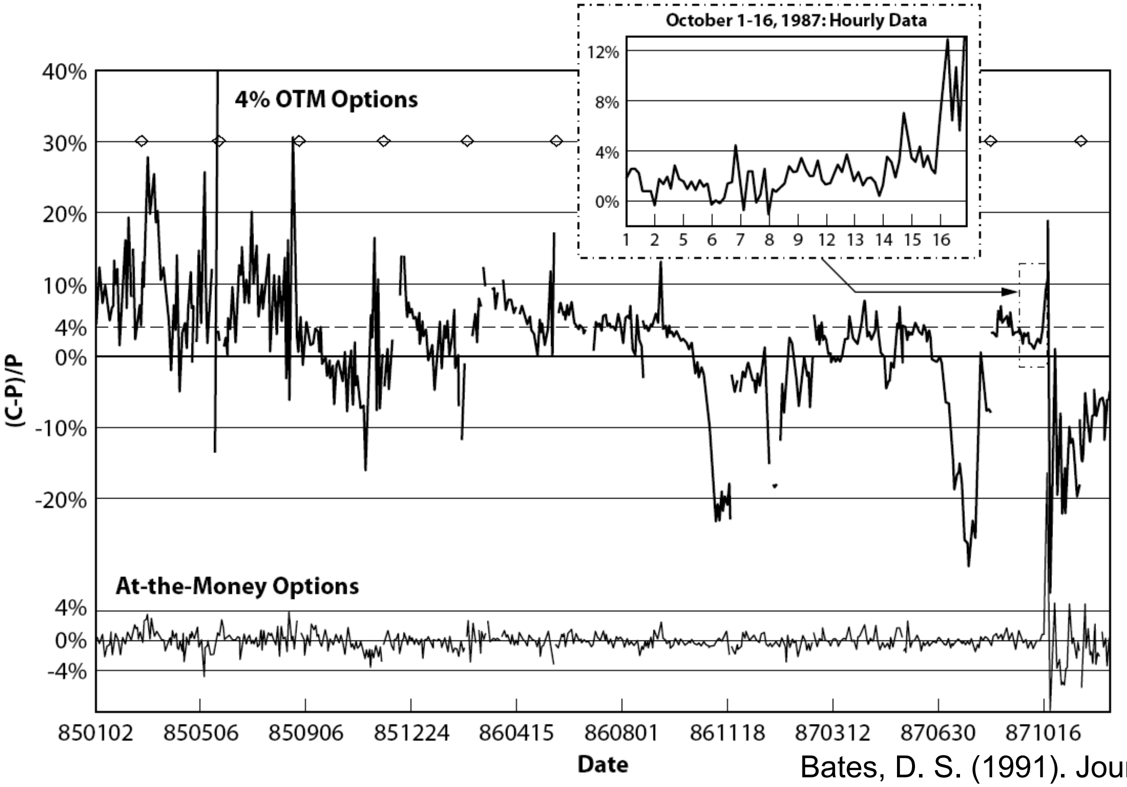




THE CRASH OF OCTOBER 1987

The Wall Street Journal on August 26, 1987, the day after the 1987 market peak: “In a market like this, every story is a positive one. Any news is good news. It’s pretty much taken for granted now that the market is going to go up.”

Intermittent anticipation of the crash reflected in out-of-the-money option prices



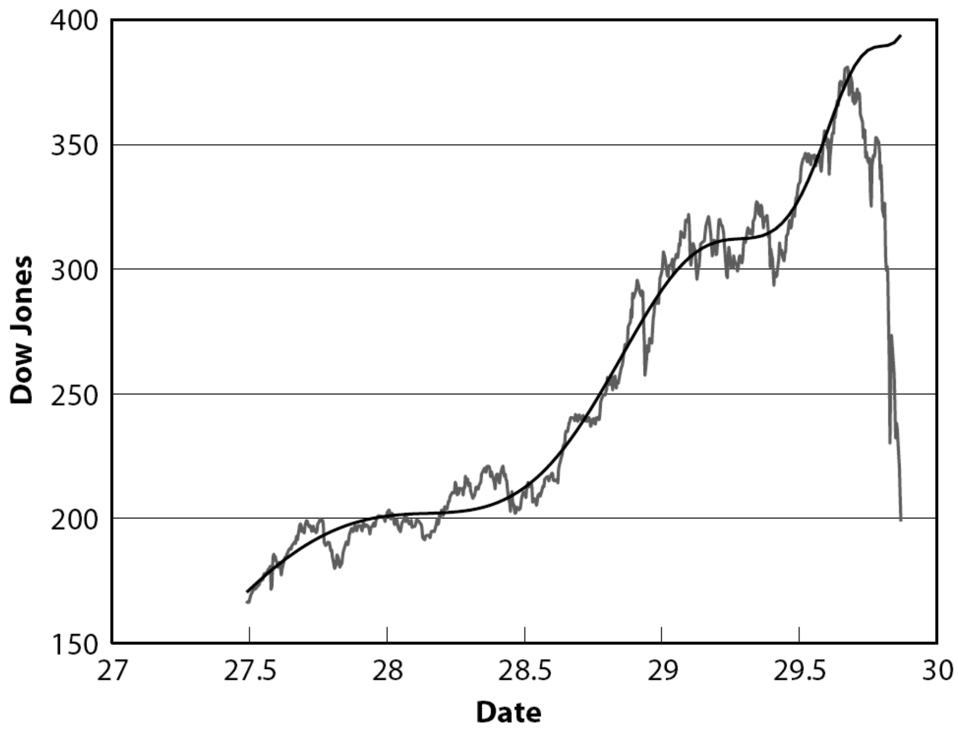
Percentage deviation (C-P)/P of call from put prices (skewness premium) for options at-the-money and 4% out-of-the-money, over 1985–87. The percentage deviation (C-P)/P is a measure of the asymmetry between the perceived distribution of future large upward moves compared to large downward moves of the S&P 500 index. Deviations above (below) 0% indicate optimism (fear) for a bullish market (of large potential drops). The inset shows the same quantity (C-P)/P calculated hourly during October 1987 prior to the crash: ironically, the market forgot its “fears” close to the crash.

Bates, D. S. (1991). Journal of Finance 46, 1009–1044.

THE CRASH OF OCTOBER 1929

Stock market crashes are often unforeseen for most people, especially economists. “In a few months, I expect to see the stock market much higher than today.” Irving Fisher, famous economist and professor of economics at Yale University,14 days before Wall Street crashed on Black Tuesday, October 29, 1929.

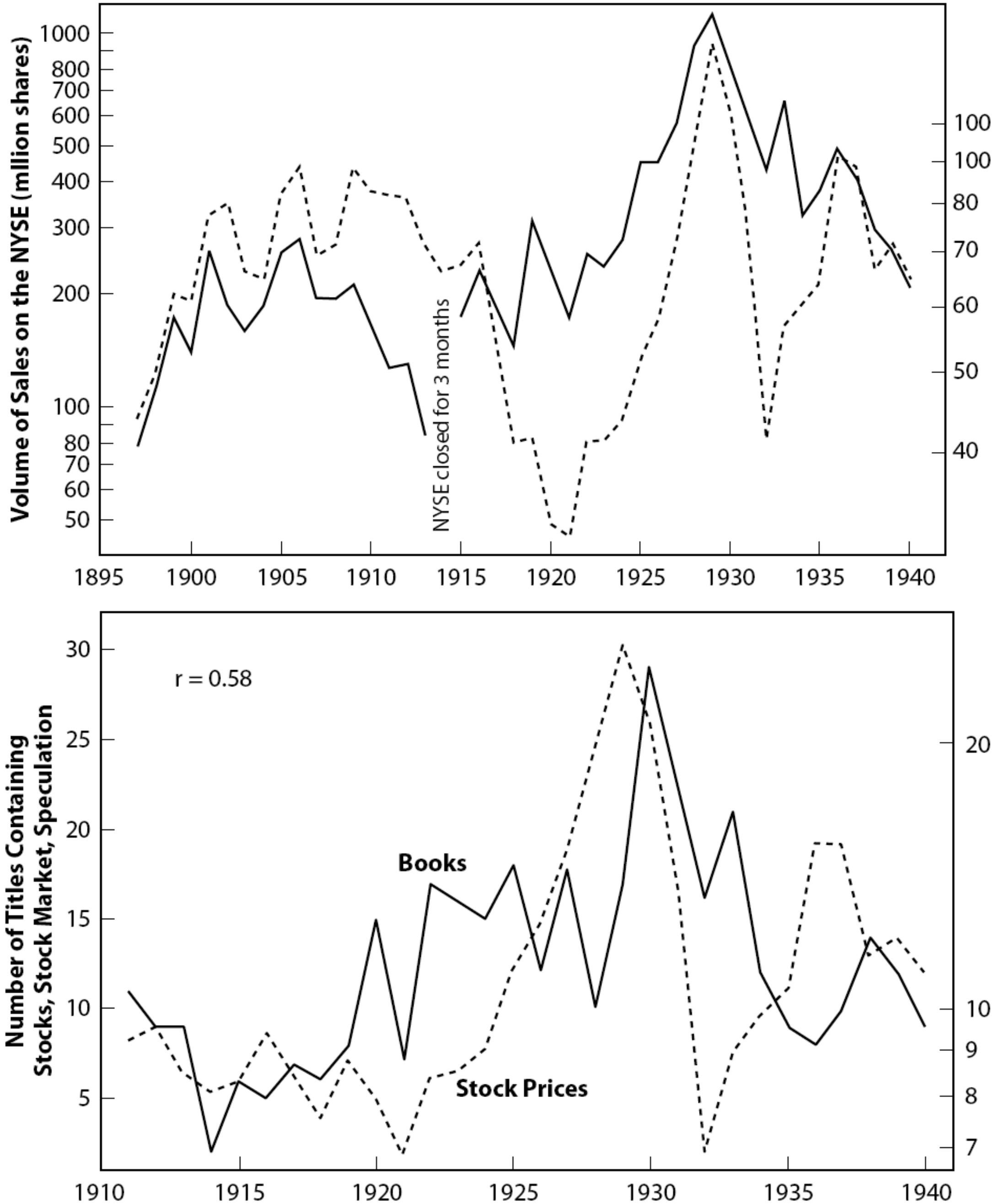
“A severe depression such as 1920–21 is outside the range of probability. We are not facing a protracted liquidation.” This was the analysis offered days after the crash by the Harvard Economic Society to its subscribers… It closed its doors in 1932.



The DJIA prior to the October 1929 crash on Wall Street.

THE CRASH OF OCTOBER 1929

- A financial collapse has never happened when things look bad.
- Macroeconomic flows look good before crashes.
- Before every collapse, economists say the economy is in the best of all worlds.
- Everything looks rosy, stock markets go up…
- Macroeconomic flows (output, employment, etc.) appear to be improving further and further.
- A crash catches most people, especially economists, by surprise.
- The good times are extrapolated linearly into the future.
- Is it not perceived as senseless by most people in a time of general euphoria to talk about crash and depression?



growing interest in the public for the commodity in question,whether it consists of stocks, diamonds, or coins.

B.M. Roehner and D. Sornette, “Thermometers" of Speculative Frenzy”, European Physical Journal B 16, 729-739 (2000)

THE TULIP MANIA

- Between 1585 and 1650, Amsterdam became the chief commercial emporium, the center of the trade of the northwestern part of Europe, owing to the growing commercial activity in newly discovered America.
- The tulip as a cultivated flower was imported into western Europe from Turkey and it is first mentioned around 1554.
- The scarcity of tulips and their beautiful colors made them a must for members of the upper classes of society

FIG. 1.1. A variety of tulip (the Viceroy) whose bulb was one of the most expensive at the time of the tulip mania in Amsterdam, from *The Tulip Book* of P. Cos, including weights and prices from the years of speculative tulip mania (1637); Wageningen UR Library, Special Collections.

The Tulip Mania

- What we now call the "tulip mania" of the seventeenth century was the "sure thing" investment during the period from the mid-1500s to 1636.
- Before its devastating end in 1637, those who bought tulips rarely lost money. People became too confident that this "sure thing" would always make them money.
- At the period's peak, the participants mortgaged their houses and businesses to trade tulips.
- Some tulip bulbs of a rare variety sold for the equivalent of a few tens of thousands of dollars.
- Before the crash, any suggestion that the price of tulips was irrational was dismissed by all the participants.

The Tulip Mania

•The conditions now generally associated with the first period of a boom were all present:

- -an increasing currency,
- -a new economy with novel colonial possibilities, and
- -an increasingly prosperous country

together had created the optimistic atmosphere in which booms are said to grow.

•The crisis came unexpectedly.

- -On February 4, 1637, the possibility of the tulips becoming definitely unsalable was mentioned for the first time.
- -From then until the end of May 1637, all attempts at coordination among florists, bulbgrowers, and the Netherlands government were met with failure.

Have We Learned the Lessons of Black Mondays?

19 October 1987

to

19 October 2007 to 2008...

THE NASDAQ CRASH OF APRIL 2000

•1995-2000: growing divergence between New Economy and Old Economy stocks, between technology and almost everything else.

•Over 1998 and 1999, stocks in the Standard & Poor's technology sector rose nearly fourfold, while the S&P 500 index gained just 50%. And without technology, the benchmark would be flat.

•In January 2000 alone, 30% of net inflows into mutual funds went to science and technology funds, versus just 8.7% into S&P 500 index funds.

•The average price-over-earnings ratio (P/E) for Nasdaq companies was above 200.

•New Economy was also hot in the minds and mouths of investors in the 1920s and in the early 1960s. In 1929, it was utilities; in 1962, it was the electronic sector.

•The Nasdaq composite consists mainly of stock related to the New Economy, that is, the Internet, software, computer hardware, telecommunication.

•The Nasdaq composite index dropped precipitously, with a low of 3,227 on April 17, 2000, corresponding to a cumulative loss of 37% counted from its all-time high of 5,133 reached on March10, 2000.

•A main characteristic of these companies is that their P/Es, and even more so their price-over-dividend ratios, often came in three digits prior to the crash. Some companies, such as VA LINUX, actually had a negative earnings/share of -1.68.

EXPECTATIONS of strong future growth

Proposed justifications of PRICES

•better business models (small required capital, reduced delay in payments…)

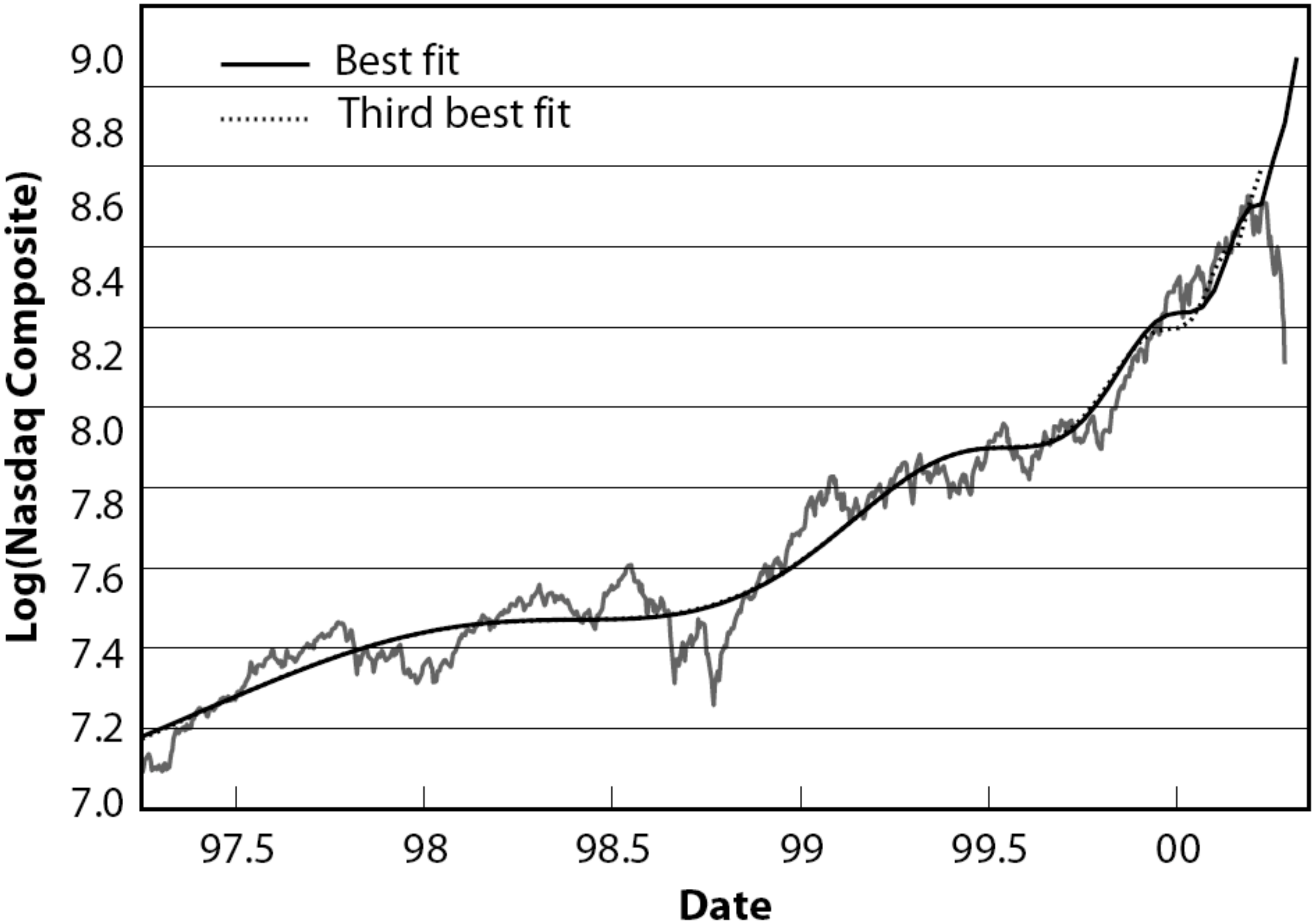
•the network effect (positive returns and positive feedbacks)

•first-to-scale advantages

•real options (value of fast adaptation to grasp new opportunities)

Probably true… but problem of timing…

THE NASDAQ CRASH OF APRIL 2000



Foreign capital inflow

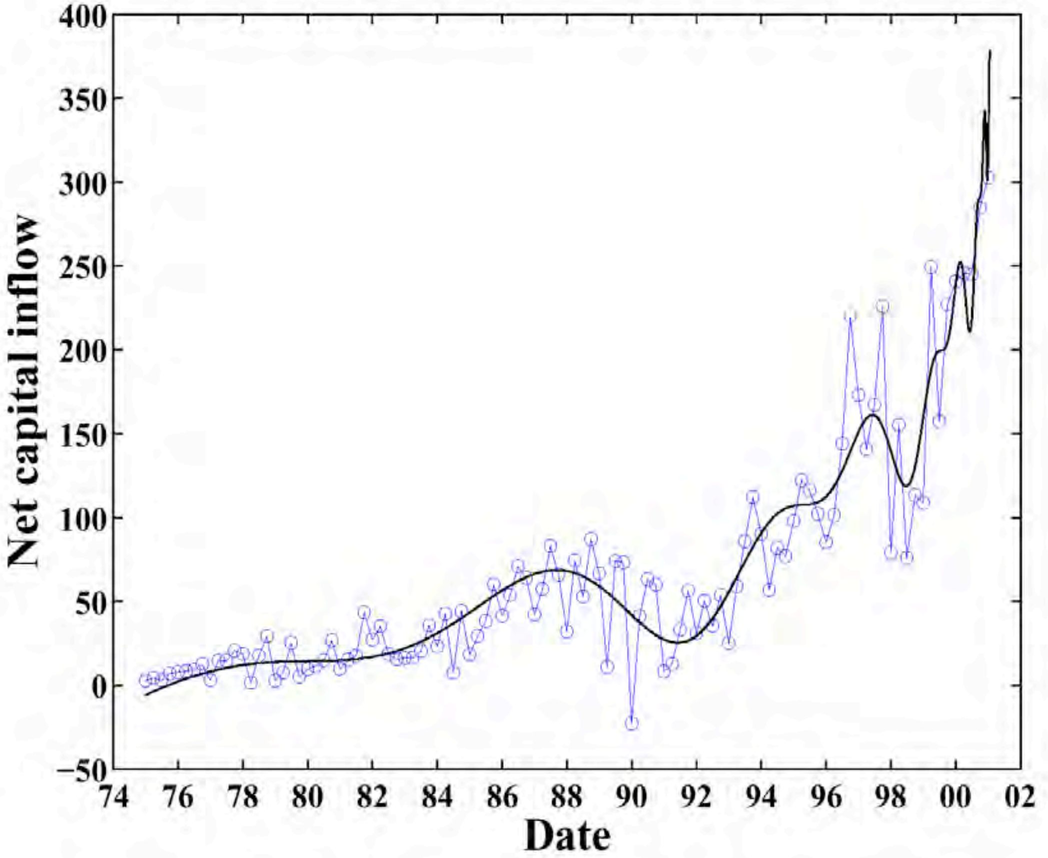
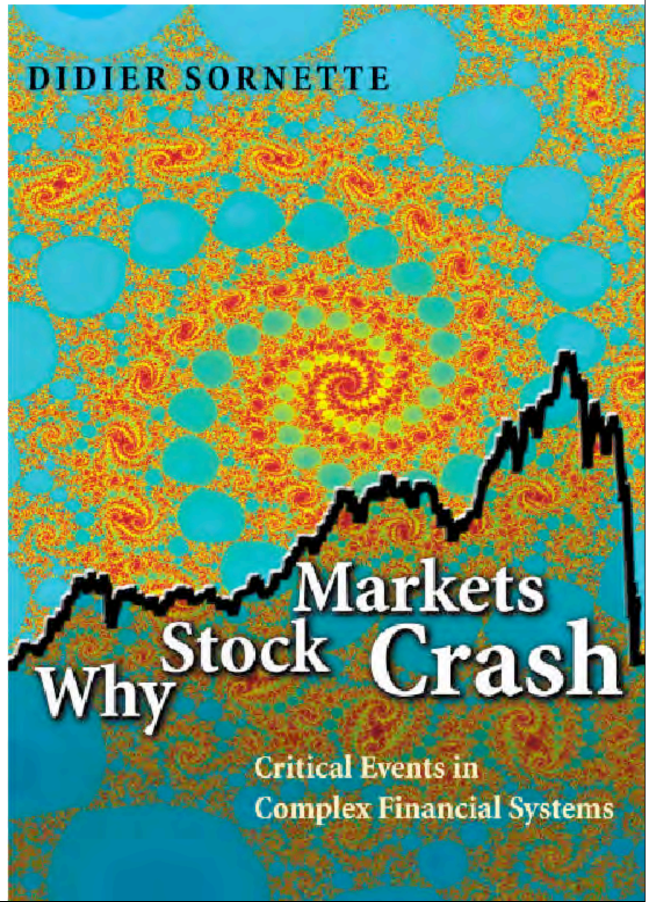


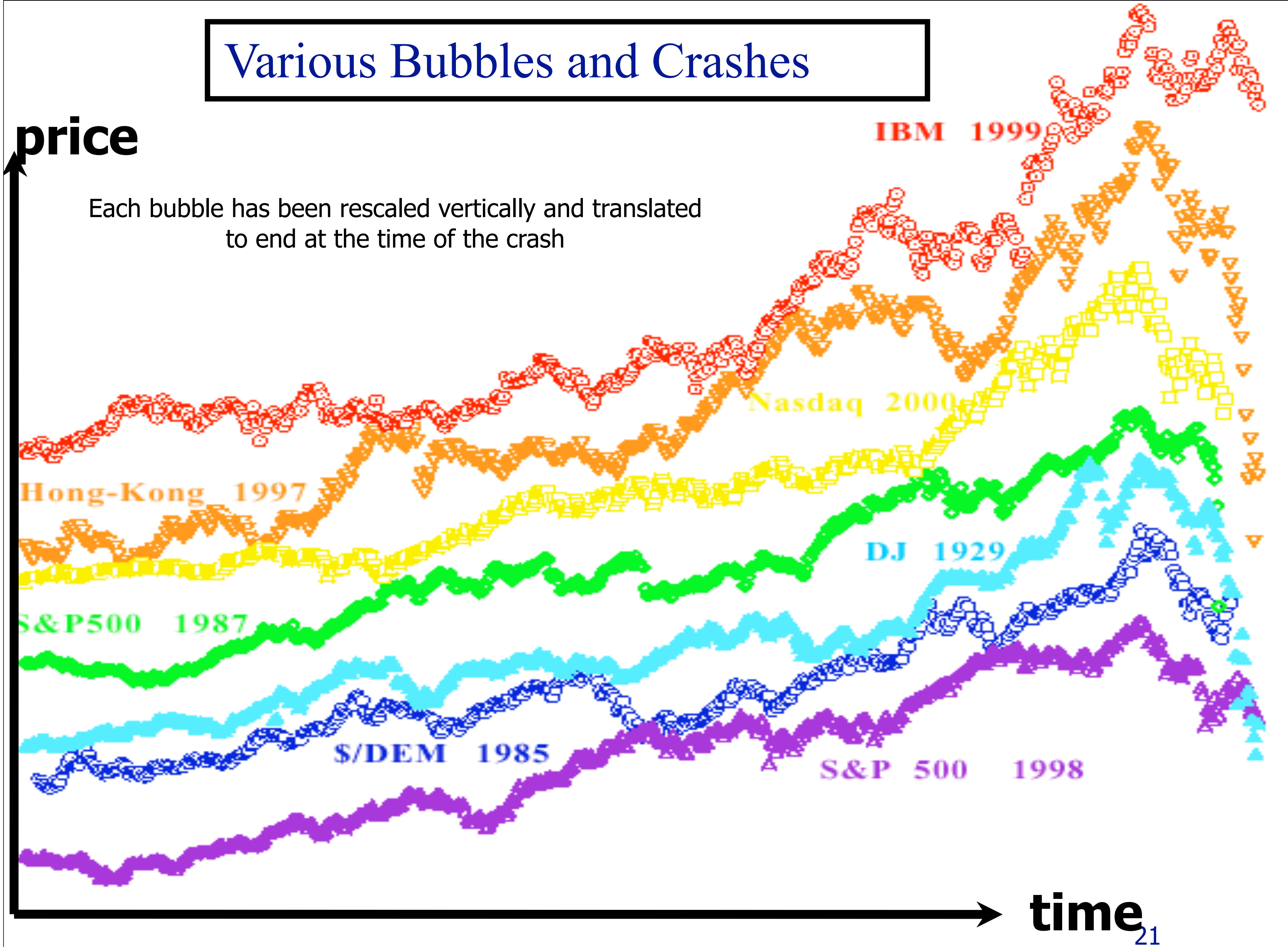
Fig. 2. Fit of the time evolution of the foreign net capital inflow $I(t)$ in the USA from 1975 till the first quarter of 2001 when it reached its maximum, by a second-order Weierstrass-type function given by expression (1). The predicted critical time is $t_c = 2001/03/12$, the power-law exponent is $m = 0.01$, and the angular log-frequency is $\omega = 4.9$. The fitted linear parameters are $A = 7355$, $B = -6719$, $C_1 = 21.5$ and $C_2 = 16.2$. The r.m.s. of the residuals of the fit is 22.810.

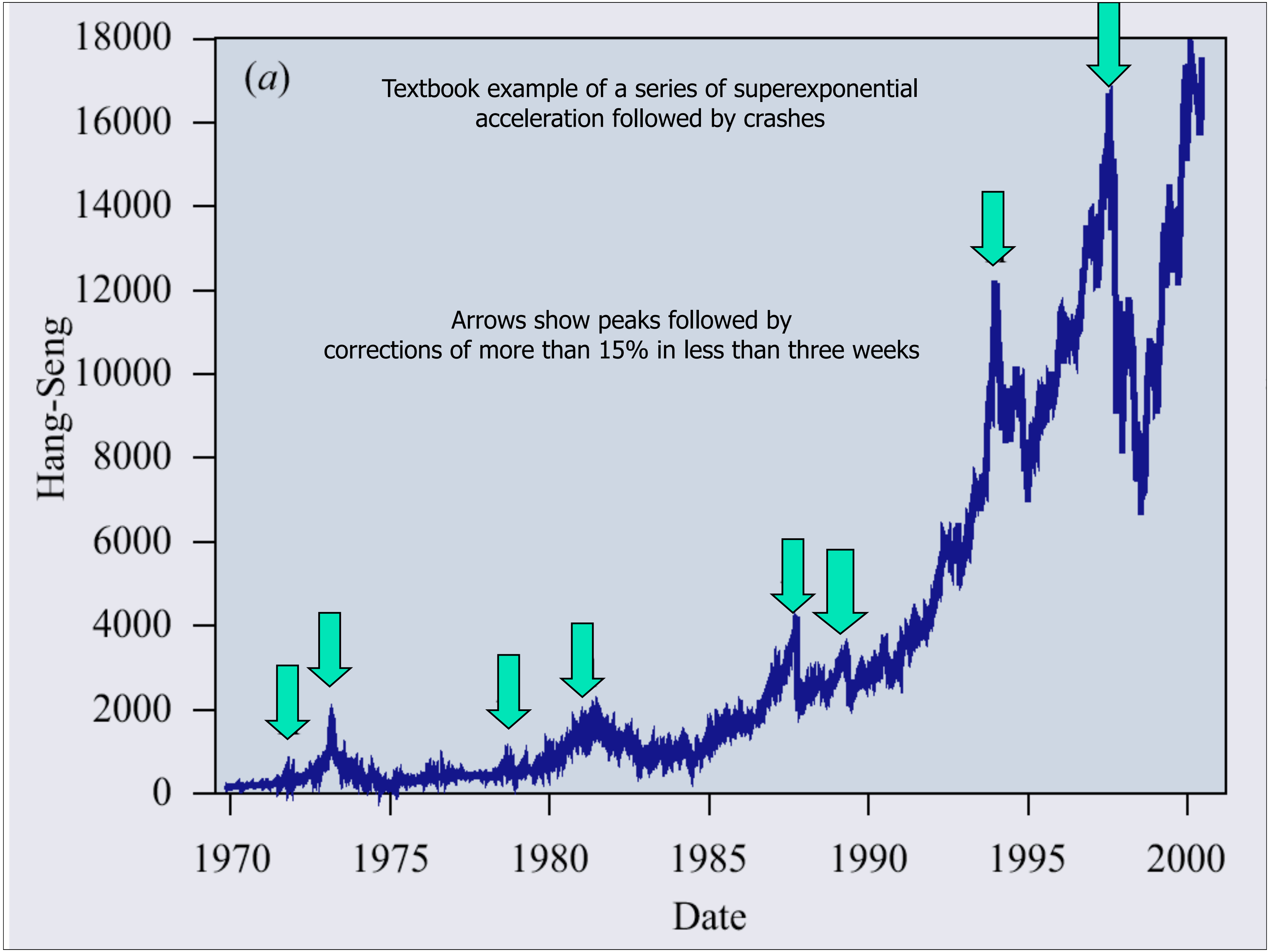
Many other bubbles and crashes

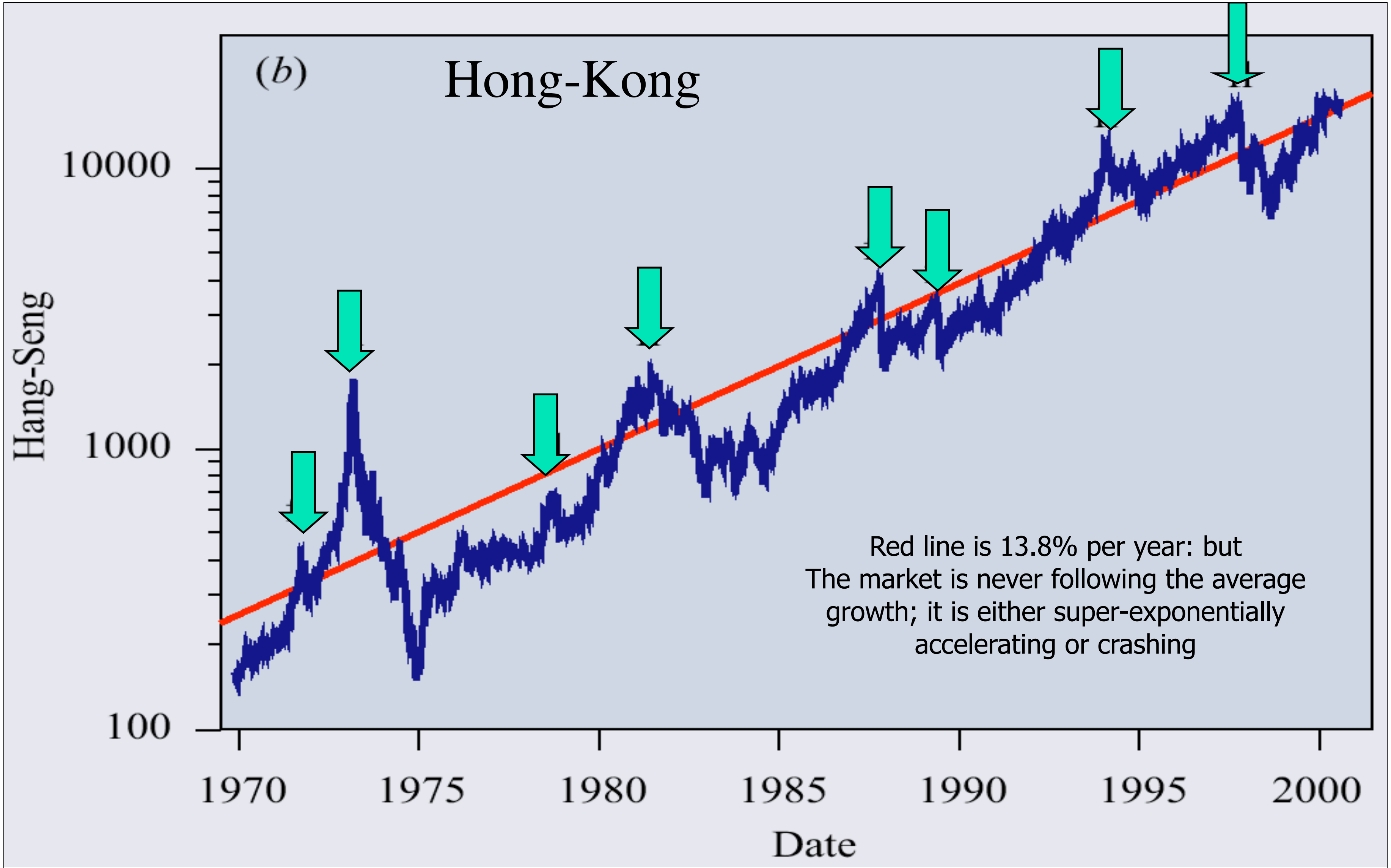
- Hong-Kong crashes: 1987, 1994, 1997 and many others
- October 1997 mini-crash
- August 1998
- Slow crash of spring 1962
- Latin-american crashes
- Asian market crashes
- Russian crashes
- Individual companies



Various Bubbles and Crashes




(a)
Textbook example of a series of superexponential acceleration followed by crashes
Arrows show peaks followed by corrections of more than 15% in less than three weeks
Hang-Seng
18000
16000
14000
12000
10000
8000
6000
4000
2000
0
1970
1975
1980
1985
1990
1995
2000
Date



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

Universal Bubble and Crash Scenario

1. The bubble starts smoothly with some increasing production and sales (or demand for some commodity) in an otherwise relatively optimistic market.

2. The attraction to investments with good potential gains then leads to increasing investments, possibly with leverage coming from novel sources, often from international investors. This leads to price appreciation.

3. This in turn attracts less sophisticated investors and, in addition, leveraging is further developed with small downpayment (small margins), which leads to the demand for stock rising faster than the rate at which real money is put in the market.

4. At this stage, the behavior of the market becomes weakly coupled or practically uncoupled from real wealth (industrial and service) production.

5. As the price skyrockets, the number of new investors entering the speculative market decreases and the market enters a phase of larger nervousness, until a point when the instability is revealed and the market collapses.

The upswing usually starts with an opportunity - new markets, new technologies or some dramatic political change - and investors looking for good returns.

· It proceeds through the euphoria of rising prices, particularly of assets, while an expansion of credit inflates the bubble.

· In the manic phase, investors scramble to get out of money and into illiquid things such as stocks, commodities, real estate or tulip bulbs: 'a larger and larger group of people seeks to become rich without a real understanding of the processes involved'.

· Ultimately, the markets stop rising and people who have borrowed heavily find themselves overstretched. This is 'distress', which generates unexpected failures, followed by 'revulsion' or 'discredit'.

· The final phase is a self-feeding panic, where the bubble bursts. People of wealth and credit scramble to unload whatever they have bought at greater and greater losses, and cash becomes king.

Charles Kindleberger, Manias, Panics and Crashes (1978)

What is the cause of the crash?

- ✓ Proximate causes: many possibilities
- ✓ Fundamental cause: maturation towards an instability

An instability is characterized by

- large or diverging susceptibility to external perturbations or influences
- exponential growth of random perturbations leading to a change of regime, or selection of a new attractor of the dynamics.

Mechanism(s)
Complex Systems

-positive feedbacks

-non sustainable regimes

-rupture

Thomas Robert Malthus (1766–1834)

1798

autocatalitic proliferation: $\frac{dx}{dt} = a \cdot x$

with a =birth rate - death rate

exponential solution: $X(t) = X(0)e^{a\,t}$

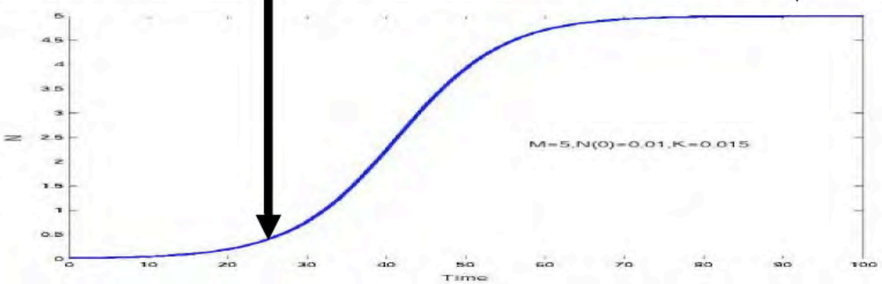
contemporary estimations= doubling of the population every 30yrs

Pierre François Verhulst (1804-1849)

way out exponential explosion:

$dX/dt = a\,X - c\,X^2$ **1838**

Solution: exponential ==========→saturation at X= a / c



For humans data at the time could not discriminate between:
1. exponential growth of Malthus
2. logistic growth of Verhulst

But data fit on animal population: sheep in Tasmania

- exponential in the first 20 years after their introduction and completely saturated after about half a century. ==> Verhulst

Positive feedbacks and finite-time singularity

Conjecture: Many systems exhibit transient FTS as "ghost-like" solutions that the system follows for a while before being attenuated.
Analogous to exponential sensitivity to initial condition with reinjection → chaos **but** here FTS blow-up.

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

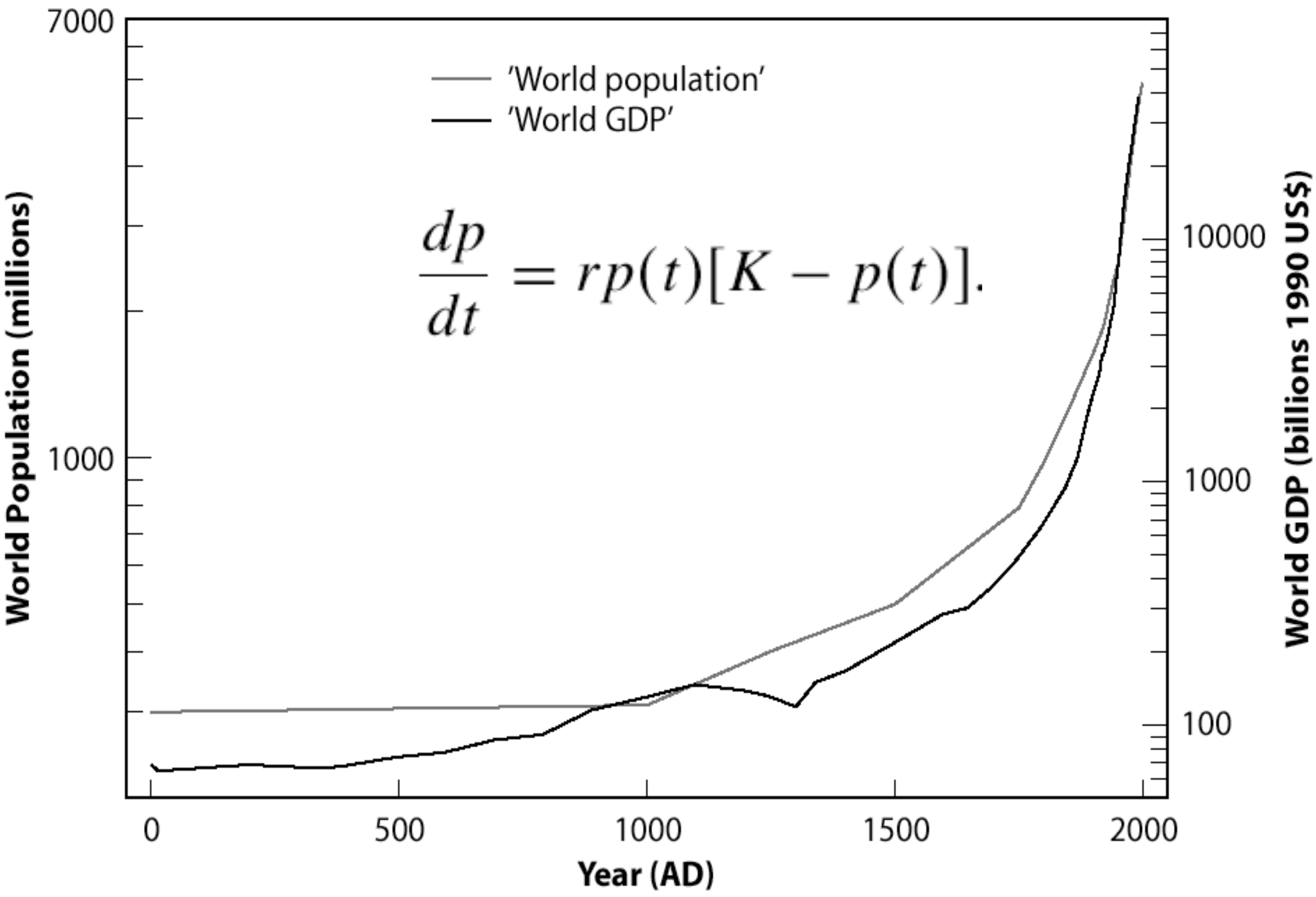
$$\frac{dp}{dt} = r[p(t)]^{1+\delta}$$

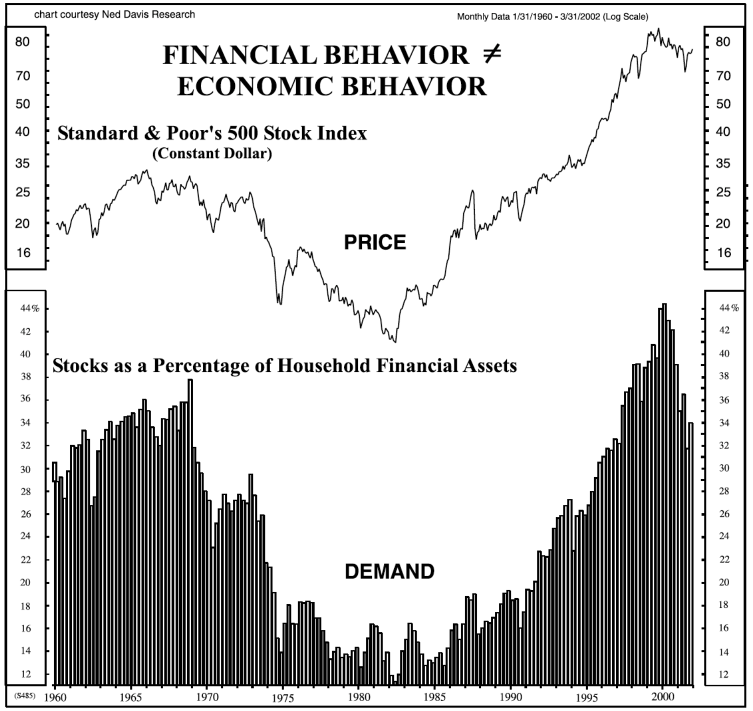
with $K \propto p^{\delta}$

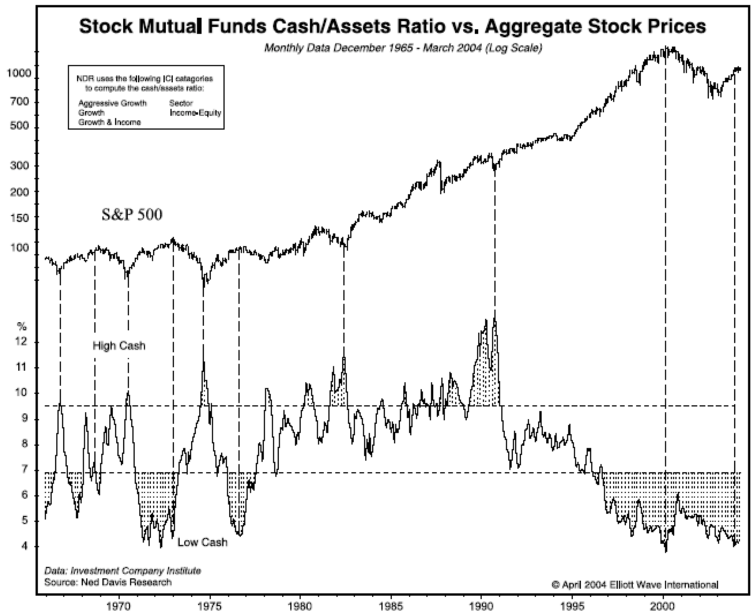
$$p(t) \propto (t_c - t)^z, \text{ with } z = -\frac{1}{\delta} \text{ and } t \text{ close to } t_c.$$

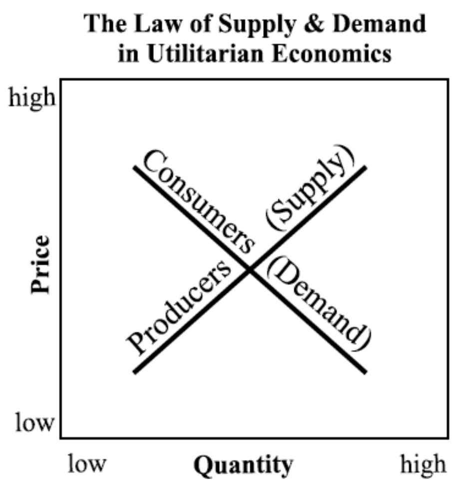
Multi-dimensional generalization: multi-variate positive feedbacks

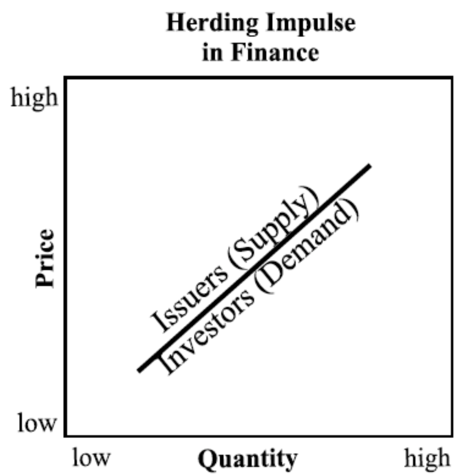
Super-exponential growth











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Faster than exponential growth

Suppose GROWTH RATE doubles when POPULATION doubles

POPULATION	GROWTH RATE	DOUBLING TIME
1000	1%	69y
2000	2%	69/2y
4000	4%	69/4y
…	…	…
2^n x 1000	2^n %	$69/2^n$ y

Population diverges in finite time

69+69/2+69/4+69/8…=69x(1+1/2+1/4+1/8+…)=69x2=138y

Zeno paradox

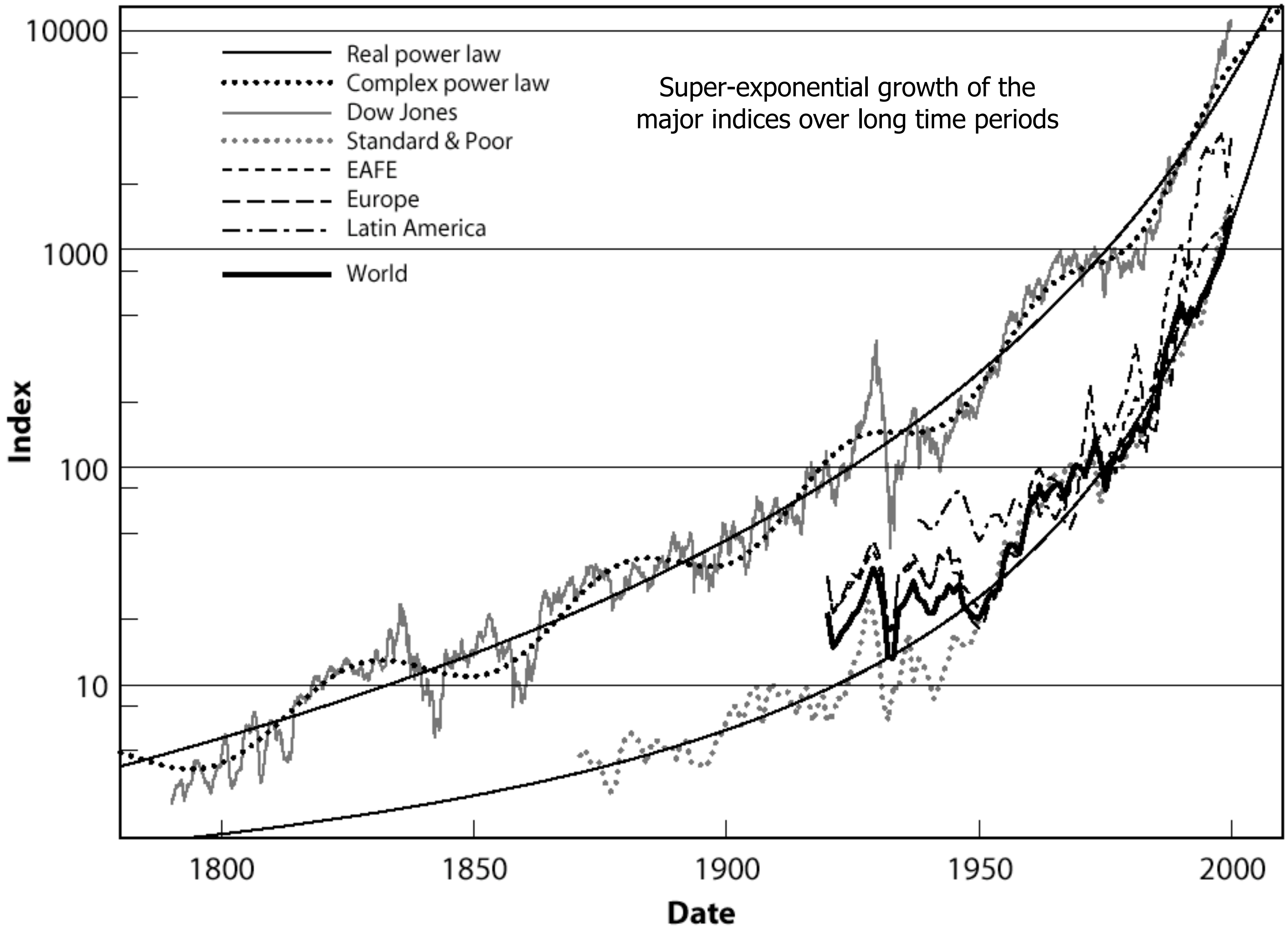
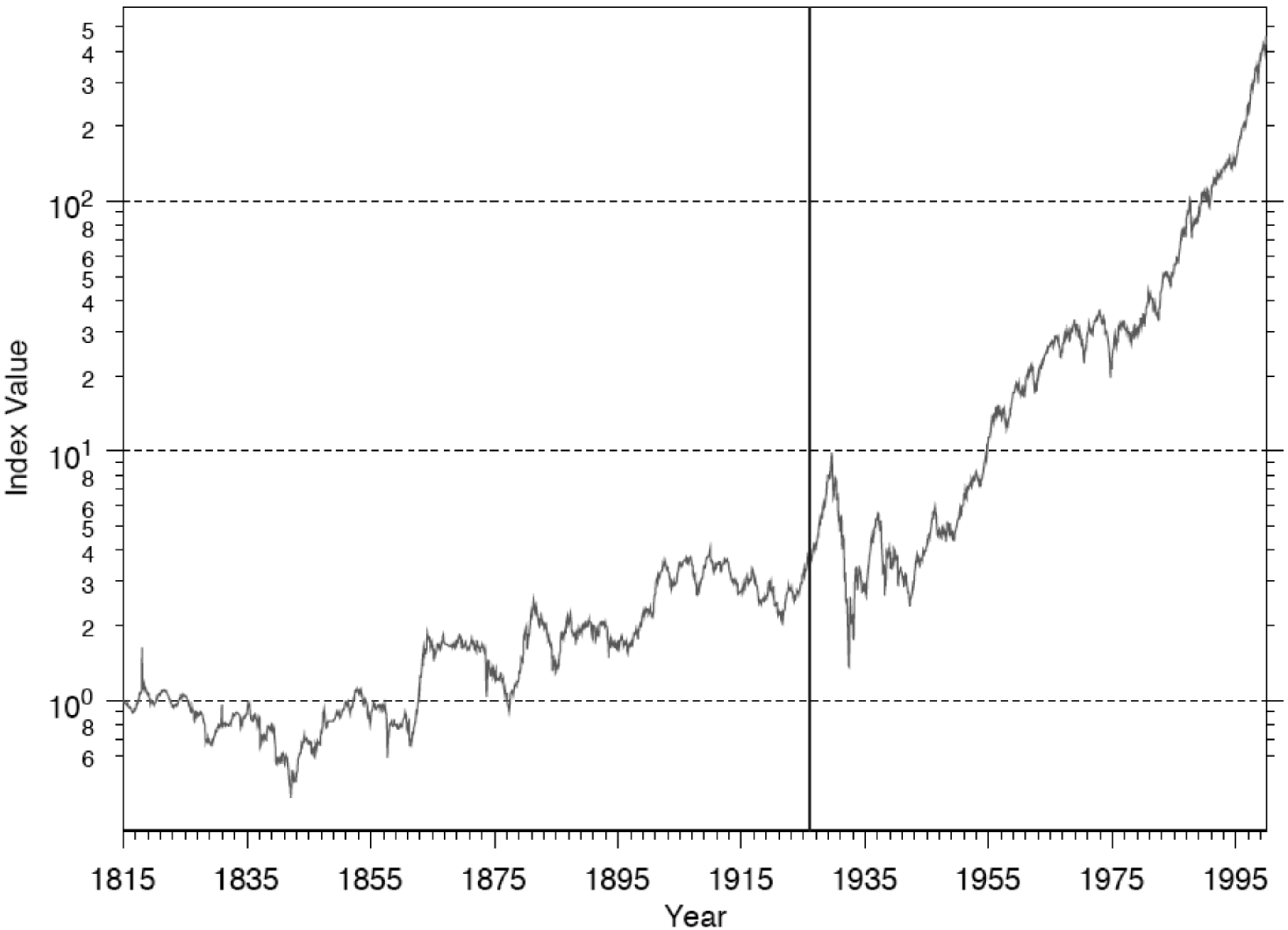

10000
1000
100
10
Real power law
Complex power law
Dow Jones
Standard & Poor
EAFE
Europe
Latin America
World
Super-exponential growth of the major indices over long time periods
Index
1800
1850
1900
1950
2000
Date

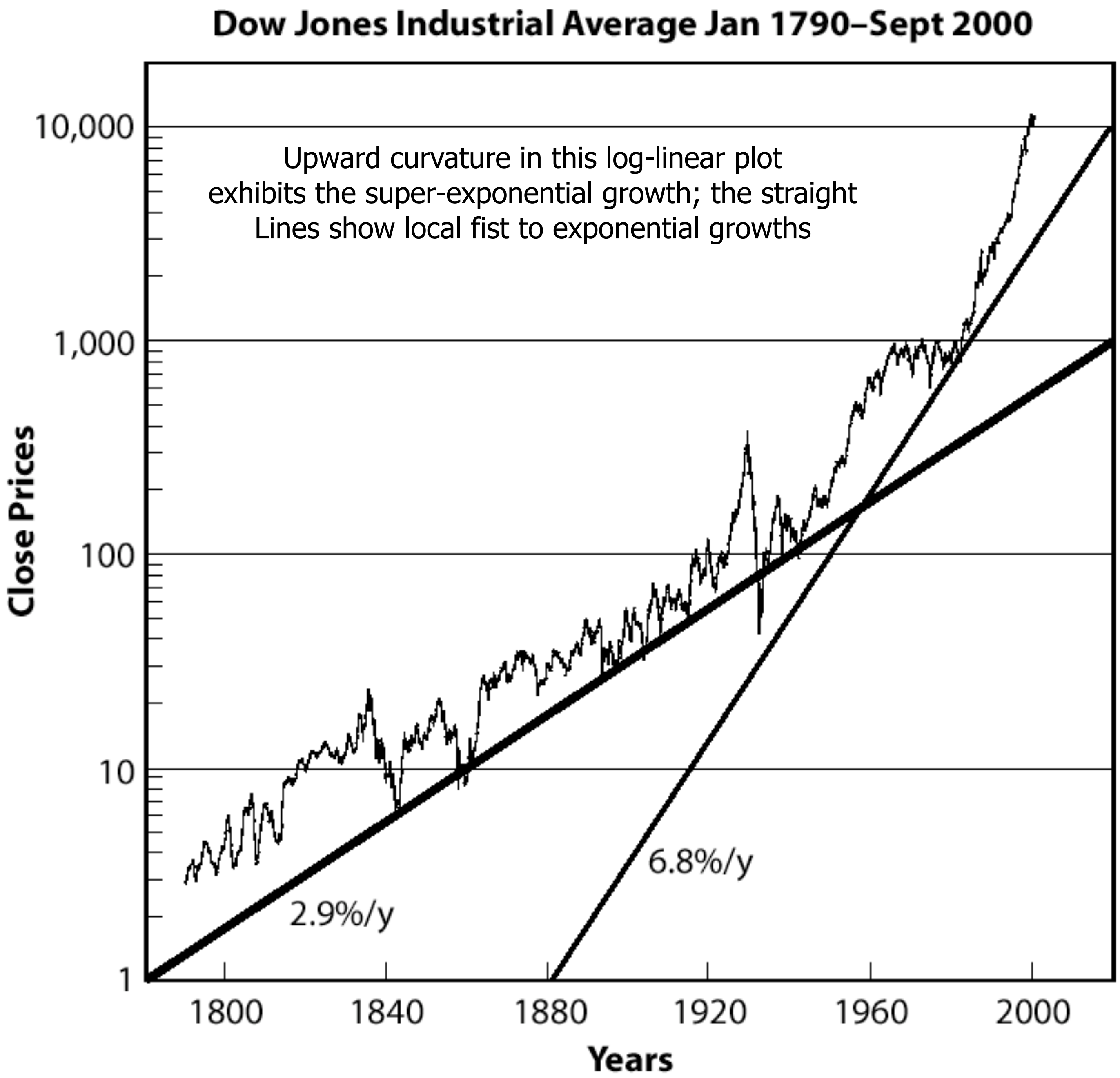
Figure 1: Monthly Capital Appreciation Index 1/1815-12/1999



Price-weighted NYSE Index (1/1815-12/1925) with Ibbotson and Sinquefield Index (1/1926-12/1999)

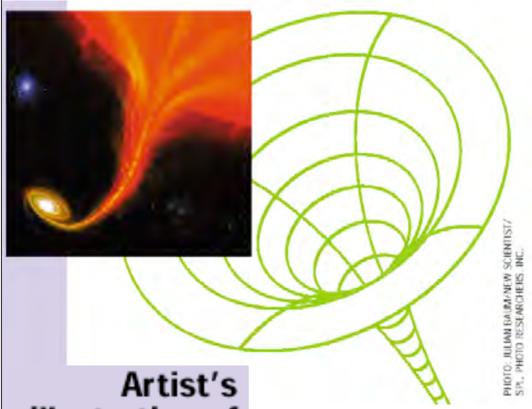
A NEW HISTORICAL DATABASE FOR THE NYSE 1815 TO 1925: PERFORMANCE AND PREDICTABILITY

W.N. Goetzmann, R.G. Ibbotson and L. Peng
Yale School of Management, July 14, 2000



Dow Jones Industrial Average Jan 1790–Sept 2000
Upward curvature in this log-linear plot
exhibits the super-exponential growth; the straight
Lines show local fist to exponential growths
6.8%/y
2.9%/y
Close Prices
10,000
1,000
100
10
1
1800
1840
1880
1920
1960
2000
Years

Finite-time Singularity



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

- 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...

Mechanisms for positive feedbacks in the stock market

- Technical and rational mechanisms
  1. Option hedging
  2. Insurance portfolio strategies
  3. Trend following investment strategies
  4. Asymmetric information on hedging strategies

- Behavioral mechanisms:
  1. Breakdown of "psychological Galilean invariance"
  2. Imitation(many persons)
     a) It is rational to imitate
     b) It is the highest cognitive task to imitate
     c) We mostly learn by imitation
     d) The concept of "CONVENTION" (Orléan)

Utility theory

$$\sum_i p_i u(w_i) > \sum_i q_i u(w_i)$$

Von Neumann and Morgenstern

Behavioral Finance:one person

- Fear and Greed
- Over-confidence
- Anchoring
- Law of small numbers (gambler's fallacy)
- Representativeness (=>weight recent past too heavily)
- Availability and rational inattention
- Allais' paradox: relative reference level
- Subjective probabilities
- Procedure Utility

$$\sum_i \pi(p_i)v(\Delta w_i) > \sum_i \pi(q_i)v(\Delta w_i)$$

*Prospect theory

Kahneman and Tversky

Kal


JUST A NORMAL DAY AT THE NATION'S MOST IMPORTANT FINANCIAL INSTITUTION...
I'VE GOT A STOCK HERE THAT COULD REALLY EXCEL
REALLY EXCEL?
EXCEL?
SELL?
SELL?
SELL
SE
SELL!
SELL!
KAL
SELL!
SELL!
ELL!
SELL!
THIS IS MADNESS! I CAN'T TAKE ANYMORE
GOOD BYE?
GOOD BYE!
BYE?
Buy?
BUY!
Buy!
BUY!!
Buy!
Bu
BUY!
I'VE GOT A STOCK HERE..
CARTOONISTS & WRITERS SYNDICATE http://CartoonWeb.com


THIS WAY TO THE
Bull Market!
Almost there. . . 300 feet. . . Don't Miss The Fun!
I'm a trader.
Hey this Koolaid tastes great!
Must own Yahoo.
Stoopid bears.
Don't be negative.
Take a deep breath!
I'm flying mommy!
El Cliffo

Imitation

-Imitation is considered an efficient mechanism of social learning.

- Experiments in developmental psychology suggest that infants use imitation to get to know persons, possibly applying a ‘like-me’ test (‘persons which I can imitate and which imitate me’).

- Imitation 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 (humans and chimpanzees, whales and dolphins, parrots).

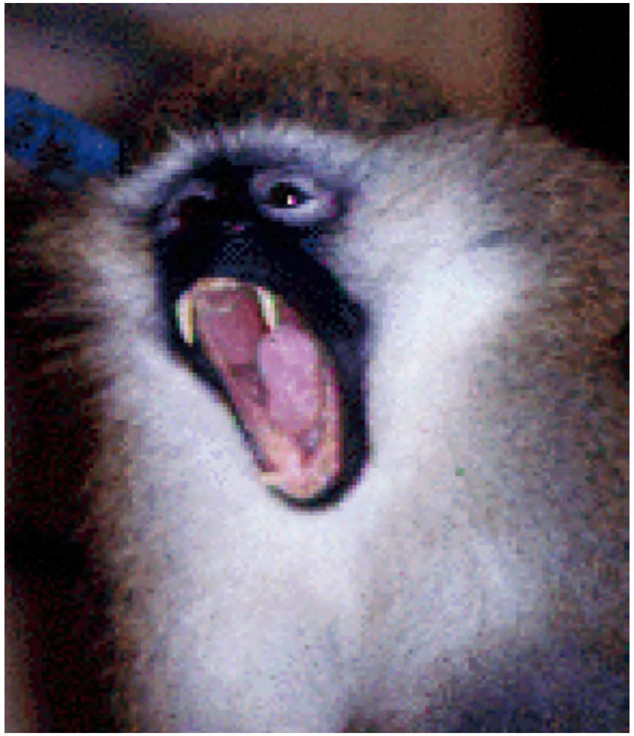
- In non-natural agents as robots, tool for easing the programming of complex tasks or endowing groups of robots with the ability to share skills without the intervention of a programmer. Imitation plays an important role in the more general context of interaction and collaboration between software agents and human users.

OBSERVATIONAL LEARNING

For evolutionary fears, monkeys and people learn by watching what other animals and people do (not by doing themselves and learning from the consequences).

Hands-on learning may not always be the best! THE APE AND THE SUSHI MASTER (Frans de Waal's book): in Japan, apprentice sushi cooks spend three years just watching the sushi master prepare sushi. When the apprentice finally prepares his first sushi, he does a good job of it. ("The watching of skilled models firmly plants action sequences in the Head that come in handy, sometimes much later, when the same taskes need to be carried out." The ape and the sushi Master: cultural reflections of a primatologist (New York: Basic Books, 2001)

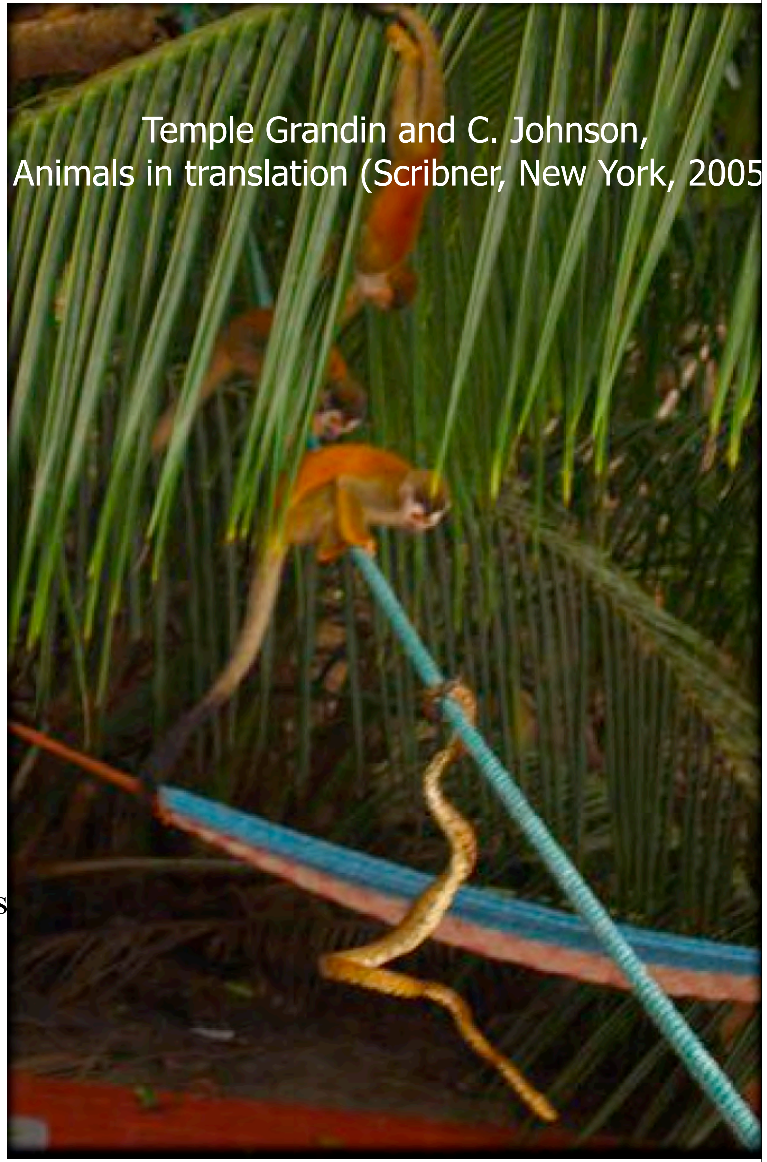
Temple Grandin and C. Johnson,
Animals in translation (Scribner, New York, 2005)



VERVET MONKEY

EXAMPLES OF STRONG IMITATION EFFECTS:

Red squirrel monkeys and six-foot Costa Rica snake



Temple Grandin and C. Johnson,
Animals in translation (Scribner, New York, 2005

FEARS ARE CONTAGIOUS

Psychologist S. Mineka's experiments with monkeys and snakes :
lots of phobias and fears are CONTAGIOUS

Monkeys in the wild are terrified by snakes
Monkeys in the lab are not worried by snakes

Dr. Mineka taught a lab monkey to be just a terrified of snakes as any monkey living in the wild. When Dr. Mineka exposes her fearless monkeys to wild-reared monkeys acting afraid of snakes, the lab monkeys instantly got scared themselves, and they stayed scared for life. The lab-monkeys learned the same level of fear as the demonstrator-monkey.
If the demonstrator-monkey was scared but not panicked, the observer-monkey became scared but not panicked.

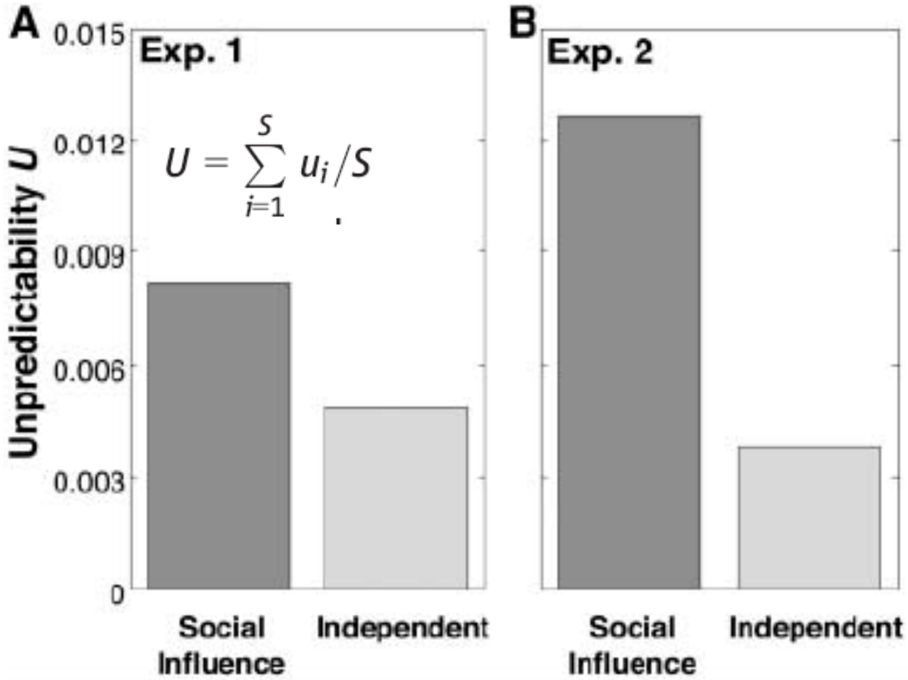
It is impossible to teach a monkey to be afraid of a flower by the same technique! (video tape of a flower followed by a monkey acting terrified).

Fear of snake is SEMI-INNATE: monkeys are born ready to fear snakes at the first hint of trouble (prepared stimulus)

One can protect an animal from developing fear: If Dr. Mineka first exposed a lab-rearer monkey to another lab-reared Monkey NOT acting afraid of a snake, that gave him "immunity": after that, if he saw a wild-reared monkey acting scared of a snake, he did NOT develop snake fear himself. He held to his first lesson.

Unpredictability of success

$$u_i = \sum_{j=1}^{W} \sum_{k=j+1}^{W} |m_{i,j} - m_{i,k}| / \binom{W}{2}$$



Random order of popularity Ranked popularity

With a little help from my friends. When making choices, individuals are influenced by what others think is best, making the final outcome unpredictable.

Popular songs became more popular and unpopular songs became less popular when individuals influenced one another.

The structure of social action—that is, the pattern and strength of social influence—in and of itself is of considerable importance for explaining the social phenomena we observe.

M. J. Salganik, P. S. Dodds, D. J. Watts, *Science* **311**, 854 (2006)

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

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

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

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.

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) Shiller (2000)

Humans Appear Hardwired To Learn By 'Over-Imitation'

ScienceDaily (Dec. 6, 2007) — Children learn by imitating adults--so much so that they will rethink how an object works if they observe an adult taking unnecessary steps when using that object, according to a new Yale study.

Are two heads better than one?

Yes IF:

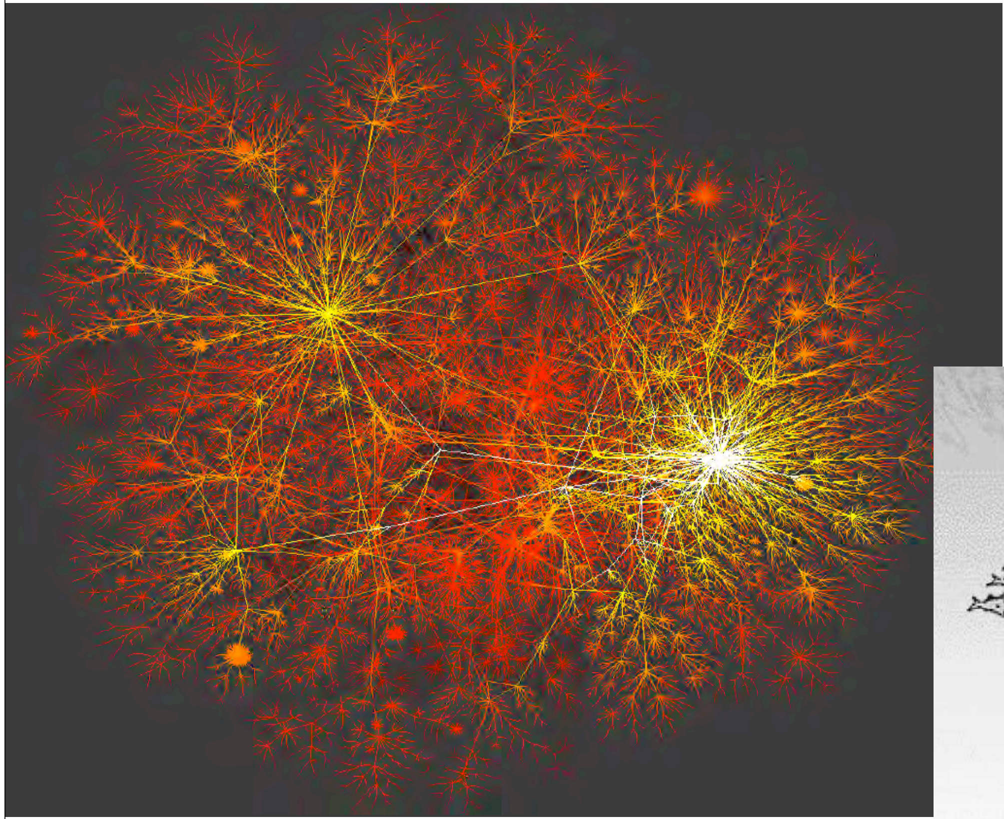
1. Only one solution (otherwise "average of Nice and LA is in the Atlantic")
2. Independence between decisions (otherwise: inadequate sampling)
3. No feedbacks between people's decisions (otherwise: self-reinforcing bias)

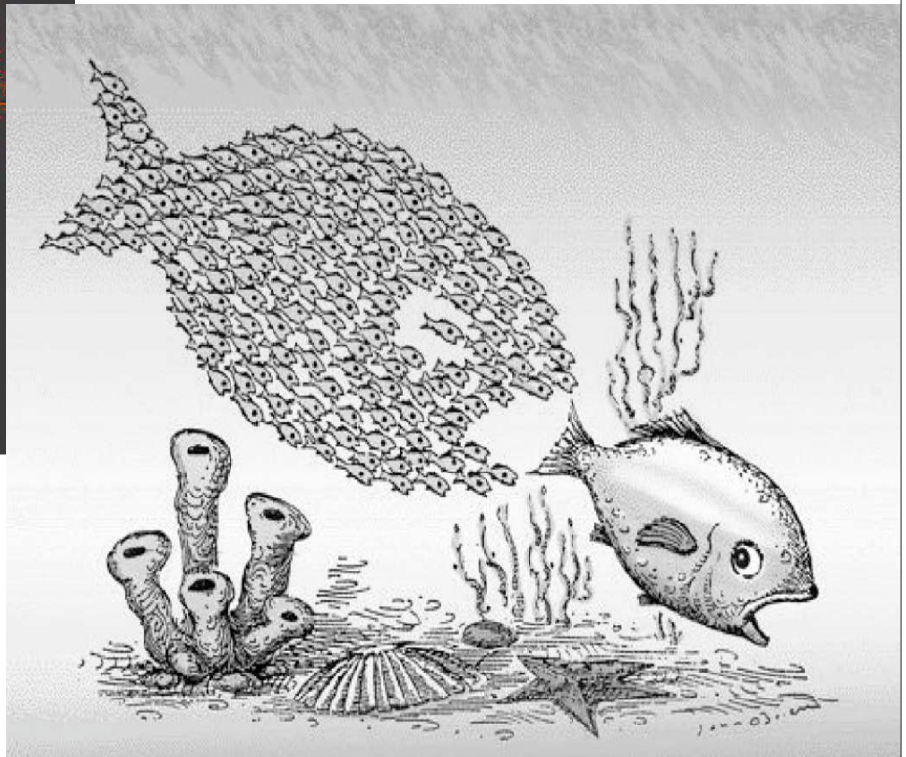
Dresdner Kleinwort Wasserstein Seven Sins of Fund Management

Groupthink is often characterised by:

- A tendency to examine too few alternatives
- A lack of critical assessment of each other's ideas
- A high degree of selectivity in information gathering
- A lack of contingency plans
- Poor decisions are often rationalized
- The group has an illusion of invulnerability and shared morality
- True feelings and beliefs are suppressed
- An illusion of unanimity is maintained
- Mind guards (essentially information sentinels) may be appointed to protect the group from negative information

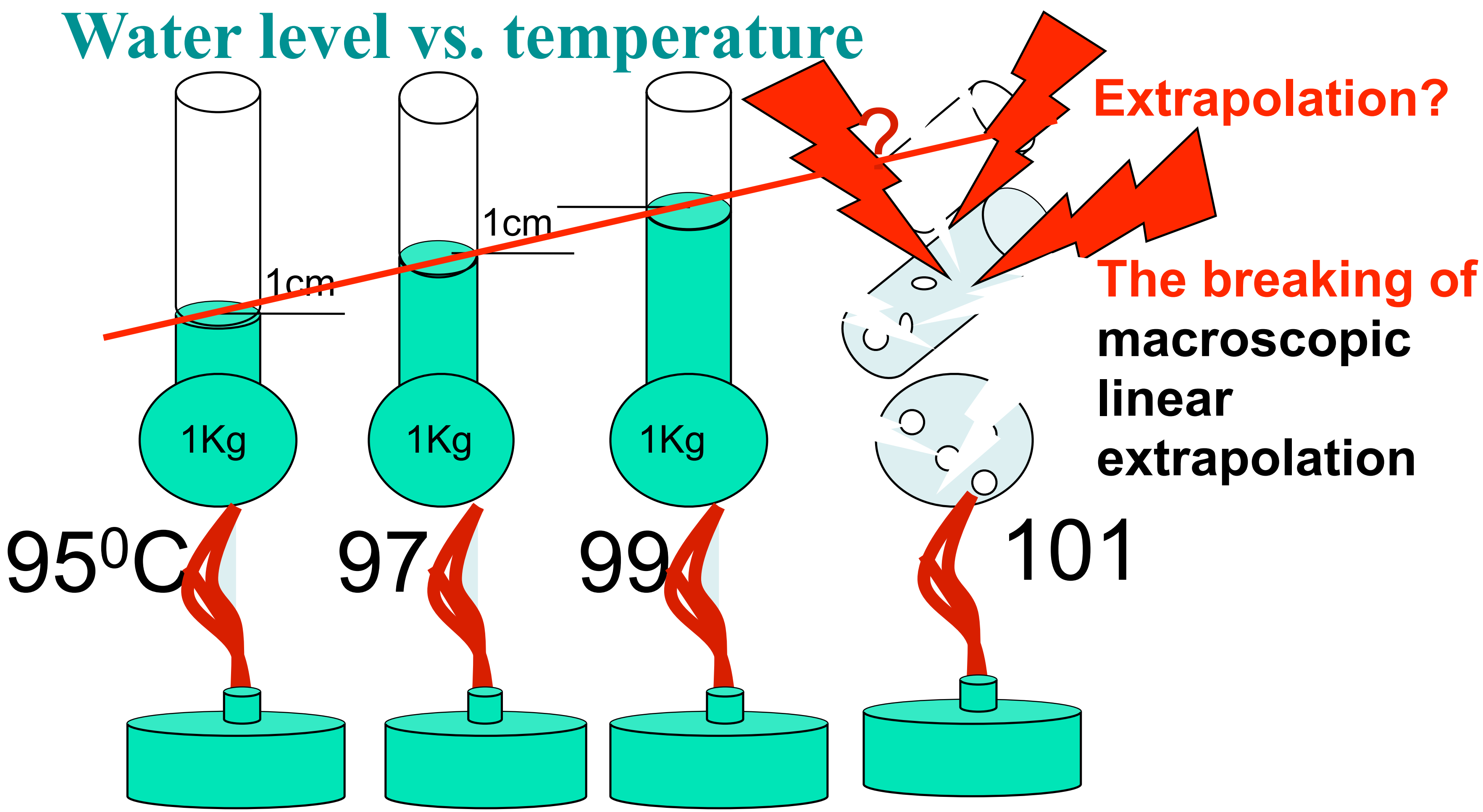
Network effects and Collective behavior





Courtesy of B. A. Huberman.

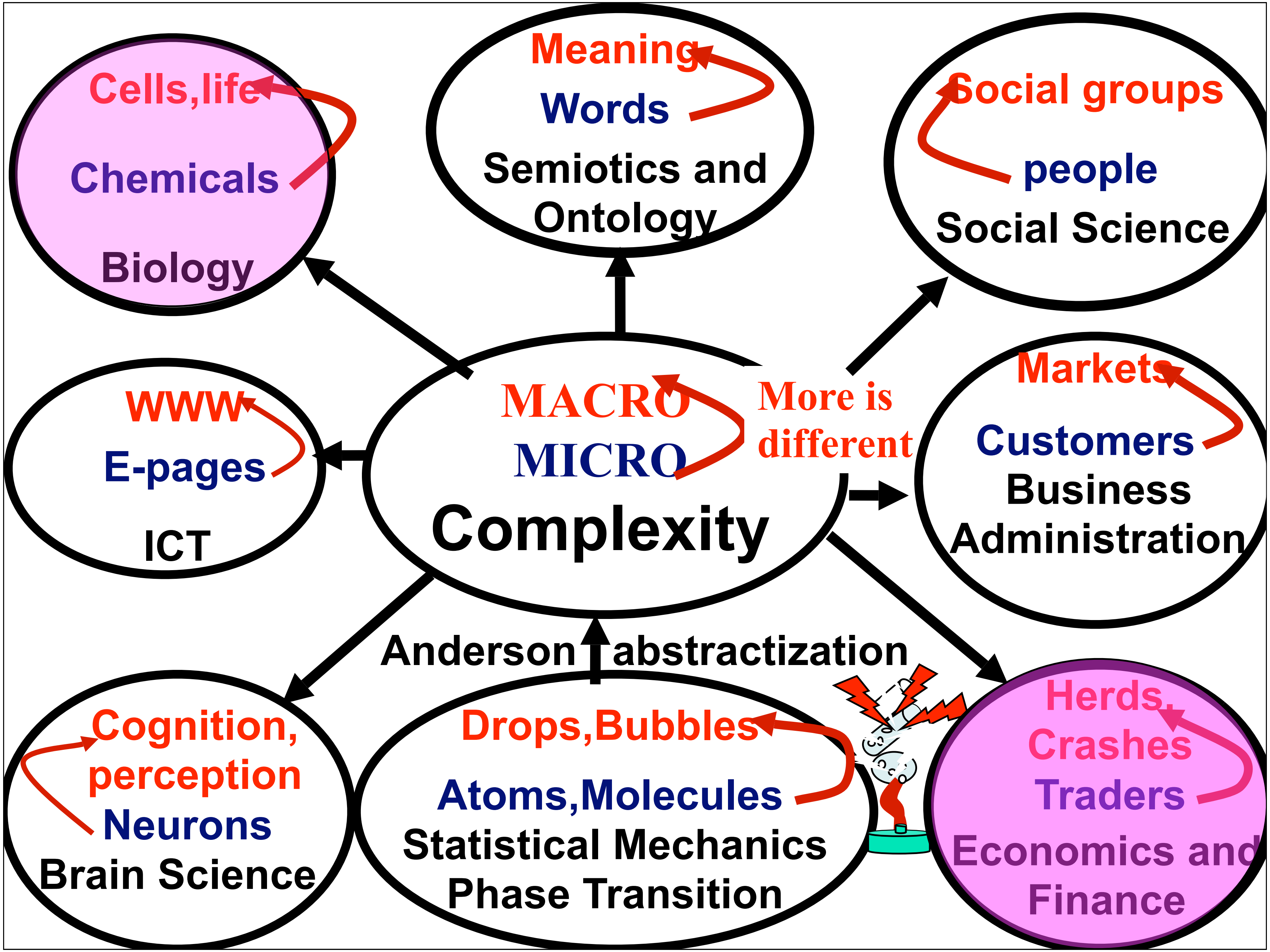
Simplest Example of a "More is Different" Transition



BOILING PHASE TRANSITION

More is different: a single molecule does not boil at $100C^0$

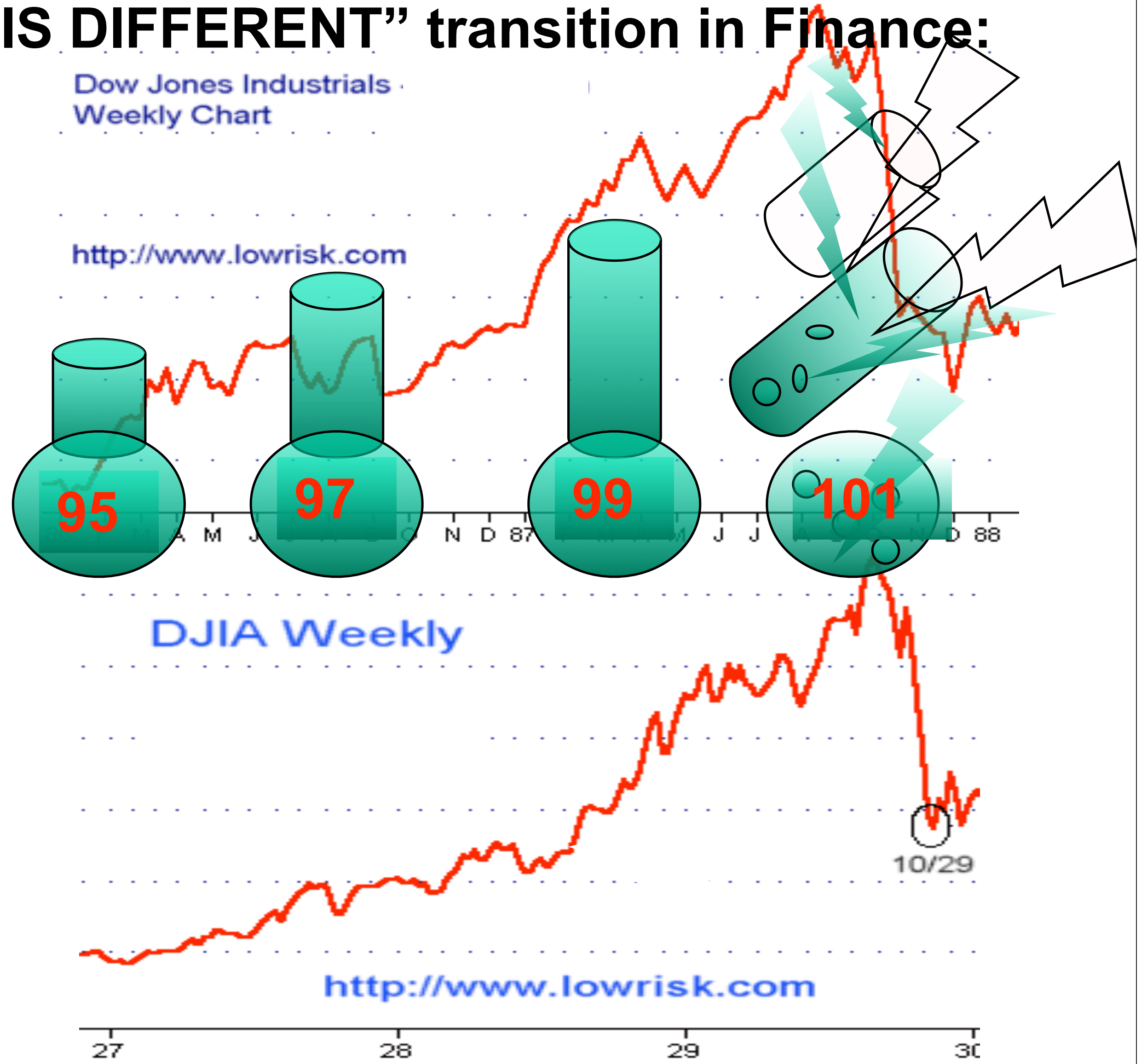
(S. Solomon)


Meaning
Words
Semiotics and Ontology
Cells,life
Chemicals
Biology
Social groups
people
Social Science
WWW
E-pages
ICT
MACRO
MICRO
Complexity
More is different
Markets
Customers
Business Administration
Anderson abstractization
Cognition, perception
Neurons
Brain Science
Drops,Bubbles
Atoms,Molecules
Statistical Mechanics
Phase Transition
Herds, Crashes
Traders
Economics and Finance

Example of "MORE IS DIFFERENT" transition in Finance:

Instead of Water Level:

-economic index (Dow-Jones etc…)



Crash = result of collective behavior of individual traders

(S. Solomon)

Optimal strategy obtained under limited information

Equation showing optimal imitation solution of decision in absence of intrinsic information and in the presence of information coming from actions of connected "neighbors"

$$s_i(t+1) = \text{sign}\left(K \sum_{j \in N_i} s_j + \varepsilon_i \right)$$

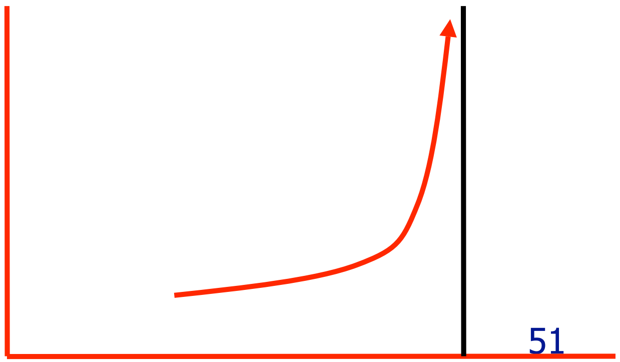
This equation gives rise to critical transition=bubbles and crashes

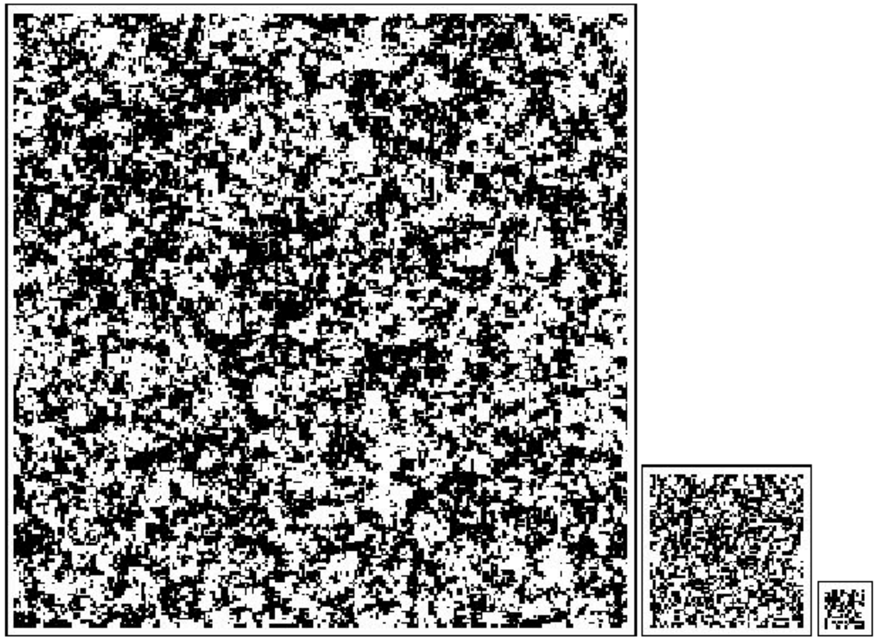
-Crash = coordinated sell-off of a large number of investors
-single cluster of connected investors to set the market off-balance
-Crash if 1) large cluster s>s*   and 2) active

-Proba(crash) = n(s)
-Proba(active cluster) ~ s^a with 1 < a < 2   (coupling between decisions)

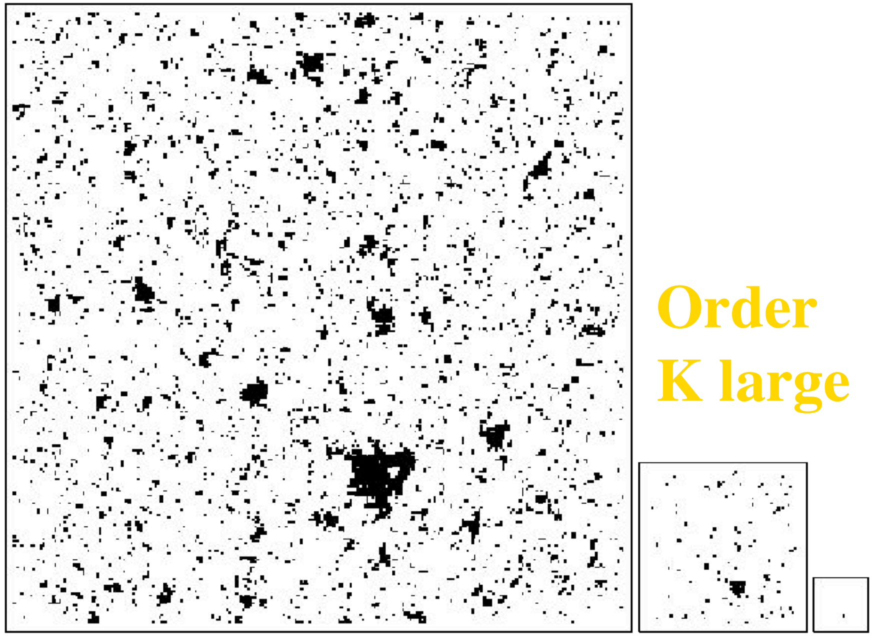
Proba(crash) ~ $\sum_{s>s*}$ n(s) s^a

If a=2, $\sum_{s>s*}$ n(s) s^2 ~ $|K-Kc|^{-\gamma}$



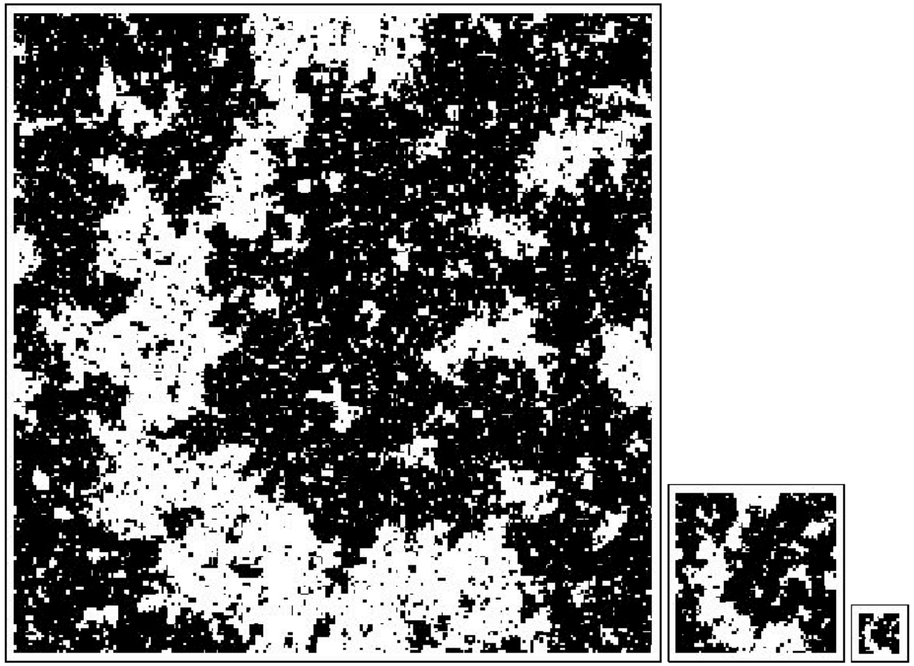


Disorder : K small



Order
K large

Renormalization group:
Organization of the description scale by scale



Critical:
K=critical value

Importance of Positive Feedbacks and Over-confidence in a Self-Fulfilling Ising Model of Financial Markets

$$s_i(t) = \mathrm{sign}\left[\sum_{j \in \mathcal{N}} K_{ij}(t)\mathrm{E}[s_j](t) + \sigma_i(t)G(t) + \epsilon_i(t)\right]$$

Imitation **News** **Private information**

$$K_{ij}(t) = b_{ij} + \alpha_i K_{ij}(t-1) + \beta r(t-1)G(t-1)$$

(generalizes Carlos Pedro Gonçalves, who generalized Johansen-Ledoit-Sornette)

β: propensity to be influenced by the felling of others

1. **β<0: rational agents**

- **β>0: over-confident agents**

Didier Sornette and Wei-Xing Zhou, Physica A 370 (2), 704-726 (2006))

News:

$$G(t) = \begin{cases} 1 & \text{if } I(t) > 0, \\ -1 & \text{if } I(t) \leqslant 0. \end{cases}$$

Price:

$$p(t) = p(t-1)\exp[r(t)],$$

$$r(t) = \frac{\sum_{i \in \mathcal{N}} s_i(t)}{\lambda N}$$

(1) the agents make decisions based on a combination of three ingredients: imitation, news and private information

(2) they are boundedly rational

(3) traders are heterogeneous (K_{ij} and σ_i);

(4) The propensity to imitate and herd is evolving adaptively as an interpretation that the agents make of past successes of the news to predict the direction of the market.

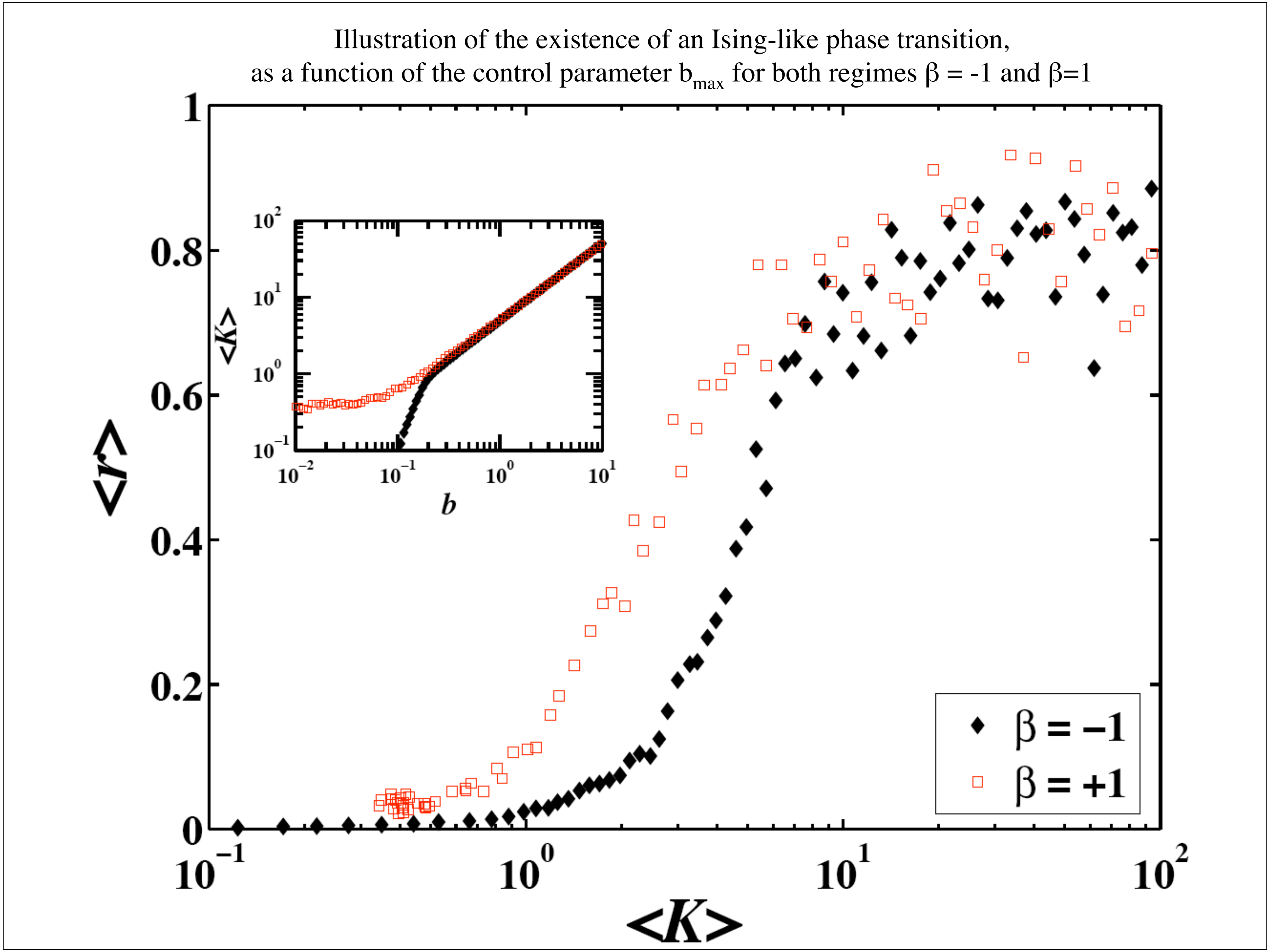
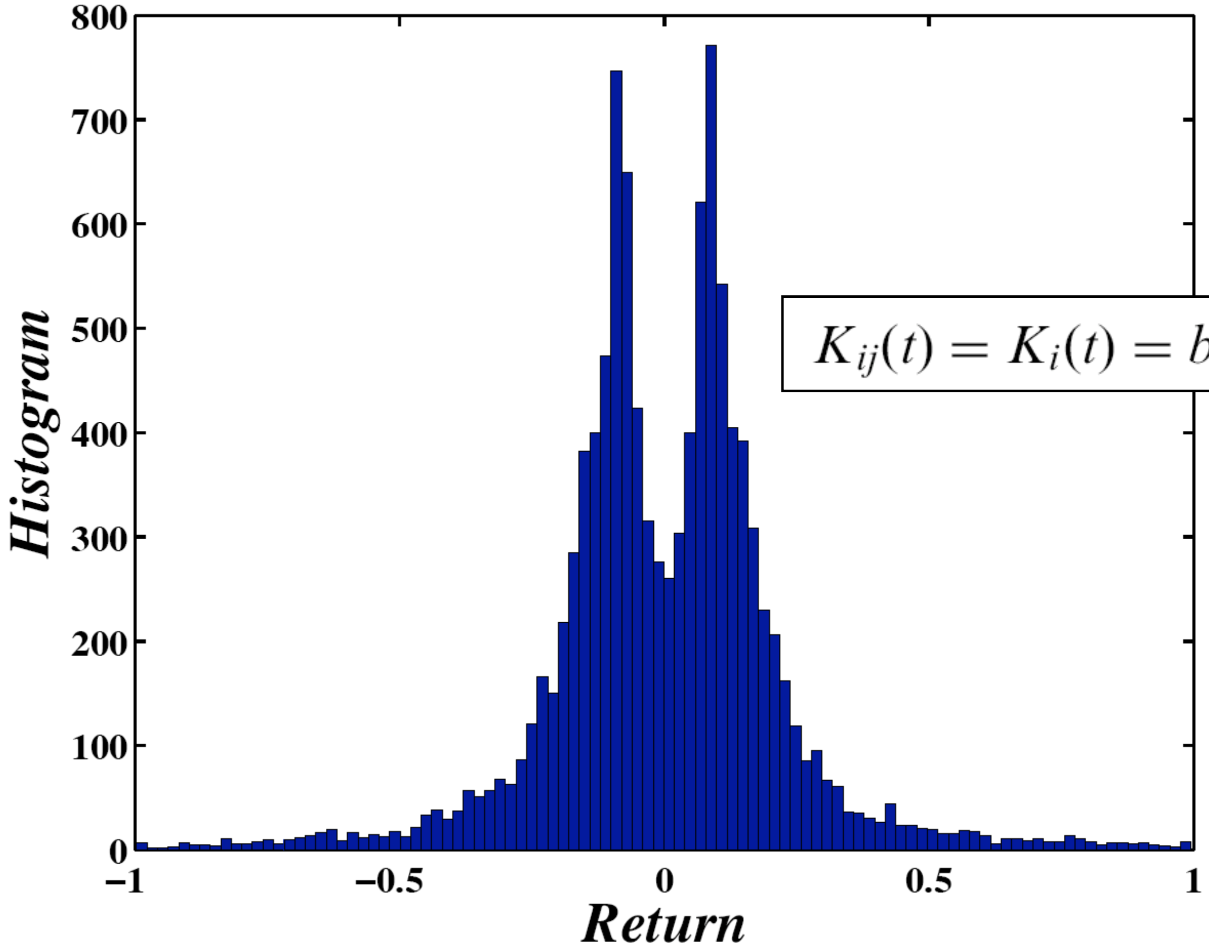


Illustration of the existence of an Ising-like phase transition,
as a function of the control parameter b_max for both regimes β = -1 and β=1
<r>
<K>
β = −1
β = +1
b

$\alpha_i = 0$ *corresponding to the absence of memory of the coefficients* K_{ij}*'s*



$$K_{ij}(t) = K_i(t) = b_i + \beta r(t-1)G(t-1)$$

Fig. 1. Density distribution of returns r_1 for a realization of the artificial stock market model formulated by Gonçalves (2003) generated using $b_{\max} = 0.22 \sim 0.24$, $\sigma_{\max} = 0.14 \sim 0.15$ and $CV = 0.8 \sim 0.9$ as recommended by this author. The time series of returns have been kindly provided by Gonçalves. Our own simulations reproduce the same results.

News predicts the next return → decrease of imitation: $\beta = -1$

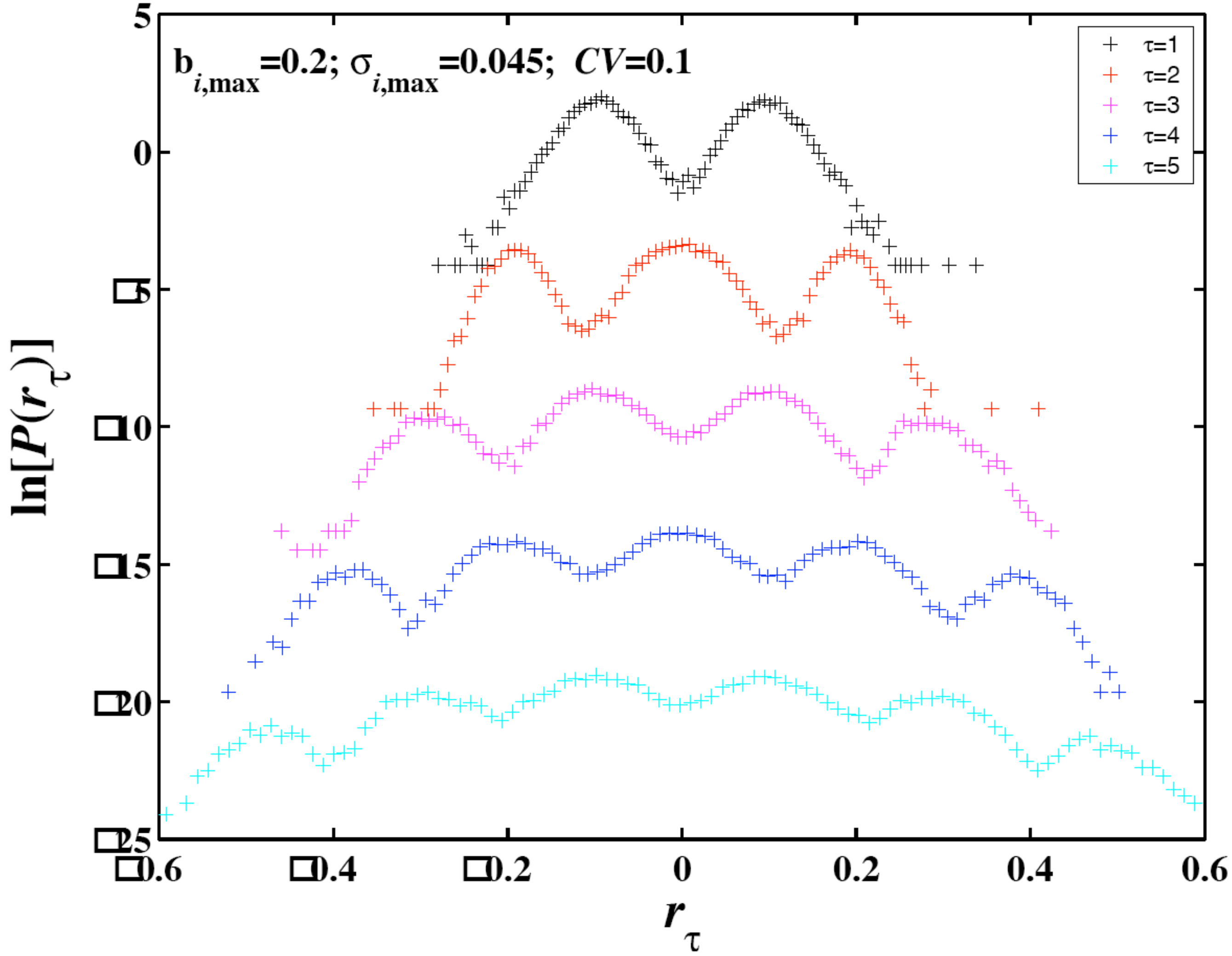


Fig. 2. A typical example of the multimodal distribution for $b_{\max} = 0.2$, $\sigma_{\max} = 0.045$, and $CV = 0.1$.

Case $\beta = +1$ ("over-confident" agents)

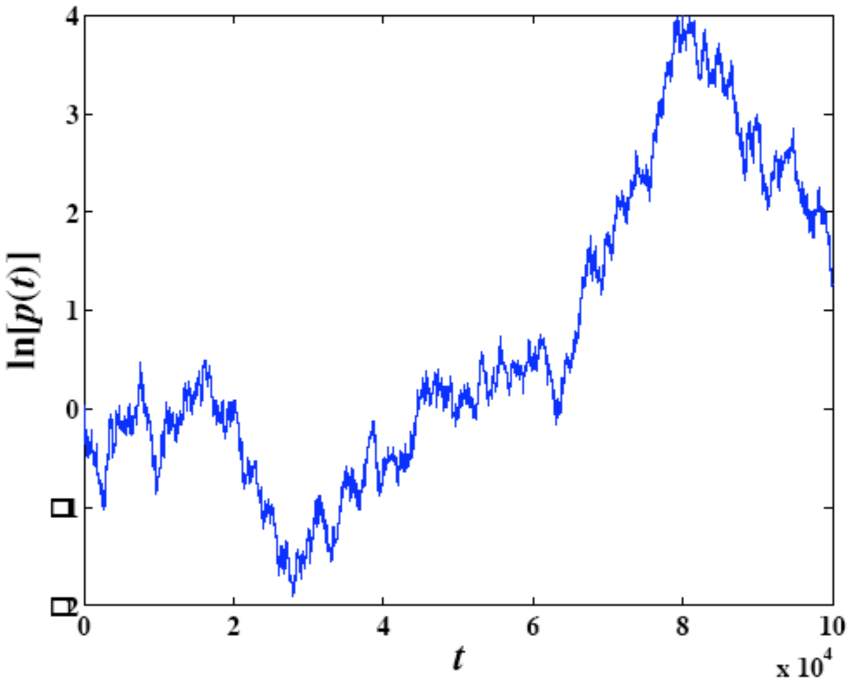


Fig. 3. A realization of the logarithm of the price over 10^5 time steps generated using $\alpha = 0.2$, $b_{\max} = 0.3$, $\sigma_{\max} = 0.03$ and $CV = 0.1$ of the generalized artificial stock market model defined by (1), (4) and (10).

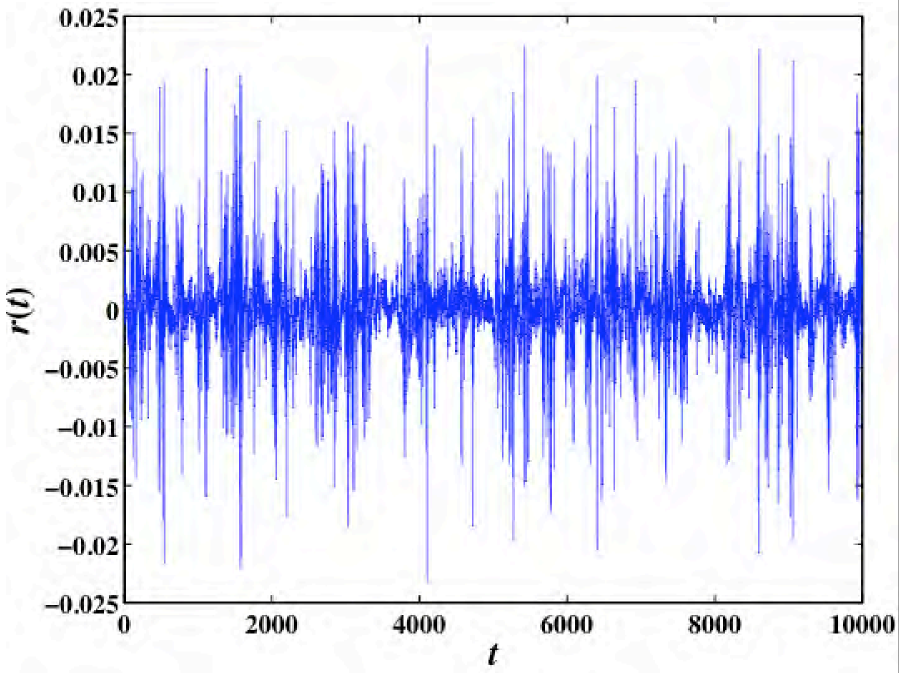
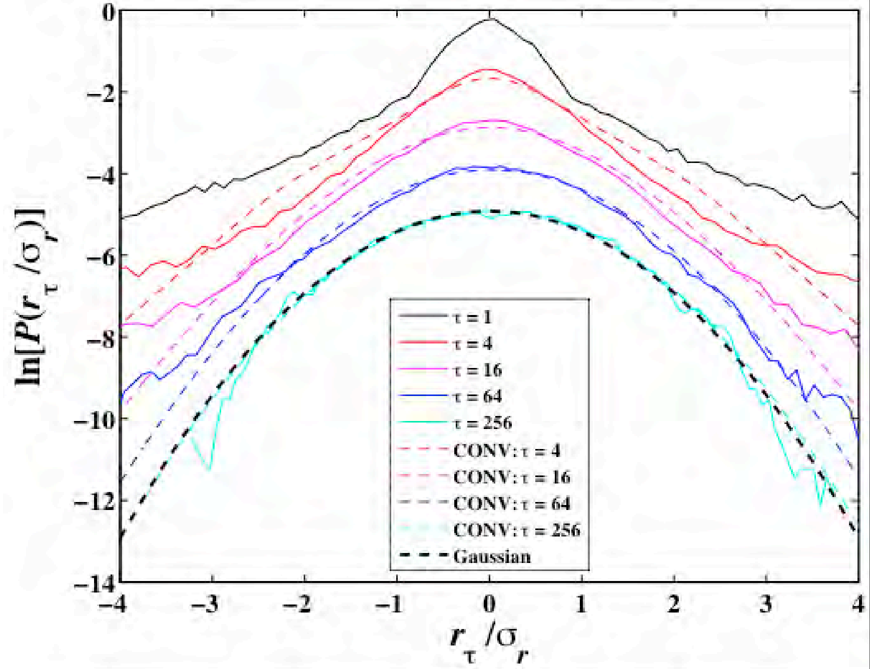
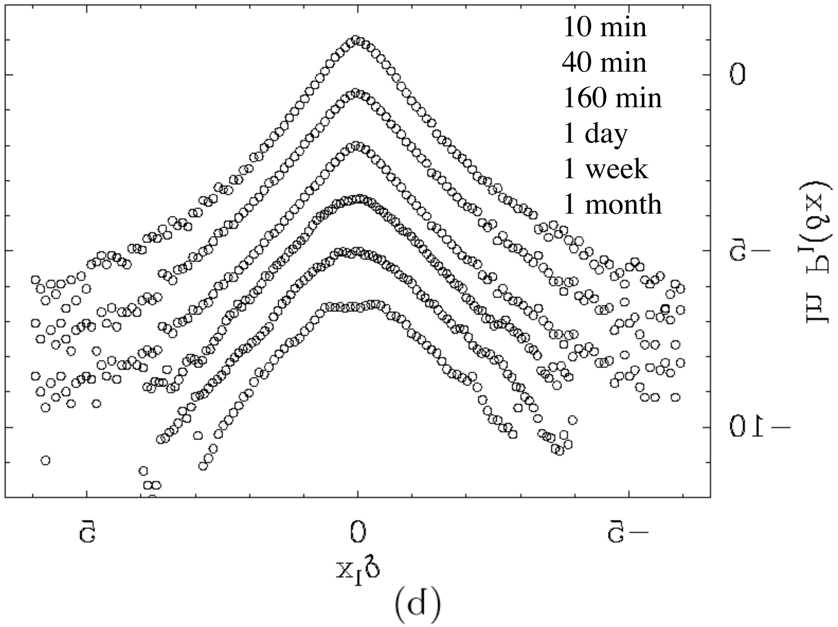
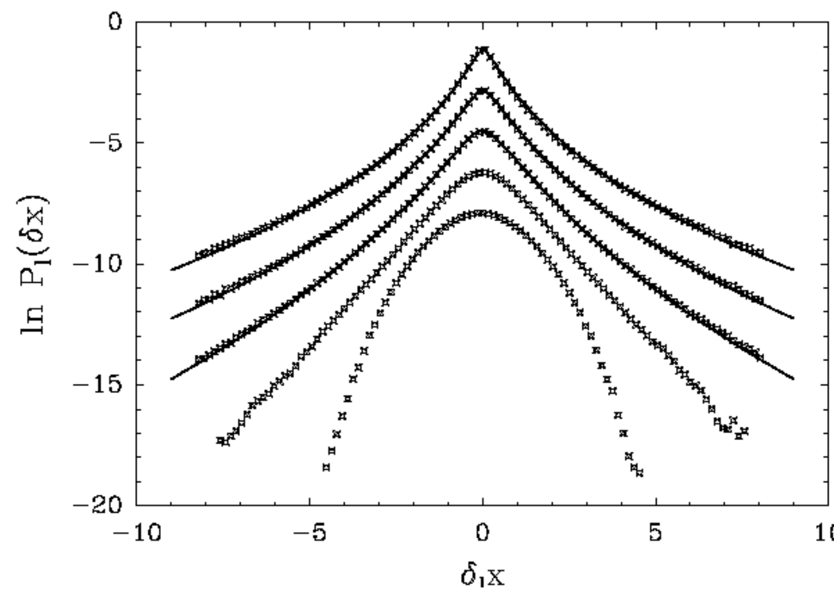


Fig. 4. Time series of the log-returns of the price shown in Fig. 3.

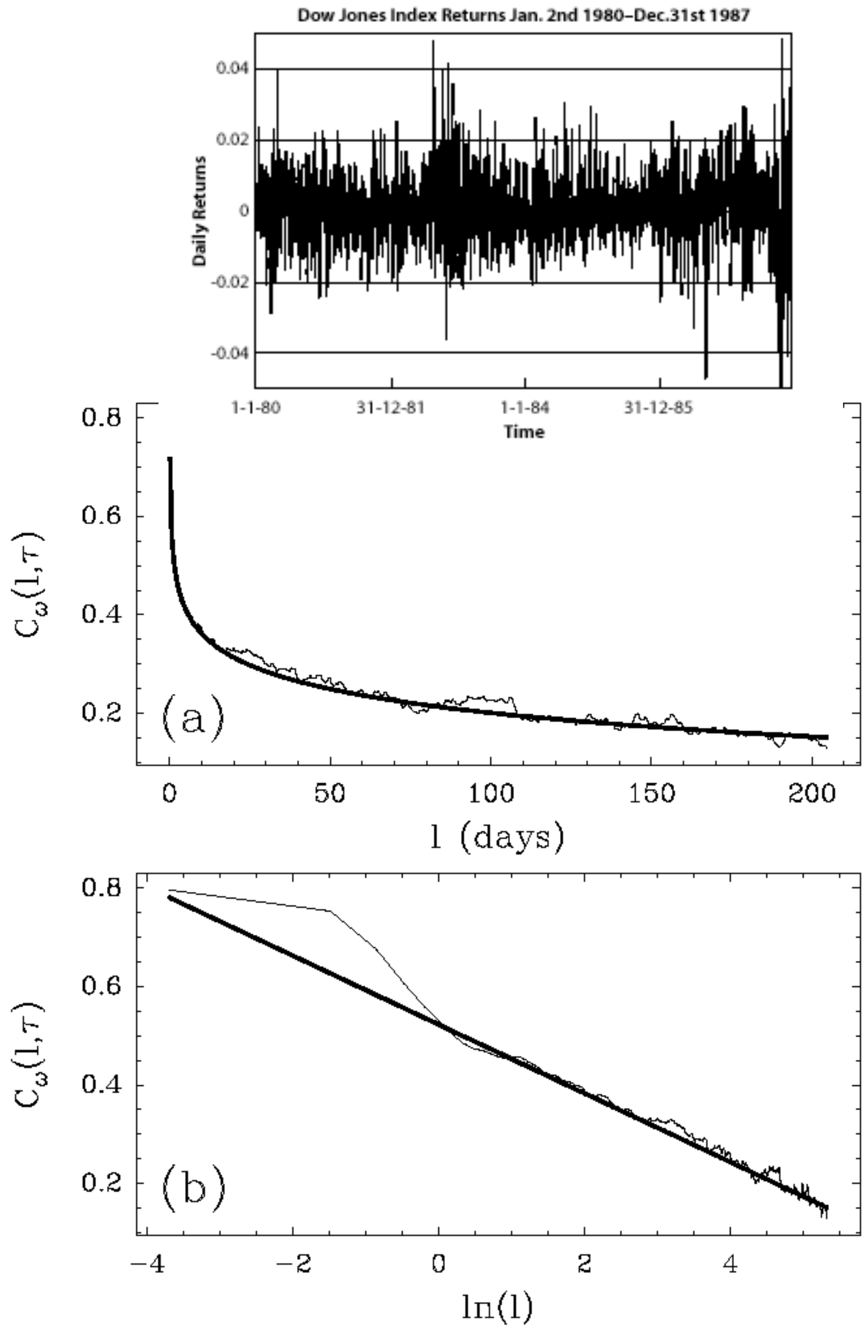
Fig. 5. (Color online) Empirical (solid lines) and theoretical (dashed thin lines) probability distribution density (in logarithmic scales) of log-returns at different time scales τ of the price time series shown in Fig. 3. The log-returns r_τ are normalized by their corresponding standard deviations σ_τ. The pdf curves are translated vertically for clarity. The thick dashed line is the Gaussian pdf.







Multifractal random walk



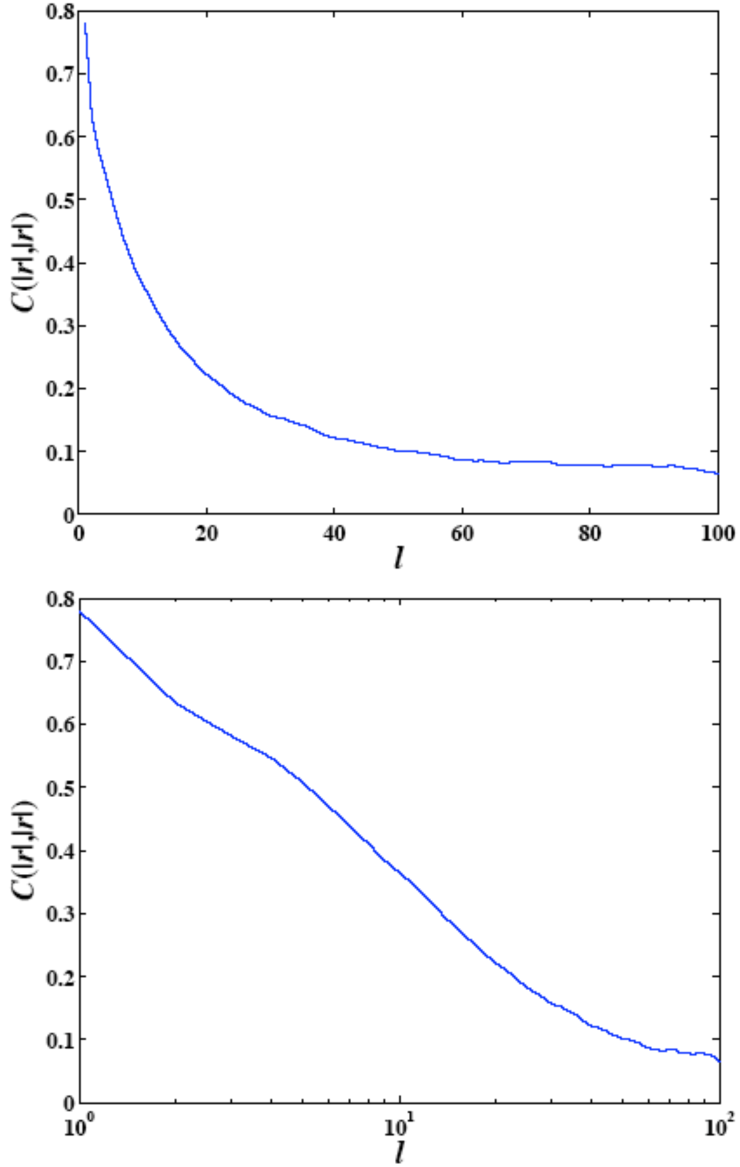


Fig. 7. Autocorrelation function of the absolute value of log-returns of the realization shown in Fig. 3. The top panel show the correlation in linear-linear scale. The bottom panel plots the correlation function as a function of the logarithm of the time lag, as suggested by the multifractal random walk model (see text).

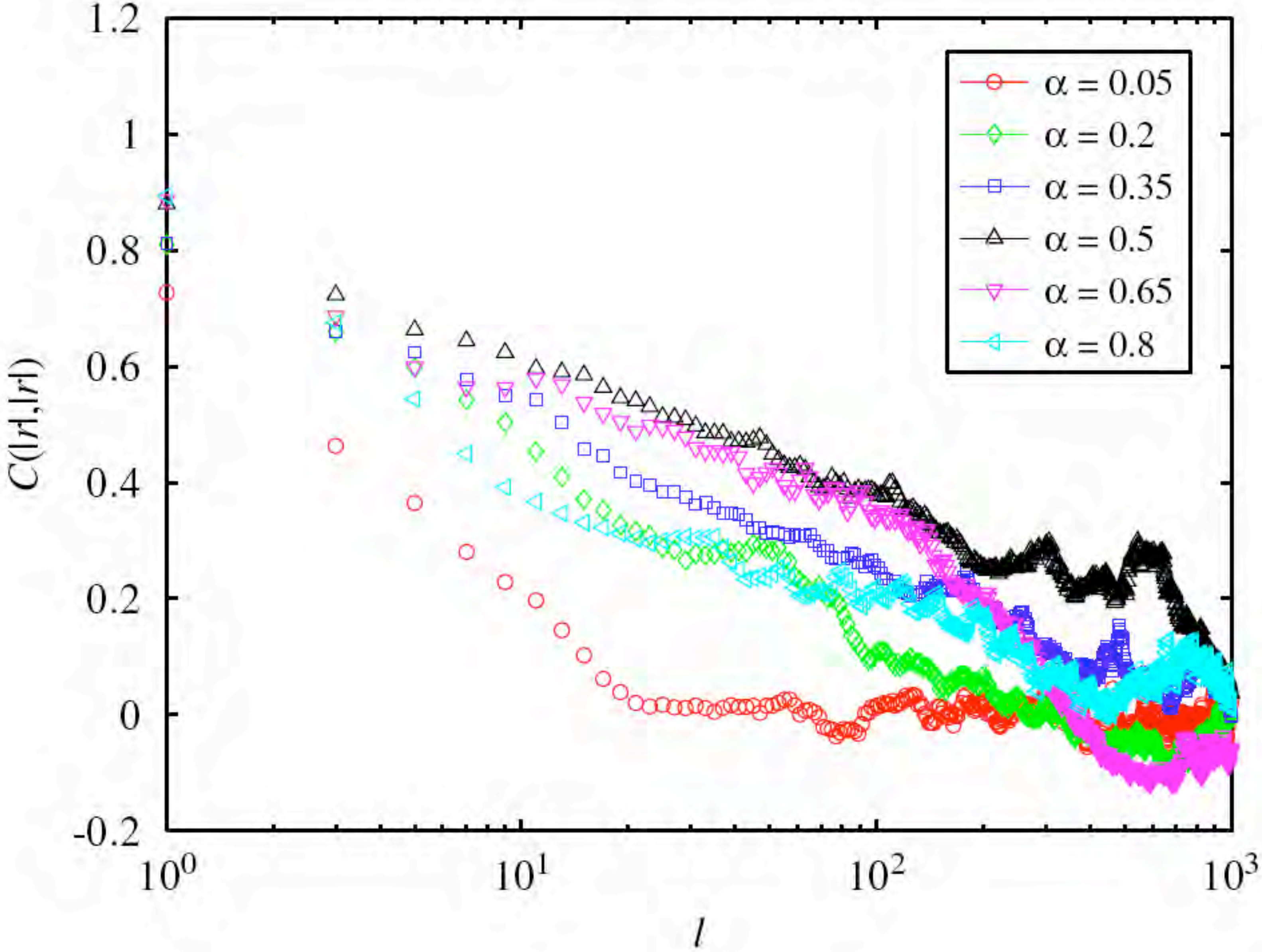


Fig. 8. The impact of α on the auto-correlation of the absolute values of the returns and of the returns.

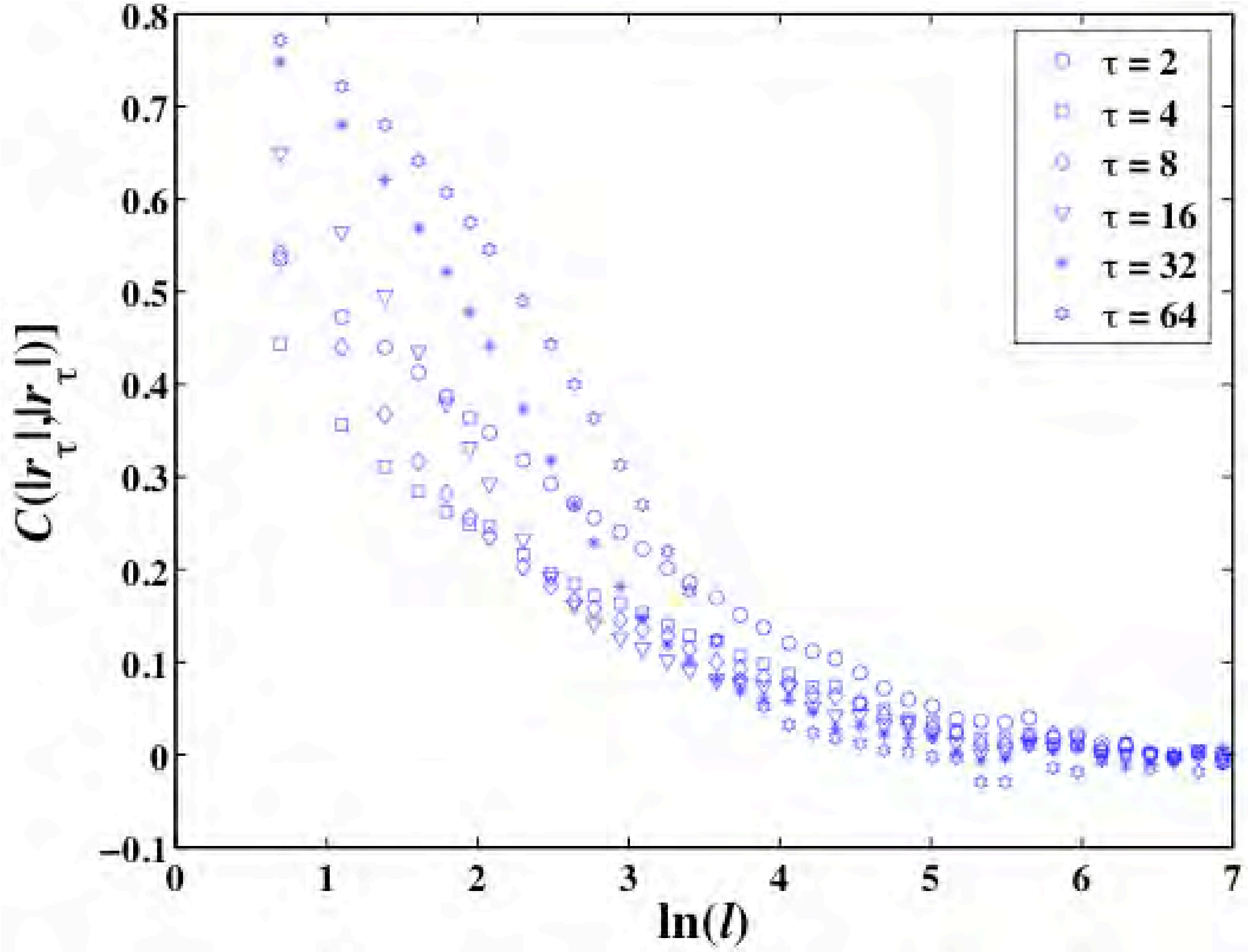


Fig. 9. Scaling of the autocorrelation functions of $|r_\tau(t)|$ for different time scales τ of the realization shown in Fig. 3.

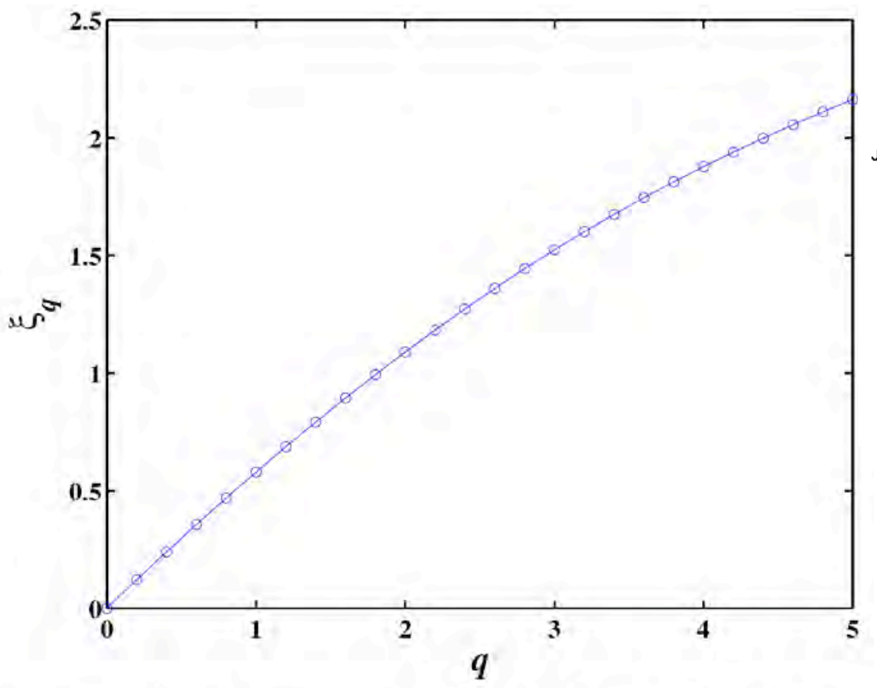
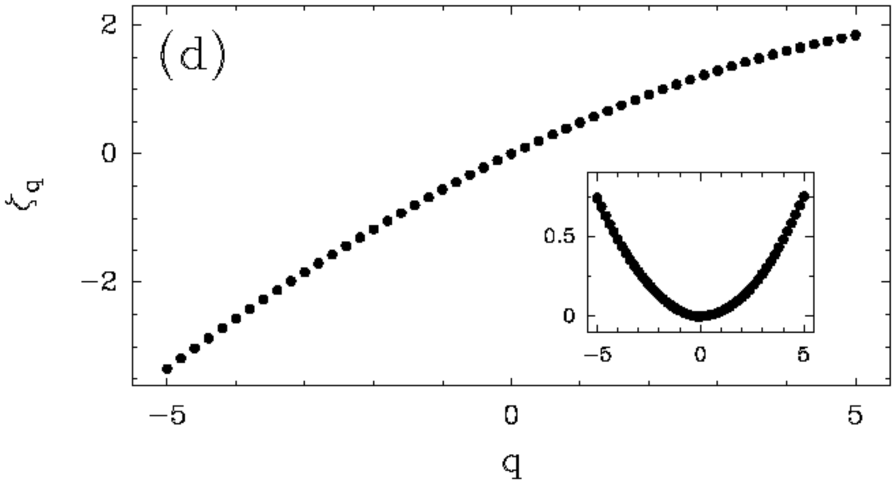


Fig. 11. Dependence of the scaling exponents ξ_q defined in (14) as a function of the order q of the structure functions $M_q(\tau) \sim \tau^{\xi_q}$. The concavity of ξ_q as a function q is the hallmark of multifractality.



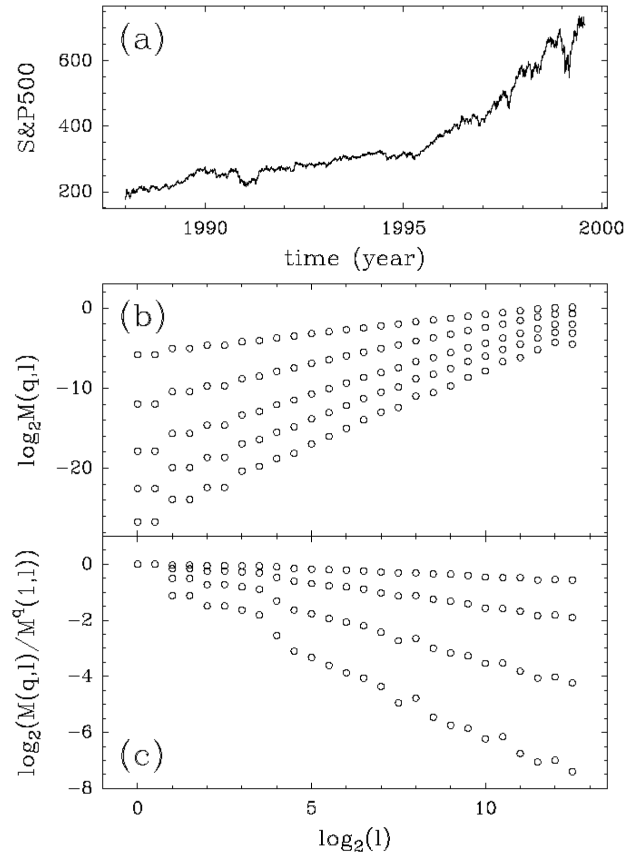


Fig. 1. Multifractal analysis of the intraday future S&P500 index over the period 1988–1999. (a) Plot of the original index time-series. The analyzed time-series is the detrended and de-seasonalized logarithm of this series. (b) Log-log plots of $M(q,l)$ *versus* l for $q = 1,2,3,4,5$. The time scales l range from 10 minutes to 1 year. (c) $\log_2(M(q,l)/M(1,l)^q)$ for $q = 2,3,4,5$. Such plots should be horizontal for a process that is not multifractal. (d) ζ_q spectrum for the S&P 500 fluctuations. The plot in the inset is the parabolic nonlinear part of ζ_q.

The Multifractal Randow Walk (MRW) model

$$r_{\Delta t}(t) = \epsilon(t) \cdot \sigma_{\Delta t}(t) = \epsilon(t) \cdot e^{\omega_{\Delta t}(t)}$$

$$\mu_{\Delta t} = \frac{1}{2} \ln(\sigma^2 \Delta t) - C_{\Delta t}(0)$$

$$C_{\Delta t}(\tau) = \mathrm{Cov}[\omega_{\Delta t}(t), \omega_{\Delta t}(t+\tau)] = \lambda^2 \ln\left(\frac{T}{|\tau| + e^{-3/2}\Delta t}\right)$$

$$\omega_{\Delta t}(t) = \mu_{\Delta t} + \int_{-\infty}^{t} d\tau \; \eta(\tau) \; K_{\Delta t}(t-\tau)$$

$\omega_{\Delta t}(t)$ is Gaussian with mean $\mu_{\Delta t}$ and variance $V_{\Delta t} = \int_0^\infty d\tau \; K_{\Delta t}^2(\tau) = \lambda^2 \ln\left(\frac{T e^{3/2}}{\Delta t}\right)$

$$C_{\Delta t}(\tau) = \int_0^\infty dt \; K_{\Delta t}(t) K_{\Delta t}(t + |\tau|)$$

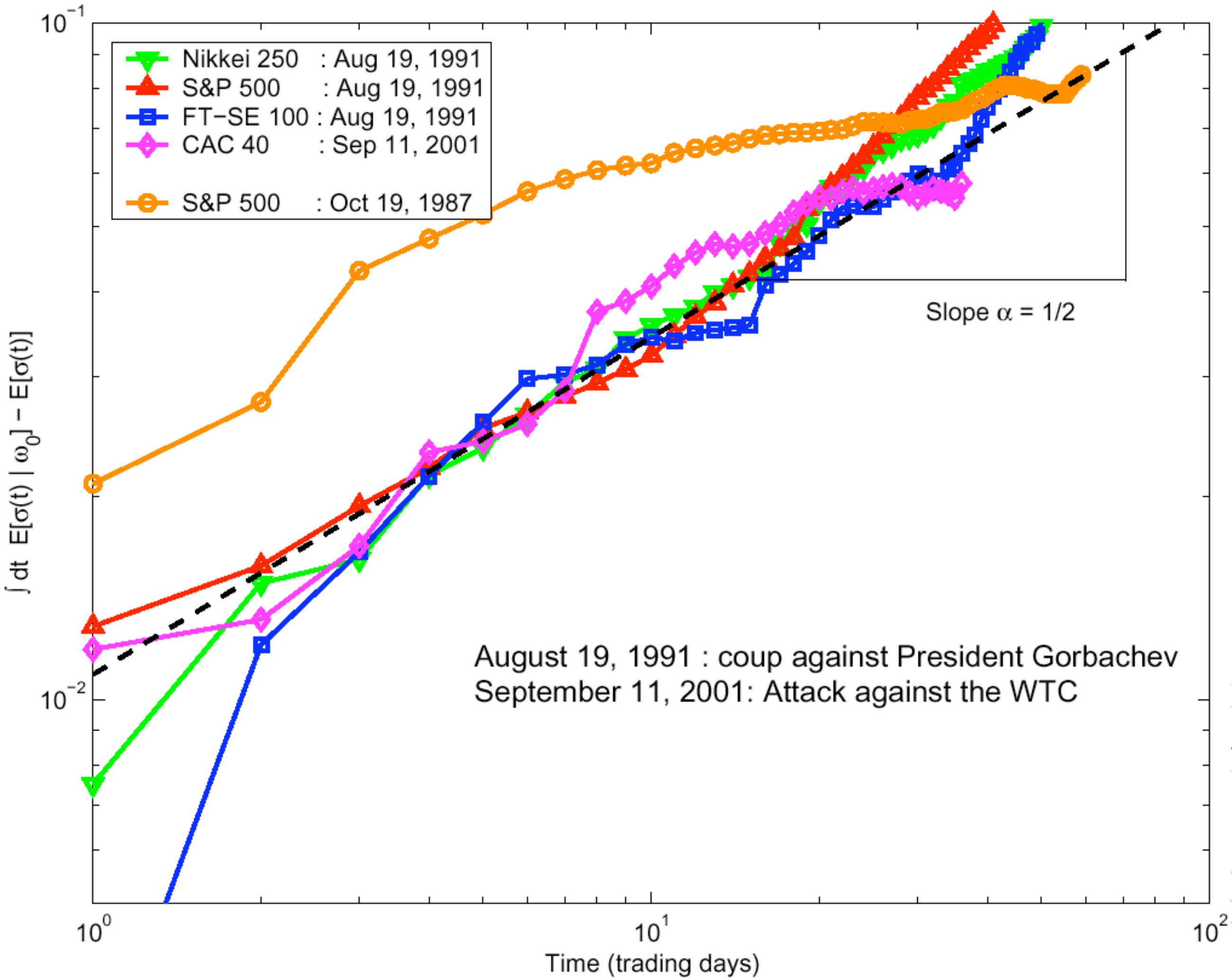
$$\hat{K}_{\Delta t}(f)^2 = \hat{C}_{\Delta t}(f) = 2\lambda^2 \; f^{-1} \left[\int_0^{Tf} \frac{\sin(t)}{t} dt + O\left(f \Delta t \ln(f \Delta t)\right)\right]$$

$$K_{\Delta t}(\tau) \sim K_0 \sqrt{\frac{\lambda^2 T}{\tau}} \quad \text{for } \; \Delta t << \tau << T$$

D. Sornette, Y. Malevergne and J.F. Muzy, Volatility fingerprints of large shocks: Endogeneous versus exogeneous, Risk 16 (2), 67-71 (2003)((http://arXiv.org/abs/cond-mat/0204626)

Linear response to an external shock

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



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)

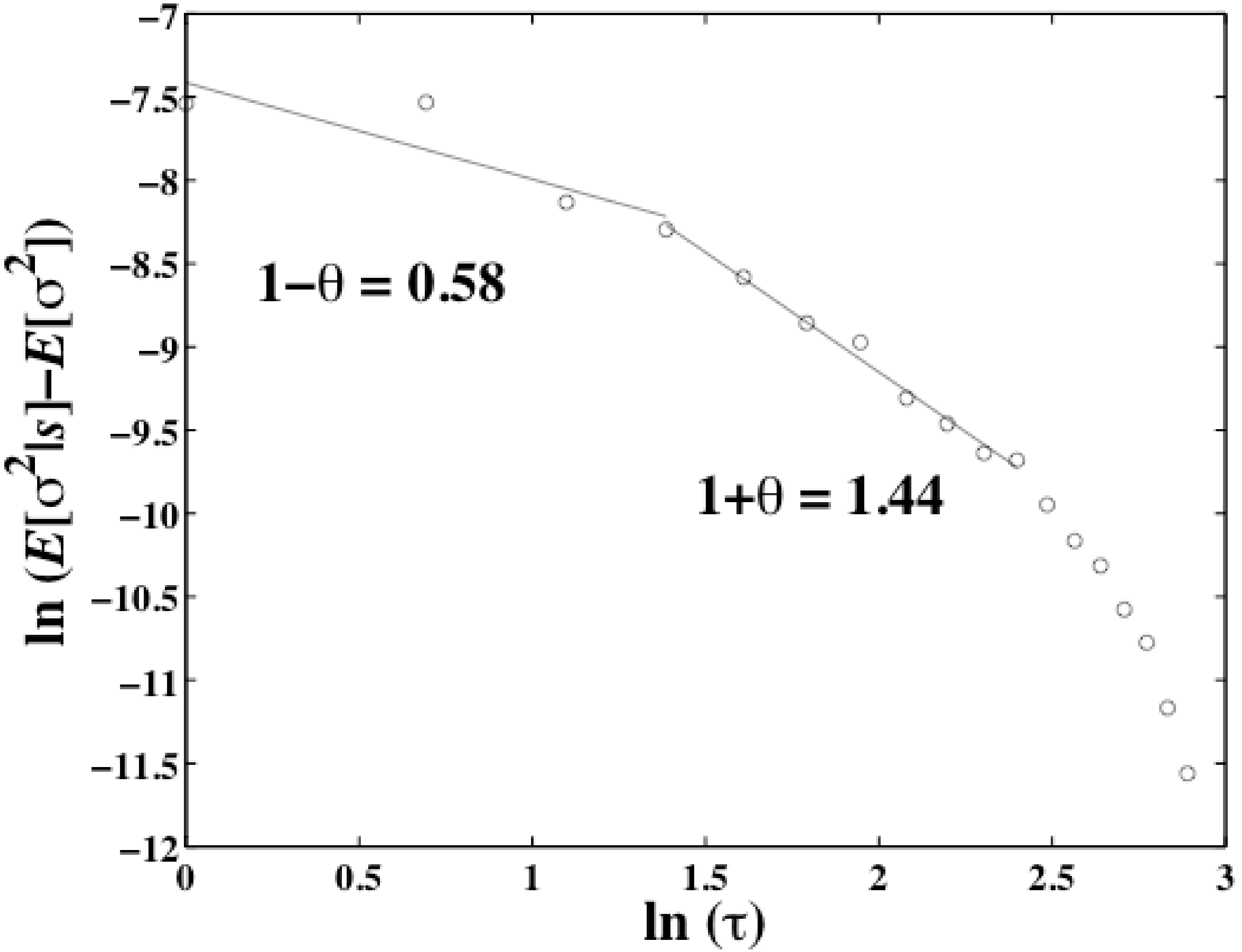


Fig. 14. Relaxation of superposed excess volatility after exogenous shocks obtained by imposing a very large news $G(t_s)$ for $\Delta t = 1$.

“Conditional response” to an endogeneous shock

$$\mathrm{E}_{\mathrm{endo}}[\sigma^2(t) \mid \omega_0] = \overline{\sigma^2(t)} \exp\left[2(\omega_0 - \mu) \cdot \frac{C(t)}{C(0)} - 2\frac{C^2(t)}{C(0)}\right]$$
$$= \overline{\sigma^2(t)} \left(\frac{T}{t}\right)^{\alpha(s)+\beta(t)}$$

Interplay between
-long memory
-exponential

where

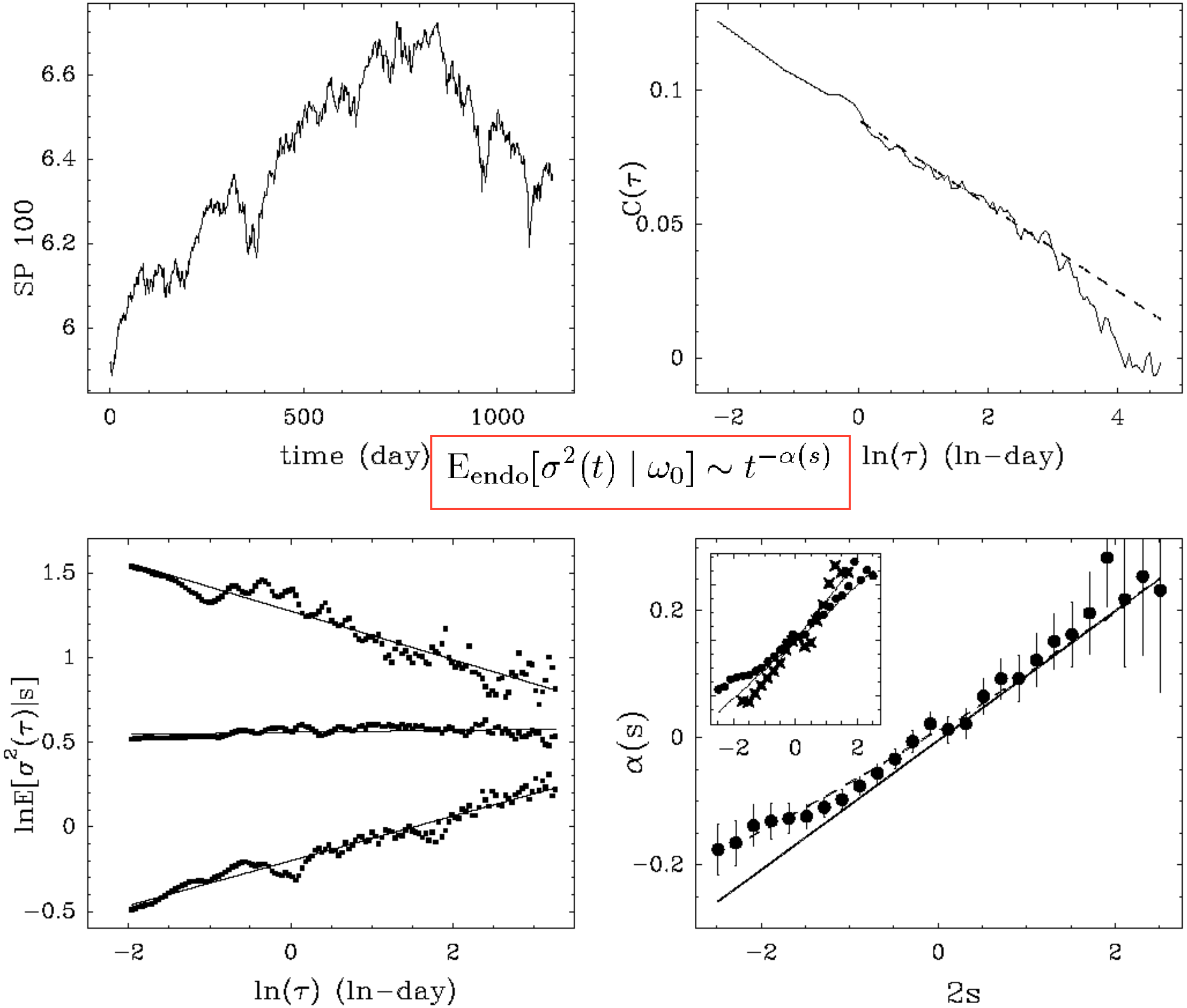
$$\alpha(s) = \frac{2s}{\ln\left(\frac{Te^{3/2}}{\Delta t}\right)},$$

$$\beta(t) = 2\lambda^2 \frac{\ln(t/\Delta t)}{\ln(Te^{3/2}/\Delta t)}$$

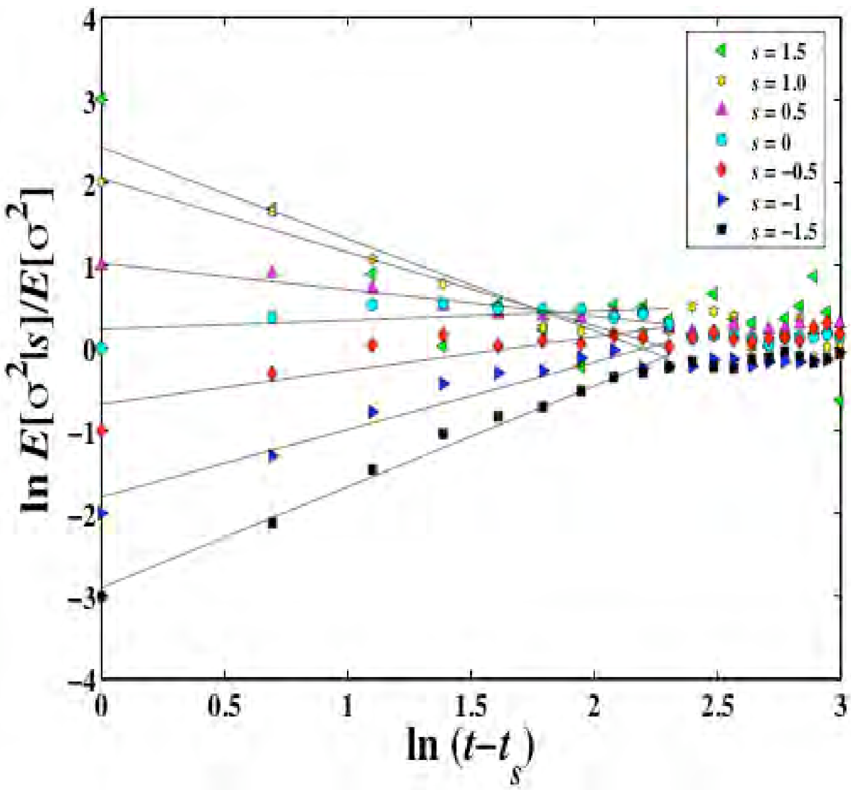
Within the range $\Delta t < t << \Delta t e^{\frac{|s|}{\lambda^2}}$, $\beta(t) << \alpha(s)$

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

Real Data and Multifractal Random Walk model



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



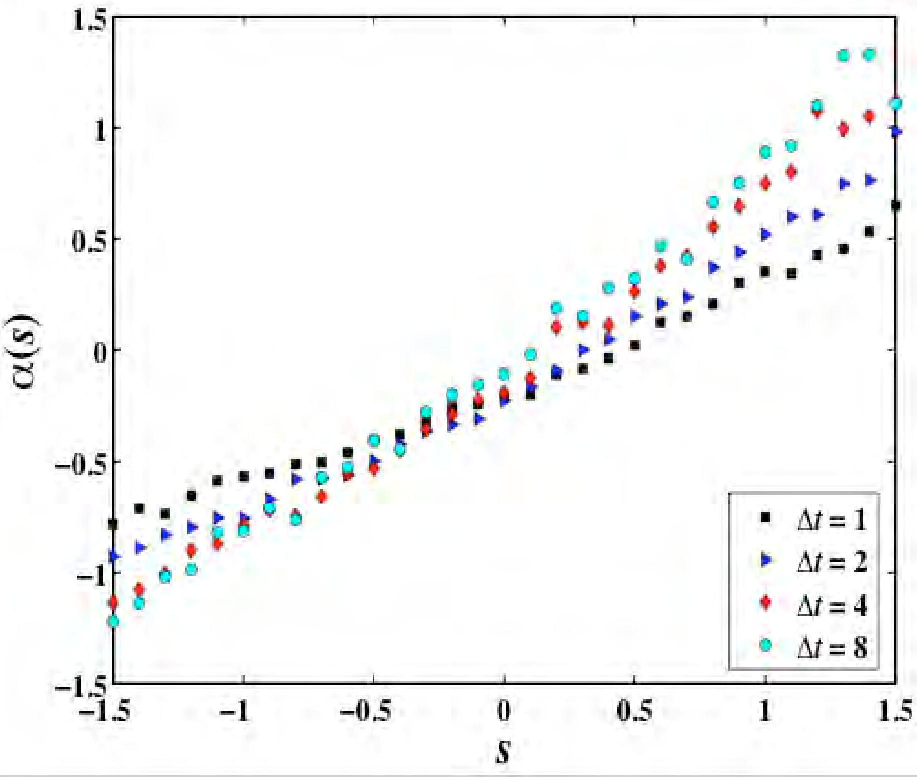
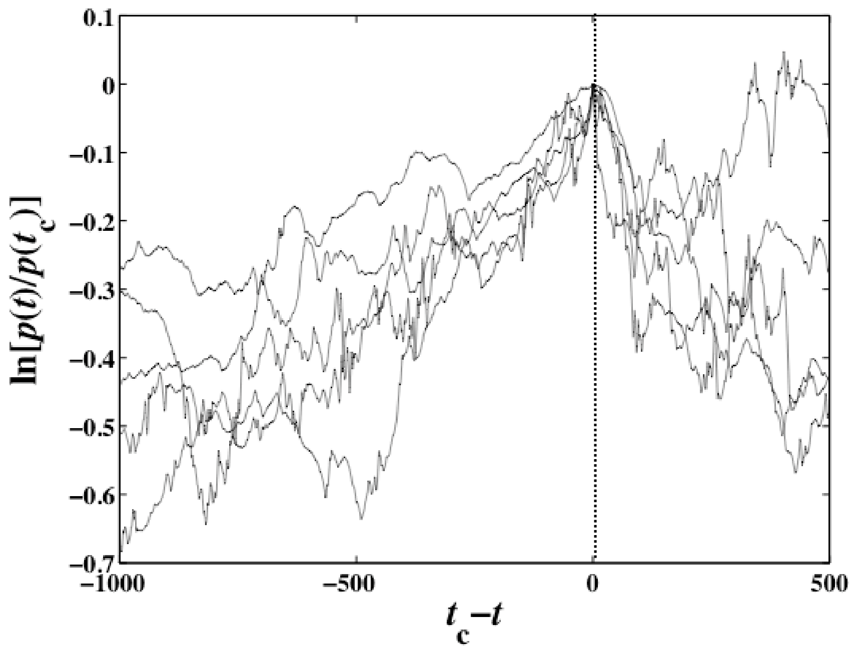


Fig. 12. Average normalized conditional volatility $\sigma^2_{\Delta t}(t)/E[\sigma^2]$ as a function of the time $t - t_s$ from the local burst of volatility at time t_s for different log-amplitudes s in double logarithmic coordinates.

Fig. 13. Exponent $\alpha(s)$ of the conditional volatility response as a function of the endogenous shock amplitude S for $\Delta t = 1, 2, 4,$ and 8.

Bubbles and crashes

Fig. 15. Five price trajectories showing bubbles preceding crashes that occur at the shifted time 0. The five time series have been translated so that the time of their crash is placed at the origin $t = 0$.



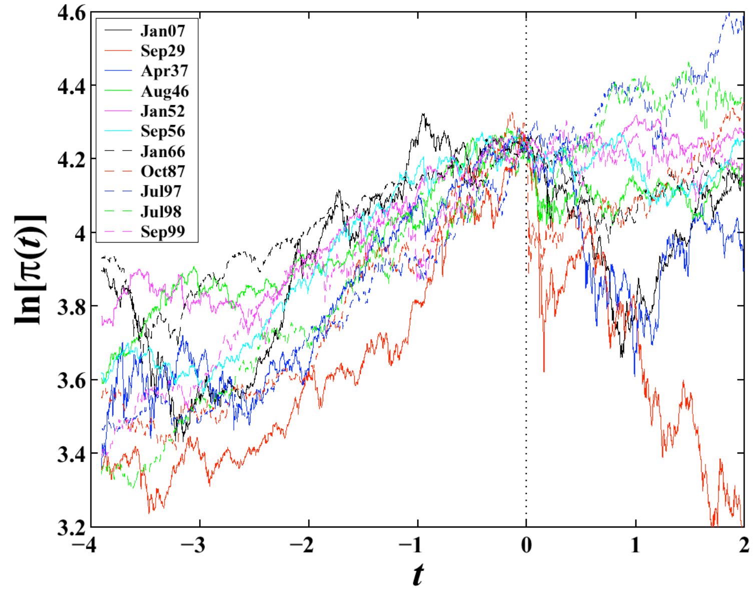


Figure 4: (Color online) Superposed epoch analysis of the 11 time intervals, each of 6 years long, of the DJIA index centered on the time of the maxima of the 11 predictor peaks above $AI = 0.3$ of the alarm index shown in Fig. 3.

D. Sornette and W.-X. Zhou
Predictability of Large Future Changes in major financial indices,
International Journal of Forecasting 22, 153-168 (2006)

All stylized facts are reproduced when

•The system operates close to the Ising critical point (large susceptibility and anomalous volatility: Shiller’s paradox)

•Agents over-interpret or mis-attribute the origin of price changes

No feedback of the price on the decision making process

INFORMATION: normal people's high level of general intelligence makes them too smart for their own good.

In 1909, a broker using the pseudonym Don Guyon wrote a small book called One-Way Pockets. He was utterly mystified as to why, after a full cycle of rise and fall after which stocks were valued just where they were at the start, all his clients lost money. His answer, in a nutshell, is herding. His clients felt fearful at the start of bull markets and so traded in and out constantly. At the market's peak, they felt confidently bullish and held much more stock "for the long run,"

Rats beat humans:

The rats and the humans had to look at a TV screen and press the lever anytime a dot appeared in the top half of the screen. The experimenters did not tell the human subjects that's' what they were supposed to do; they had to figure it out for themselves the same way the rats did. The experiment was set up so that 70% of the time the dot was in the top of the screen. Since there was no punishment for a wrong response, the smartest strategy was just to push the bar 100% of the time. That way, you get the reward 70% of the time, even though you have not clue of what is the pattern.

That's what the rats did.

But the humans never figured this out!
They kept trying to come up with a rule, so sometimes they pressed the bar and sometimes they would not, trying to figure it out. Some of them thought they had come up with a rule. But they were of course deluded and their performance was much less than the rats.

People makes STORIES! Normal people have an "interpreter" in their left brain that takes all the random, contradictory details of whatever they are doing or remembering at the moment, and smoothes everything in one coherent story. If there are details that do not fit, they are edited out or revised!

Temple Grandin and C. Johnson, Animals in translation (Scribner, New York, 2005)

Endogenous versus exogenous origins of financial bubbles and crashes

Georges Harras & Didier Sornette

http://arXiv.org/abs/0806.2989

http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1156348}

Opinion formation

$$\text{opinion}_i(t) = c_{1i} \cdot \sum_{j=1}^{J} k_{ij}(t-1) \cdot E_i[s_j(t)] + c_{2i} \cdot u(t-1) \cdot \text{news}(t) + c_{3i} \cdot \epsilon_i(t)$$

Trading decision

$$\begin{array}{llcl}
\text{- if opinion}_i(t) > |\text{opinion-th}_i| & : \; s_i(t) & = & +1 \\
 & \;\; a_i(t) & = & g \cdot \frac{cash_i(t)}{price(t-1)} \\
\text{- if opinion}_i(t) < -|\text{opinion-th}_i| & : \; s_i(t) & = & -1 \\
 & \;\; a_i(t) & = & g \cdot stocks_i(t),
\end{array}$$

Learning and adaptation

$$\begin{aligned}
u(t) &= \alpha \cdot u(t-1) + r(t) \cdot news(t-1) \cdot \frac{1-\alpha}{\sigma_r} \\
k_{ij}(t) &= \alpha \cdot k_{ij}(t-1) + r(t) \cdot E_i[s_j(t-1)] \cdot \frac{1-\alpha}{\sigma_r}.
\end{aligned}$$

Price clearing condition

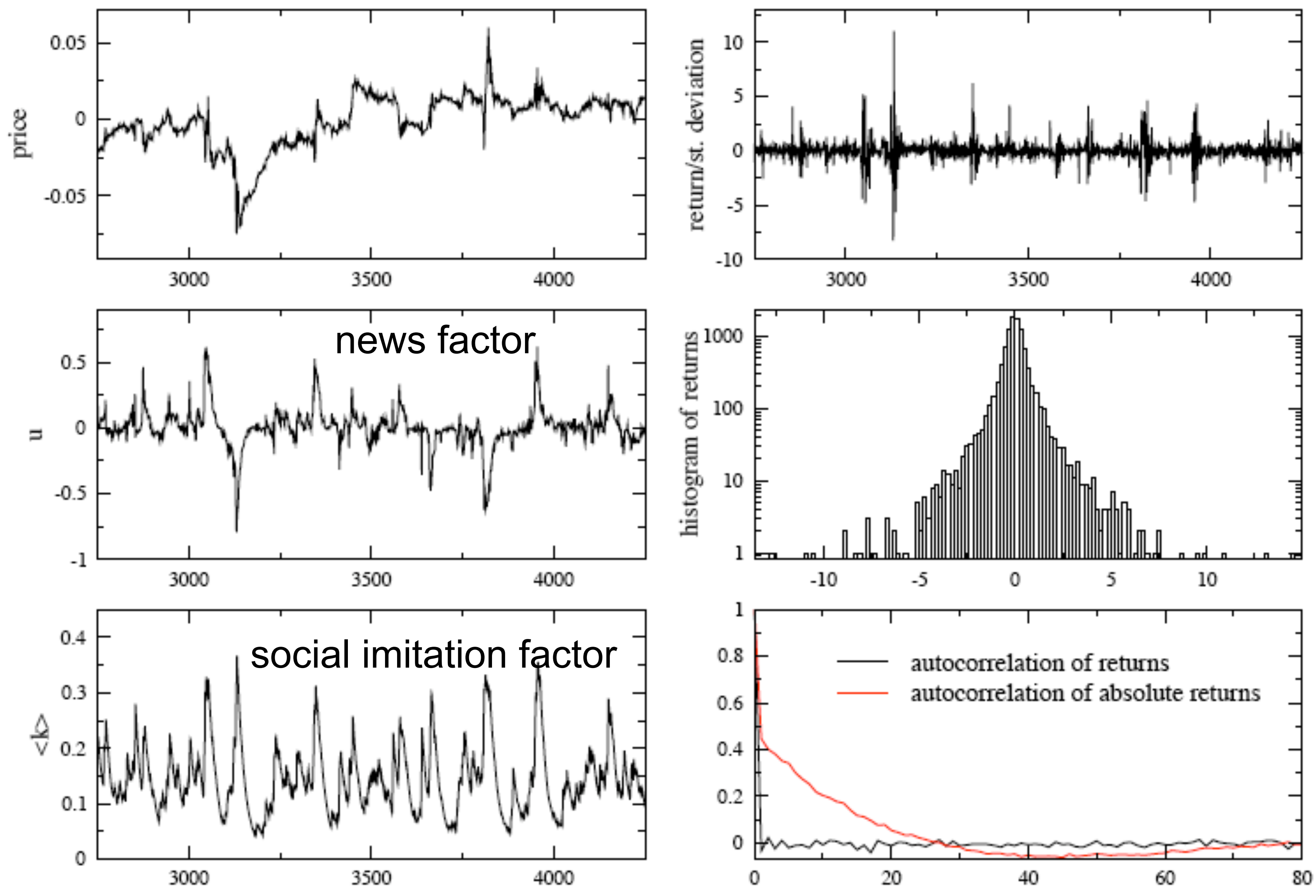
$$r(t) = \frac{1}{\lambda \cdot N} \sum_{i=1}^{N} s_i(t) \cdot a_i(t)$$

$$\log[\text{price}(t)] = \log[\text{price}(t-1)] + r(t),$$

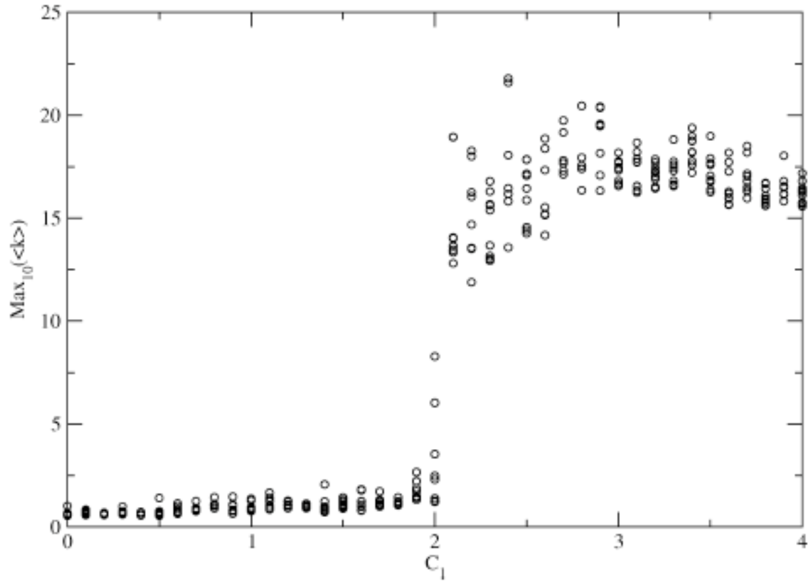
Wealth evolution

$$cash_i(t) = cash_i(t-1) - a_i(t) \cdot \text{price}(t)$$

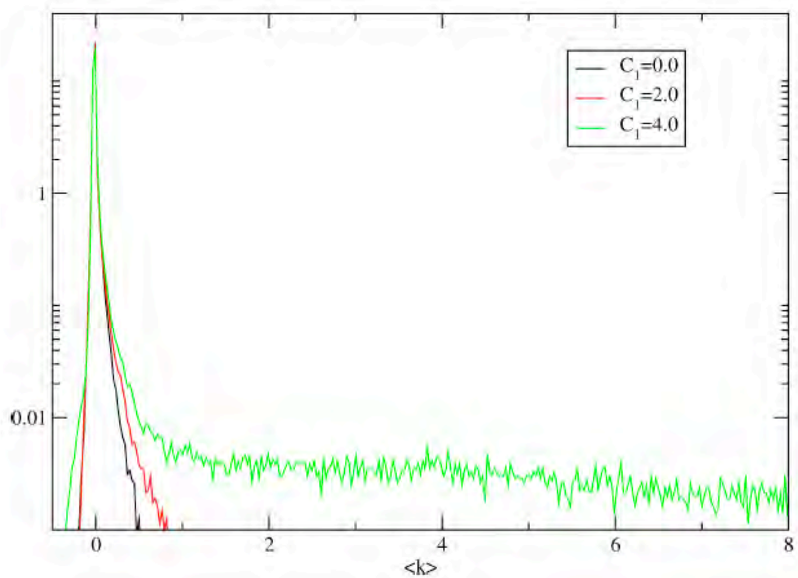
$$stocks_i(t) = stocks_i(t-1) + a_i(t).$$


price
return/st. deviation
news factor
u
histogram of returns
social imitation factor
<k>
autocorrelation of returns
autocorrelation of absolute returns

$$C_1 = C_2 = C_3 = 1.0$$

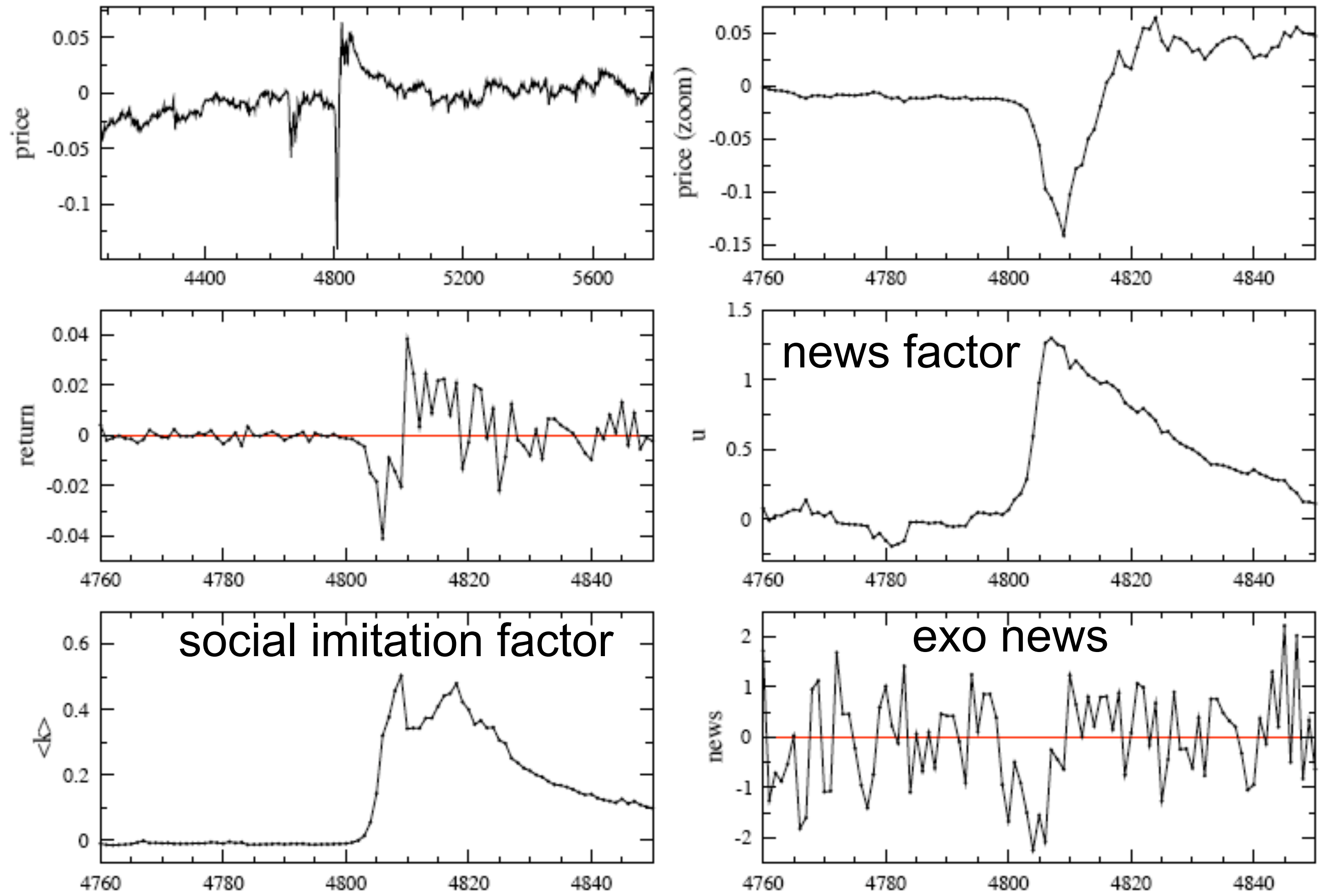


10 largest peaks in $< k > (t)$ for C_1 ranging from 0 to 4.



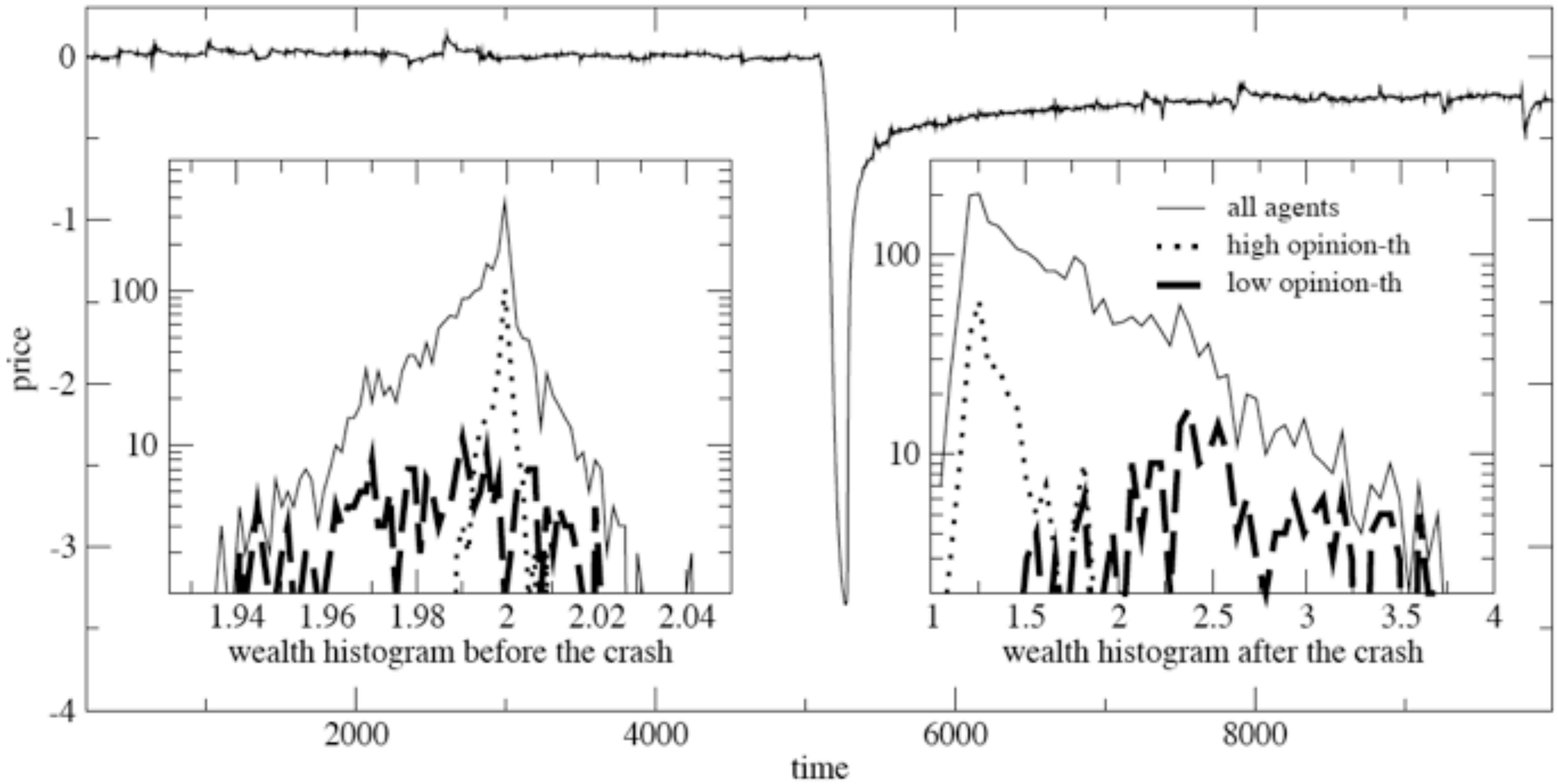
Normalised histogram of $< k >$ for different values of C_1.

NEWS IMPACT



Impact of the news to some values, generated with $C_1 = C_2 = C_3 = 1.0$.

- ENDO-EXO view of bubbles and crashes; Transient runs of news are sufficient to trigger large crashes in a system of over-learning and over-controlling agents



Price evolution for a system with $C_1 = 3.0$, $C_2 = C_3 = 1.0$ around a crash. The two insets show the histograms of the agents' wealth before (left inset) and after (right inset) the crash. The three curves correspond to agents with different values of their opinion threshold parameter 'opinion-th', as defined in section 2.4, which controls their risk aversion: continuous line (all agents); dotted line (agents with high 'opinion-th', i.e. high risk aversion); thick dashed line (agents with low 'opinion-th', i.e. low risk aversion).

Rational Expectation Bubbles and Crashes (Blanchard-Watson)

Martingale hypothesis ("no free lunch"):

$$\text{for all} \quad t' > t \qquad \mathrm{E}_t[p(t')] = p(t)$$

If crashes are depletions of bubbles:

$$dp = \mu(t)\, p(t)\, dt - \kappa[p(t) - p_1]dj$$

Martingale gives

$$\mu(t)p(t) = \kappa[p(t) - p_1]h(t) \ ,$$

i.e., if crash hazard rate $h(t)$ increases, so must the return (bounded rationality)

A. Johansen, D. Sornette and O. Ledoit
Predicting Financial Crashes using discrete scale invariance,
Journal of Risk, vol. 1, number 4, 5-32 (1999)

A. Johansen, O. Ledoit and D. Sornette, Crashes as critical points, International Journal of Theoretical and Applied Finance Vol. 3, No. 2 219-255 (2000)

Bubble with stochastic finite-time singularity due to positive feedbacks

$$\frac{dB(t)}{B(t)} = \mu dt + \sigma dW_t - \kappa dj$$

$$\mu(B)B = \frac{m}{2B}[B\sigma(B)]^2 + \mu_0[B(t)/B_0]^m$$
$$\sigma(B)B = \sigma_0[B(t)/B_0]^m \ ,$$

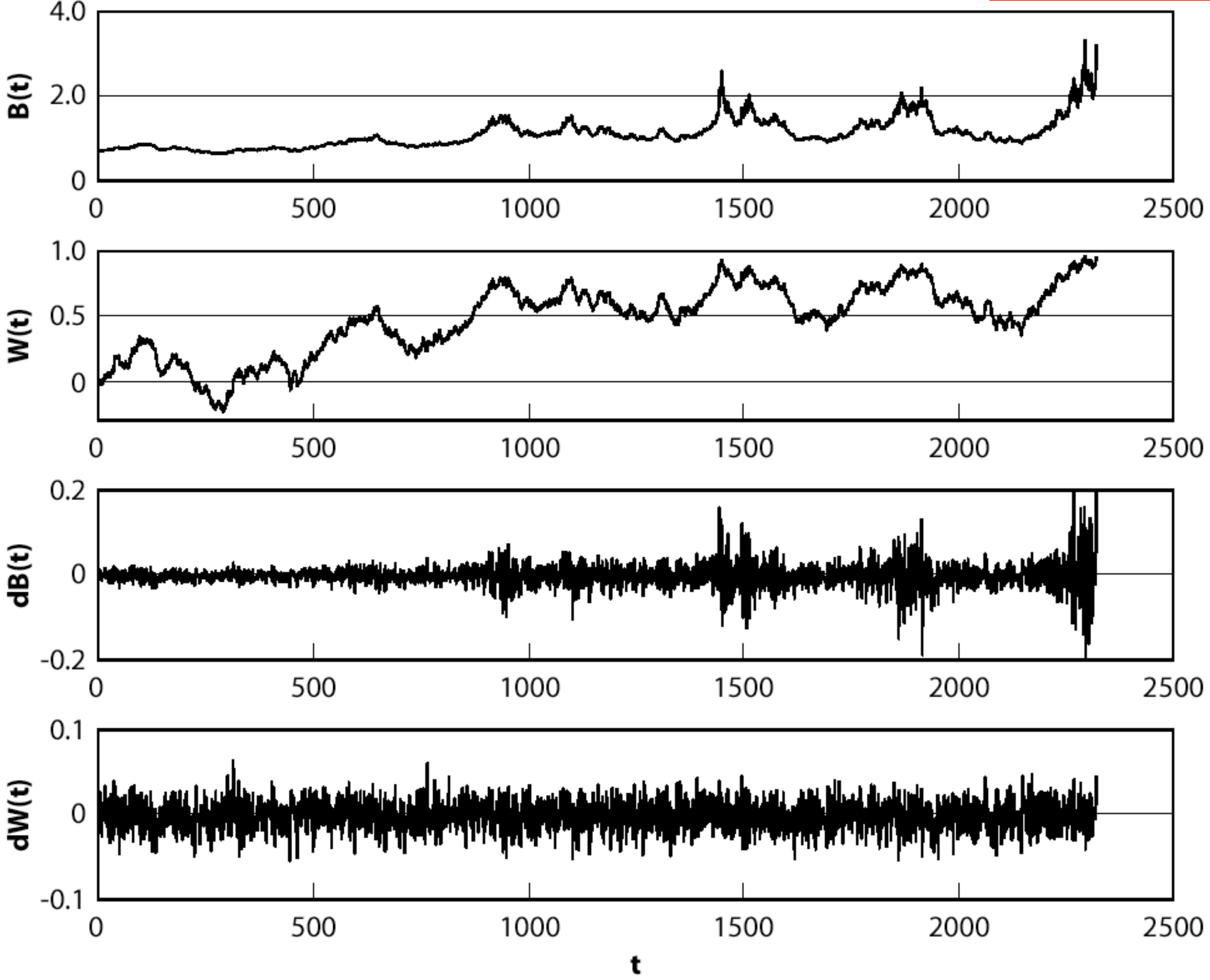
$$\frac{dB}{dt} = (a\mu_0 + b\eta)\ B^m - \kappa B dj \qquad h(t) = \frac{\mu(B(t))}{\langle\kappa\rangle}$$

$$B(t) = \alpha^\alpha \frac{1}{\left(\mu_0[t_c - t] - \frac{\sigma_0}{B_0^m} W(t)\right)^\alpha} \ , \quad \text{where } \alpha \equiv \frac{1}{m-1}$$

Stochastic finite-time singularity

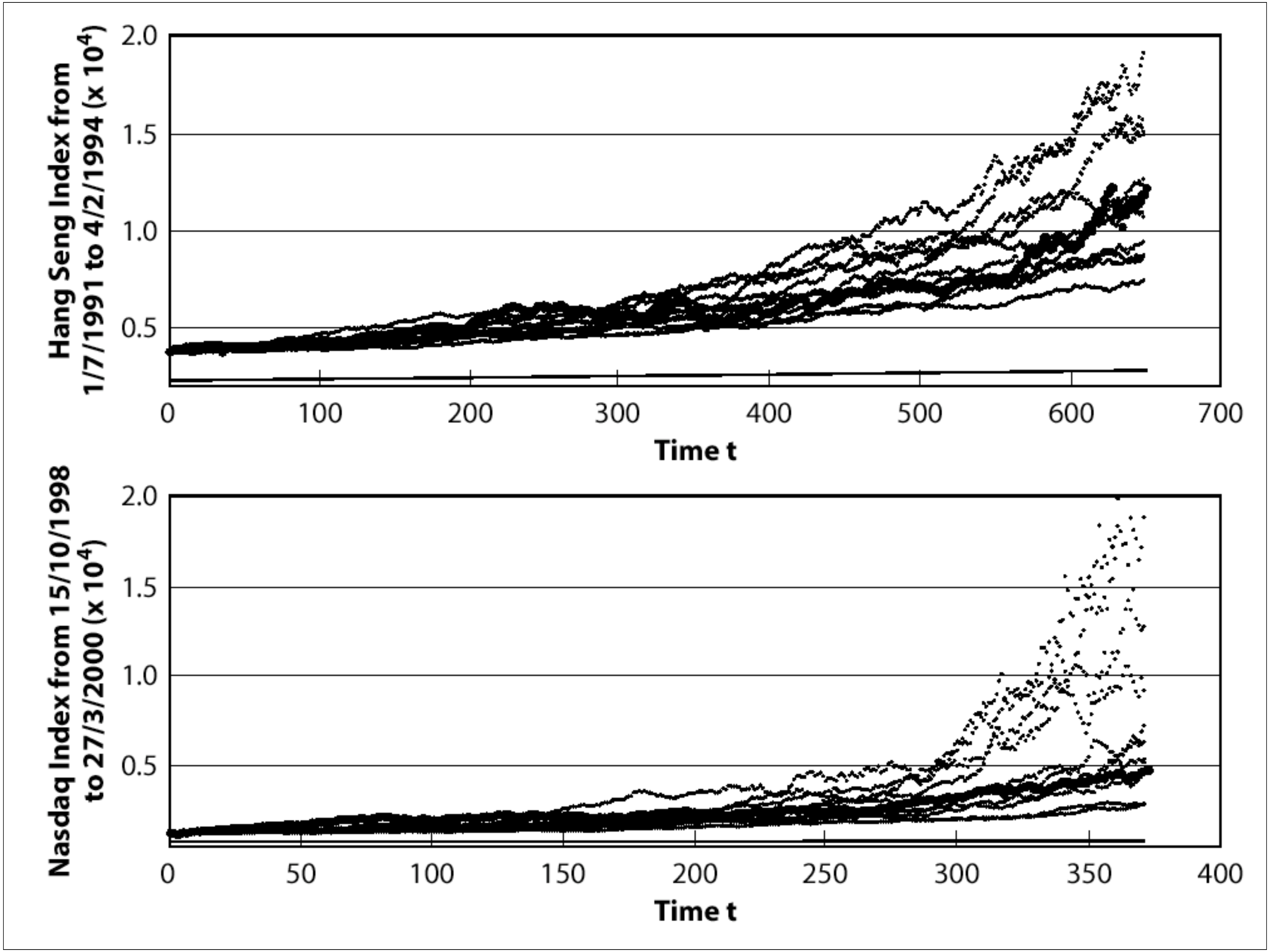
Nonlinear Super-Exponential Rational Model of Speculative Financial Bubbles

$$B(t) = \alpha^{\alpha} \frac{1}{(\mu_0[t_c - t] - (\sigma_0/B_0^m)W(t))^{\alpha}}$$



The price drives the crash hazard rate.

D. Sornette and J.V. Andersen
A Nonlinear Super-Exponential Rational Model of Speculative Financial Bubbles,
Int. J. Mod. Phys. C 13 (2), 171-188 (2002)



Hang Seng Index from 1/7/1991 to 4/2/1994 (x 10^4)
2.0
1.5
1.0
0.5
0
100
200
300
400
500
600
700
Time t
Nasdaq Index from 15/10/1998 to 27/3/2000 (x 10^4)
2.0
1.5
1.0
0.5
0
50
100
150
200
250
300
350
400
Time t

$$B(t) = \alpha^{\alpha} \frac{1}{(\mu_0[t_c - t] - (\sigma_0/B_0^m)W(t))^{\alpha}} \quad \text{where } \alpha \equiv 1/m - 1$$

Contains two ingredients:

(1) growth faster than exponential

(2) growth of volatility

$$\text{limit } 1/\alpha \rightarrow 0 \ (m \rightarrow 1)$$

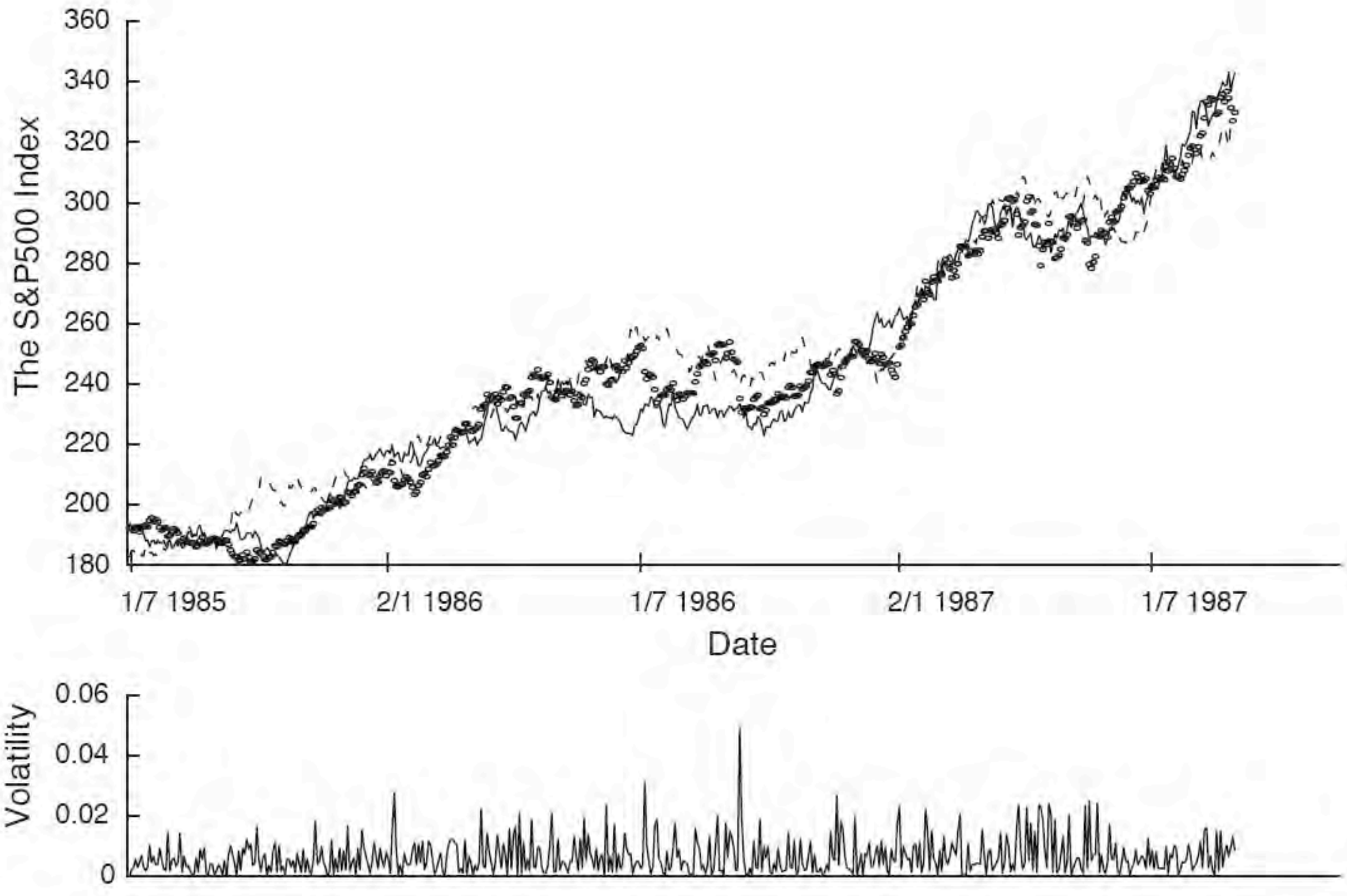
$$B_{BS}(t) = \exp(\mu_0 t + \sigma_0 W(t))$$ **Standard Geometric random walk**

Wilks' test of embedded hypotheses

Test of the existence of both ingredients

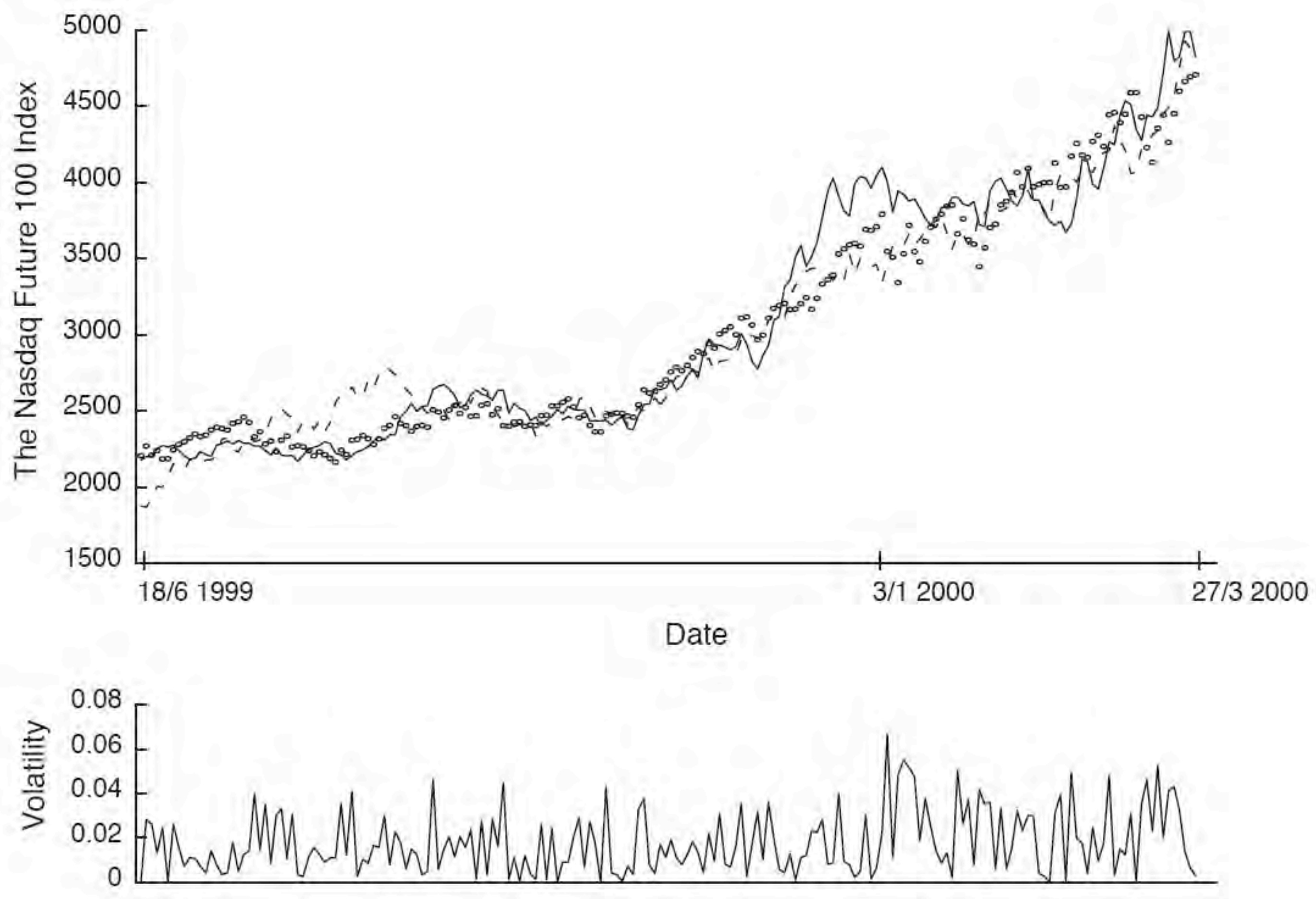
J.V. Andersen, D. Sornette / Physica A 337 (2004) 565–585

Example of a “fearful” super-exponential bubble



S&P 500 index from 1/7 1985 to 31/8 1987						
Percentage of 100 searches $P_{SB} = 0.70$, $P_{BS} = 0.28$						
Parameters of the curves in the figure	F	r	σ	μ	α	T_c
SB	110.64	2.0×10^{-5}	4.59×10^{-5}	7.36×10^{-4}	3.0	3390.54
BS	185.06	2.0×10^{-4}	7.81×10^{-5}	9.65×10^{-4}	–	–
T=183.71 Prob.(SB) > 0.9999						

Example of a "fearless" super-exponential bubble

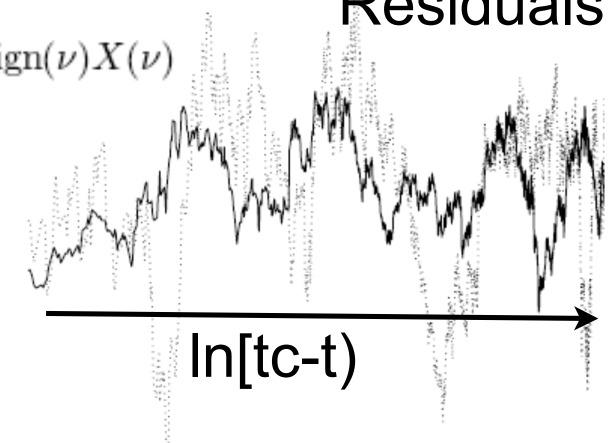


Nasdaq future 100 index from 18/6 1999 to 27/3 2000						
Percentage of 100 searches $P_{SB} = 0.03$, $P_{BS} = 0.97$						
Parameters of the curves in the figure	F	r	σ	μ	α	T_c
SB	1262.08	2.0×10^{-5}	8.89×10^{-5}	1.55×10^{-3}	1.0	368.34
BS	1845.20	1.60×10^{-4}	5.10×10^{-4}	3.73×10^{-3}	–	–
$T = -45.30$ Prob.(BS) > 0.9999						

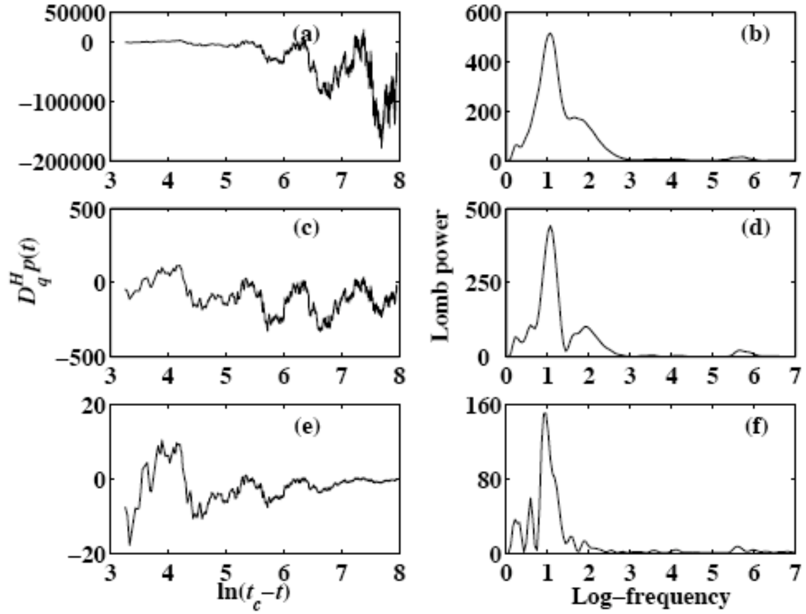
NONPARAMETRIC ANALYSES OF LOG-PERIODIC PRECURSORS TO FINANCIAL CRASHES (W.-X. Zhou and D. Sornette)

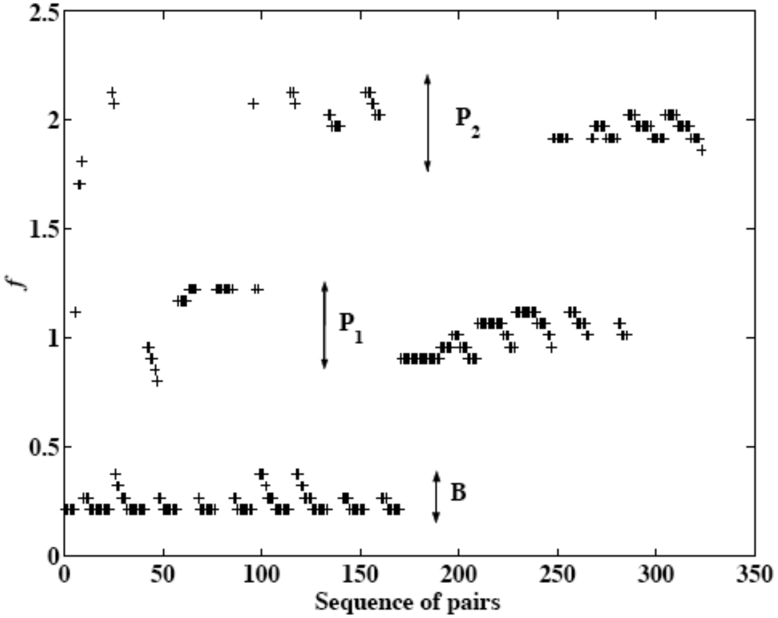
(H,q) derivatives and Hilbert transform

$$D_q^H f(x) \stackrel{d}{=} \frac{f(x) - f(qx)}{[(1-q)x]^H} \qquad \hat{x}(s) = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{x(t)}{s-t} dt \quad \hat{X}(\nu) = -j\ \mathrm{sign}(\nu) X(\nu)$$



(1) the Dow Jones Industrial Average, October 1987 Crash,
(2) the Dow Jones Industrial Average, October 1997 strong correction,
(3) the S&P 500 Index, October 1987 crash,
(4) the S&P 500 Index, October 1997 strong correction,
(5) the Nasdaq Index, October 1987 crash,
(6) the Nasdaq Index, October 1997 strong correction, and
(7) the Nasdaq Index, April 2000 crash.





International Journal of Modern Physics C 14 (8) (2003) 1107-1125.

$$I(t) = A + B(t_c - t)^z + C(t_c - t)^z \cos(\omega \log(t_c - t) - \phi)$$

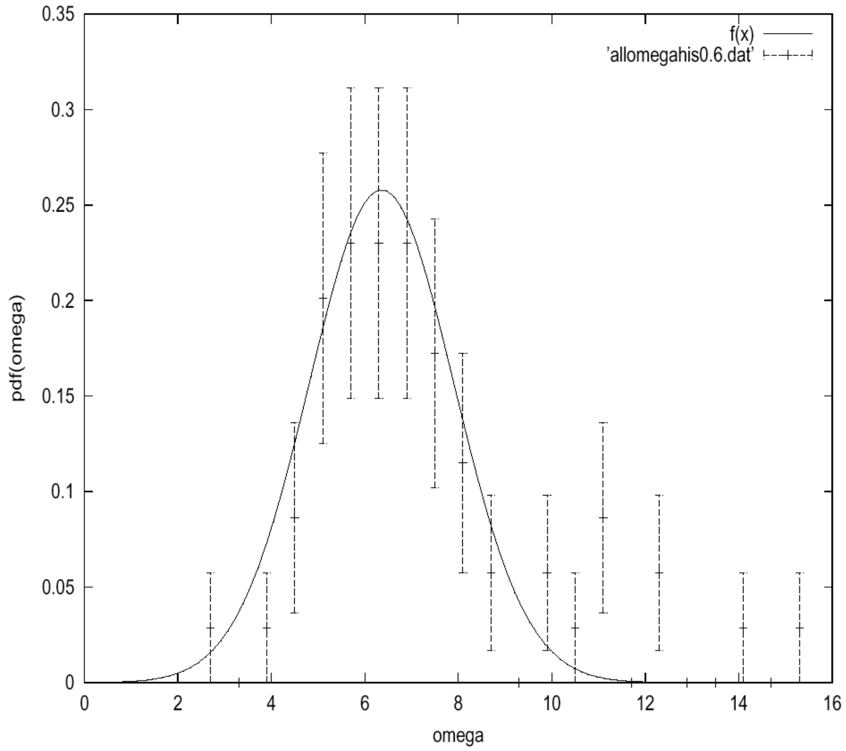


Figure 5: Empirical distribution of the log-periodic angular frequency ω in eq. (1) for over thirty case studies. The fit with a Gaussian distribution gives $\omega \approx 6.36 \pm 1.55$. The smaller peak centered on $11-12$ suggests the existence of a second discernable harmonics at $2\omega \approx 12$.

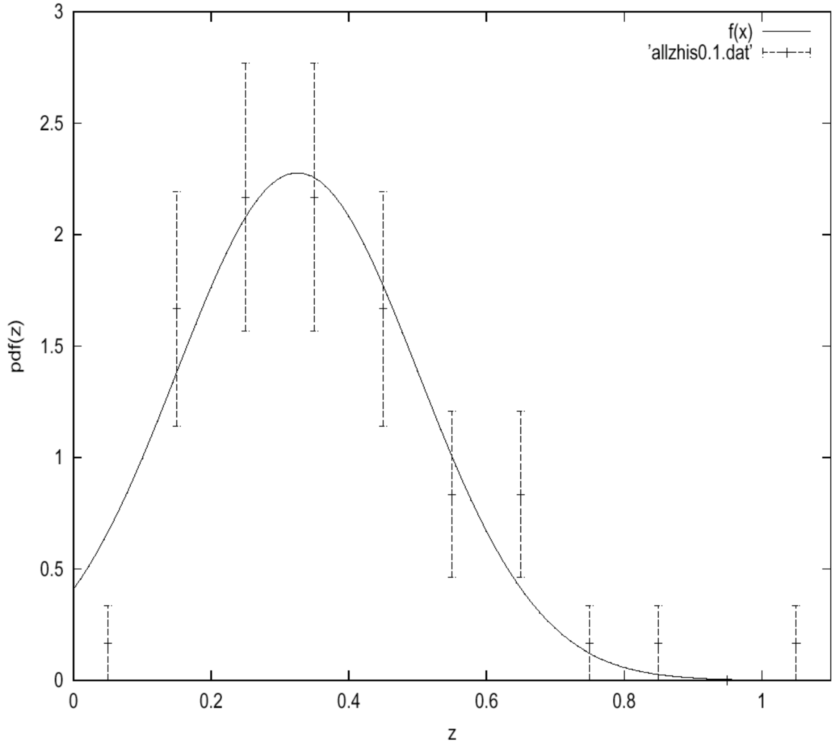


Figure 6: Empirical distribution of the exponent z of the power law in eq. (1) for over thirty case studies. The fit with a Gaussian distribution gives $\beta \approx 0.33 \pm 0.18$.

Demonstration of universal values of z and omega across many different bubbles at different epochs and different markets

A. Johansen and D. Sornette, Shocks, Crashes and Bubbles in Financial Markets, Brussels Economic Review (Cahiers economiques de Bruxelles), 49 (3/4), (2006)

DISCRETE HIERARCHY OF THE AGENT NETWORK

Presentation of three different mechanisms leading to discrete scale invariance, discrete hierarchies and log-periodic signatures

- Co-evolution of brain size and group size
  (Why do we have a big Brain?)

- Interplay between nonlinear positive and negative feedbacks and inertia

- Discrete scale invariance
  Complex fractal dimension
  Log-periodicity

Why do we have a big brain?

- Epiphenomenal hypothesis: large brains are unavoidable consequences of a large body
- Developmental hypothesis: maternal energy constraints determine energy capacity for fetal brain growth (frugivory=richer diet)
- Ecological hypothesis: brain evolved to process information of ecological relevance (frugivory, home range navigation, extractive foraging)
- Social hypothesis: brain size constrains size of social network (group size) (memory on relationships, social skills) (Prof. R. Dunbar)

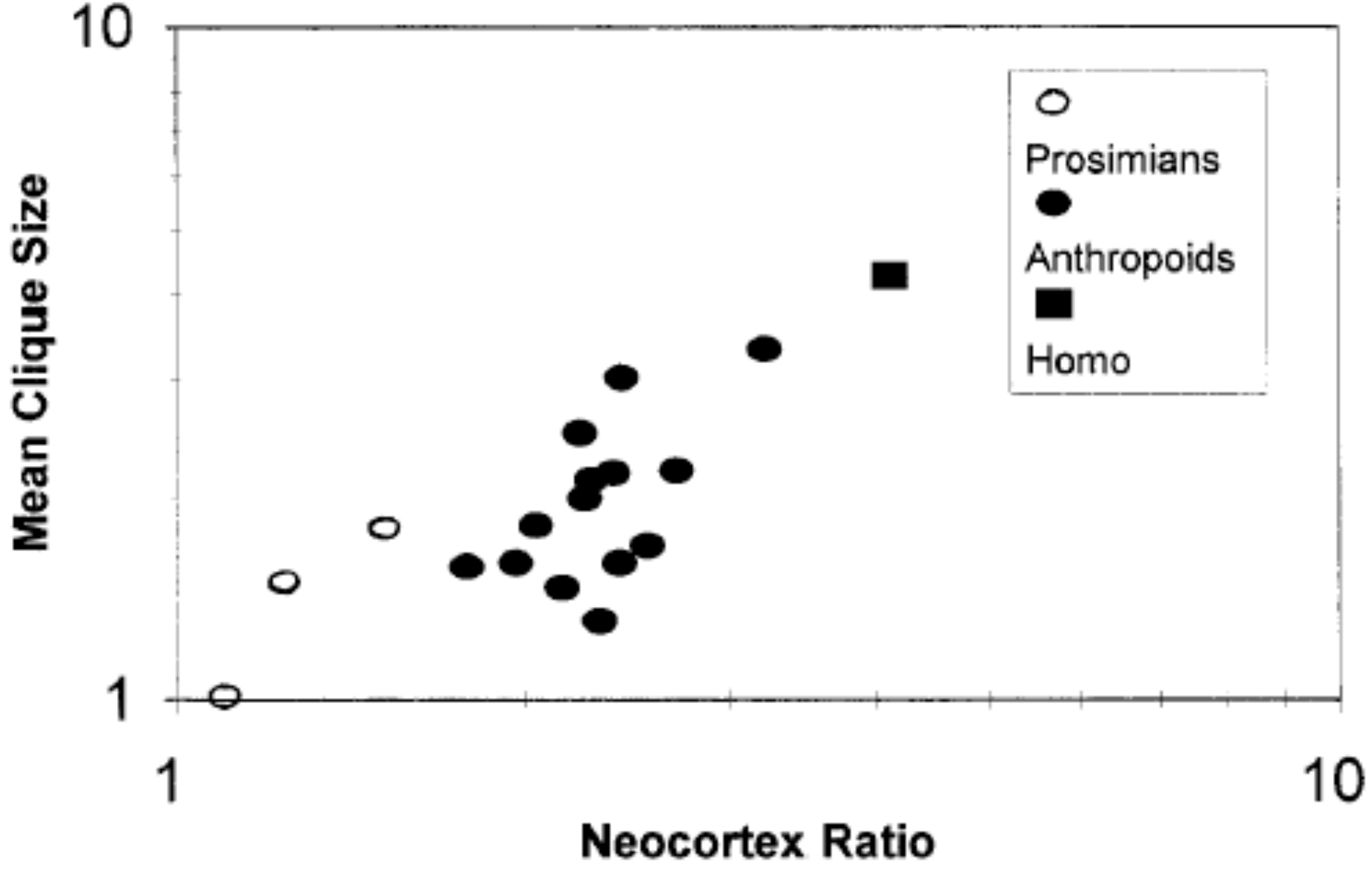


Figure 6. Mean grooming clique size plotted against mean neocortex ratio for individual primate genera. The square is *Homo sapiens*. Species sampled are *L. catta, L. fulvus, Propithecus, Indri, S. sciureus, C. apella, C. torquatus, A. geoffroyi, A. fusciceps, P. badius, P. entellus, P. pileata, P. johnii, C. campbelli, C. diana, C. aethiops, C. mitis, E. patas, M. mulatta, M. fuscata, M. arctoides, M. sylvana, M. radiata, P. anubis, P. ursinus, P. cynocephalus, P. hamadryas, T. gelada, P. troglodytes, P. paniscus.* (Redrawn from Kudo, Lowen, and Dunbar,[51] Fig. 4a.)

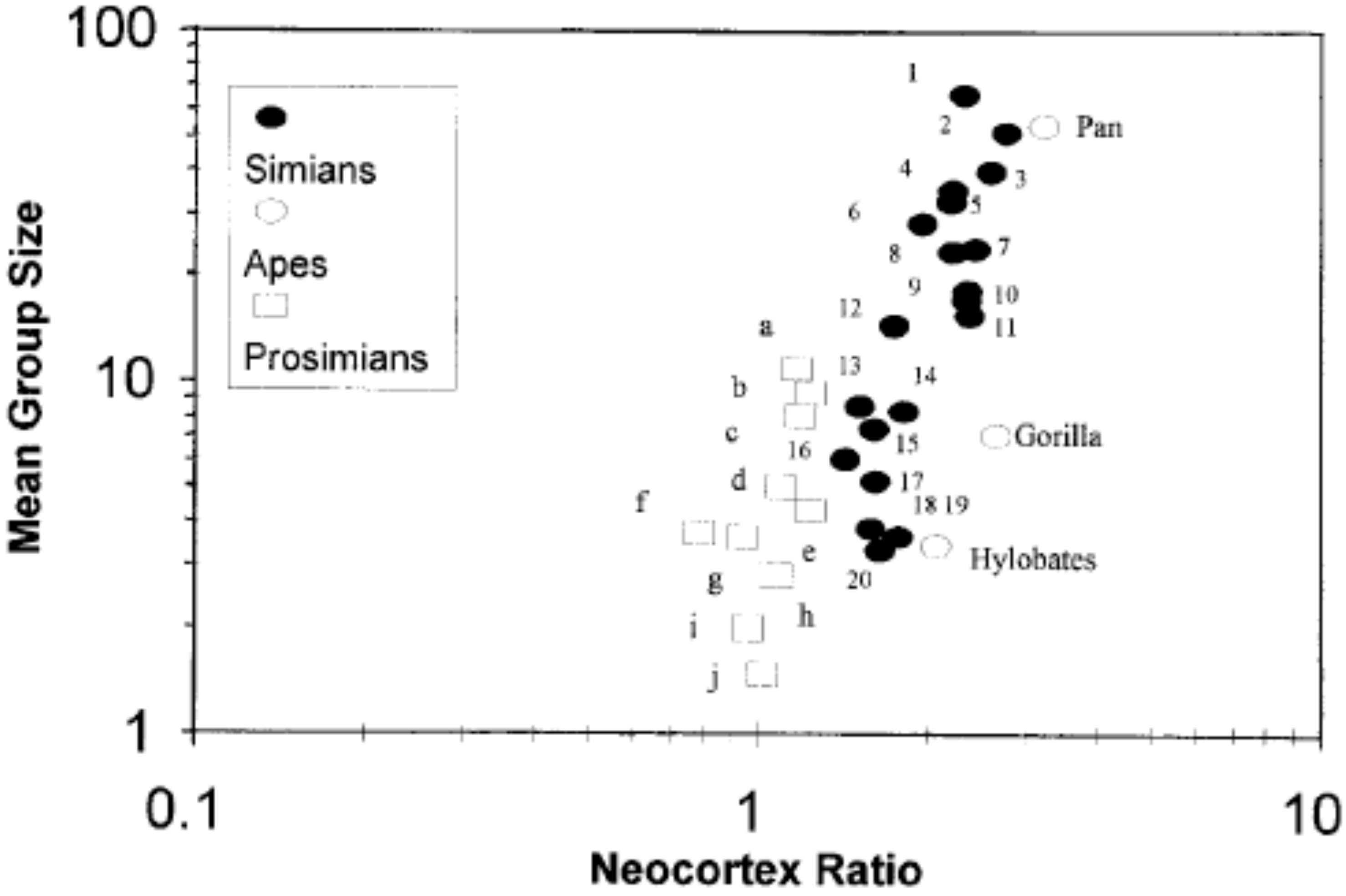
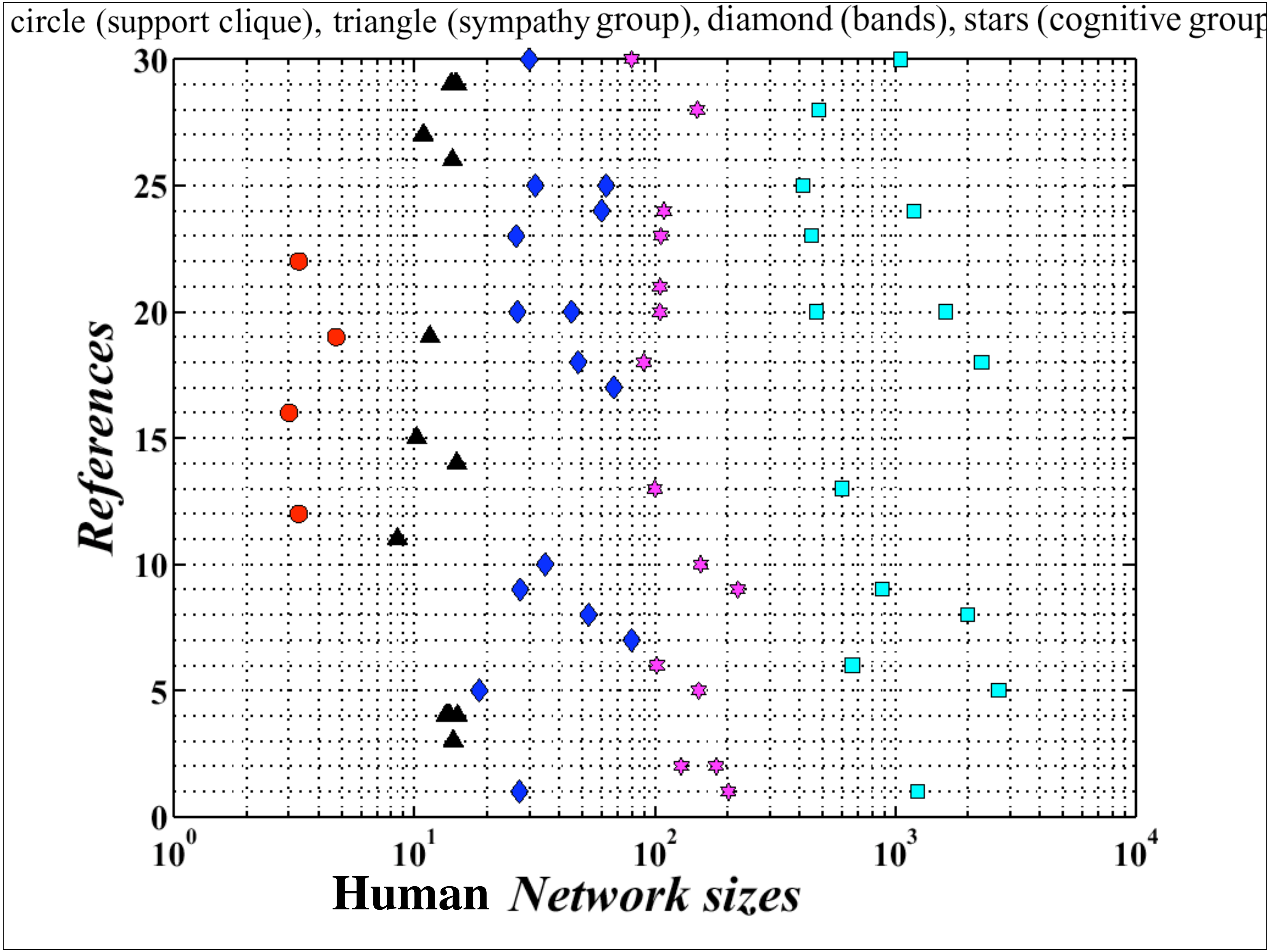


Figure 3. Mean group size plotted against neocortex ratio for individual genera, shown separately for prosimian, simian, and hominoid primates. Prosimian group size data, from Dunbar and Joffe,[25] include species for which neocortex ratio is estimated from total brain volume. Anthropoid data are from Dunbar.[24] Simians: 1, *Miopithecus;* 2, *Papio;* 3, *Macaca;* 4, *Procolobus;* 5, *Saimiri;* 6, *Erythrocebus;* 7, *Cercopithecus;* 8, *Lagothrix;* 9, *Cebus;* 10, *Ateles;* 11, *Cercocebus;* 12, *Nasalis;* 13, *Callicebus;* 14, *Alouatta;* 15, *Callimico;* 16, *Cebuella;* 17, *Saguinus;* 18, *Aotus;* 19, *Pithecia;* 20, *Callicebus.* Prosimians: a, *Lemur;* b, *Varecia;* c, *Eulemur;* d, *Propithecus;* e, *Indri;* f, *Microcebus;* g, *Galago;* h, *Hapalemur;* i, *Avahi;* j, *Perodictus.*

Dunbar (1998)

Source	Support Clique	Sympathy group	Camp	Village	Tribe
[11]	3.01				
[12]	3.3				
[13]	4.47	11.6			
[14]	3.30				
[15]		10.9			
[16]		14.0/15.1/13.5/13.8			
[17]		$8 \sim 9$			
[18]		14.5			
[19]		10.2			
[20, 21]		15			
[22, 23]		15.0/14.3/14.8/14.2			
[24]		14.4			
[25]			25-30	221.5	886
[26]			27.3	202.5	1237.3
[27]			48	90	2290
[28]			26.5	53-159	450
[29]			60	109.1	1200
[30]			26.8/40-50	90-120	471/1625
[31]			21-85		2000
[32]			18.6	152.3	2693
[33]			25-35	60-100	1050
[34]			31.8/62.7		413
[35]			10-60	60-250	
[36]			50-75		
[37]			40-120		
[38]				128.7/180	
[39, 40]				60-150	
[41]				150	483
[42]				100	600
[43]				101.9	663

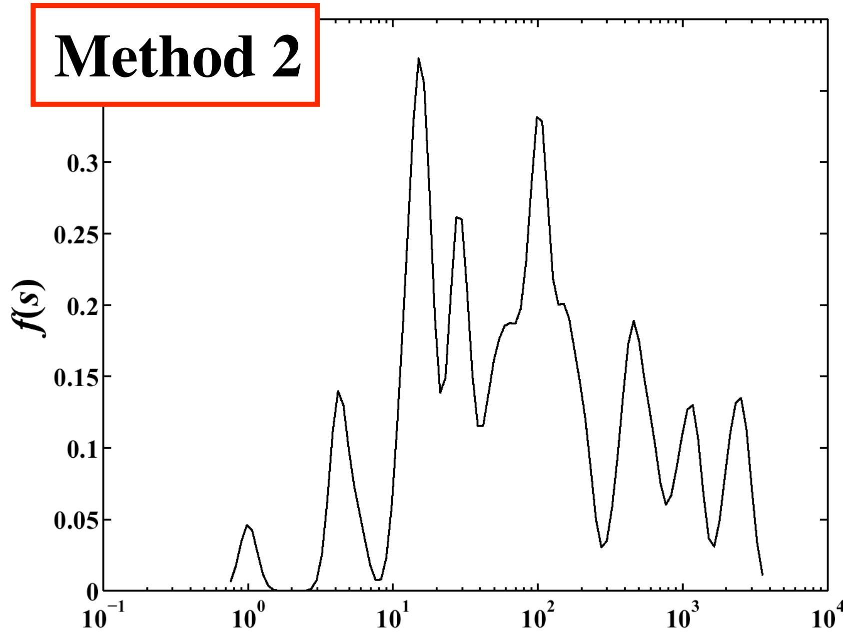

circle (support clique), triangle (sympathy group), diamond (bands), stars (cognitive group
30
25
20
15
10
5
0
References
10^0
10^1
10^2
10^3
10^4
Human Network sizes

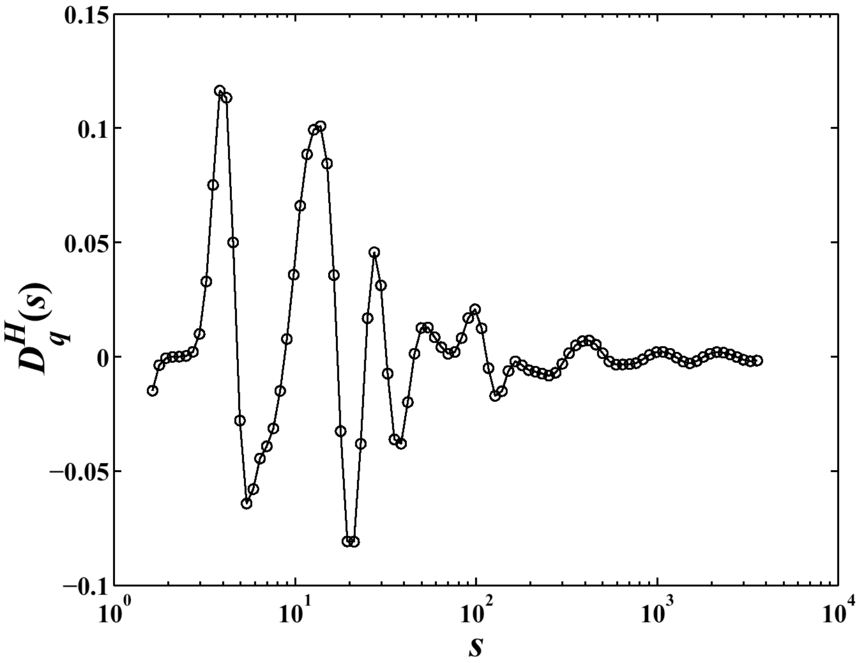
Method 1: Average sizes of different network layers. To summarize the previously cited data, we denote S_1 as the mean support clique size, S_2 the mean sympathy group, S_3 the mean band size, S_4 the mean cognitive group size, and S_5 and S_6 the size of small and large tribes. Here, we do not address the relevance of this classification (which will be done below) but only characterize it quantitatively. The previously cited data gives $S_0 = 1$ (individual or ego), $S_1 = 4.6$, $S_2 = 14.3$, $S_3 = 42.6$, $S_4 = 132.5$, $S_5 = 566.6$, and $S_6 = 1728$. In order to determine the possible existence of a discrete hierarchy, we construct the series of ratios S_i/S_{i-1} of successive mean sizes:

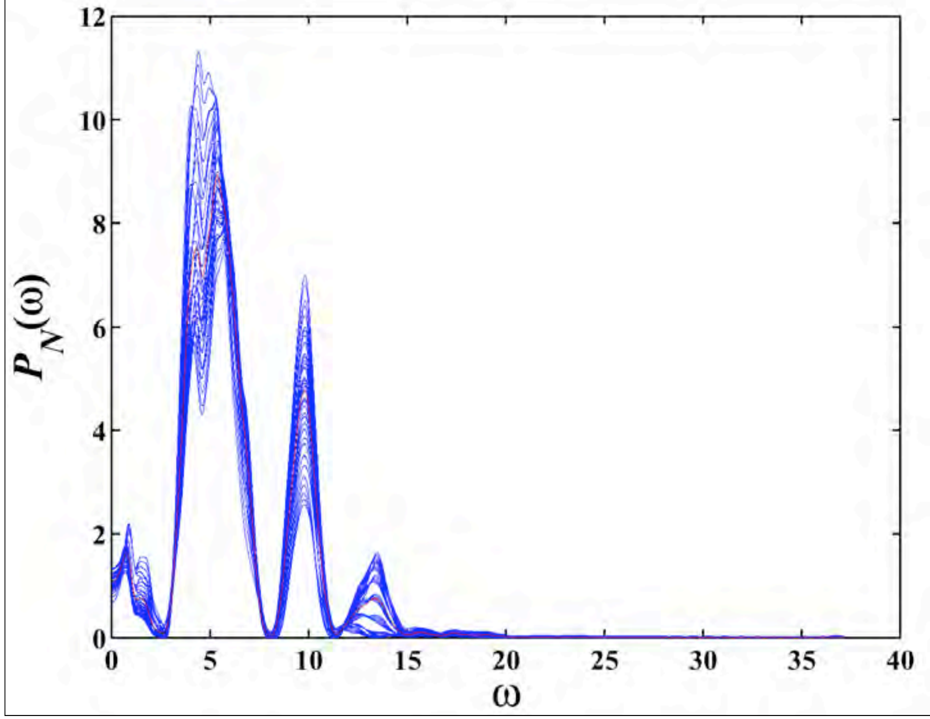
$$S_i/S_{i-1} = 4.58, 3.12, 2.98, 3.11, 4.28, 3.05 \,, \quad \text{for } i = 1, \cdots, 6 \,. \qquad (1)$$

This result suggests that humans form groups according to a discrete hierarchy with a prefered scaling ratio between 3 and 4: the mean of S_i/S_{i-1} is 3.50.

Method 2







Non-parametric analysis of human group sizes demonstrating the existence of a discrete hierarchy

Preferred scaling ratio close to 3

Discrete Hierarchical Organization of Social Group Sizes

W.-X. Zhou[1], D. Sornette[1,2,3], R.I.M. Dunbar[4] and R. Hill[5]

Proc. Royal Soc. London 272, 439-444 (2005)

Method 3: Probability density function and generalised q-analysis of individual networks. We apply the same analysis to individual social networks based upon the exchange of Christmas cards in contemporary Western Society.

Hill, R.A. and Dunbar, R.I.M., *Human Nature* **14**. 53-72 (2003).

$$D_q^H f(x) \stackrel{d}{=} \frac{f(x) - f(qx)}{[(1-q)x]^H}$$

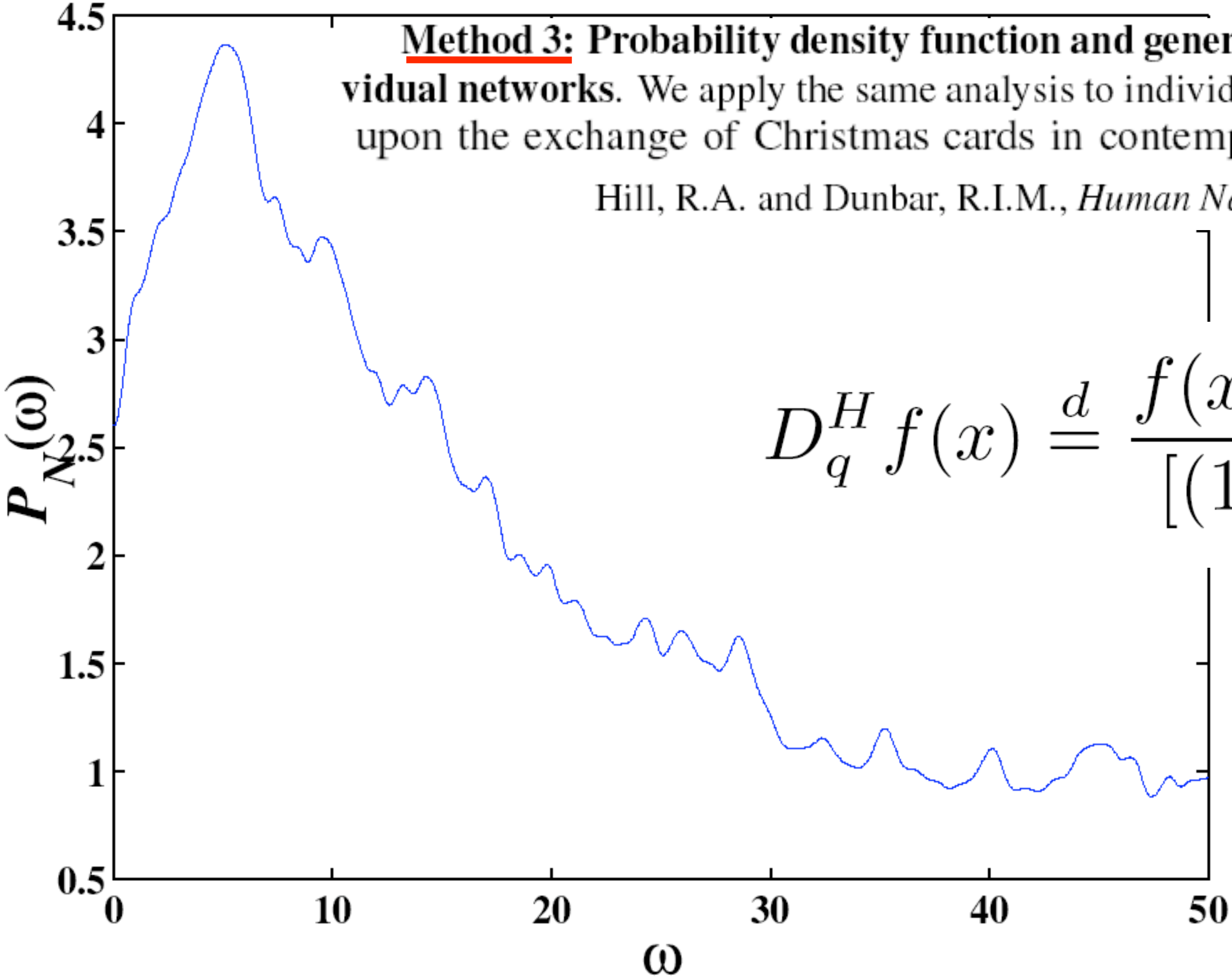


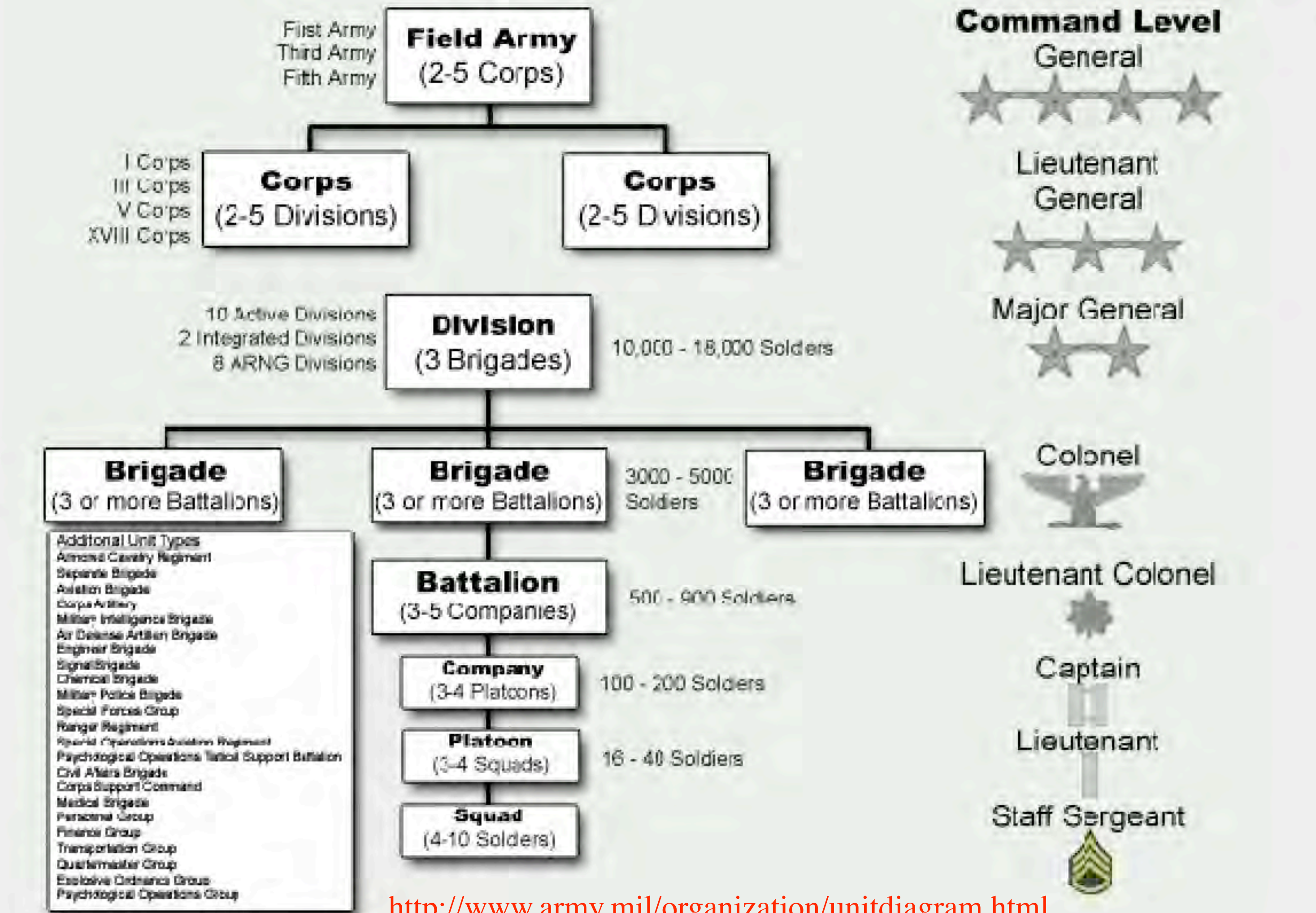
Figure 5: Average Lomb periodogram $P_N(\omega)$ of the (H,q)-derivative $D_q^H(s)$ with respect to the number of receivers of the residual contact frequency for each individual in the Christmas card experiment, as a function of the angular log-frequency ω of the (H,q)-derivative, over the 42 individuals and different pairs of (H,q) with $-1 \le H \le 1$ and $0.80 \le q \le 0.95$.

A real-life example of a hierarchical network

- Sections (squads): 10-12 soldiers
- Platoons (of 3 sections, ≈ 35 soldiers)
- Companies (3-4 platoons, ≈ 120-150 soldiers)
- Battalions (3-4 companies plus support units, ≈ 550-800)
- Regiments (or brigades) (3 battalions plus support,2500+)
- Divisions (3 regiments)
- Corps (2-3 divisions)
- Armies
- Country

Operational Unit Diagram

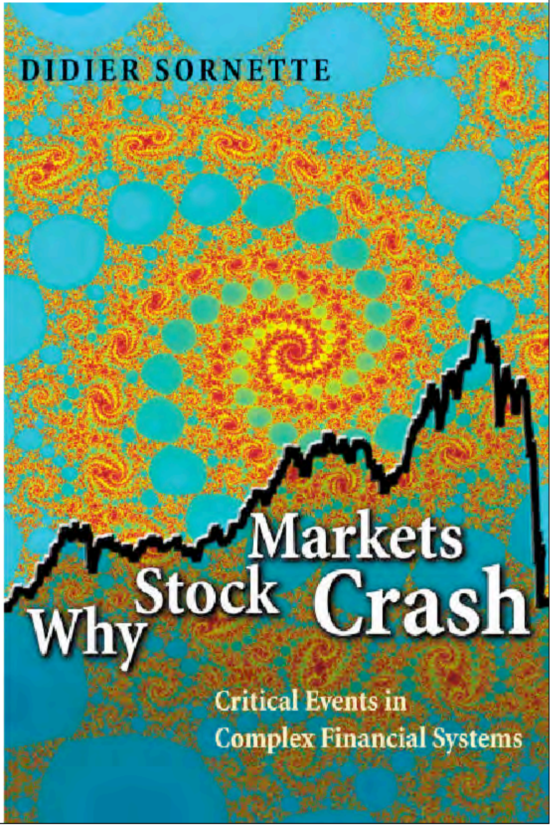
This diagram provides information on how Army operational units are organized - from the Theater Army, Field Army and Army Group level, down through Corps, Divisions, Brigades, Battalions, Companies, Platoons and ending with Squads & Sections - and the typical rank of the Commander of these type units. It also provides a listing of additional unit types that don't fall cleanly into this hierarchal structure. A short description of each organization is provided when you select a box, or when you select one of the additional unit types.



http://www.army.mil/organization/unitdiagram.html

Summary

- Discrete social hierarchies may be deeply rooted in the cognitive processing abilities of human brains.
- We suggest that this has observable consequences, such as in financial markets.
- Implications for the optimization of
  - Corporate management
  - Politics
  - Departments and universities



DISCRETE HIERARCHY OF THE AGENT NETWORK

Presentation of three different mechanisms leading to discrete scale invariance, discrete hierarchies and log-periodic signatures

- Co-evolution of brain size and group size
  (Why do we have a big Brain?)

- Interplay between nonlinear positive and negative feedbacks and inertia

- Discrete scale invariance
  Complex fractal dimension
  Log-periodicity

Oscillatory finite-time singularity

Another mechanism of LPPL (log-periodic power law)

The balance between supply and demand determines the price variation from $p(t)$ to $p(t+\delta t)$ over the time interval δt according to [Farmer, 1998]

$$\ln p(t+\delta t) - \ln p(t) = \frac{1}{L}[\Omega_{\mathrm{value}}(t) + \Omega_{\mathrm{tech}}(t)] \quad (10)$$

Fundamental value strategies

$$\Omega_{\mathrm{value}}(t) = -c \ \ln[p(t)/p_f] \, |\ln[p(t)/p_f]|^{n-1}$$

Technical analysis strategies

$$\Omega_{\mathrm{tech}}(t) = a_1[\ln p(t) - \ln p(t-\delta t)]$$
$$+a_2[\ln p(t) - \ln p(t-\delta t)] | \ln p(t) - \ln p(t-\delta t)|^{m-1}$$

Inertia + NL negative feedback + NL positive feedback

The essential element is the nonlinear (NL) nature (threshold like) of the fundamental valuation-based and of the technical analysis-based strategies

The theory becomes critical when the "mass" term vanishes, i.e., when $a_1 = L$. Rescaling t and y_1 by α and posing $y_2 = dY_1/dt$ and $\gamma = \alpha^{-(n+1)} c/L(\delta t)^2$ where $\alpha \equiv a_2 (\delta t)^{m-2}/L$, we obtain

$$\frac{dy_1}{dt} = y_2 \ ,$$

$$\frac{dy_2}{dt} = \alpha y_2 |y_2|^{m-1} - \gamma y_1 |y_1|^{n-1}$$

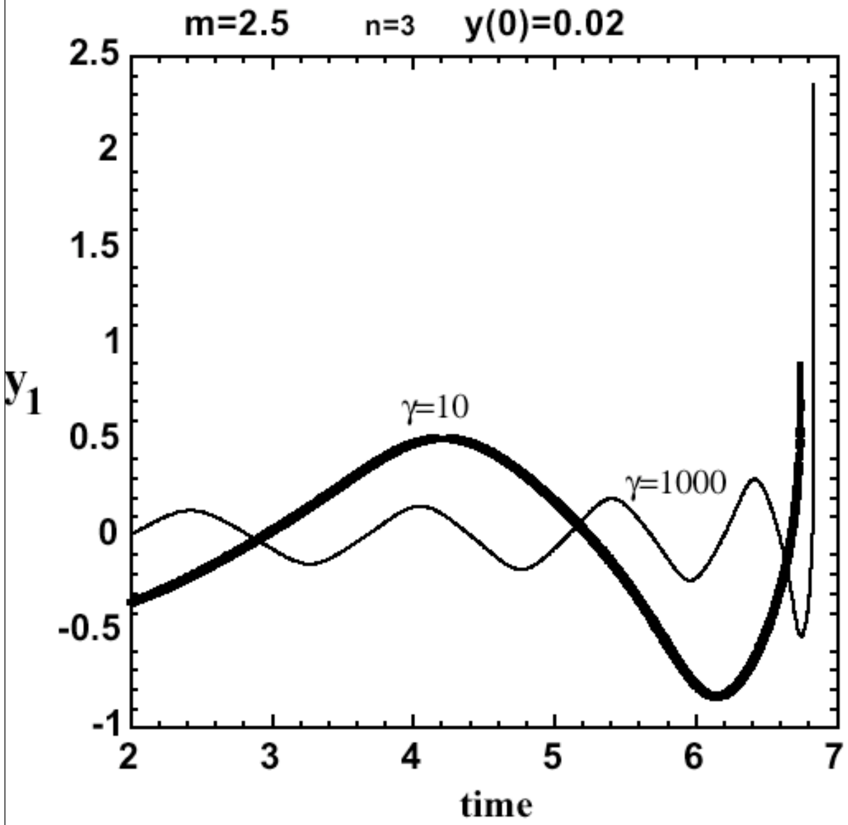
or

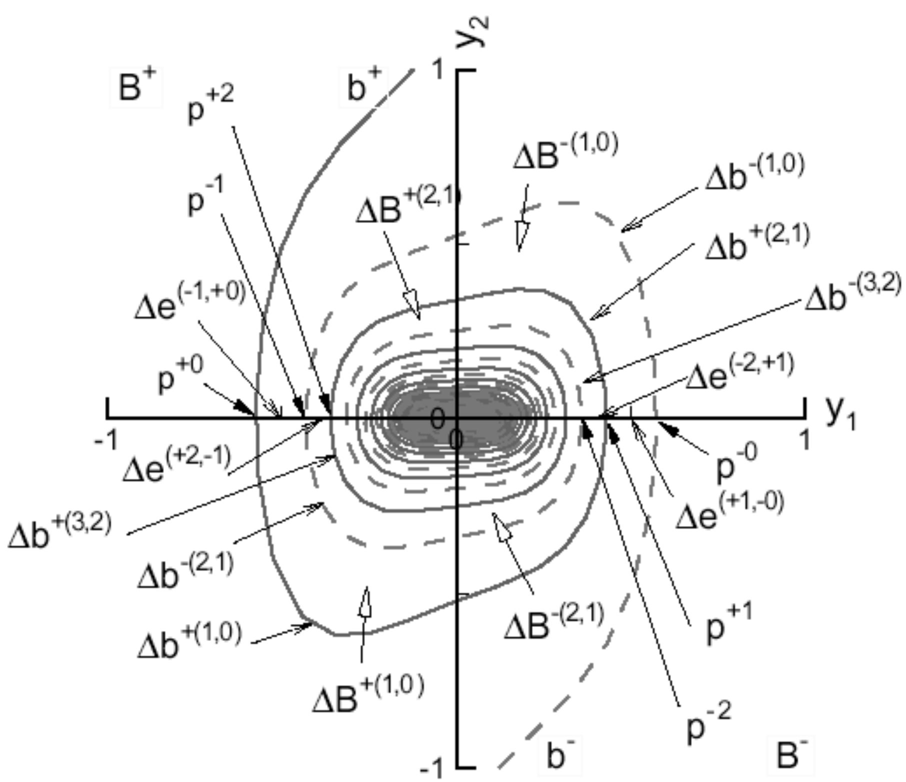
$$\frac{d^2 y_1}{dt^2} = -\gamma y_1 |y_1|^{n-1} + \alpha \frac{dy_1}{dt} \left| \frac{dy_1}{dt} \right|^{m-1}$$

Oscillatory finite-time singularity

-Non-linear fundamental value strategies
-Non-linear technical analysis strategies
-Inertia

K. Ide and D. Sornette
Oscillatory Finite-Time Singularities in Finance, Population and Rupture,
Physica A 307 (1-2), 63-106 (2002)





DISCRETE HIERARCHY OF THE AGENT NETWORK

Presentation of three different mechanisms leading to discrete scale invariance, discrete hierarchies and log-periodic signatures

- Co-evolution of brain size and group size
  (Why do we have a big Brain?)

- Interplay between nonlinear positive and negative feedbacks and inertia

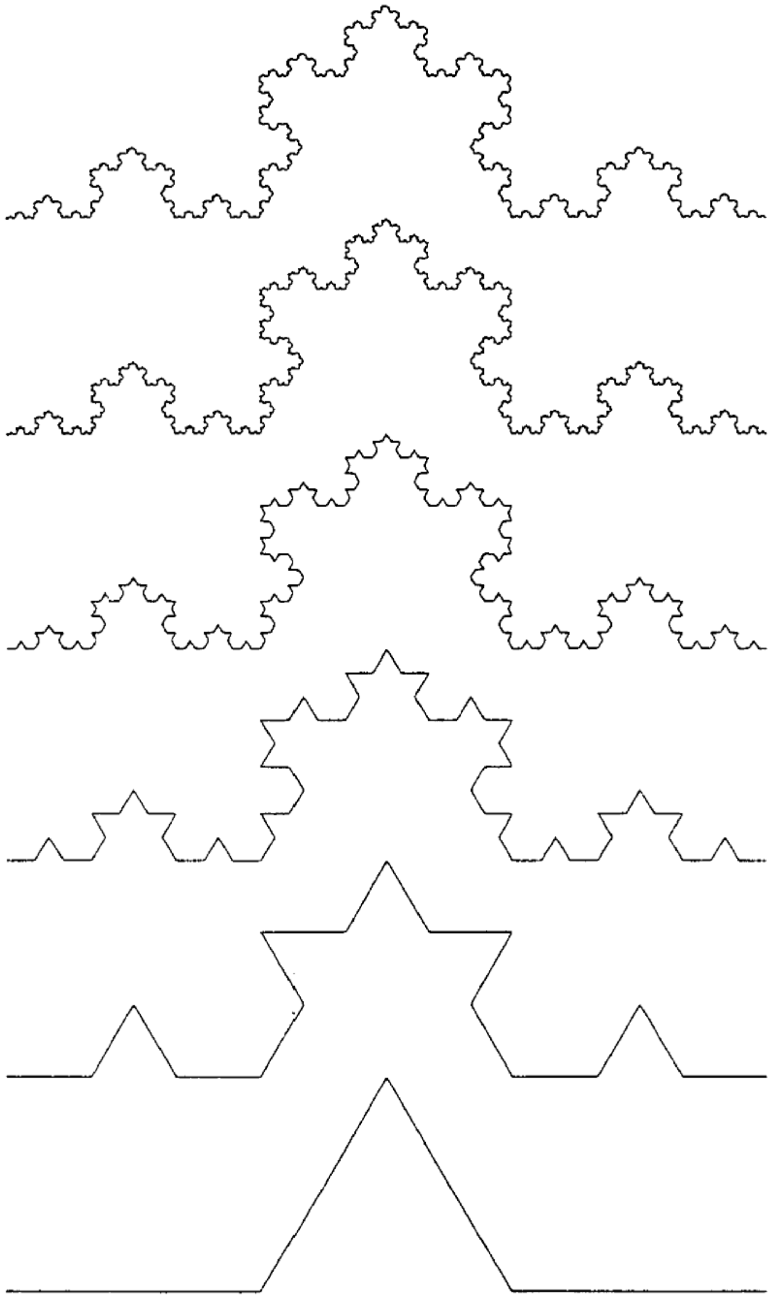
- Discrete scale invariance
  Complex fractal dimension
  Log-periodicity

FRACTALS

1) $d \in N$ Euclid (ca. 325-270 BC)

2) $d \in R$ Mandelbrot (1960-1980)
(Weierstrass, Hausdorff, Holder, …)

3) $d \in C$

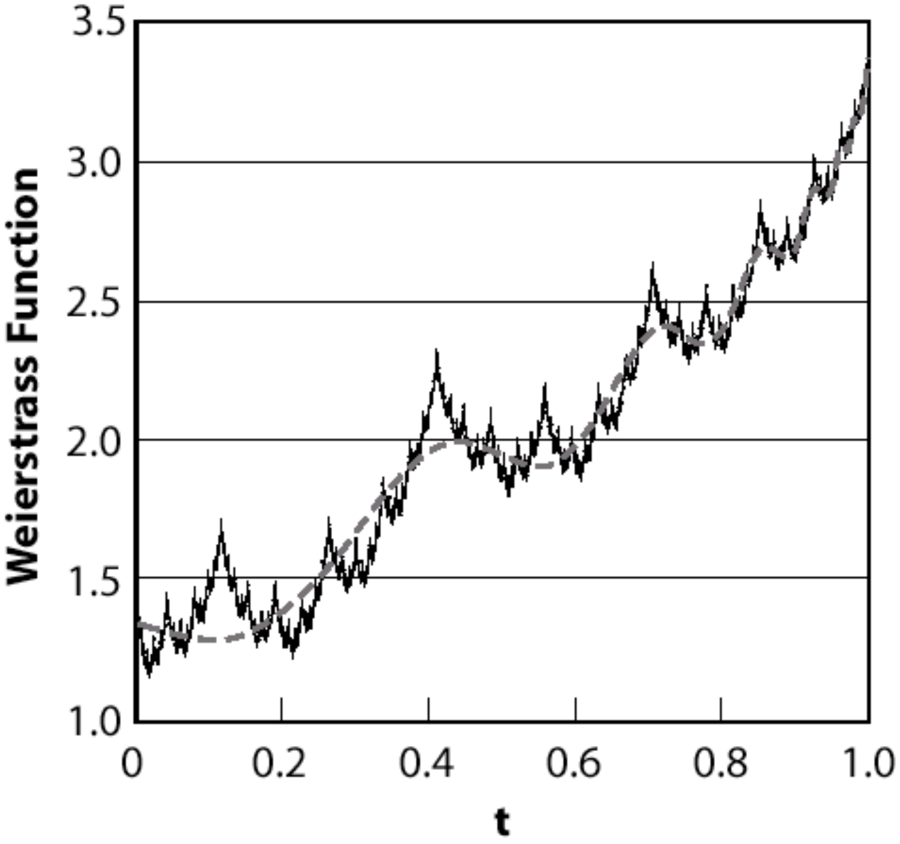


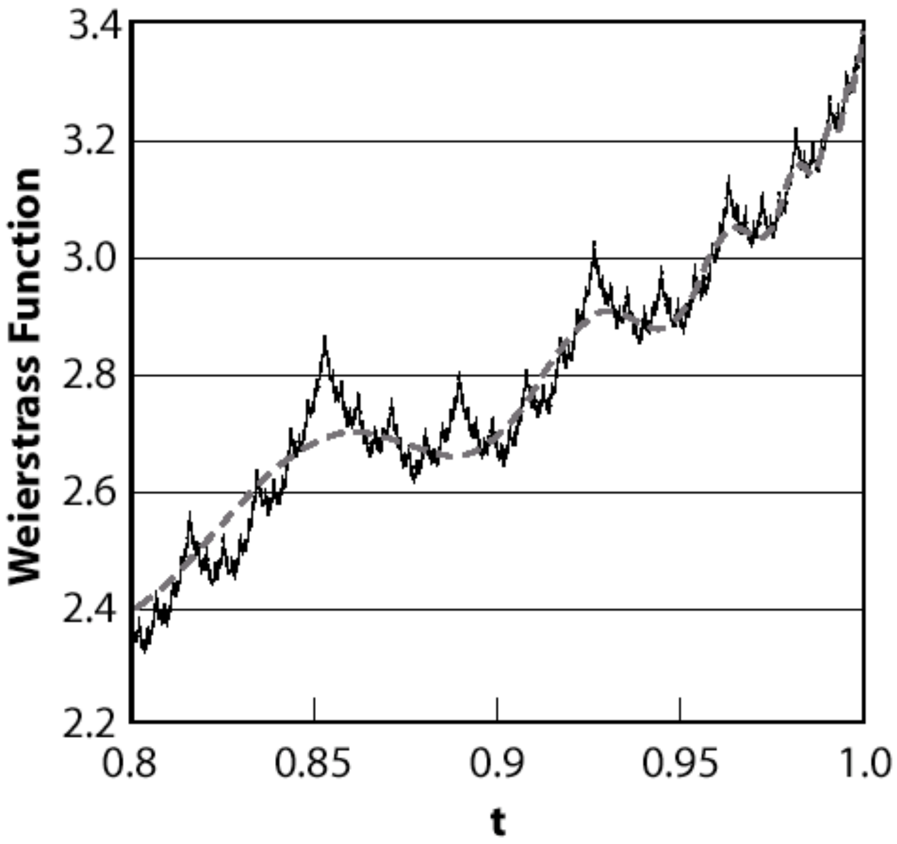
Discrete scale invariance
Complex fractal dimension
Log-periodicity

Prefered scaling ratio is 3

$$D(n) = \ln 4/\ln 3 + i\, 2\pi n/\ln 3$$

Fractal function
(Weierstrass)





Log-periodic route to fractal functions

$$f(K)=g(K)+\frac{1}{\mu}f[R(K)]$$

(Derrida, Eckmann, Erzan, 1983)

$$f(K)=\sum_{n=0}^{\infty}\frac{1}{\mu^n}g[R^{(n)}(K)],$$

$$f(x)=\sum_{n=0}^{\infty}\frac{1}{\mu^n}g[\gamma^n x]$$

$$f_W=\sum_{n=0}^{\infty}b^n\cos[a^n\pi x],$$

$$f(x)=\frac{1}{2\pi i}\int_{c-i\infty}^{c+i\infty}\hat{f}(s)x^{-s}ds,$$

Inverse Mellin transform

$$f(x)=f_s(x)+f_r(x)$$

$$f_s(x)=\sum_{n=0}^{\infty}A_n x^{-s_n}$$

$$f_r(x)=\sum_{n=0}^{\infty}B_n x^n$$

$$A_n=\frac{\hat{g}(s_n)}{\ln\gamma}$$

$$s_n=-m+i\frac{2\pi}{\ln\gamma}n$$

$$=-m+i\omega n$$

S. Gluzman and D. Sornette, Log-periodic route to fractal functions, art. no. 036142, Phys. Rev. E V6503 N3 PT2A:U418-U436 (2002)

$$f(K) = g(K) + \frac{1}{\mu} f[R(K)] \qquad f_s(x) = \sum_{n=0}^{\infty} A_n x^{-s_n}$$

TABLE I. Synthesis of the different classes of Weierstrass-type functions according to the general classification (21), $A_n \sim (1/n^p) e^{-\kappa n} e^{i\psi_n}$ of the expansion (18) in terms of a series of power laws x^{-s_n}. The parameters p, $\kappa \geq 0$, and ψ_n are determined by the form of $g(x)$ and the values of μ and γ. All numerical values given in this table correspond to $m=0.5, \omega=7.7$ corresponding to $\gamma=2.26$ and $\mu=\sqrt{\gamma}=1.5$. The last two columns quantify the amplitude of the log-periodic oscillations with respect to the leading real power law.

$g(x)$	p	κ	ψ_n	$\lvert A_{n=1}/A_{n=0}\rvert$	$\lvert A_{n=2}/A_{n=0}\rvert$
$\cos(x)$	$m+1/2$	0	$\omega n \ln(\omega n)$	0.065	0.032
$\exp(-x)$	$m+1/2$	$(\pi/2)\omega$	$\omega n \ln(\omega n)$	5.12×10^{-7}	1.432×10^{-12}
$\exp[-cx]\cos(xs)$[a]	$m+1/2$	$([\pi/2]-\alpha)\omega$	$\omega n \ln(\omega n)$		
$(1+x^2)^{-1}$	0	$(\pi/2)\omega$	$(\pi/2)m$	9.901×10^{-6}	4.414×10^{-11}
$\log(1+x)$	1	$\pi\omega$	$-\pi m$	4.045×10^{-12}	≈ 0
$\exp(-x^h)$	$m/h+1/2$	$(\pi/2h)\omega$	$[(\omega n)/h]\ln(\omega n)$	0.064 $(h=50)$	0.03 $(h=50)$
				4.386×10^{-4} $(h=2)$	6.177×10^{-7} $(h=2)$
$\sin(x)/x^\delta$	$m+\delta+1/2$	0	$-\omega n \ln(\omega n)$	0.044 $(\delta=0.1)$	0.021 $(\delta=0.1)$
				0.091 $(\delta=-0.1)$	0.049 $(\delta=-0.1)$
$\mathrm{Si}(x)$	$m+3/2$	0	$\omega n \ln(\omega n)$	4.199×10^{-3}	1.053×10^{-3}
$1-x^h$ $0<x<1$	2	0	π	0.064 $(h=50)$	0.031 $(h=50)$
				0.012 $(h=2)$	3.146×10^{-3} $(h=2)$

[a] $c=\cos\alpha$ and $s=\sin\alpha$.

Mechanism for large log-periodic corrections to scaling:
The non-universal function g(K) must be either quasi-periodic or with compact support

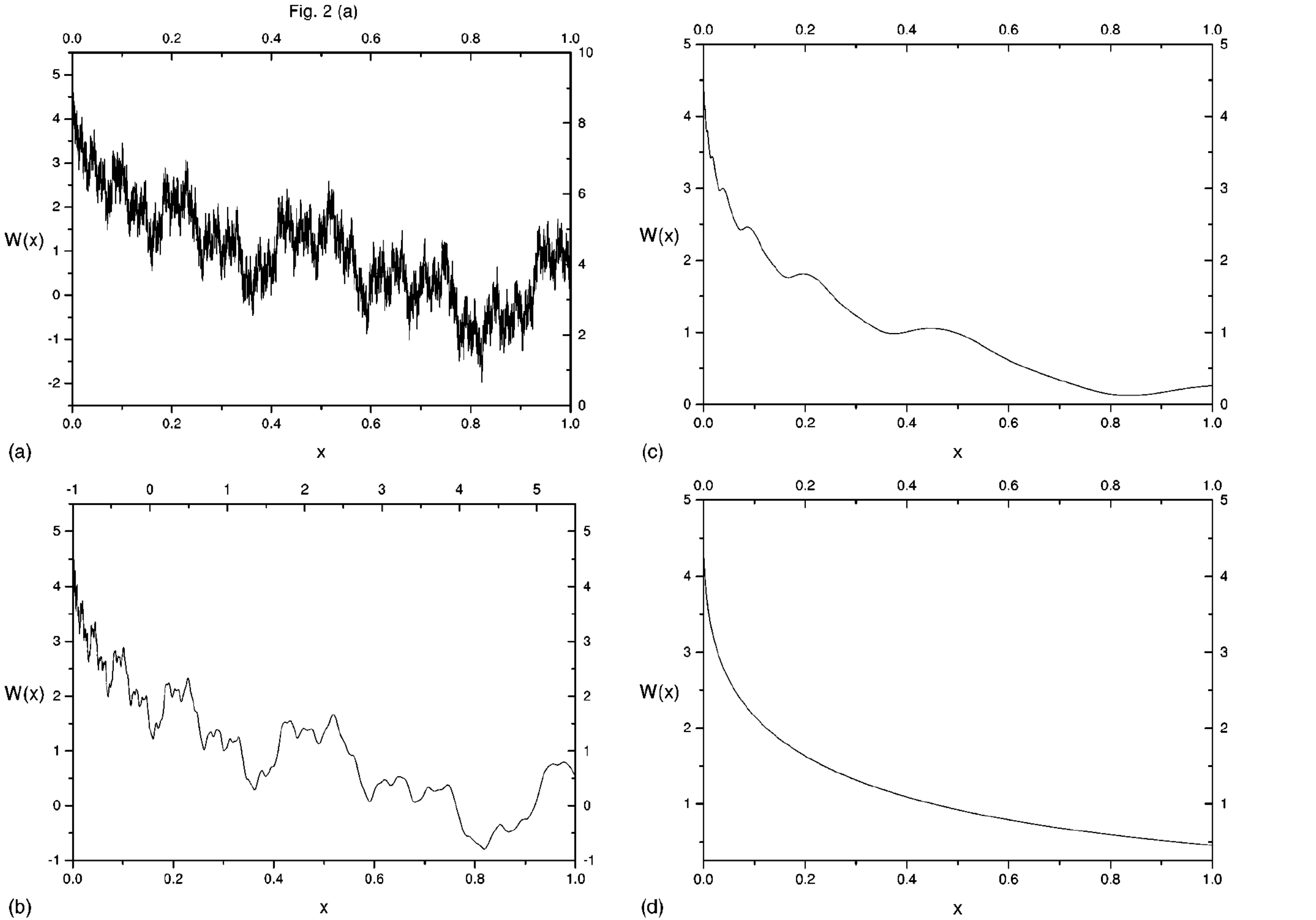


FIG. 2. Quasi-Weierstrass function for (a) $\alpha=\pi/2$, (b) $\alpha=0.993\pi/2=1.56$, (c) $\alpha=0.9\pi/2=1.414$, and (d) $\alpha=0$, for $m=0.25,\omega=7.7$, using $N=32$ terms to estimate the sums (51). Increasing N does not change the results.

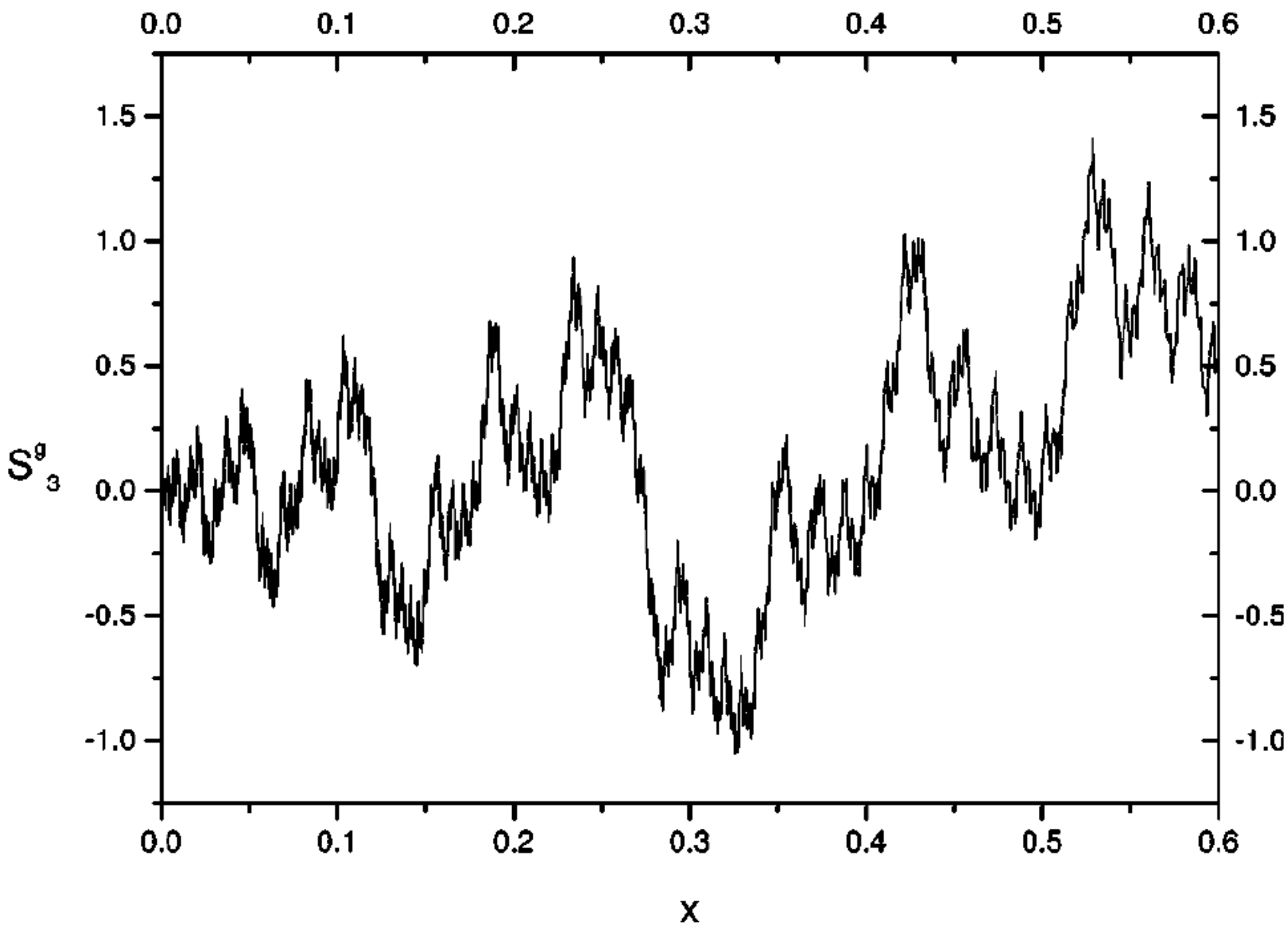


FIG. 8. “Golden-mean log-periodic Weierstrass function” $S_3^{(g)}(x)$ defined by Eq. (69) with Eq. (72) for $m=0.5,\omega=7.7,N=500$.

$$\psi_{n+1}^{(3)}=\psi_n^{(3)}+2\pi Rn.$$

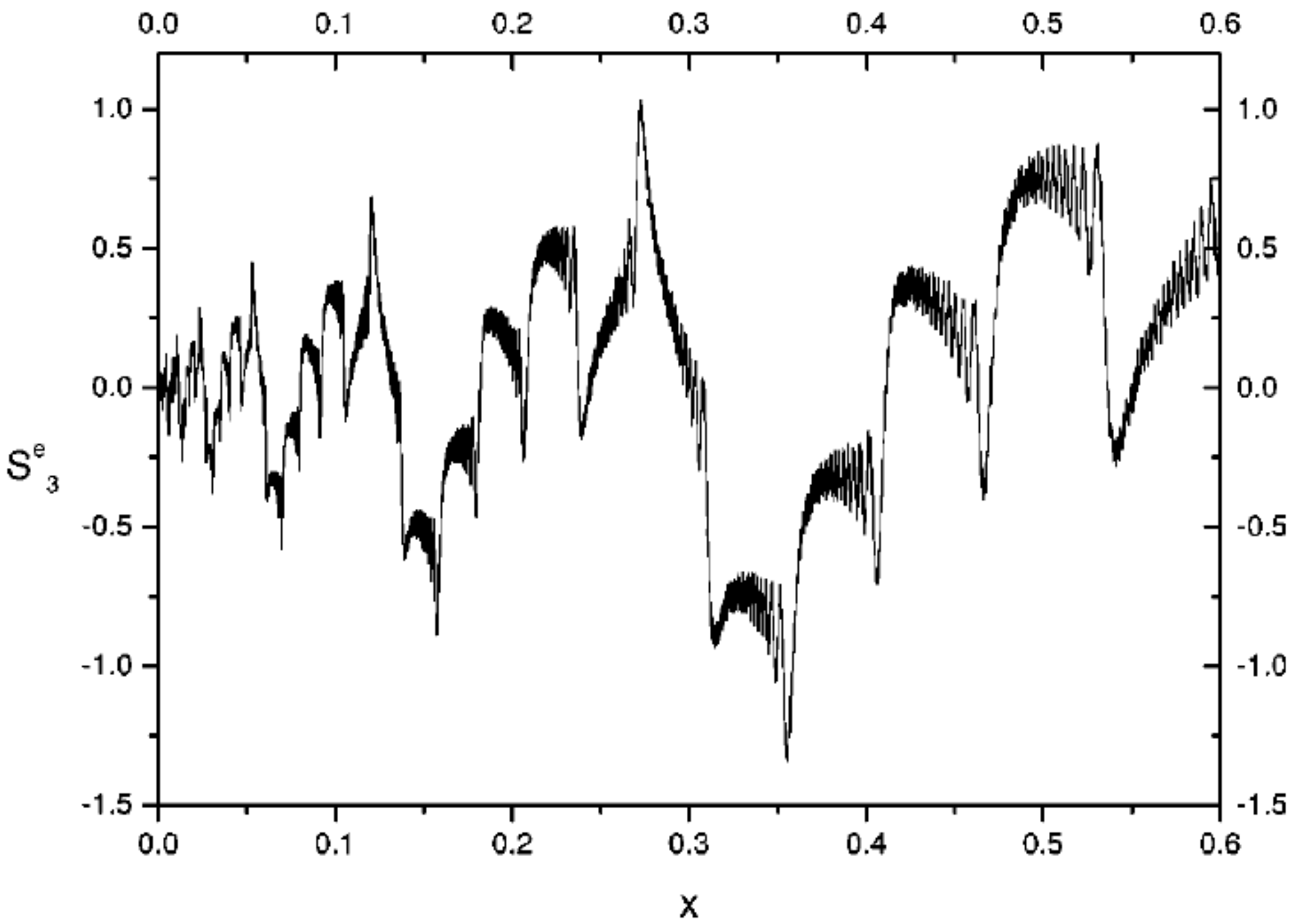


FIG. 10. "e-log-periodic Weierstrass function" $S_3^{(e)}$ defined by Eq. (69) with Eq. (72) and $R=e=2.718\ldots$ for $m=0.5,\omega=7.7,N=500$. $\psi_{n+1}^{(3)}=\psi_n^{(3)}+2\pi Rn$.

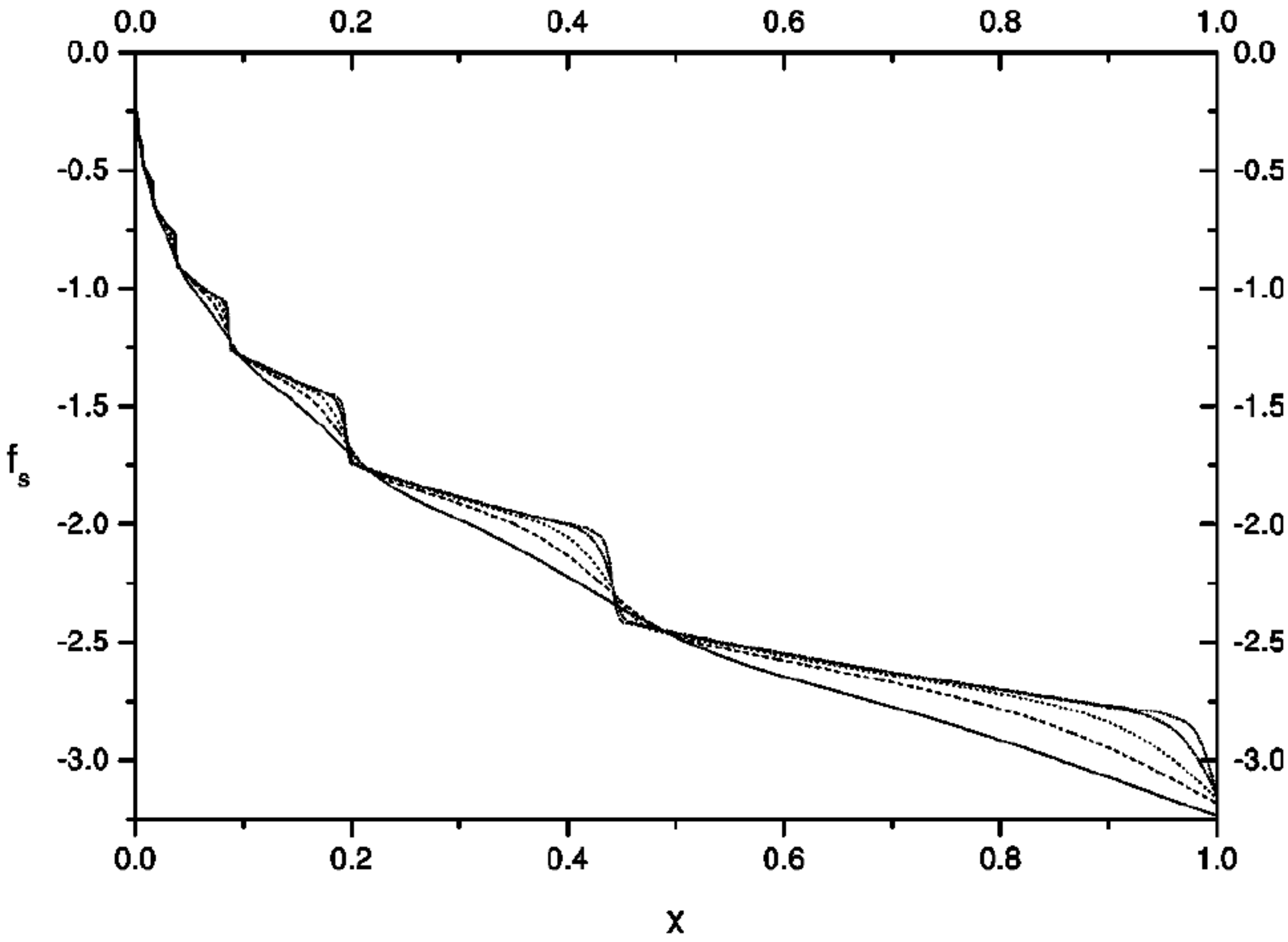


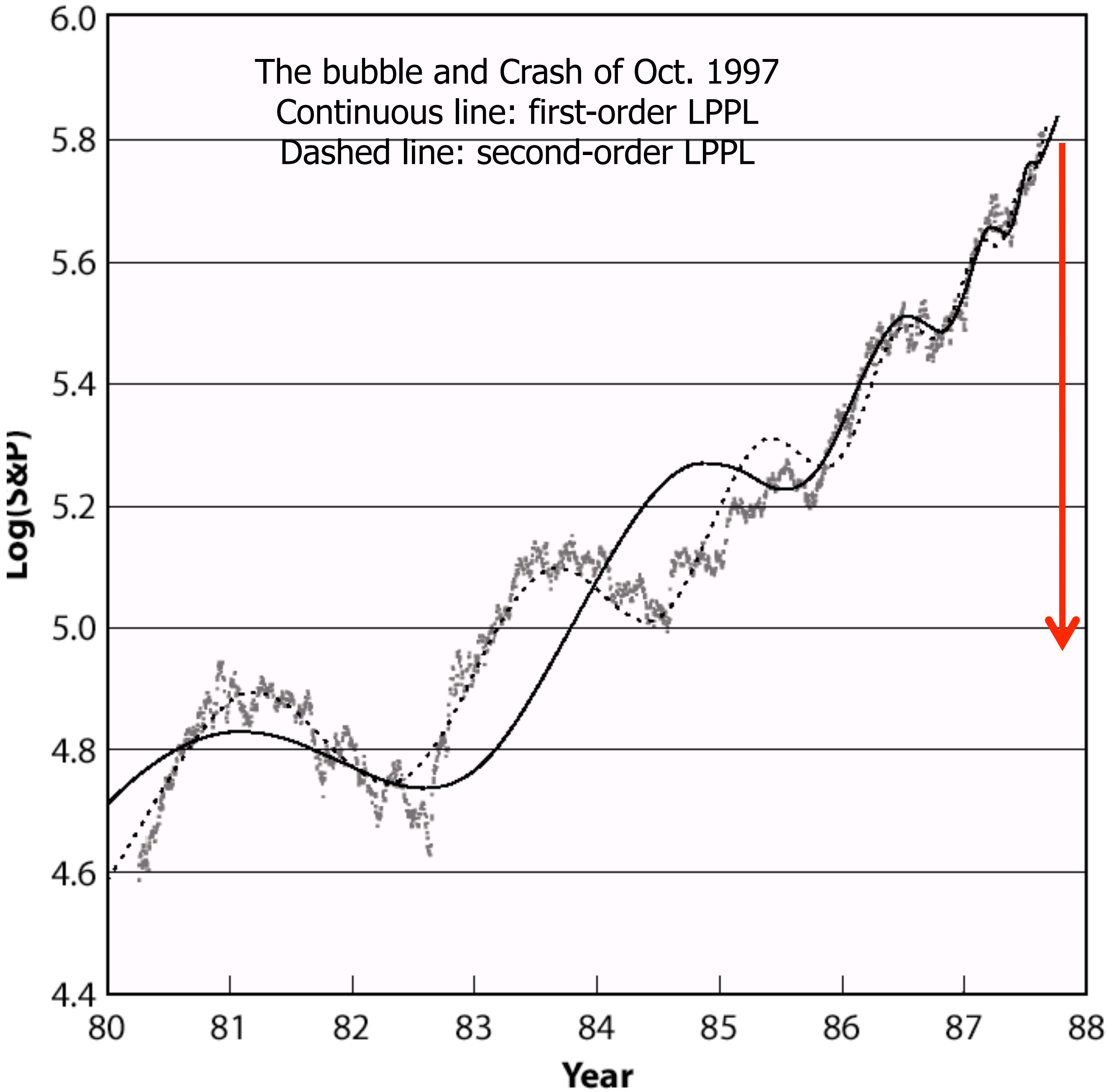
FIG. 11. Singular part $f_s(x)$ of the Weierstrass-like function for the regular function $g(x)$ equal to the stretched exponential (82) for $h=5$ (solid line), $h=10$ (dashed line), $h=20$ (dotted line), $h=50$ (dashed-dotted line), and $h=100$ (dashed-dot-dotted line), for $m=0.4, \omega=7.7, N=22$.

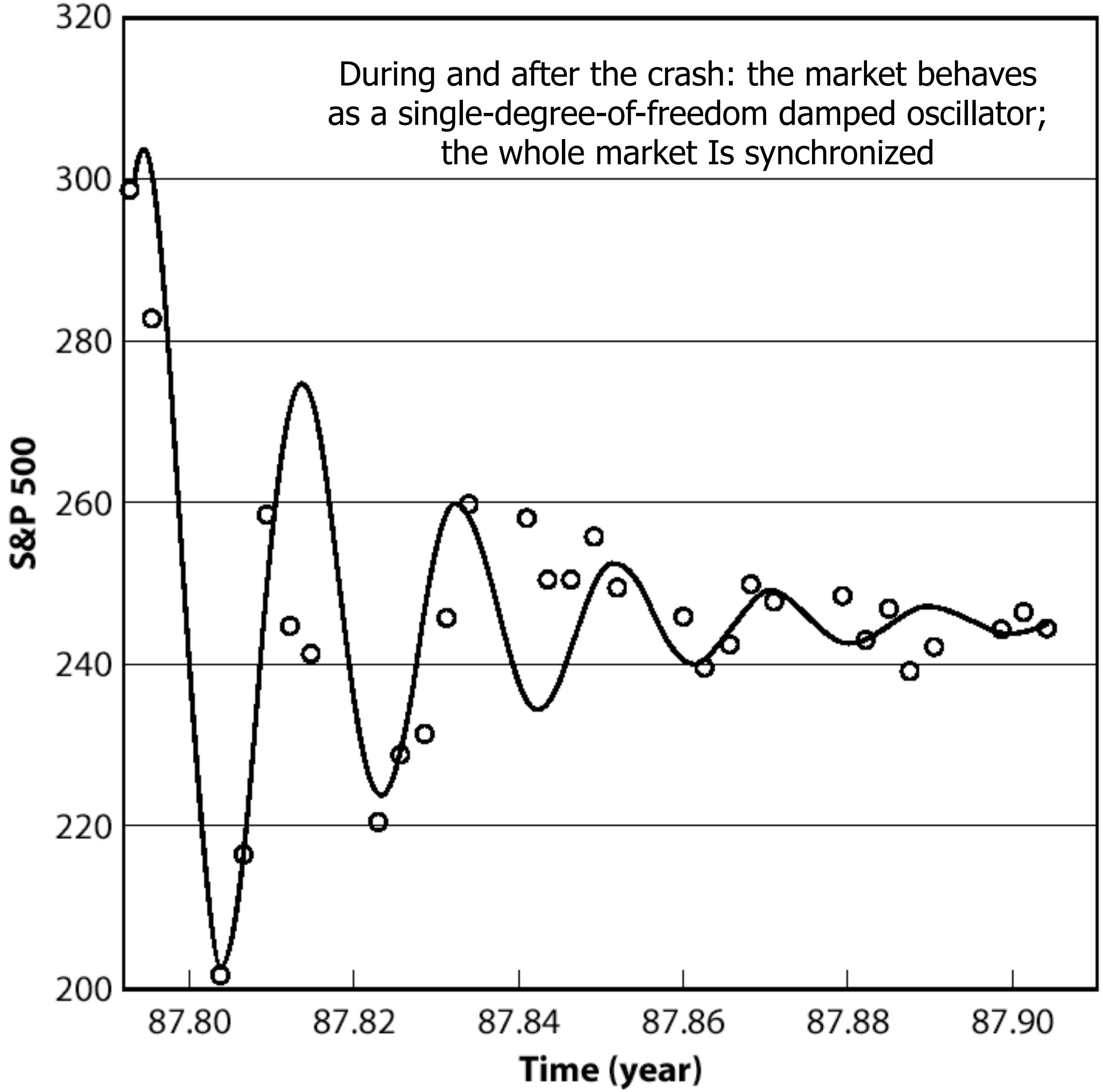
Positive feedbacks + hierarchies

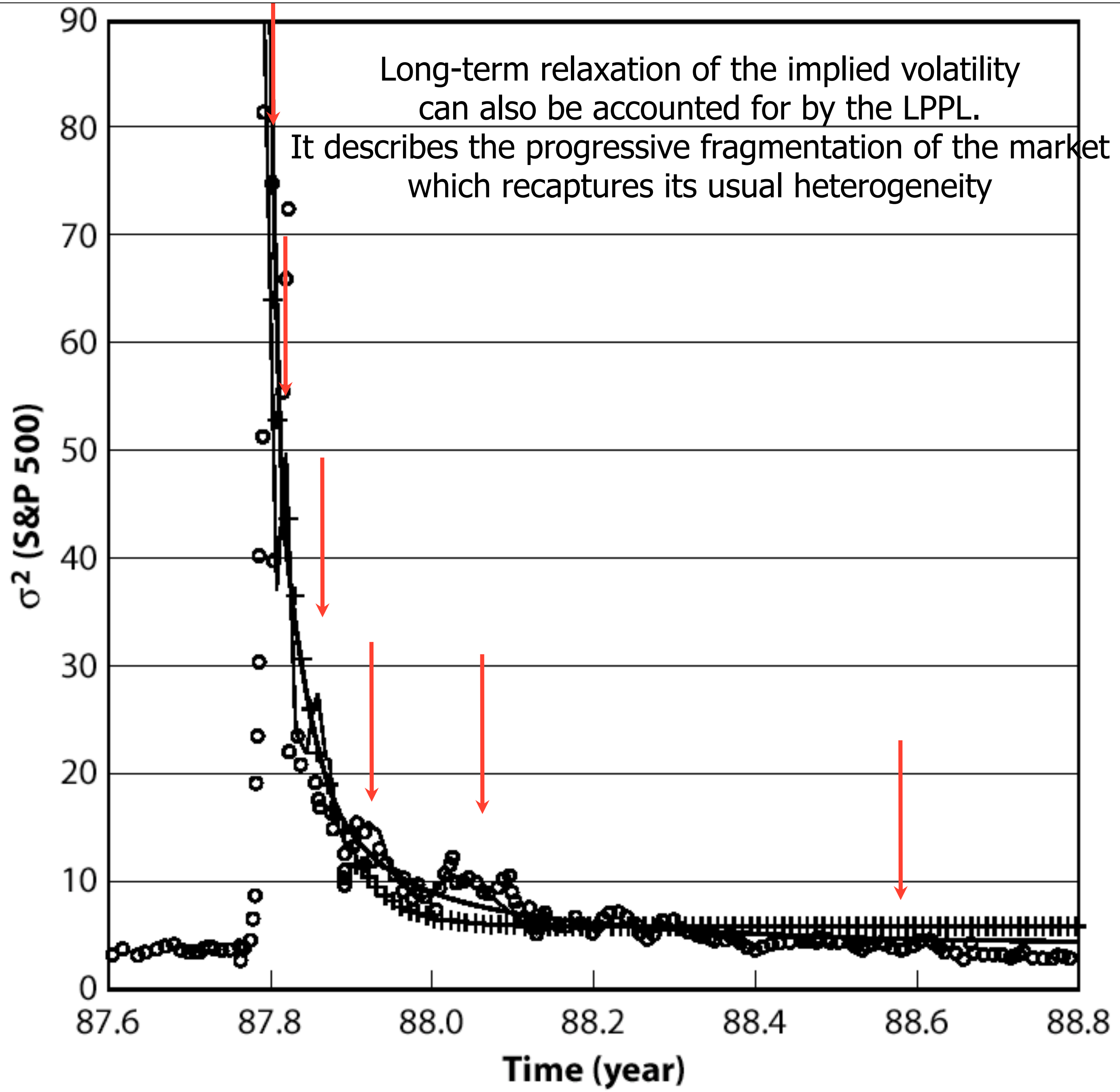
↓

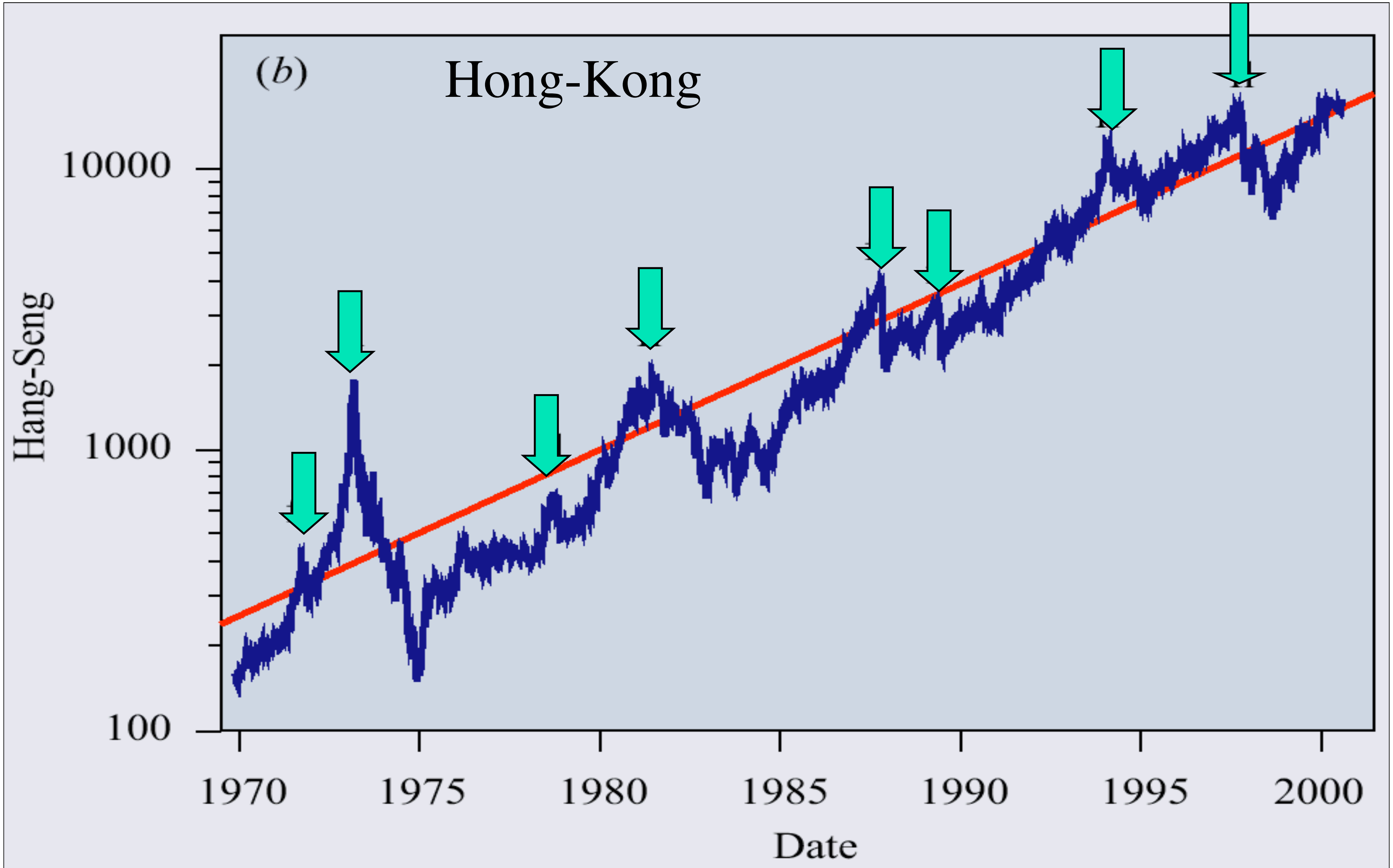
New theory of bubbles and crashes

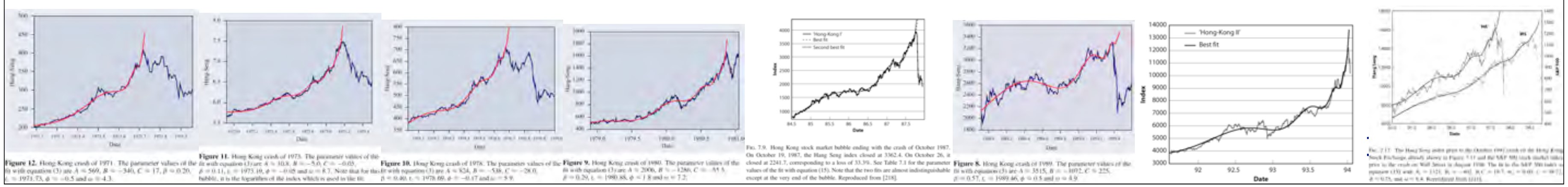
(Log-periodic power law)


The bubble and Crash of Oct. 1997
Continuous line: first-order LPPL
Dashed line: second-order LPPL
6.0
5.8
5.6
5.4
5.2
5.0
4.8
4.6
4.4
Log(S&P)
80
81
82
83
84
85
86
87
88
Year


During and after the crash: the market behaves
as a single-degree-of-freedom damped oscillator;
the whole market Is synchronized
320
300
280
260
240
220
200
S&P 500
87.80
87.82
87.84
87.86
87.88
87.90
Time (year)


Long-term relaxation of the implied volatility
can also be accounted for by the LPPL.
It describes the progressive fragmentation of the market
which recaptures its usual heterogeneity
σ² (S&P 500)
90
80
70
60
50
40
30
20
10
0
87.6
87.8
88.0
88.2
88.4
88.6
88.8
Time (year)


(b)
Hong-Kong
Hang-Seng
10000
1000
100
1970
1975
1980
1985
1990
1995
2000
Date



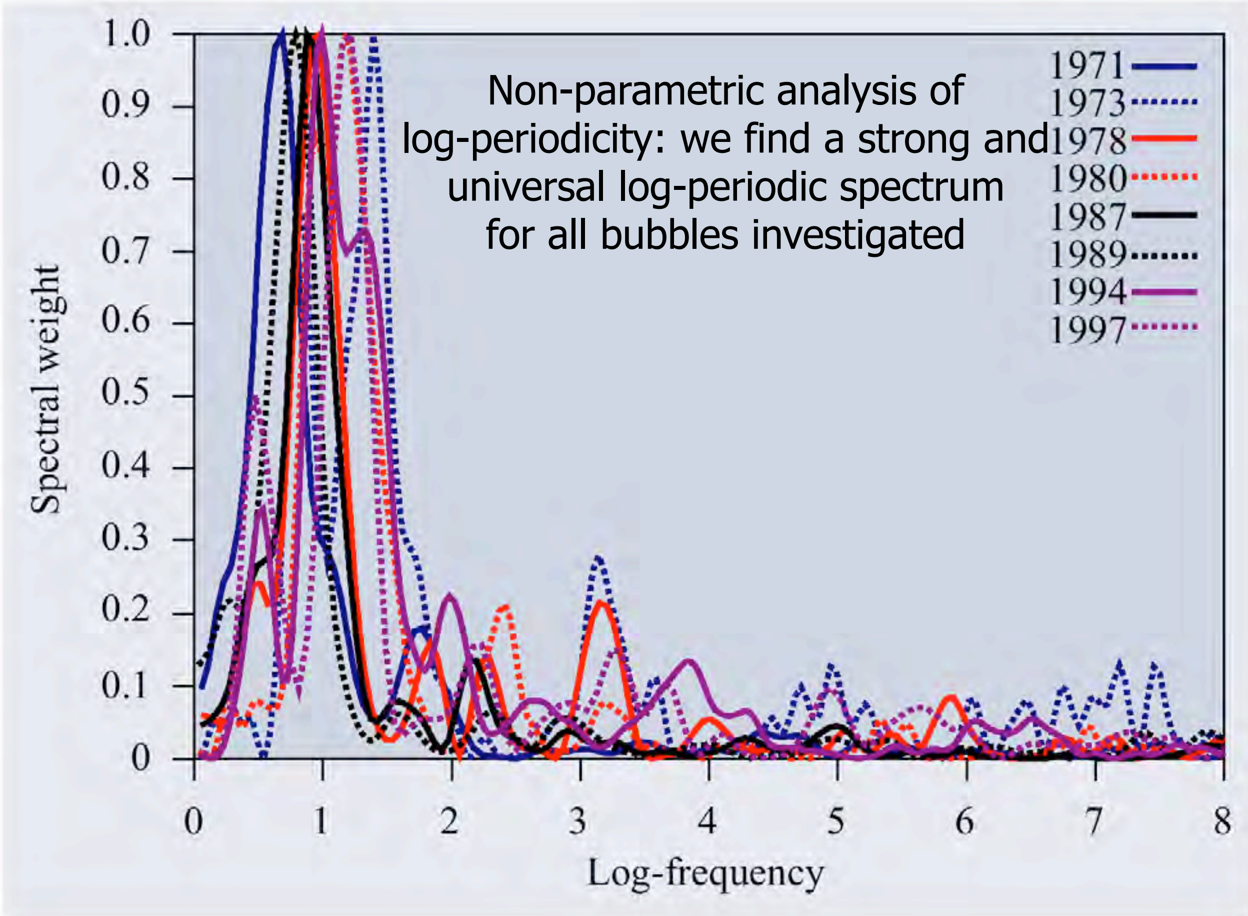


Figure 1. The Lomb periodogram of the log-periodic component of the Hang-Seng price index (Hong Kong) for the eight bubbles followed by crashes observed in figure 13, ending in October 1971, in February 1973, in September 1978, in October 1980, in October 1987, in April 1989, in January 1994 and in October 1997. See Johansen *et al* (1999) for details on how to calculate the Lomb periodogram.

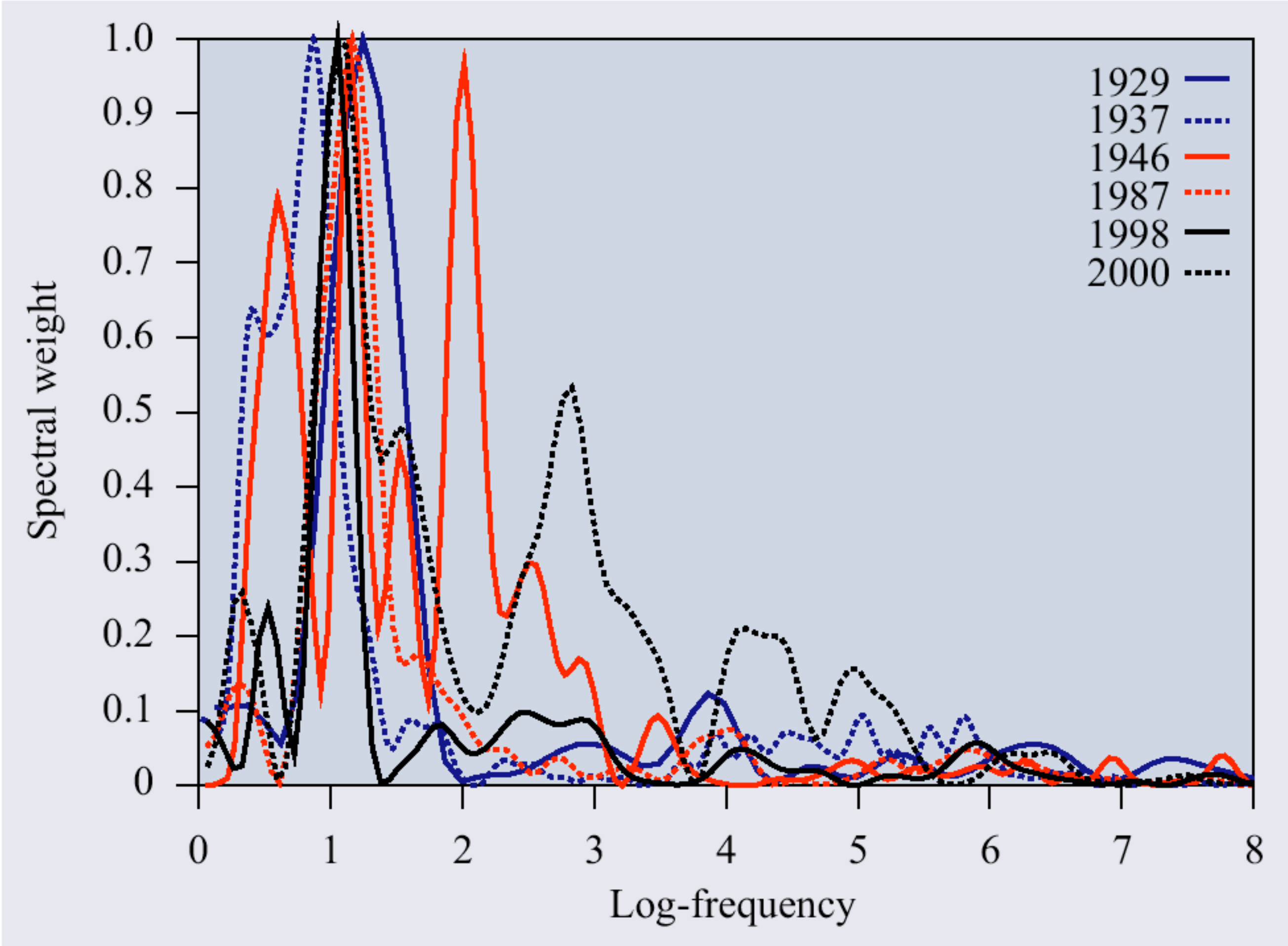


Figure 2. Log-periodic spectra for all the major bubbles ending in crashes on the Dow Jones and SP500 index in the twentieth century as well as the NASDAQ crash of 2000. Observe that the sub-harmonics (half log-frequency) and two harmonics $2f$ and $3f$ are quite strong in some of the data sets. See Johansen *et al* (1999) for details on how to calculate the Lomb periodogram.

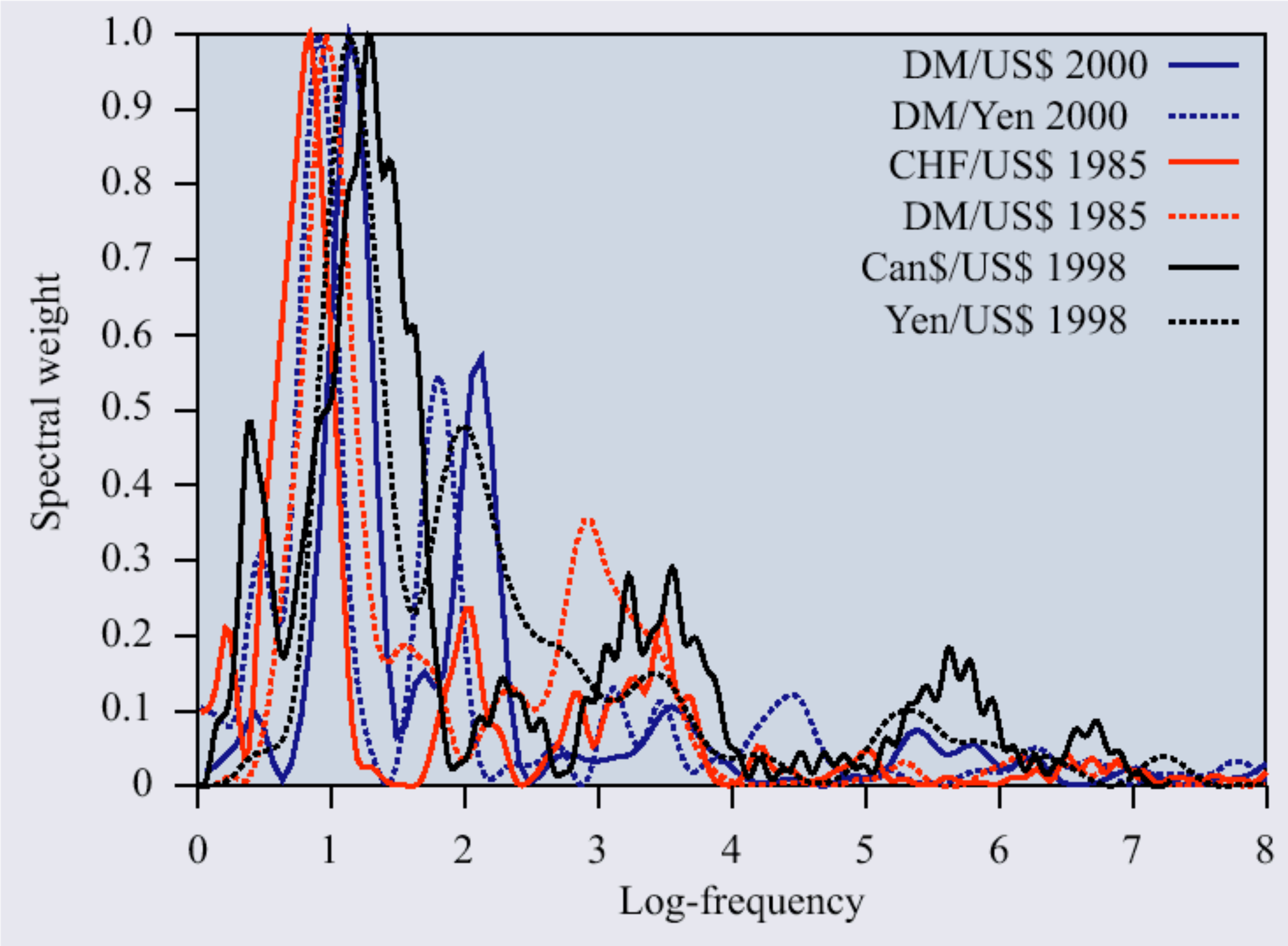


Figure 3. Log-periodic spectra for the major recent bubbles on currencies. See Johansen *et al* (1999) for details on how to calculate the Lomb periodogram.

Crash	t_c	t_{max}	t_{min}	*% drop*	m_2	ω	λ
1929 (DJ)	30.22	29.65	29.87	47%	0.45	7.9	2.2
1985 (DM)	85.20	85.15	85.30	14%	0.28	6.0	2.8
1985 (CHF)	85.19	85.18	85.30	15%	0.36	5.2	3.4
1987 (S&P)	87.74	87.65	87.80	30%	0.33	7.4	2.3
1987 (HK)	87.84	87.75	87.85	50%	0.29	5.6	3.1
1994 (HK)	94.02	94.01	94.04	17%	0.12	6.3	2.7
1997 (HK)	97.74	97.60	97.82	42%	0.34	7.5	2.3
1998 (S&P)	98.72	98.55	98.67	19.4%	0.60	6.4	2.7
1999 (IBM)	99.56	99.53	99.81	34%	0.24	5.2	3.4
2000 (P&G)	00.04	00.04	00.19	54%	0.35	6.6	2.6
2000 (Nasdaq)	00.34	00.22	00.29	37%	0.27	7.0	2.4

t_c is the critical time predicted from the fit of the financial time series to the equation (15). The other parameters m_2, ω, and λ of the fit are also shown. The fit is performed up to the time t_{max} at which the market index achieved its highest maximum before the crash. t_{min} is the time of the lowest point of the market before rebound. The percentage drop is calculated from the total loss from t_{max} to t_{min}. Reproduced from [218].

Out-of-sample test over 20 years of the Heng Seng

Alarms were produced in the following nine time intervals containing the date of the last point used in the fit:

(a) 1981.60 to 1981.68. This was followed by a $\approx$ 30% decline.

(b) 1984.36 to 1984.41. This was followed by a $\approx$ 30% decline.

(c) 1985.20 to 1985.30; false alarm.

(d) 1987.66 to 1987.82. This was followed by a $\approx$ 50 % decline.

(e) 1989.32 to 1989.38. This was followed by a $\approx$ 35 % decline.

(f) 1991.54 to 1991.69. This was followed by a $\approx$ 7% single day decline; considered a false alarm, nevertheless.

(g) 1992.37 to 1992.58. This was followed by a $\approx$ 15% decline. This is a marginal case.

(h) 1993.79 to 1993.90. This was followed by a $\approx$ 20% decline. This can also be considered as a marginal case, if we want to be conservative.

(i) 1997.58 to 1997.74. This was followed by $\approx$ 35% decline.

Generalization and application to emergent markets: test of a systematic procedure to detect bubbles

A. Johansen and D. Sornette Bubbles and anti-bubbles in Latin-American, Asian and Western stock markets: An empirical study, International Journal of Theoretical and Applied Finance 4 (6), 853-920 (2001)

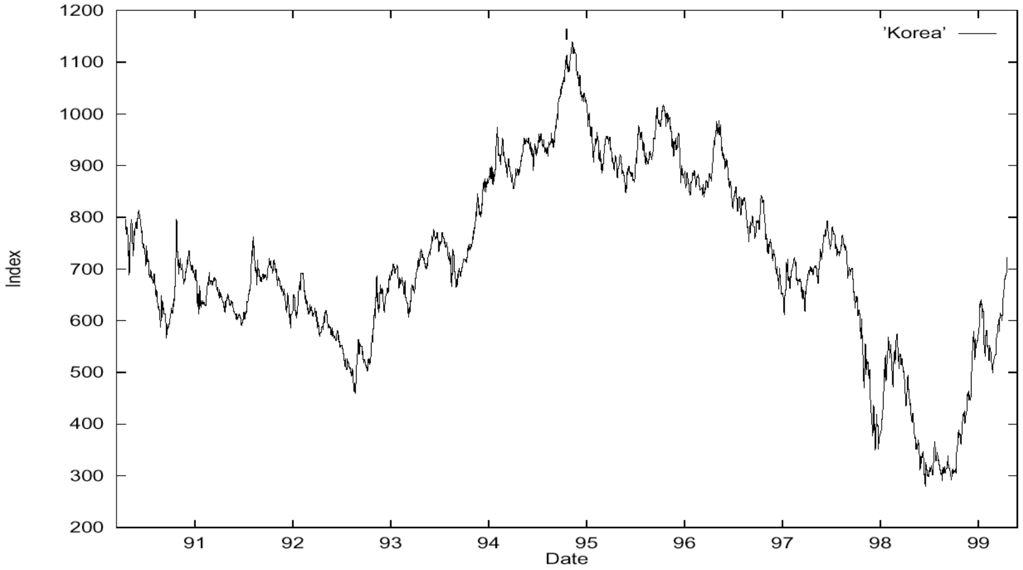


Figure 30: The Korean stock market index as a function of date. 1 bubble with a subsequent very large draw down can be identified. The approximate date is late 94.

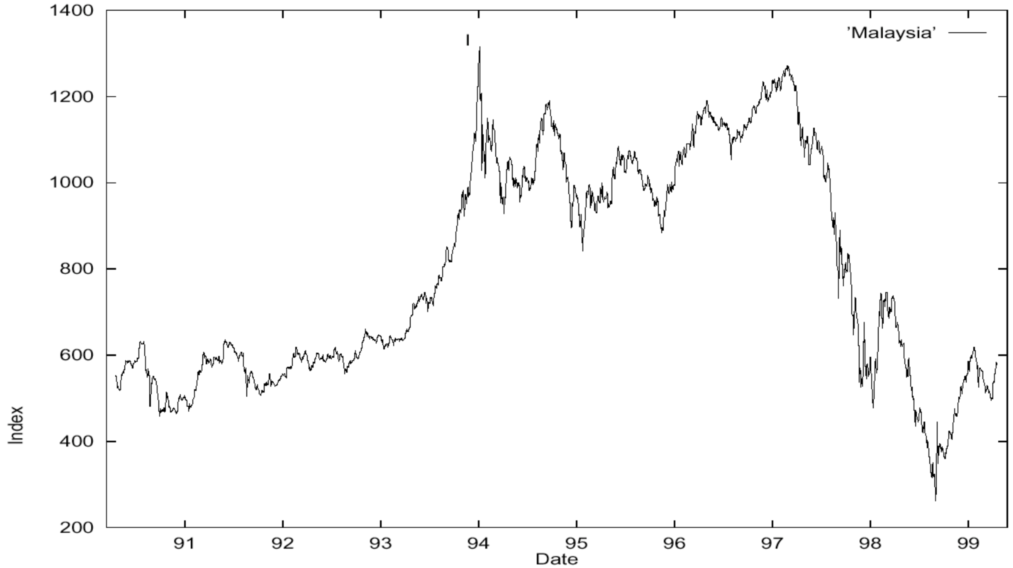


Figure 31: The Malaysian stock market index as a function of date. 1 extended bubble with a subsequent very large draw down can be identified. The approximate date for the draw down is early 94.

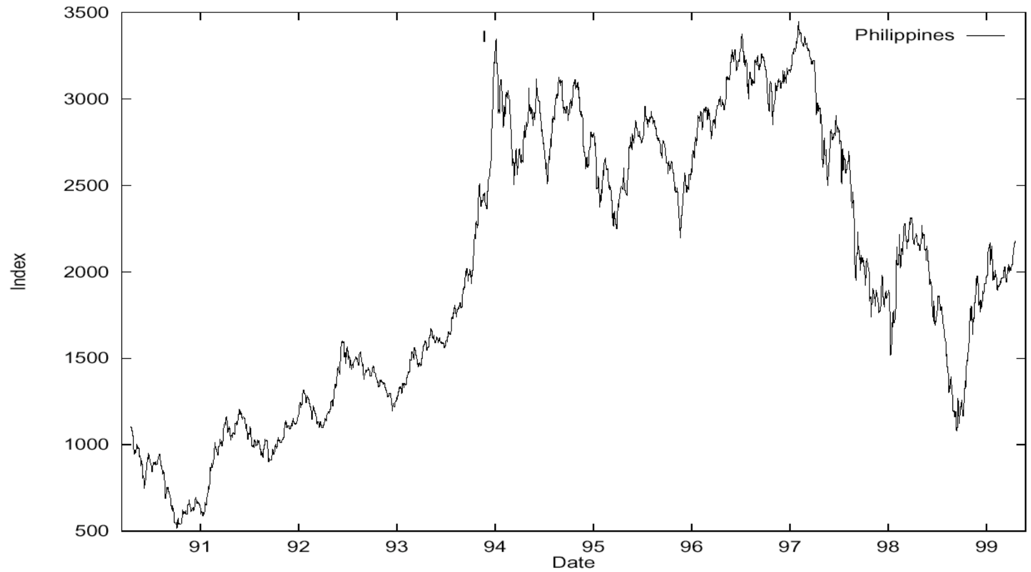


Figure 32: The Philippines stock market index as a function of date. 1 bubble with a subsequent very large draw down can be identified. The approximate date for the draw down is early 94.

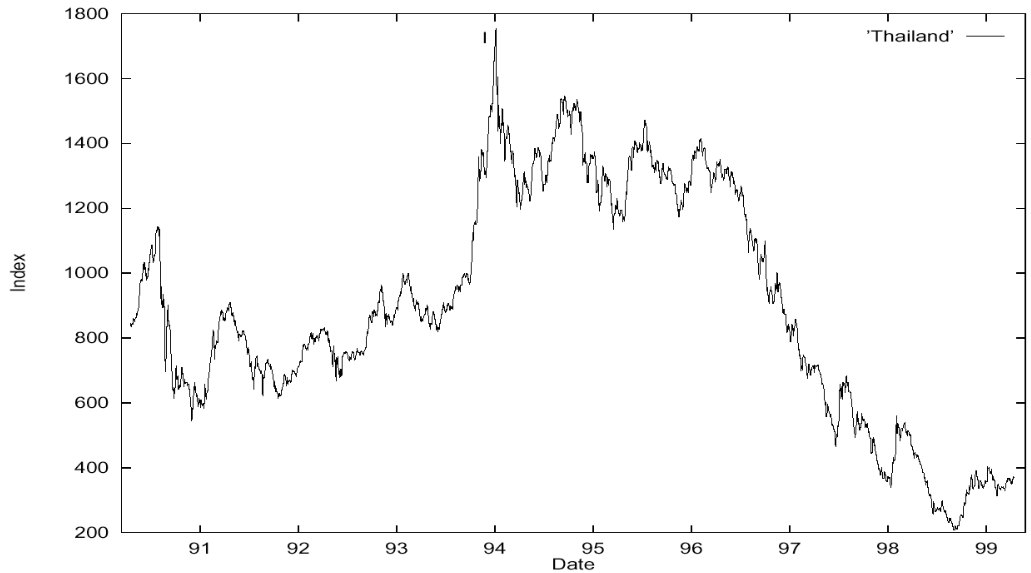


Figure 33: The Thai stock market index as a function of date. 1 bubble with a subsequent very large draw down can be identified. The approximate date for the draw down is early 94.

We show the parametric LPPL fits (left panels) and the non-parametric log-periodic spectral analyses (right panels)

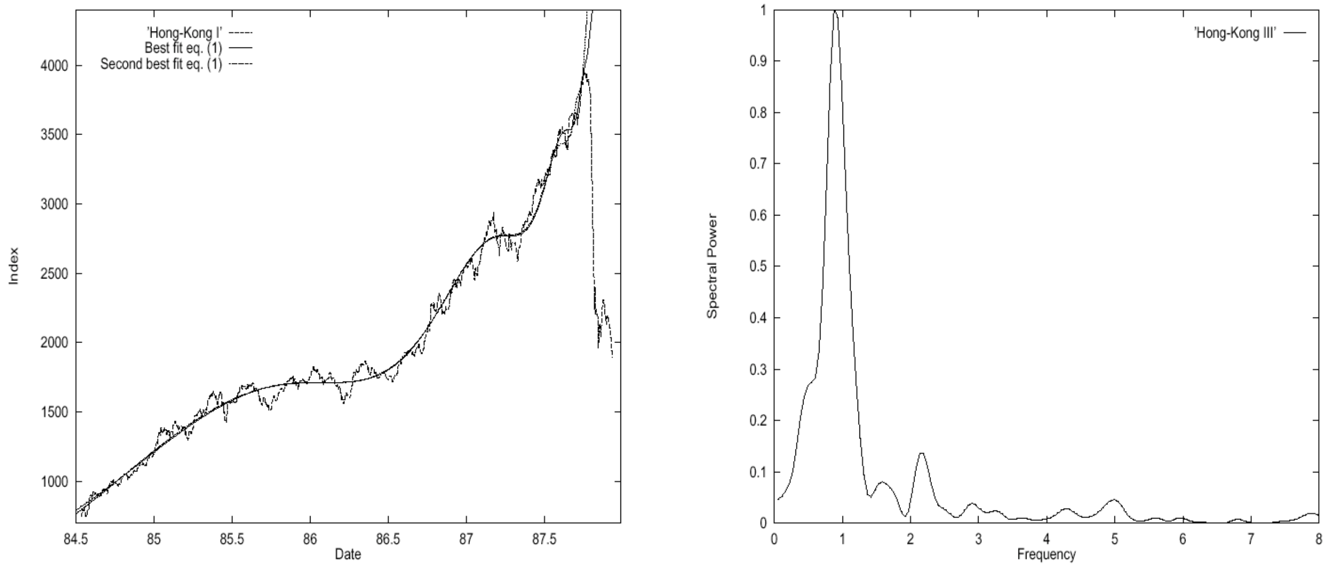


Figure 34: Hong Kong stock market bubble ending with the crash of Oct. 87. See table 5 for the parameter values of the fit with equation (1). Only the best fit is used in the Lomb periodogram.

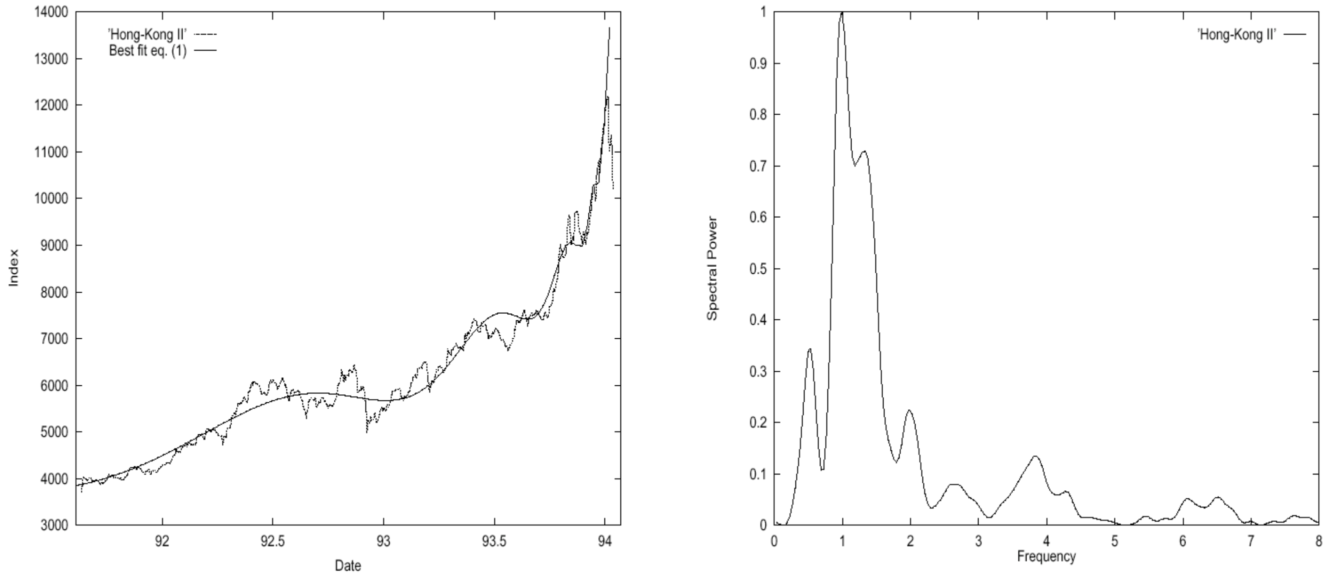


Figure 35: Hong Kong stock market bubble ending with the crash of Jan. 94. See table 5 for the parameter values of the fit with equation (1).

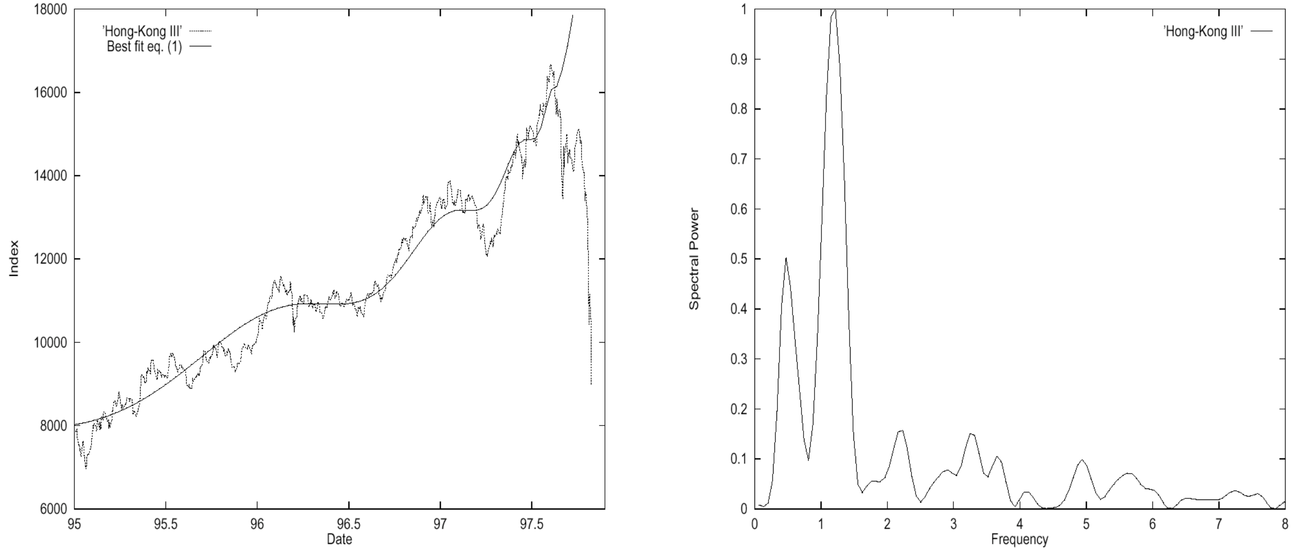


Figure 36: Hong Kong stock market bubble ending with the crash of Oct. 97. See table 5 for the parameter values of the fit with equation (1).

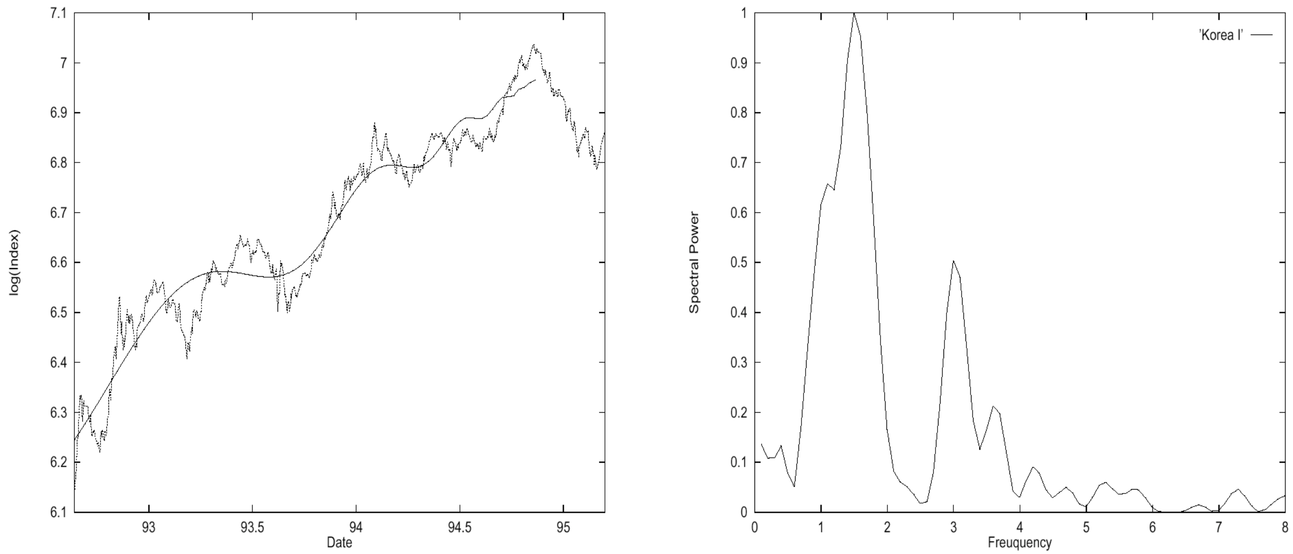


Figure 37: Korean stock market bubble ending in 1994. See table 5 for the parameter values of the fit with equation (1). The data set of the residue had to be truncated in order to eliminate a severe drift in the last part of the data close to t_c.

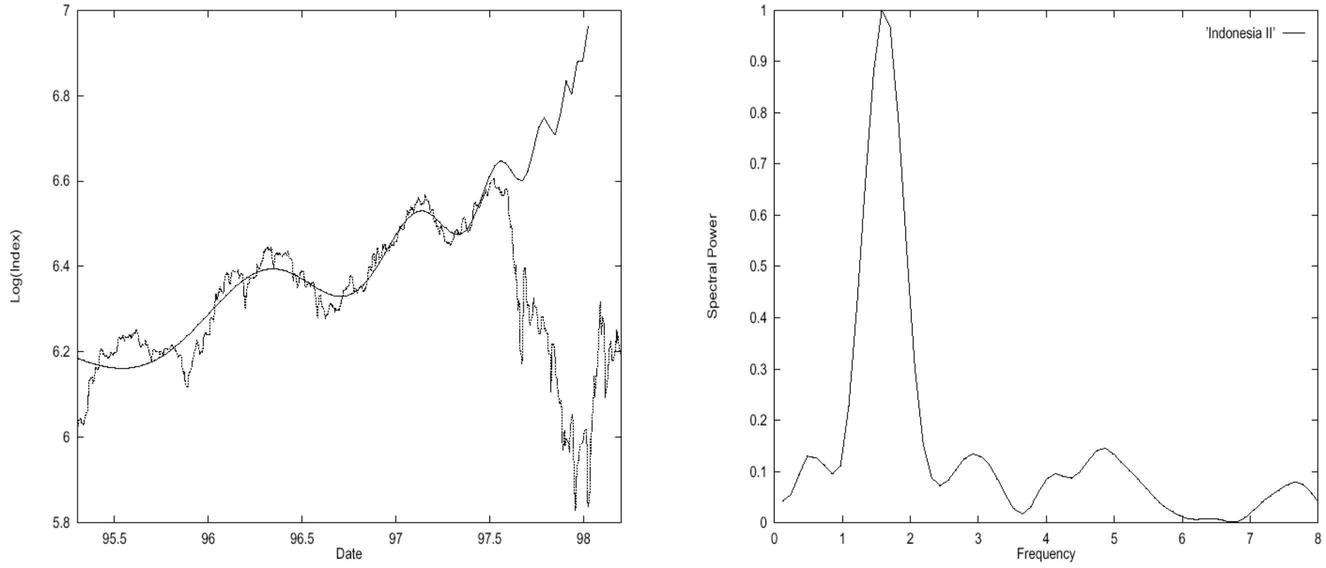


Figure 38: Indonesian stock market bubble ending in 1997. See table 5 for the parameter values of the fit with equation (1).

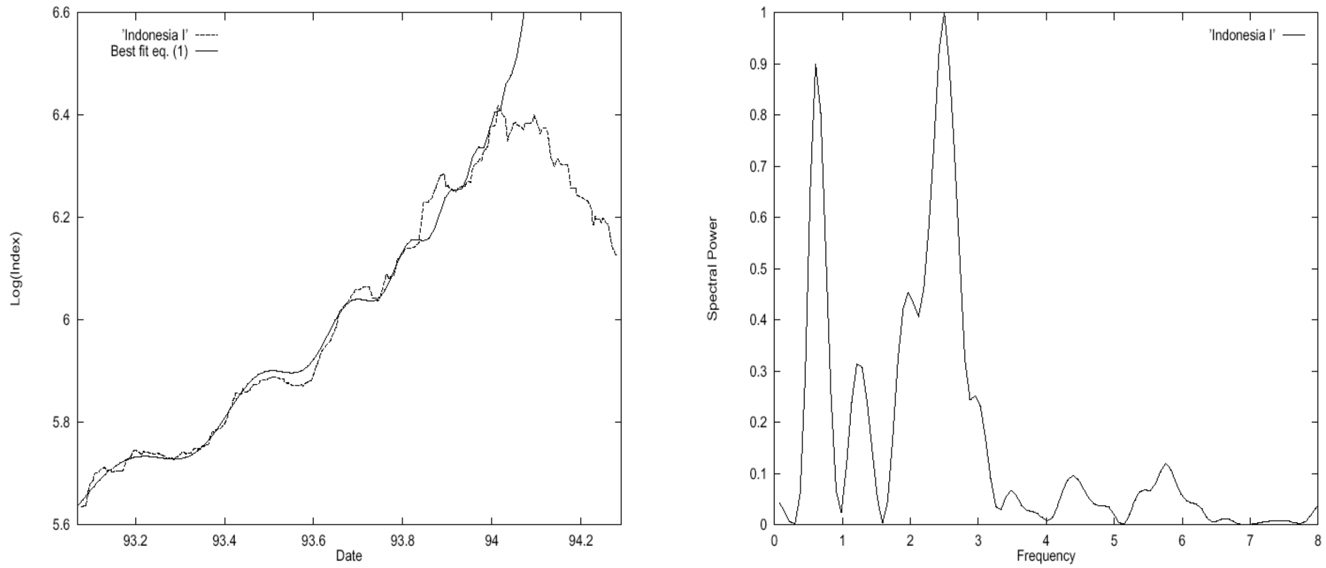


Figure 39: Indonesian stock market bubble ending in Jan. 1994. See table 5 for the parameter values of the fit with equation (1).

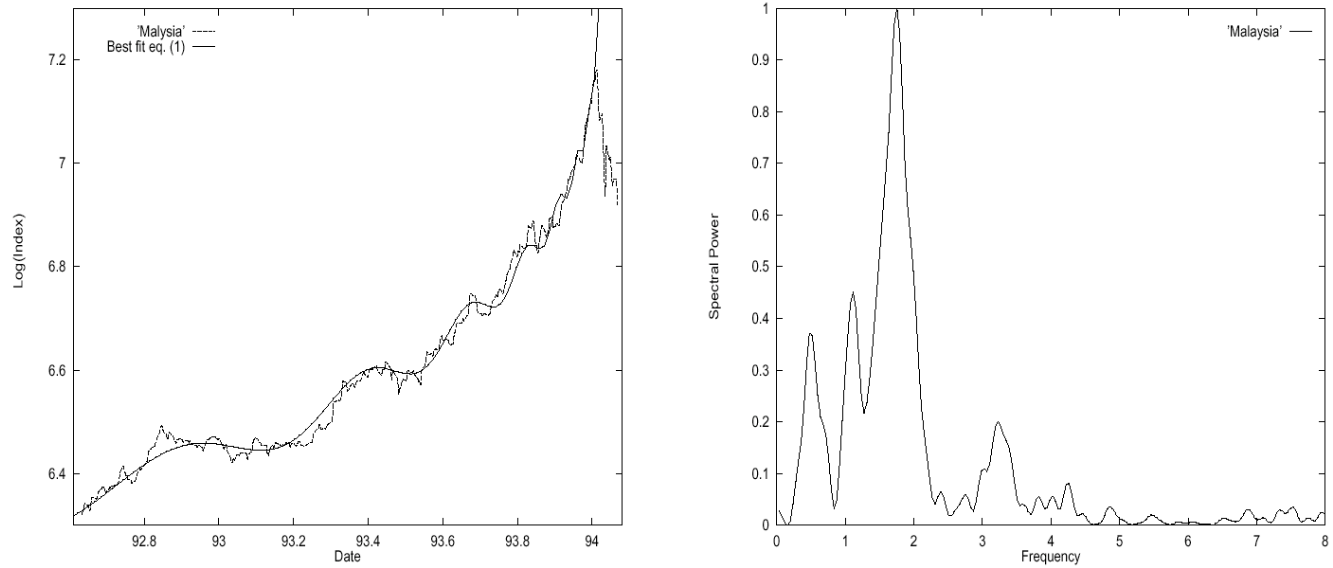


Figure 40: Malaysian stock market bubble ending with the crash of Jan. 94. See table 5 for the parameter values of the fit with equation (1).

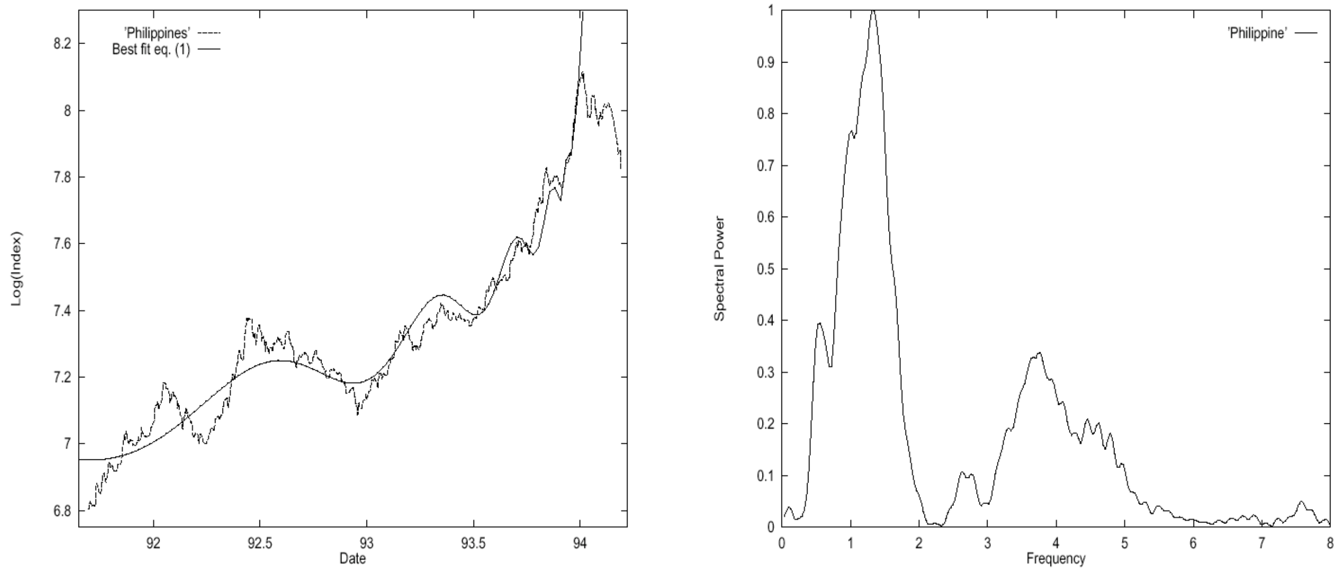


Figure 41: Philippine stock market bubble ending in Jan. 1994. See table 5 for the parameter values of the fit with equation (1).

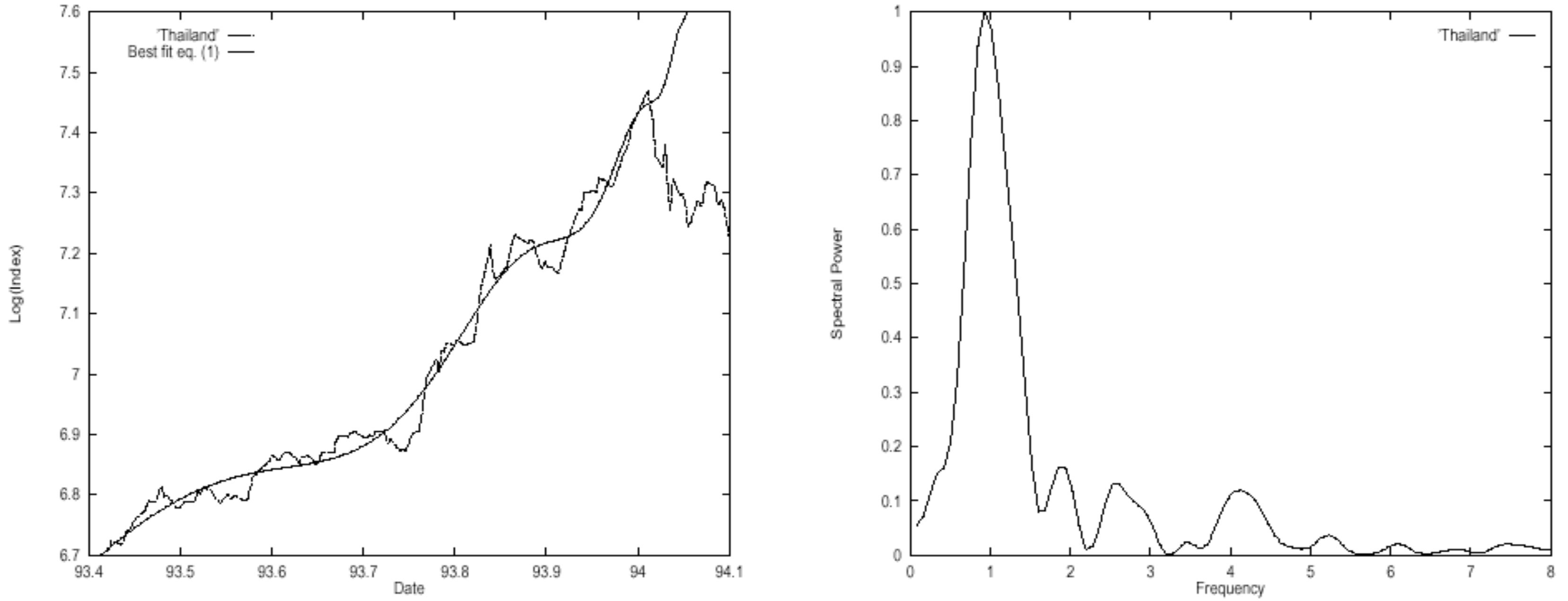


Figure 42: Thai stock market bubble ending with the crash of Jan. 94. See table 5 for the parameter values of the fit with equation (1).

$$I(t) = A + B(t_c - t)^z + C(t_c - t)^z \cos(\omega \log(t_c - t) - \phi)$$

Parameters of the log-periodic fits; z= critical exponent; omega=log-periodic frequency

Stock market	A	B	C	z	t_c	ω	ϕ
Hong-Kong I	5523; 4533	−3247; −2304	171; −174	0.29; 0.39	87.84; 87.78	5.6; 5.2	−1.6; 1.1
Hong-Kong II	21121	−15113	−429	0.12	94.02	6.3	−0.6
Hong-Kong III	20077	−8241	−397	0.34	97.74	7.5	0.8
Indonesia I	6.76	−1.11	0.039	0.44	94.09	15.6	−1.3
Indonesia II	7.38	−0.92	−0.06	0.23	98.05	10.08	5.8
Korea I	6.97	−0.28	−0.05	1.05	94.87	8.15	1.1
Malaysia I	7.61	−1.16	0.038	0.24	94.02	10.9	1.4
Philippines I	9.00	−1.74	−0.078	0.16	94.02	8.2	0.2
Thailand I	7.81	−1.41	−0.086	0.48	94.07	6.1	−0.2

$$I(t) = A + B(t_c - t)^z + C(t_c - t)^z \cos(\omega \log(t_c - t) - \phi)$$

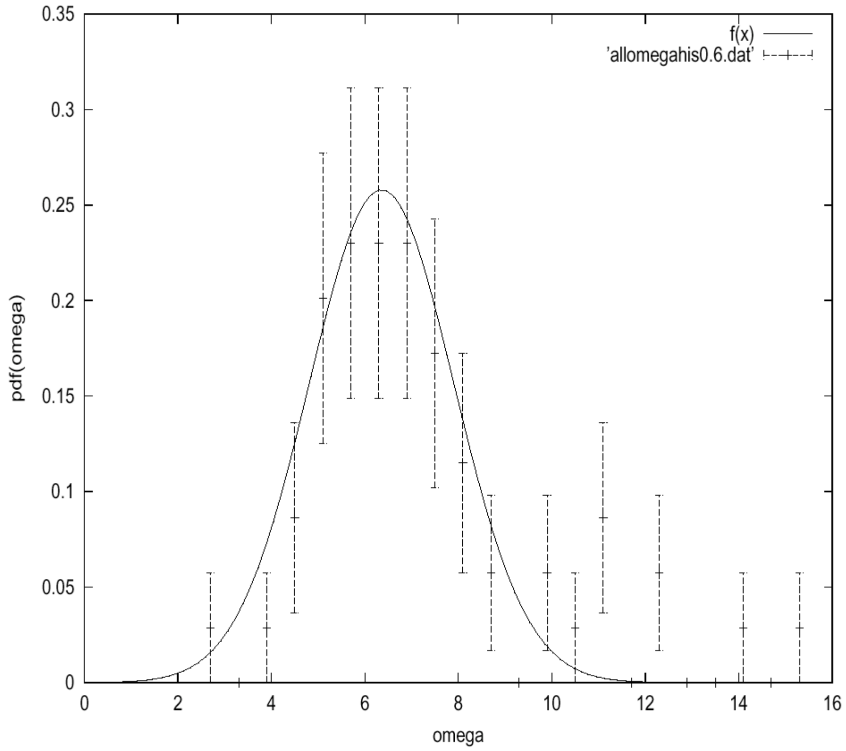


Figure 5: Empirical distribution of the log-periodic angular frequency ω in eq. (1) for over thirty case studies. The fit with a Gaussian distribution gives $\omega \approx 6.36 \pm 1.55$. The smaller peak centered on $11-12$ suggests the existence of a second discernable harmonics at $2\omega \approx 12$.

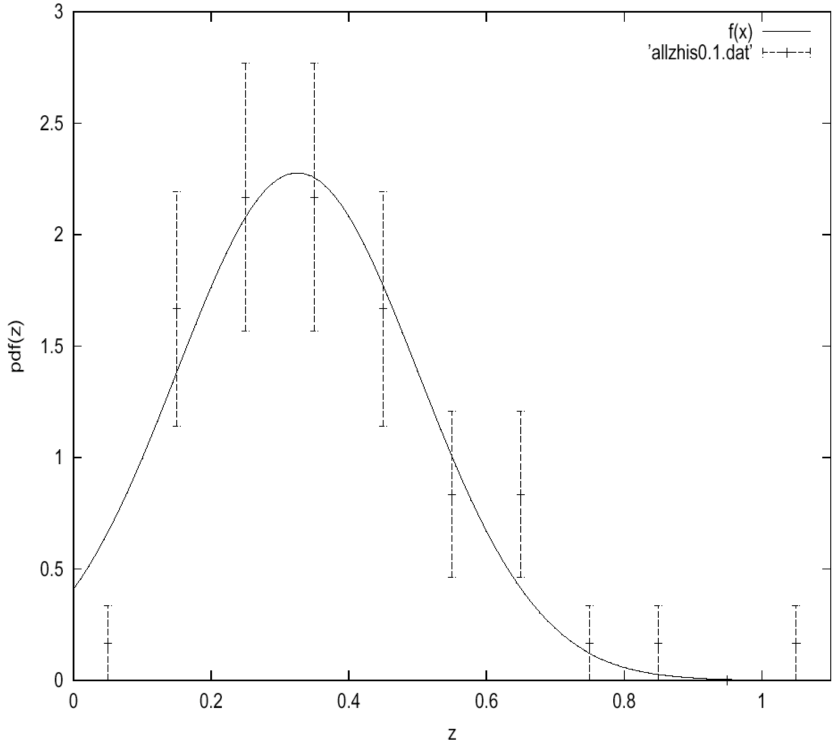
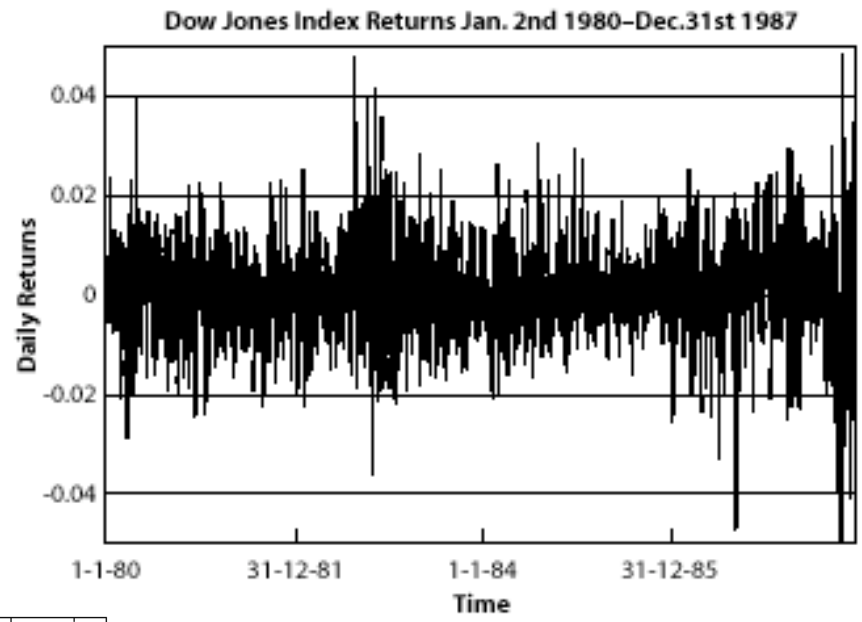


Figure 6: Empirical distribution of the exponent z of the power law in eq. (1) for over thirty case studies. The fit with a Gaussian distribution gives $\beta \approx 0.33 \pm 0.18$.

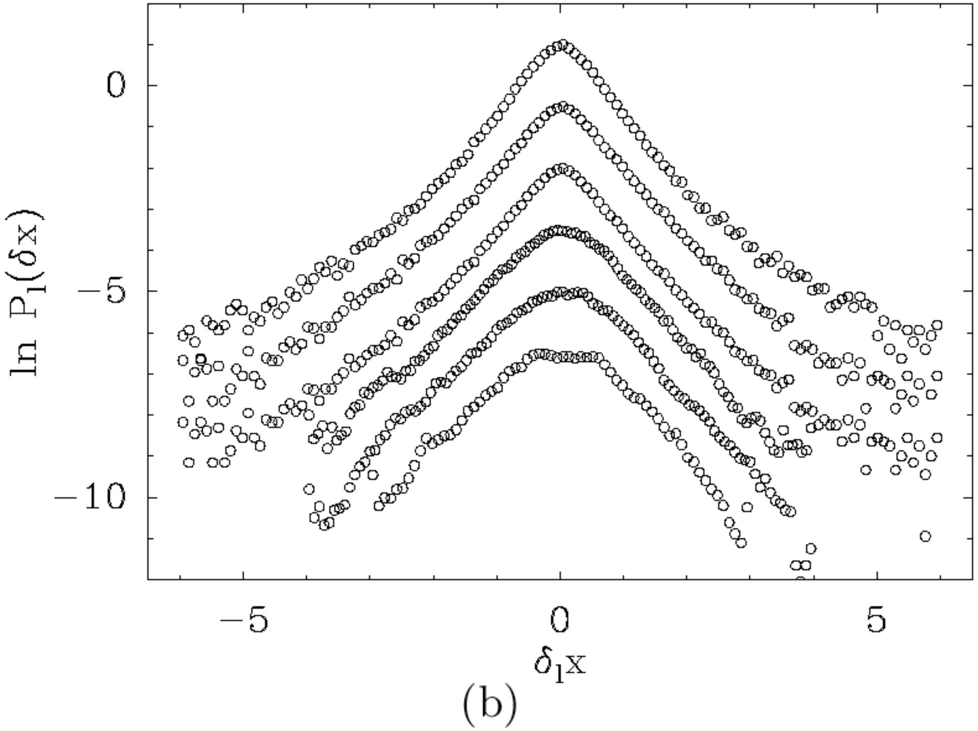
Demonstration of universal values of z and omega across many different bubbles at different epochs and different markets

A. Johansen and D. Sornette, Shocks, Crashes and Bubbles in Financial Markets, Brussels Economic Review (Cahiers economiques de Bruxelles), 49 (3/4), (2006)

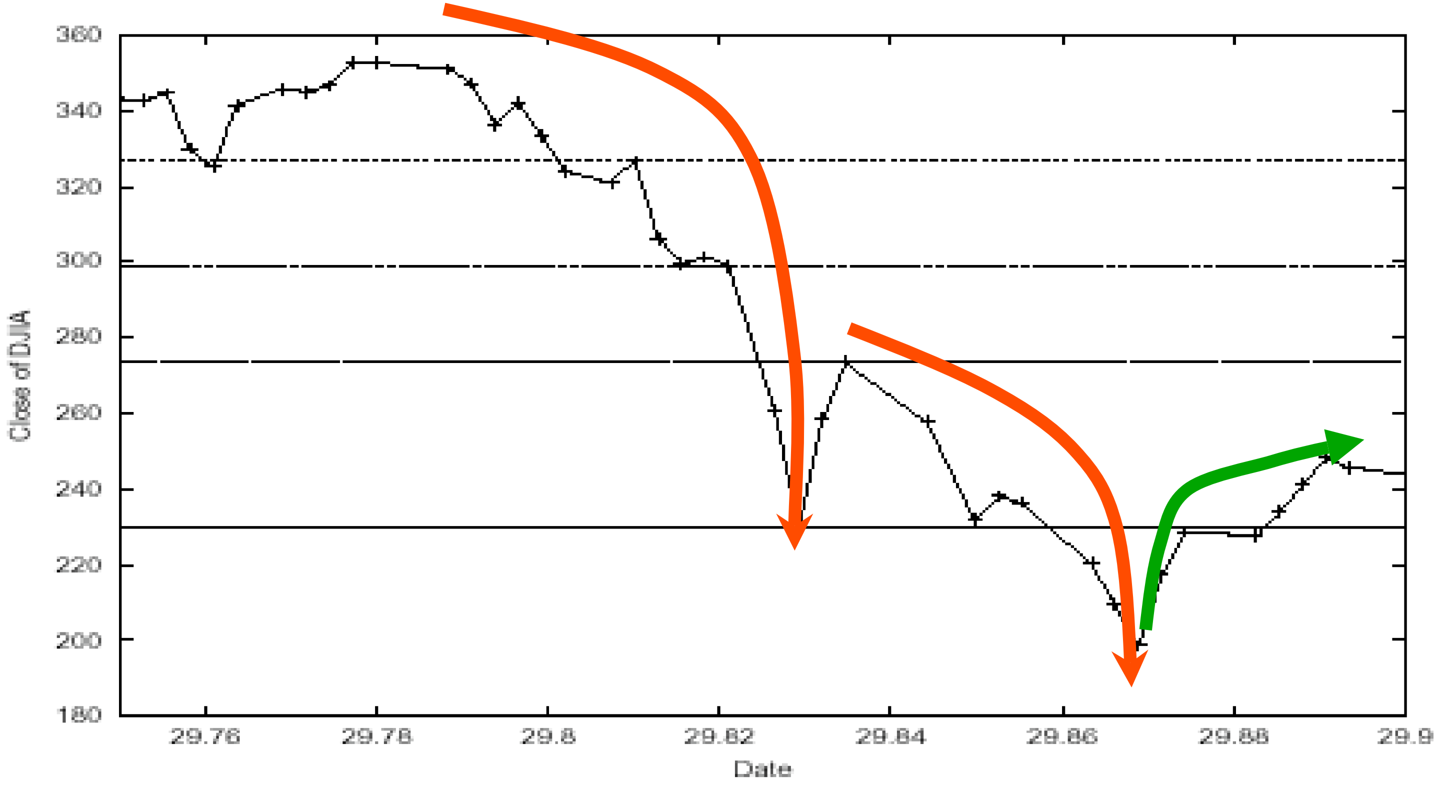
ARE CRASHES EXCEPTIONAL?

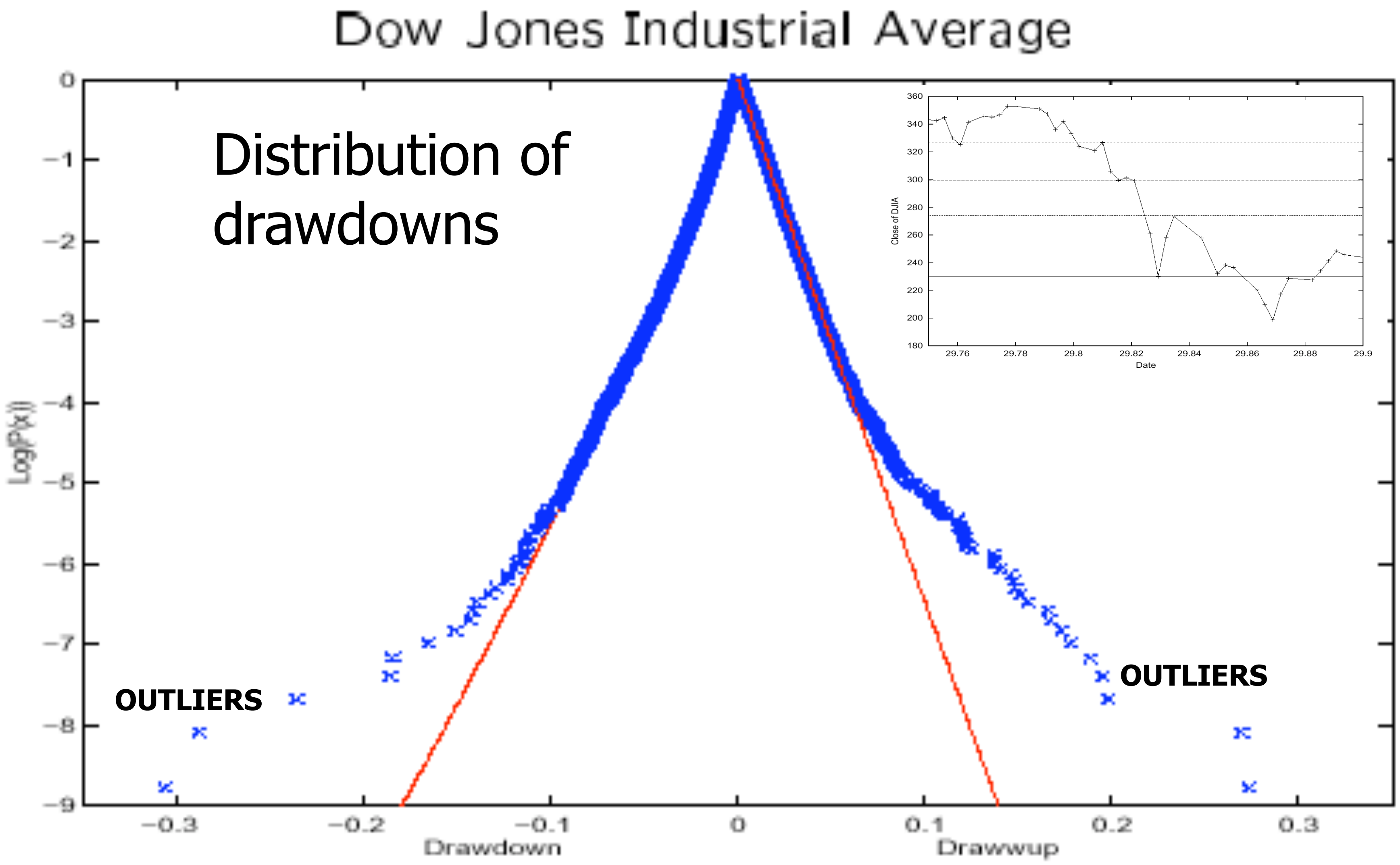


Traditional emphasis on Daily returns do not reveal any anomalous events



Better risk measure: drawdowns



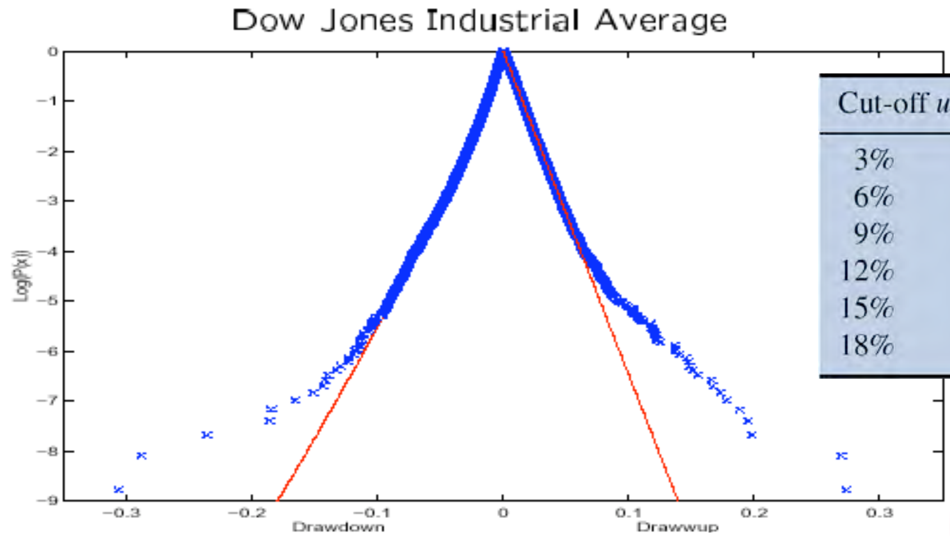


A. Johansen and D. Sornette, Stock market crashes are outliers,
European Physical Journal B 1, 141-143 (1998)

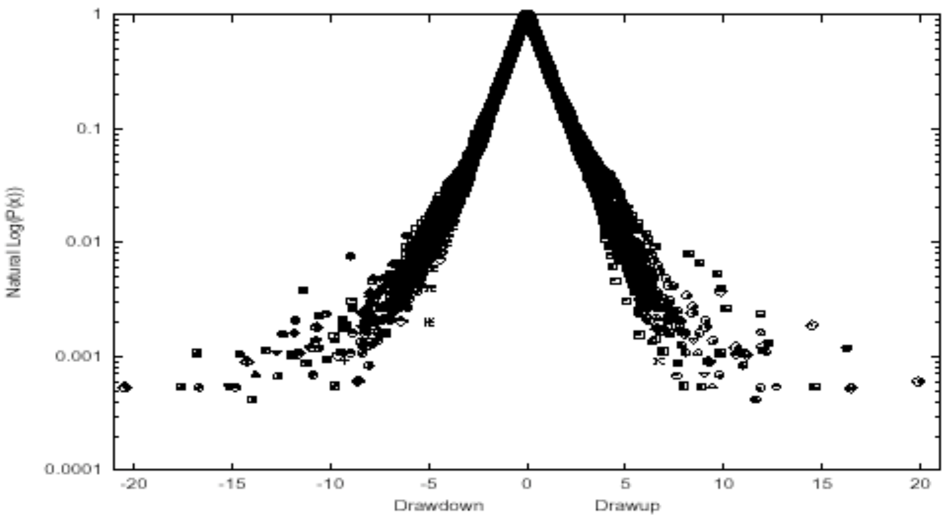
A. Johansen and D. Sornette, Large Stock Market Price Drawdowns Are Outliers,
Journal of Risk 4(2), 69-110, Winter 2001/02

Outliers, Kings

(require special mechanism and may be more predictable)



Cut-off u	Quantile	z	$\ln(L_0)$	$\ln(L_1)$	T	Proba
3%	87%	0.916, 0.940	4890.36	4891.16	1.6	20.5%
6%	97%	0.875, 0.915	4944.36	4947.06	5.4	2.0%
9%	99.0%	0.869, 0.918	4900.75	4903.66	5.8	1.6%
12%	99.7%	0.851, 0.904	4872.47	4877.46	10.0	0.16%
15%	99.7%	0.843, 0.898	4854.97	4860.77	11.6	0.07%
18%	99.9%	0.836, 0.890	4845.16	4851.94	13.6	0.02%



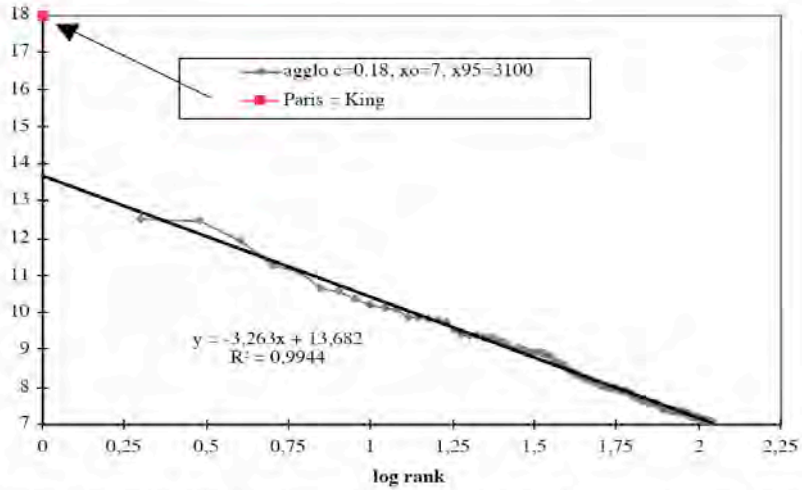


Fig. 7. French agglomerations: stretched exponential and "King effect".

Endogenous vs exogenous crashes

1. Systematic qualification of outliers/kings in pdfs of drawdowns

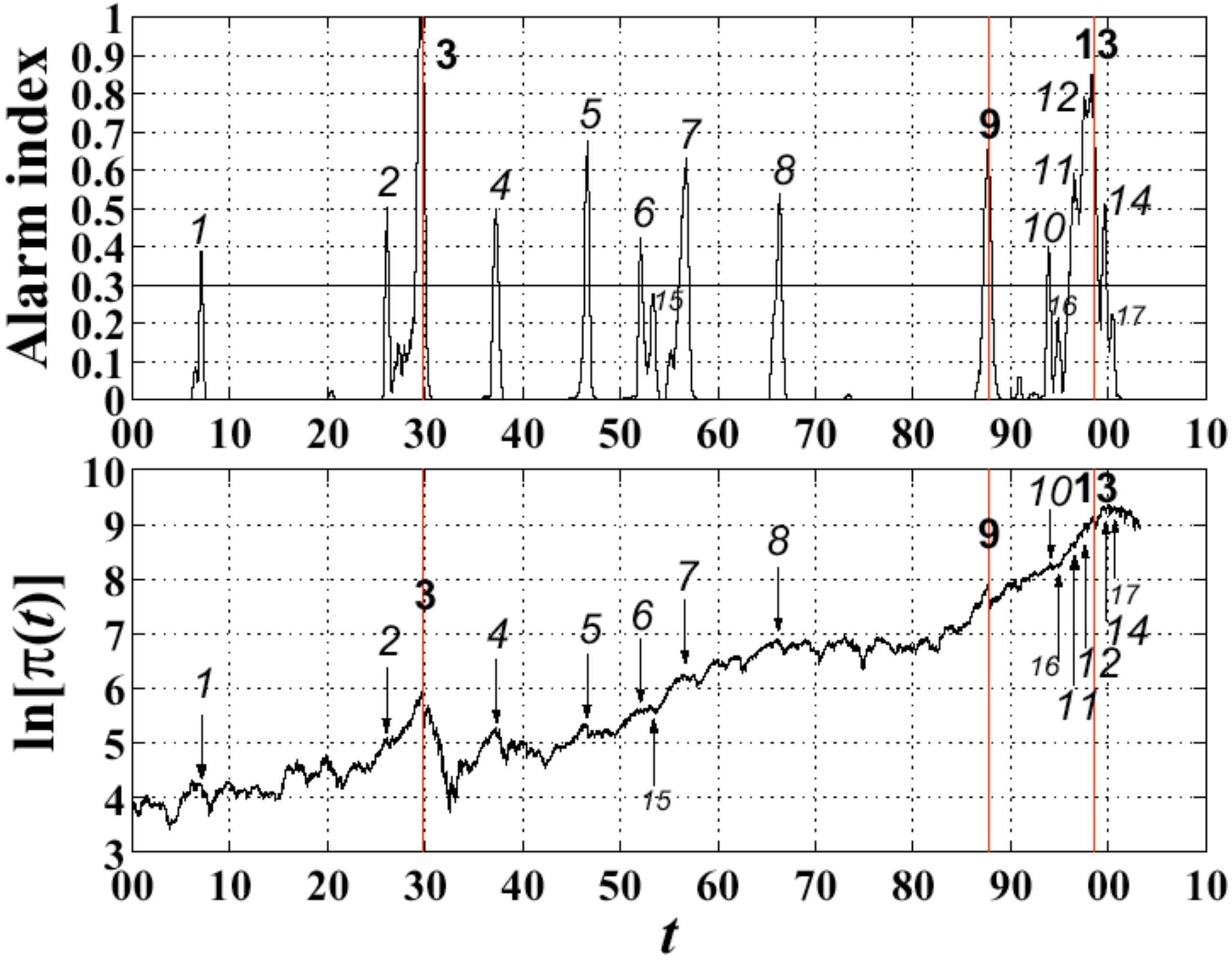
2. Existence or absence of a "critical" behavior by LPPL patterns found systematically in the price trajectories preceding this outliers

Results: In worldwide stock markets + currencies + bonds

- **21 endogenous crashes**
- **10 exogenous crashes**

A. Johansen and D. Sornette,
Endogenous versus Exogenous Crashes in Financial Markets,
in press in ``Contemporary Issues in International Finance''
(Nova Science Publishers, 2004)
(http://arXiv.org/abs/cond-mat/0210509)

Multiscale Pattern Recognition Method

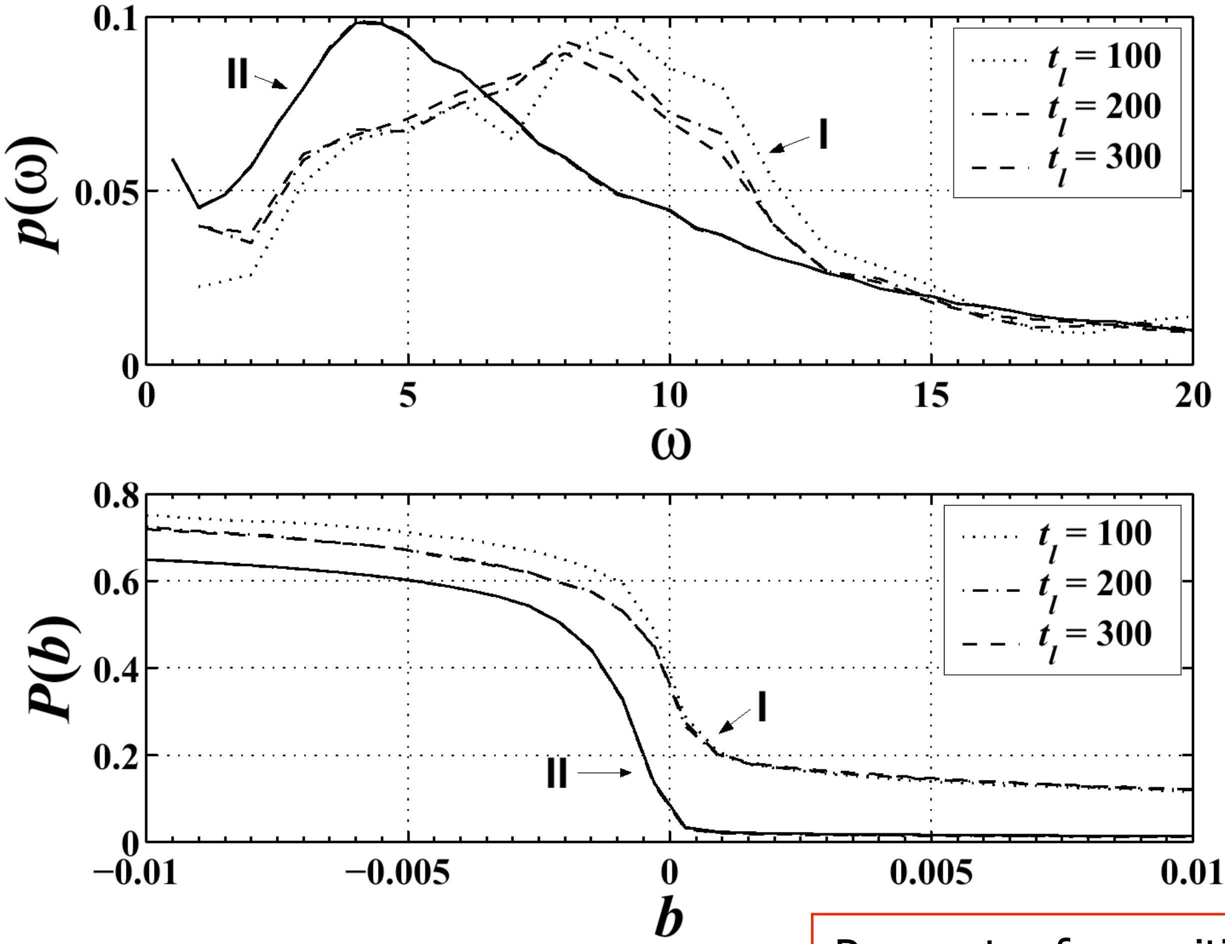


D. Sornette and W.-X. Zhou, Predictability of Large Future Changes in major financial indices, International Journal of Forecasting 22, 153-168 (2006)

Extension to a multi-scale LPPL analysis with Gelfand's method of pattern recognition to predict

Figure 3: (Color online) Alarm index $AI(t)$ (upper panel) and the DJIA index from 1900 to 2003 (lower panel). The peaks of the alarm index occur at times indicated by arrows in the bottom panel.

Determination of relevant "traits" that allow us to distinguish targets from non targets in the Learning process



$b \equiv Bm - |C|\sqrt{m^2+\omega^2} \geq 0.$

Parameter for positivity of crash hazard rate

Figure 1: Density distribution $p(\omega|\text{I or II})$ of the DSI parameter ω obtained from (1) and complementary cumulative distribution $P(b|\text{I or II})$ of the constraint parameter b obtained from (2) for the objects in classes I (dotted, dashed, and dotted-dashed) and II (continuous) for three different values of t_l.

Multi-scale approach to critical times

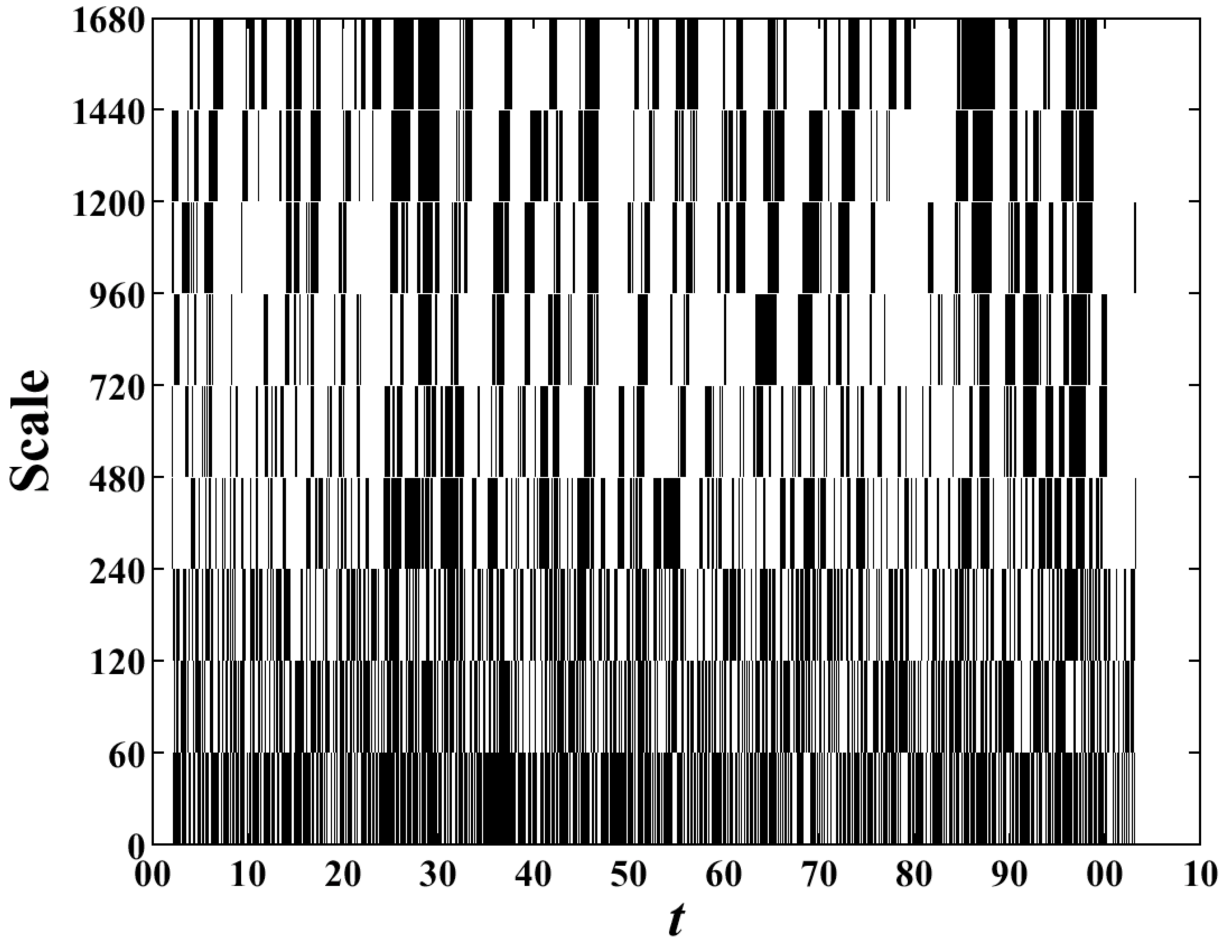


Figure 2: Alarm times t (or dangerous objects) obtained by the multiscale analysis. The alarms satisfy $b \geq 0$, $6 \leq \omega \leq 13$ and $0.1 \leq m \leq 0.9$ simultaneously. The ordinate is the investigation "scale" in trading day unit. The results are robust with reasonable changes of these bounds.

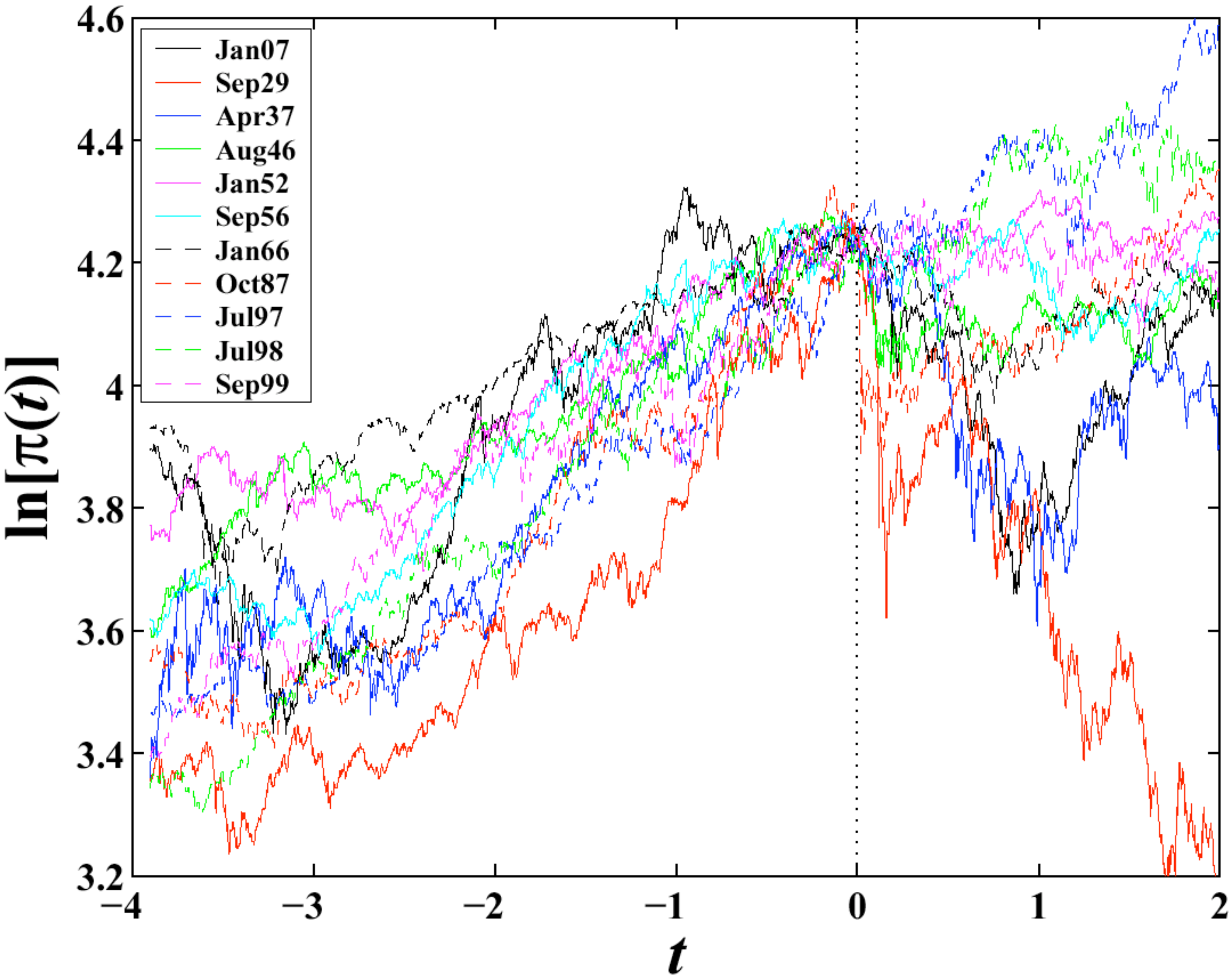
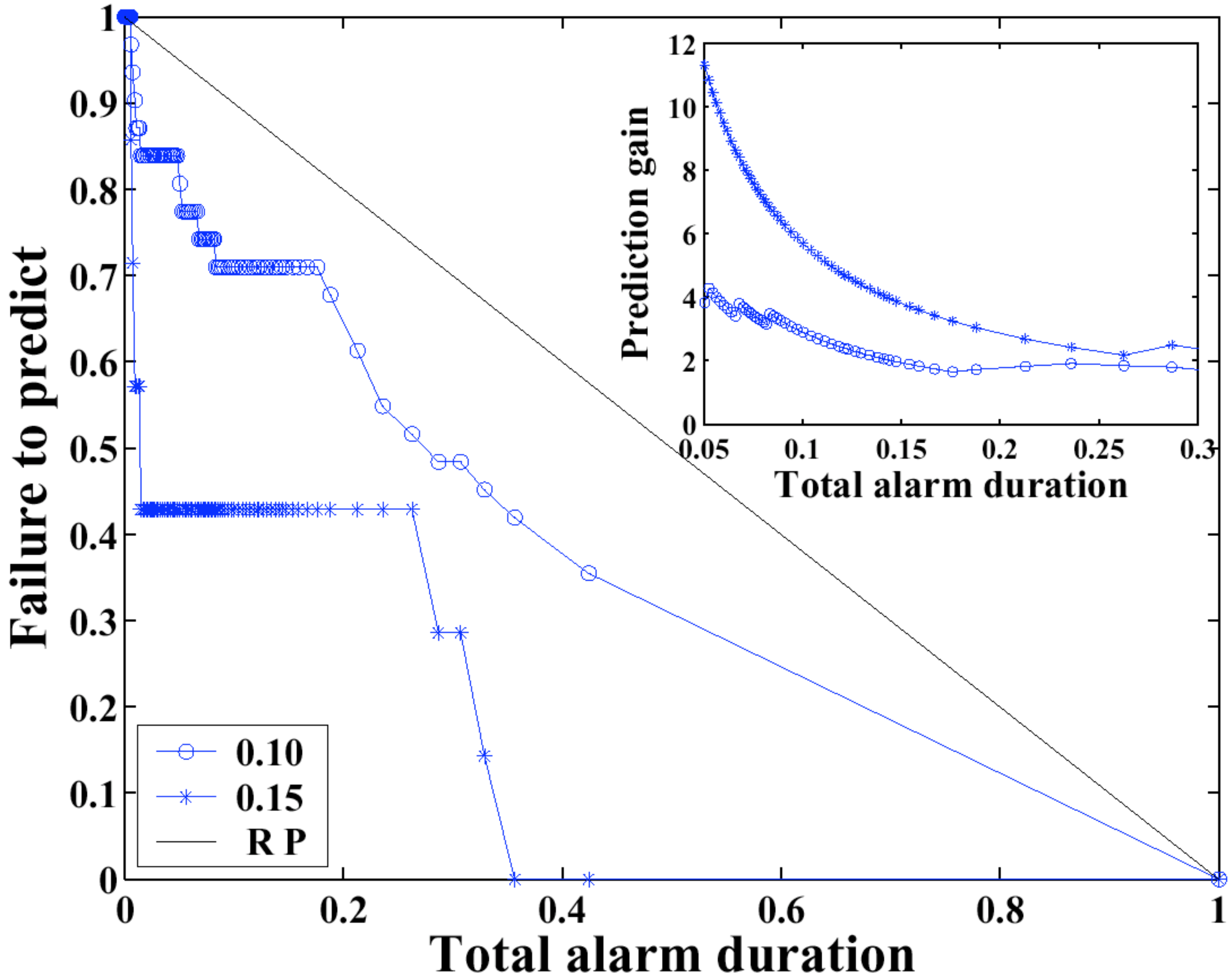


Figure 4: (Color online) Superposed epoch analysis of the 11 time intervals, each of 6 years long, of the DJIA index centered on the time of the maxima of the 11 predictor peaks above $AI = 0.3$ of the alarm index shown in Fig. 3.



We obtain very significant prediction gains

Figure 5: Error diagram for our predictions for two definitions of targets to be predicted $r_0 = 0.1$ and $r_0 = 0.15$ obtained for the DJIA. The anti-diagonal line corresponds to the random prediction result. The inset shows the prediction gain.

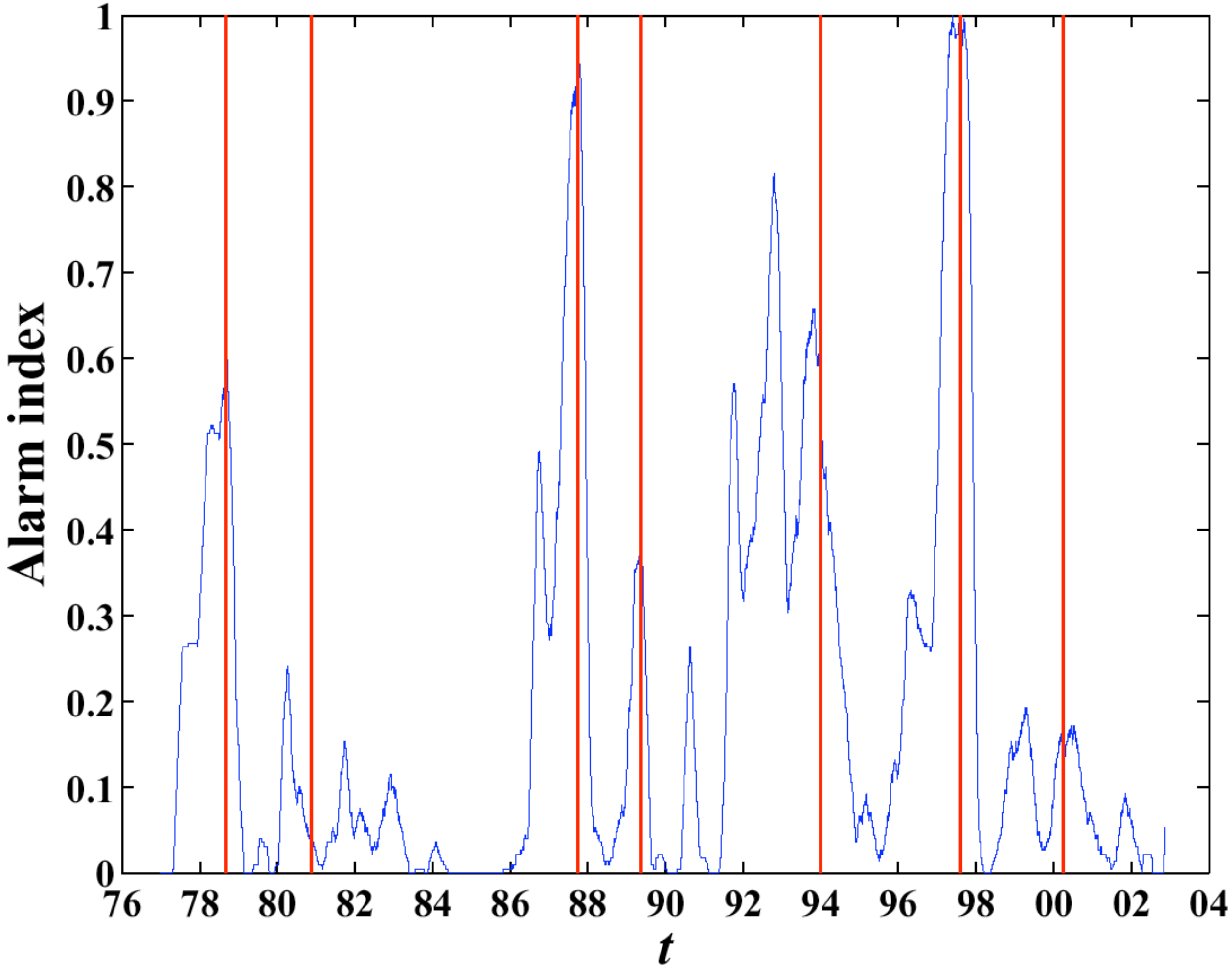


Figure 6: (Color online) Alarm index $AI(t)$ constructed by our algorithm for the Hong Kong Hang Seng composite index since 24-Nov-1969. The vertical lines indicate the timing of the seven crashes that have not been used in the training part. Note that the first two crashes are not included in the analysis since the longest window used in our multiscale analysis is seven years.

What are bubbles?
How do detect them?
How to predict them?

Academic Literature:
No consensus on what is a bubble...

The Fed: A. Greenspan (Aug., 30, 2002):
“We, at the Federal Reserve…recognized that, despite our suspicions, it was very difficult to definitively identify a bubble until after the fact, that is, when its bursting confirmed its existence… Moreover, it was far from obvious that bubbles, even if identified early, could be preempted short of the Central Bank inducing a substantial contraction in economic activity, the very outcome we would be seeking to avoid.”

What are bubbles?
How do detect them?
How to predict them?

Our proposition to the Academic Literature:
“Super exponential price acceleration” and “king” effect

Our proposition to the Fed:
Complex system approach with emphasis on
(i) positive and negative feedback interplay
(ii) collective behavior and organization lead to “EMERGENCE”

Towards a methodology to identify crash risks

- Development of methods to diagnose bubbles
- Crashes are not predictable
- Only the end of bubbles can be forecasted
- 2/3 ends in a crash
- Multi-time-scales
- Probability of crashes; alarm index
  - Successful forward predictions: Oct. 1997; Aug. 1998, April 2000
  - False alarms: Oct. 1997

- Towards a FINANCIAL CRISIS OBSERVATORY

Real-estate

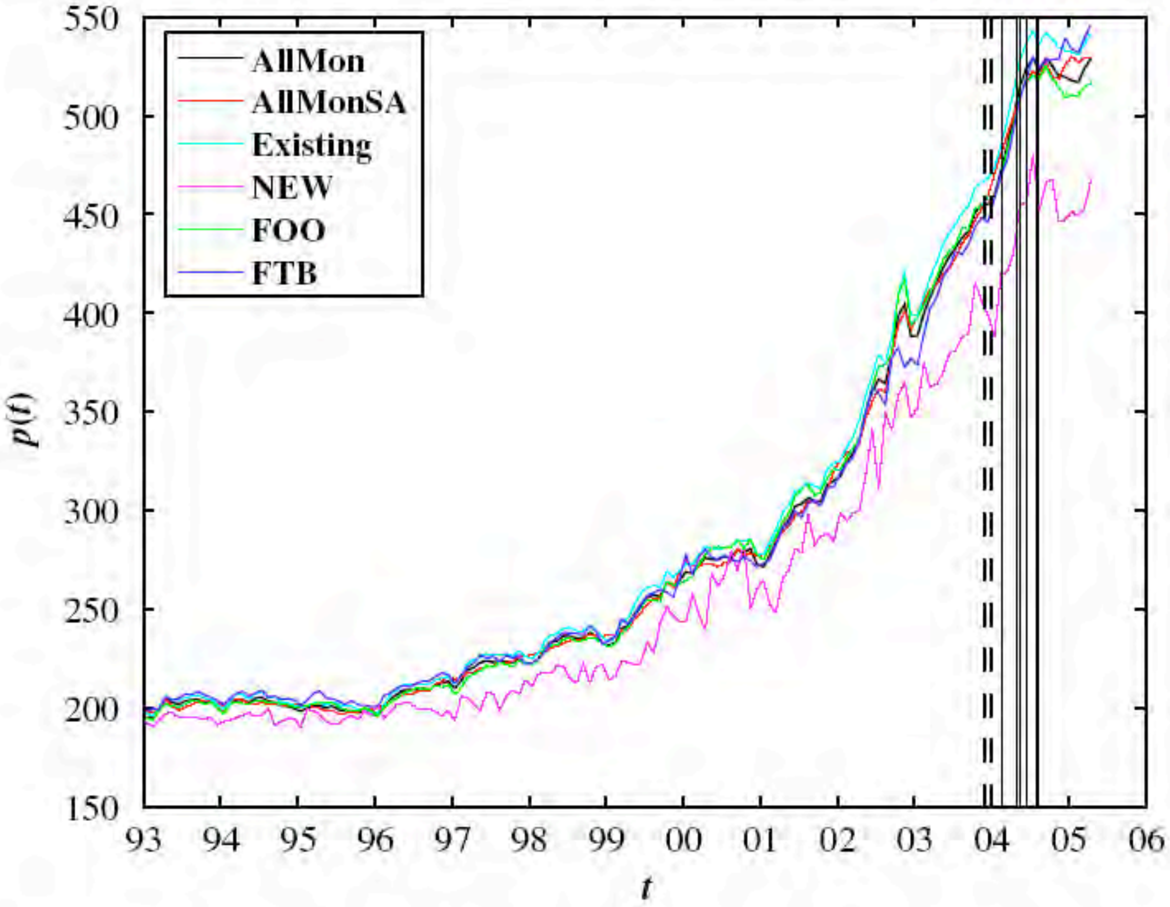


Fig. 1. (Color online) Plot of the UK Halifax house price indices from 1993 to April 2005 (the latest available quote at the time of writing). The two groups of vertical lines correspond to the two predicted turning points reported in Tables 2 and 3 of [1]: end of 2003 and mid-2004. The former (resp.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

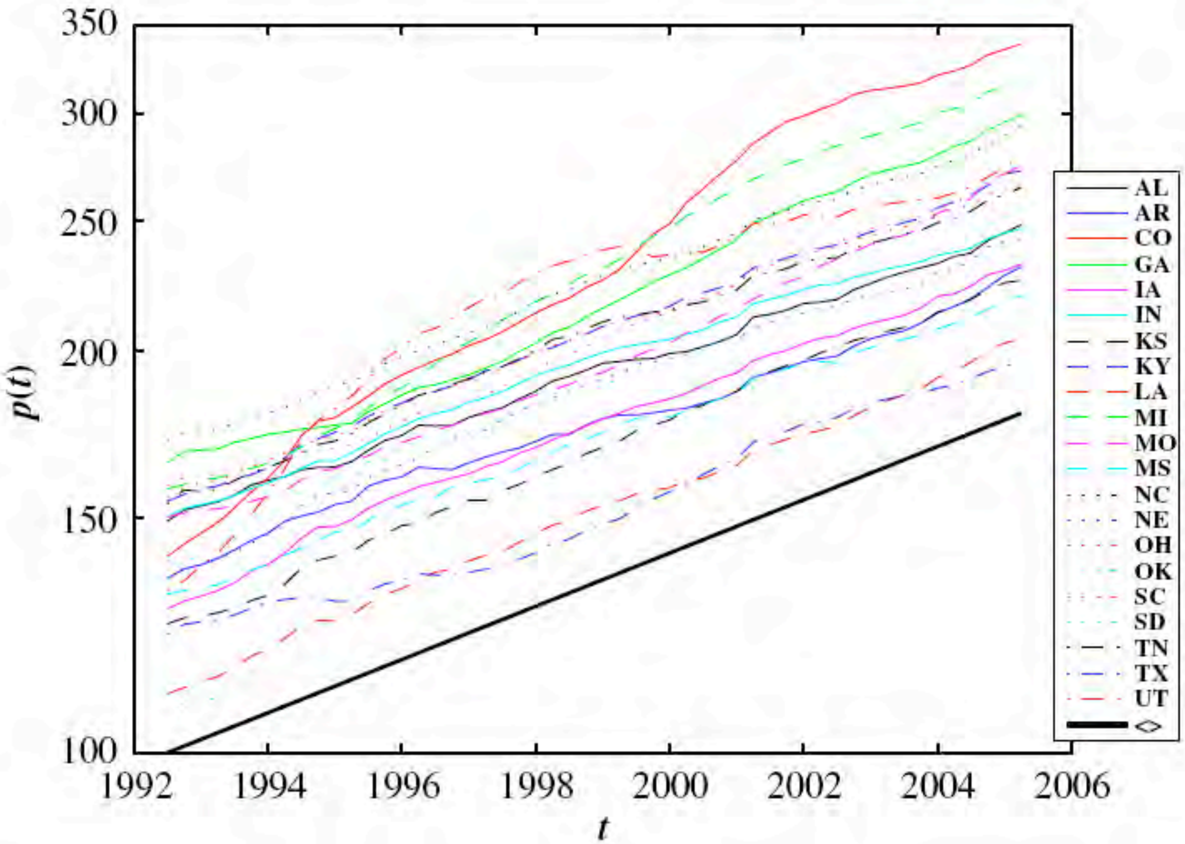


Fig. 3. (Color online) Quarterly HPI in the 21 states which have an approximately constant exponential growth, qualified by a linear trend in a linear-logarithmic scale. The thick straight line at the bottom of the figure indicates the average over all 21 states corresponding to an annual growth rate of 4.6% over the last 13 years. The corresponding states are given in the legend. Note that Colorado seems to be on a faster trend.

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

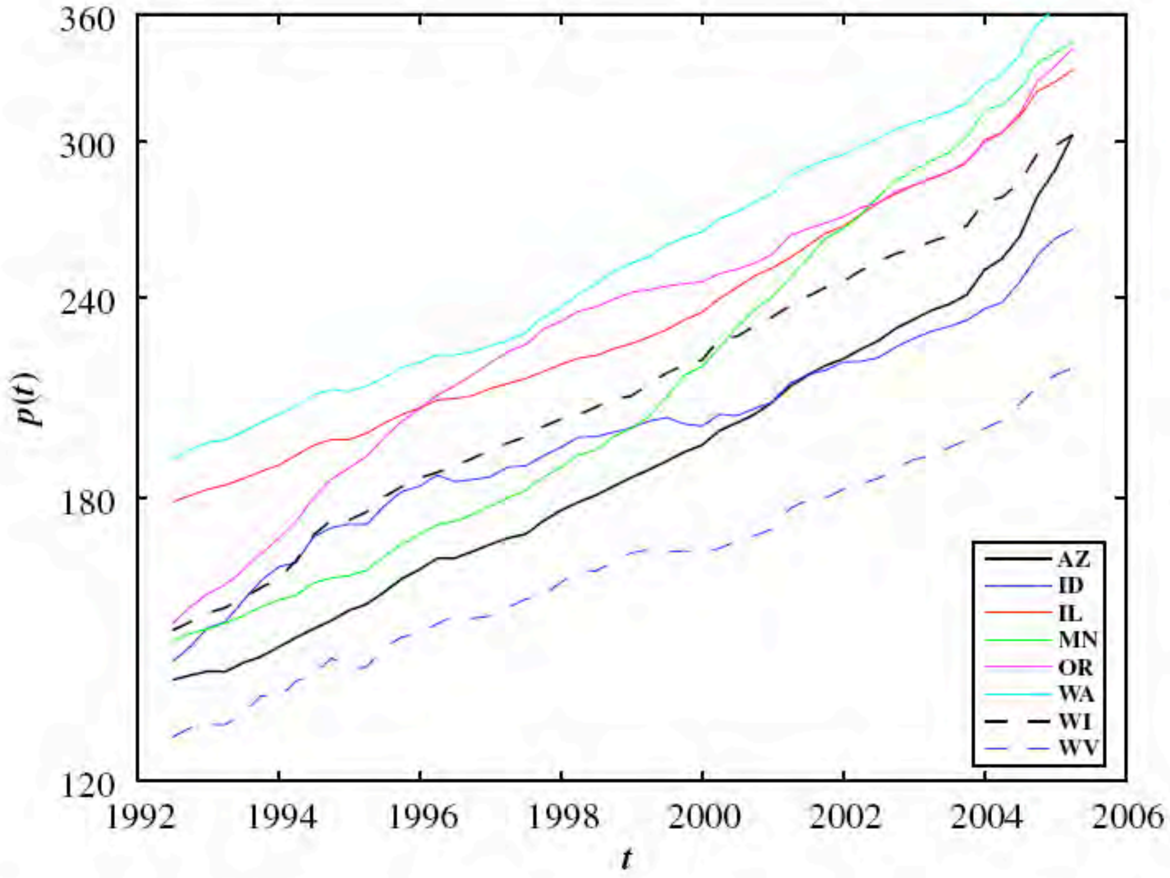


Fig. 4. (Color online) Quarterly HPI in the 8 states exhibiting a recent upward acceleration following an approximately constant exponential growth rate. The corresponding states are given in the legend.

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

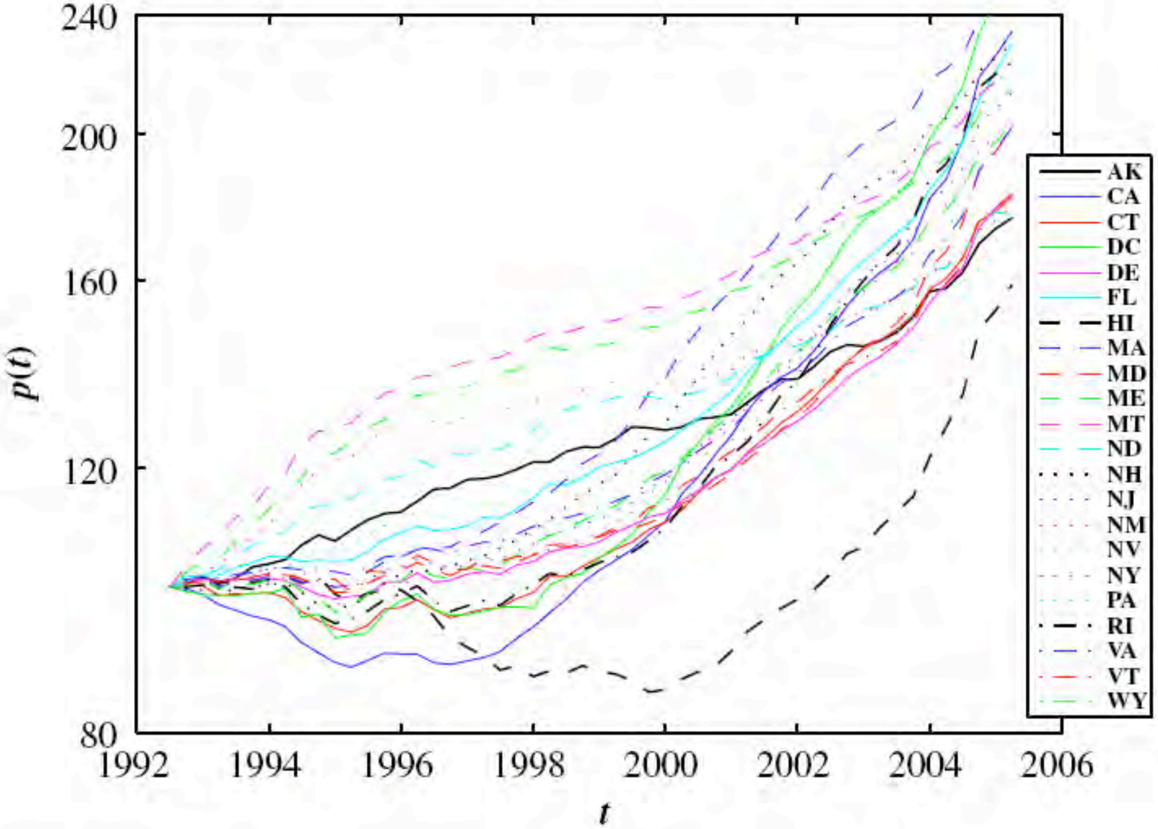
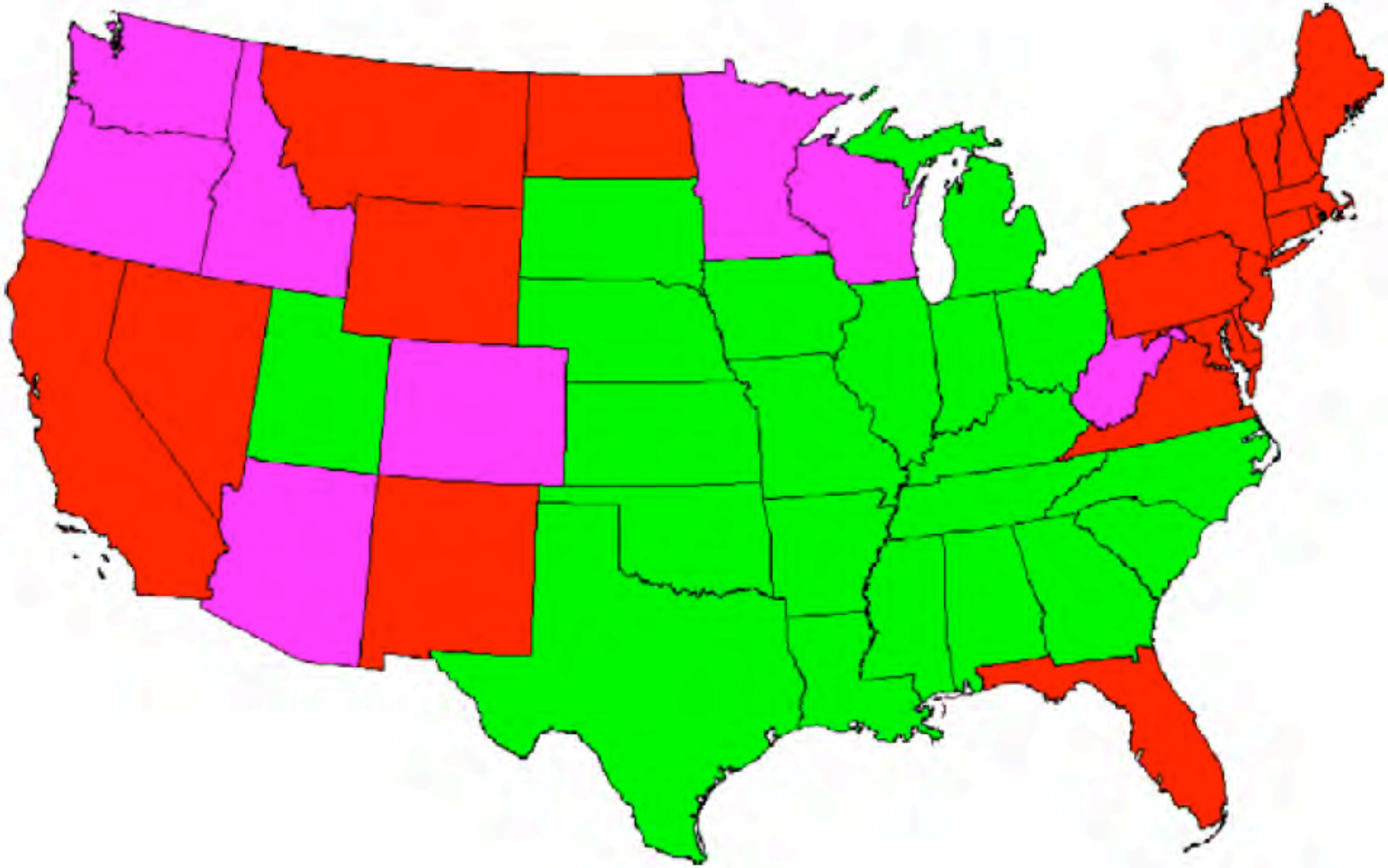


Fig. 5. (Color online) Quarterly average HPI in the 21 states and in the District of Columbia (DC) exhibiting a clear upward faster-than-exponential growth. For better representation, we have normalized the house price indices for the second quarter of 1992 to 100 in all 22 cases. The corresponding states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



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

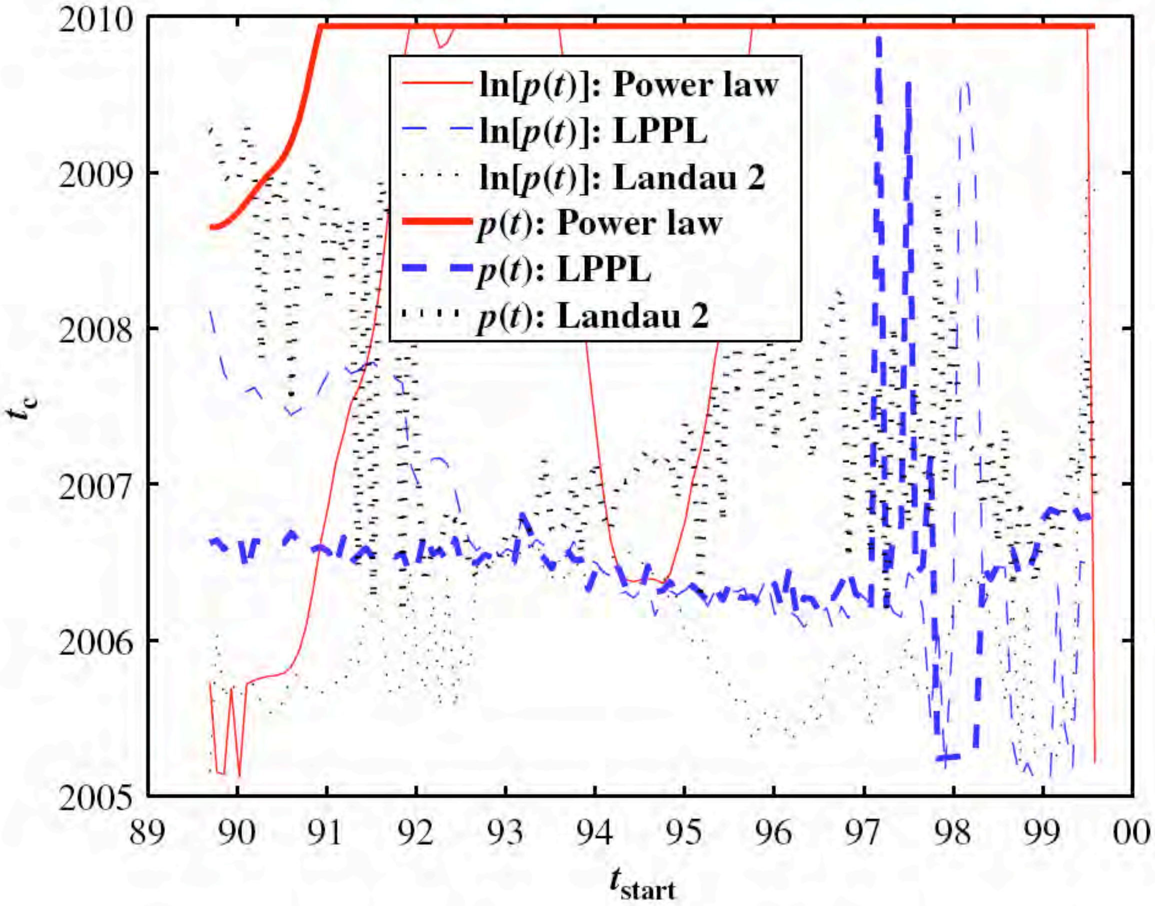


Fig. 9. (Color online) Predicted critical time t_c as a function of t_{start} obtained from the fits with the LPPL and the 2nd-order Landau LPPL models as in Fig. 8.

717 VERNON WY
BURLINGAME, CA 94010

(2005)

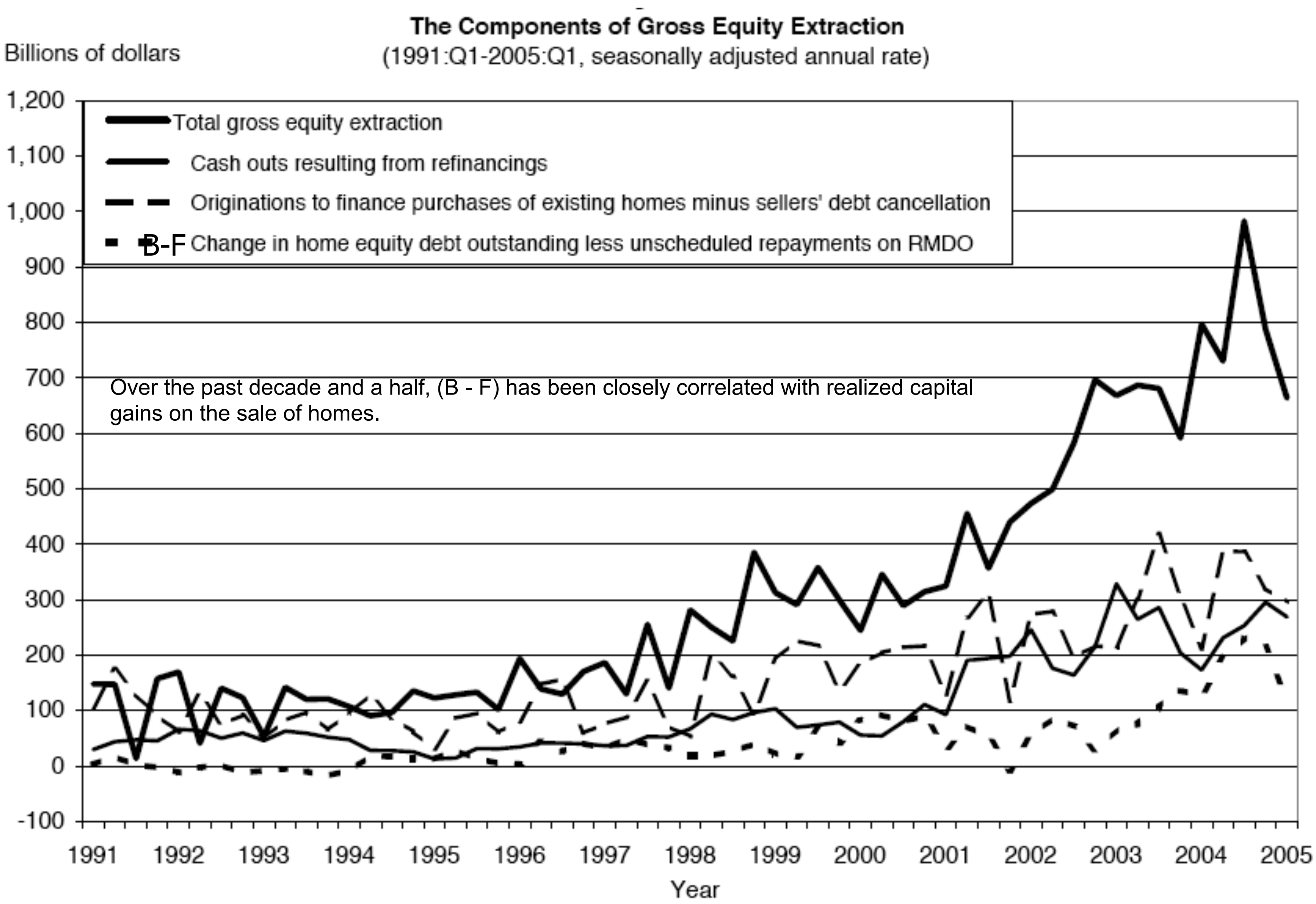
2 Bedrooms, **1** Bath(s)
1,310 Estimated Sq. Ft.

Listing #: 620130

$1,049,000

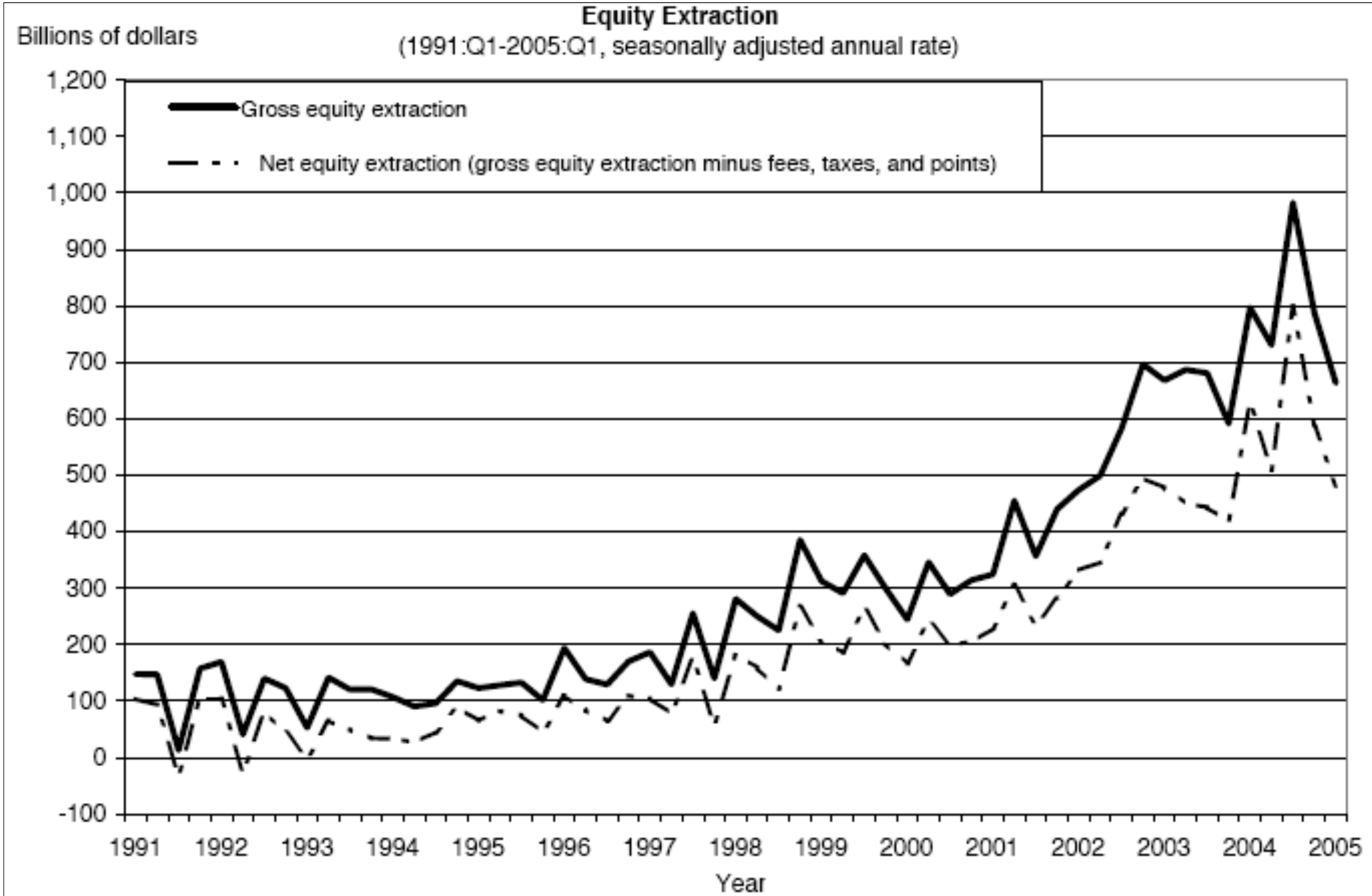
And this with the median household income in San Mateo County of ~$70,000. With 20% down, the mortgage for a "starter" $1M house would be 11-12 times the median income. Even if one were "buying up" to one of these houses, say, with equity of 50%, the mortgage/median income ratio would be 7:1!!!

From late '02 and early '03 to date--the bubbliest phase--the value of the property below is estimated to have more than DOUBLED, peaking at an estimated $1.16M in summer-fall '05, an annualized increase in value of ~14% from '96. However, before the one order of magnitude of exponential growth of the bubble commenced in late '02, the rate of growth of the value of this property was ~6.9%/yr. Were the value to regress to the pre-bubble trend, the estimated value would be $620,000-$820,000 over the course of the next 4 years or a 30% to 40-45% nominal decline and -11% to -18%/yr. in real terms (at the trend 2.7% CPI).



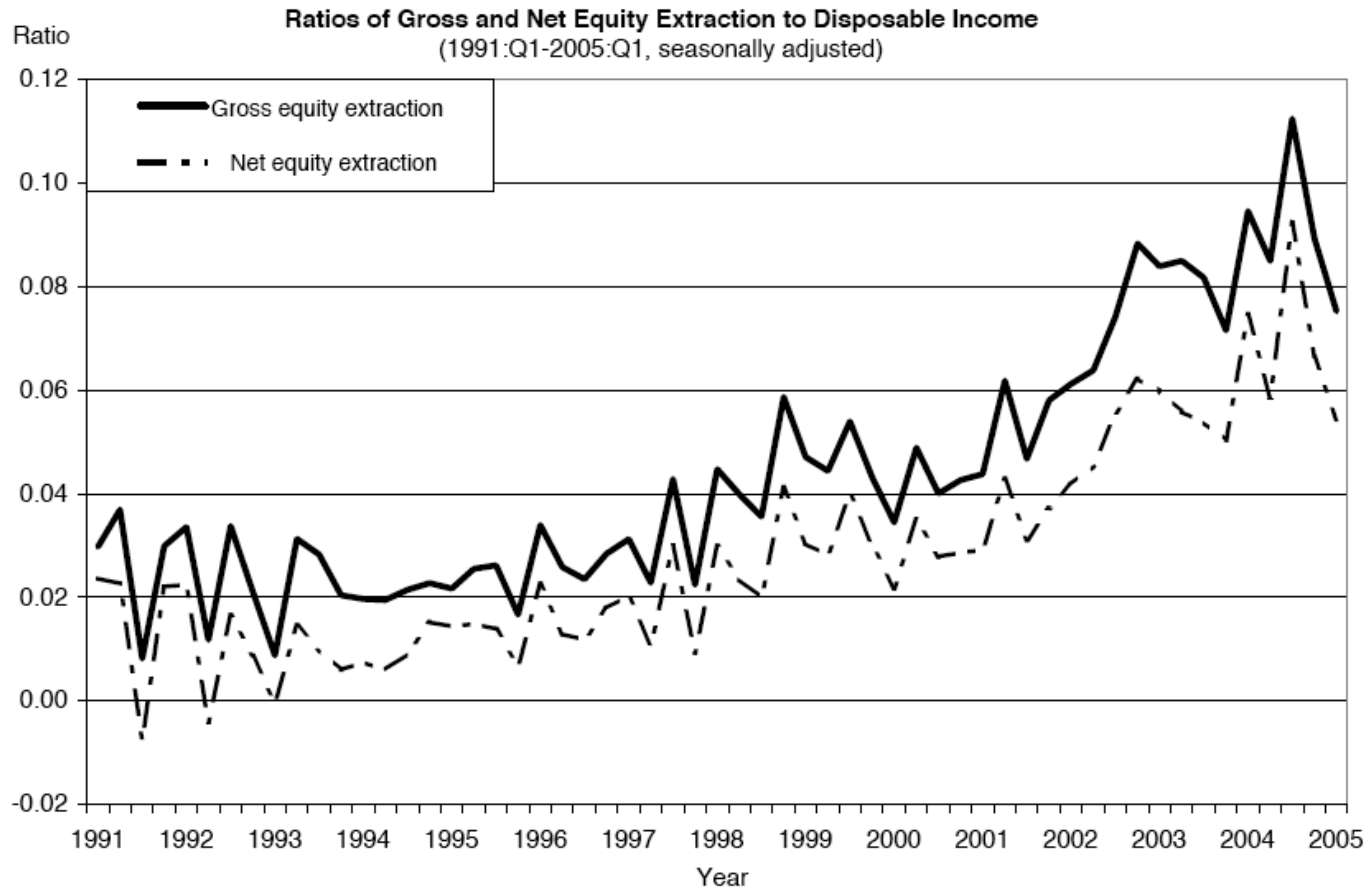
Over the past decade and a half, (B - F) has been closely correlated with realized capital gains on the sale of homes.

Alan Greenspan and James Kennedy (Nov. 2005)



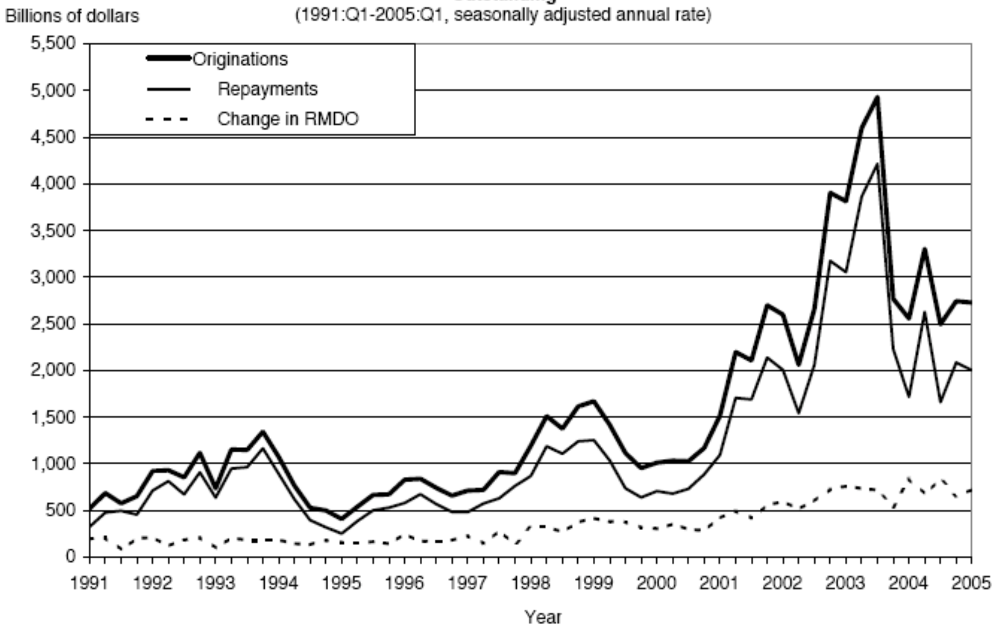
-Gross equity extraction as the change in RMDO (regular mortgage debt outstanding) minus new home originations plus scheduled amortization.

-Net equity extraction is defined as gross equity extraction less closing costs and other costs related to the extraction of home Equity.


Ratios of Gross and Net Equity Extraction to Disposable Income
(1991:Q1-2005:Q1, seasonally adjusted)
Ratio
0.12
0.10
0.08
0.06
0.04
0.02
0.00
-0.02
Gross equity extraction
Net equity extraction
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
Year

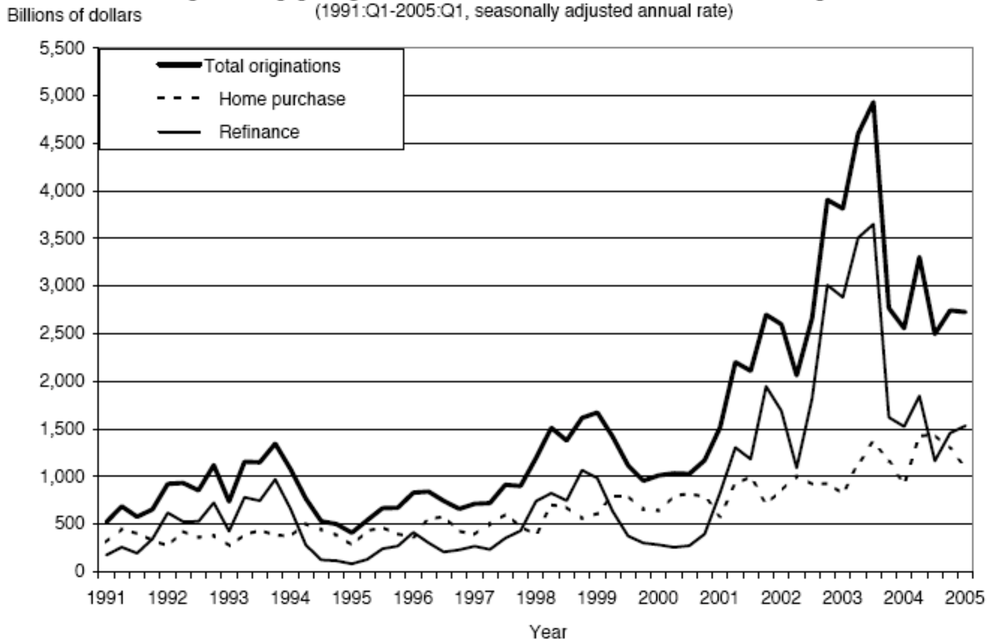
Regular Mortgages: Originations, Repayments, and the Change in Mortgage Debt Outstanding

(1991:Q1-2005:Q1, seasonally adjusted annual rate)



Regular Mortgage Originations to Purchase Homes and to Refinance Existing Loans

(1991:Q1-2005:Q1, seasonally adjusted annual rate)



LAS VEGAS

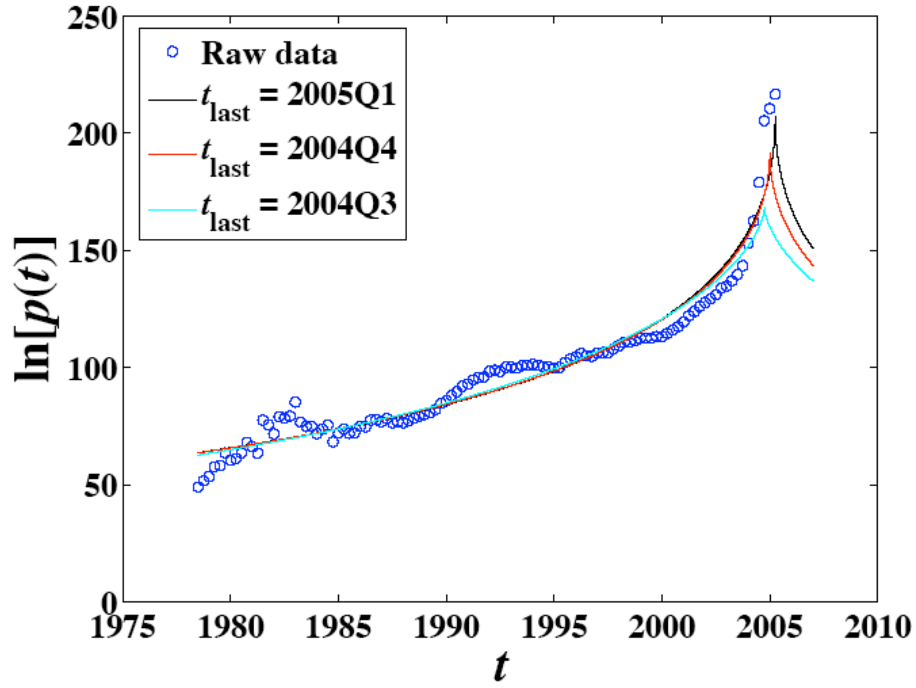
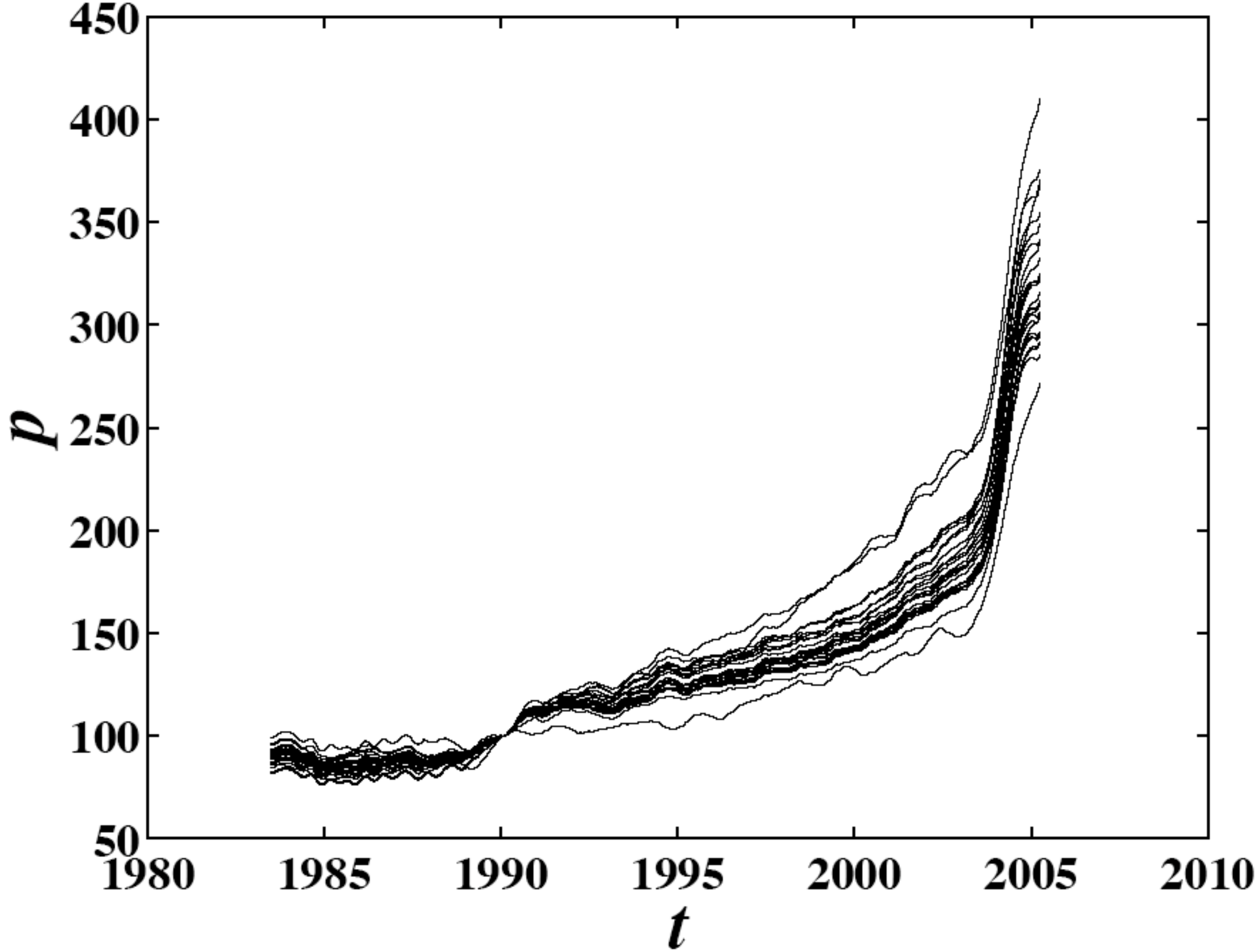


Figure 1: Three fits of the quarterly data of Las Vegas house price index from 1978Q2 to 2004Q3, to 2004Q4, and to 2005Q1, respectively, using the pure power model (9). The fit parameters for 2004Q3 are $t_c = 2004.75$ and $m = 0.63$ with the r.m.s. of the fit residuals being 0.0686. The fit parameters for 2004Q4 are $t_c = 2005.0$ and $m = 0.54$ with the r.m.s. of the fit residuals being 0.0709. The fit parameters for 2005Q1 are $t_c = 2005.25$ and $m = 0.48$ with the r.m.s. of the fit residuals being 0.0725.

Regional Case-Shiller-Weiss Indices of Las Vegas



Time evolution of the Case-Shiller-Weiss (CSW) indices of 27 Las Vegas zip codes

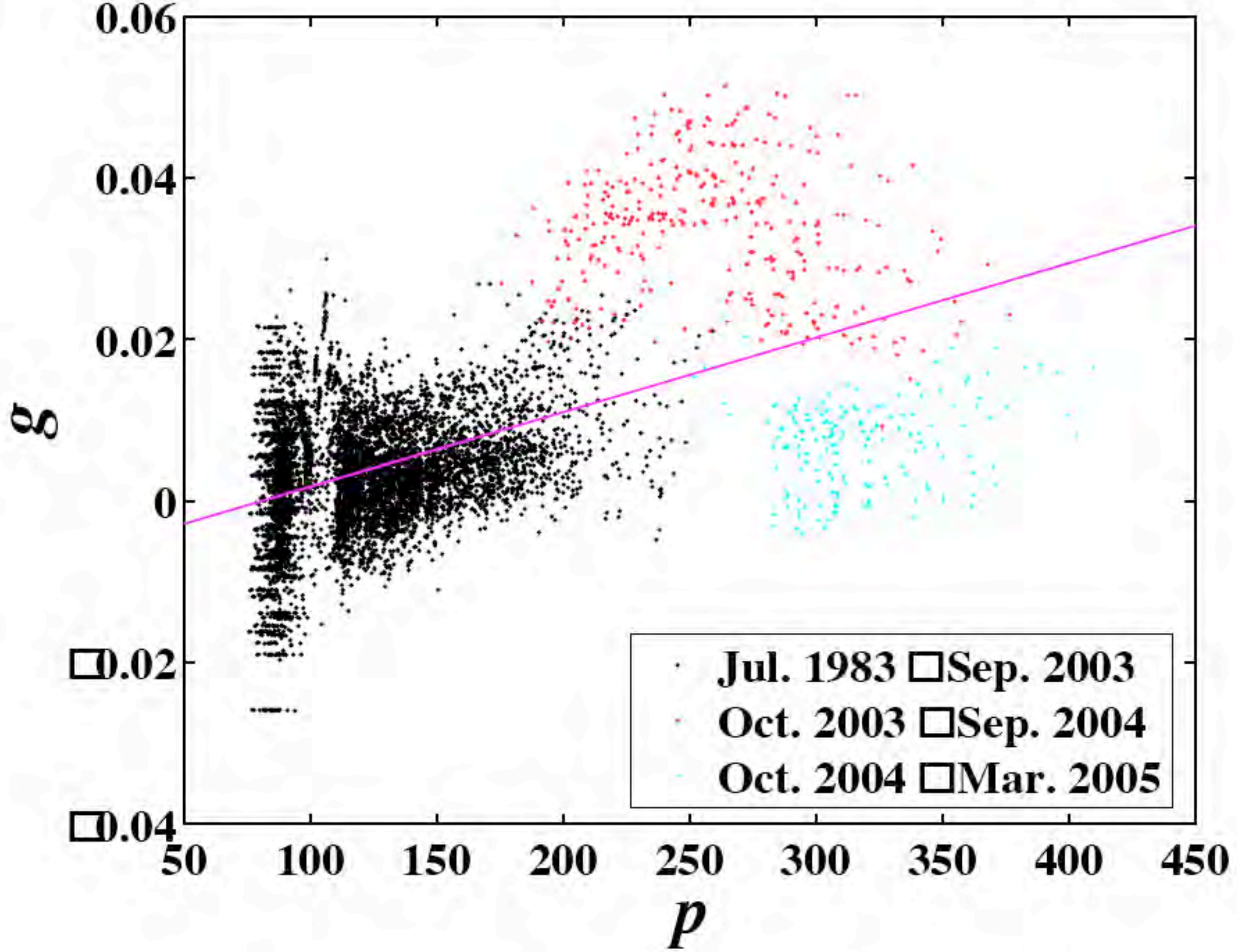


Figure 11: Dependence of the data p for all CSW indices on its growth rate g. The overall correlation coefficient is 0.494. The red line is the linear fit of the data points.

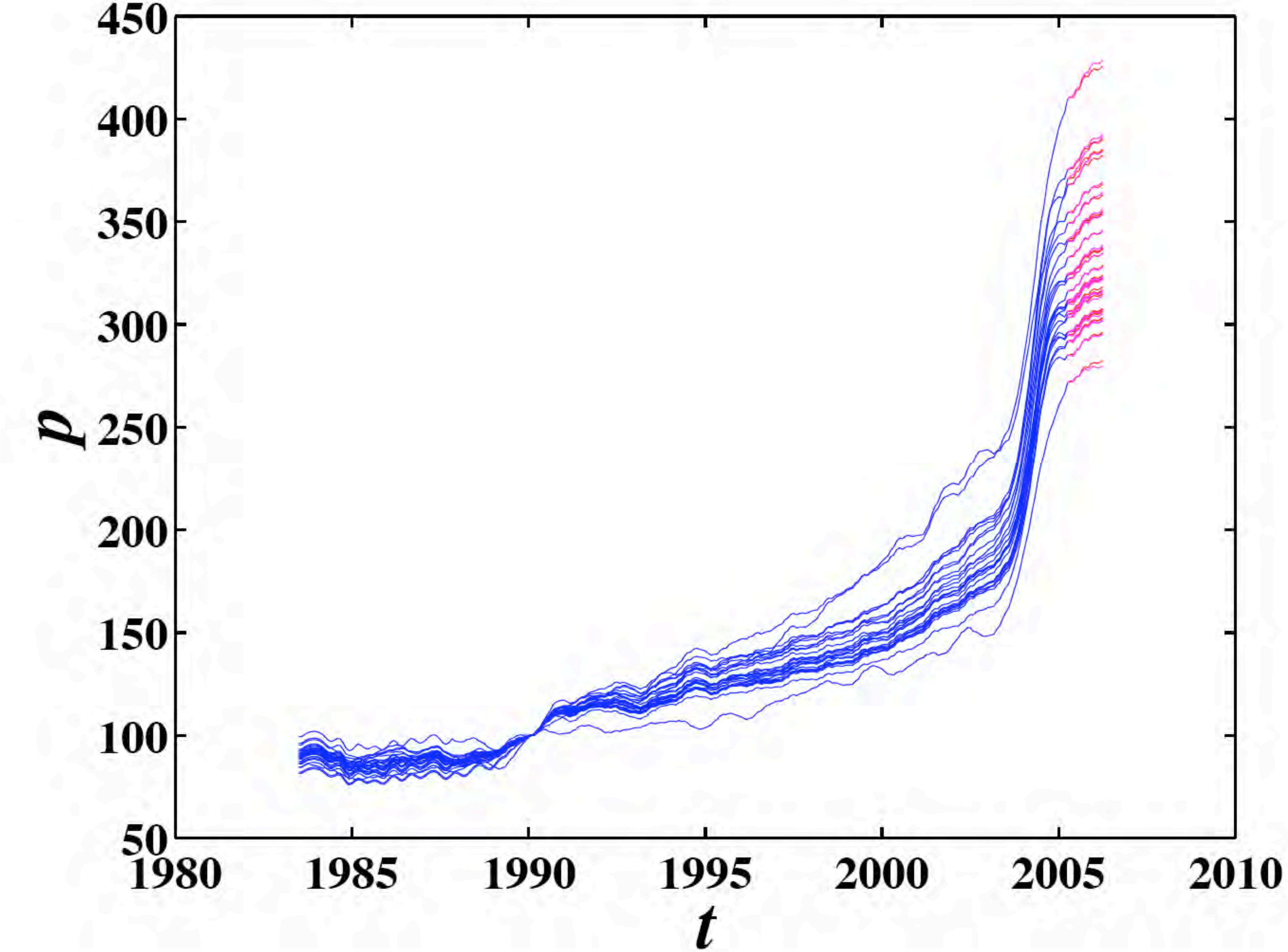
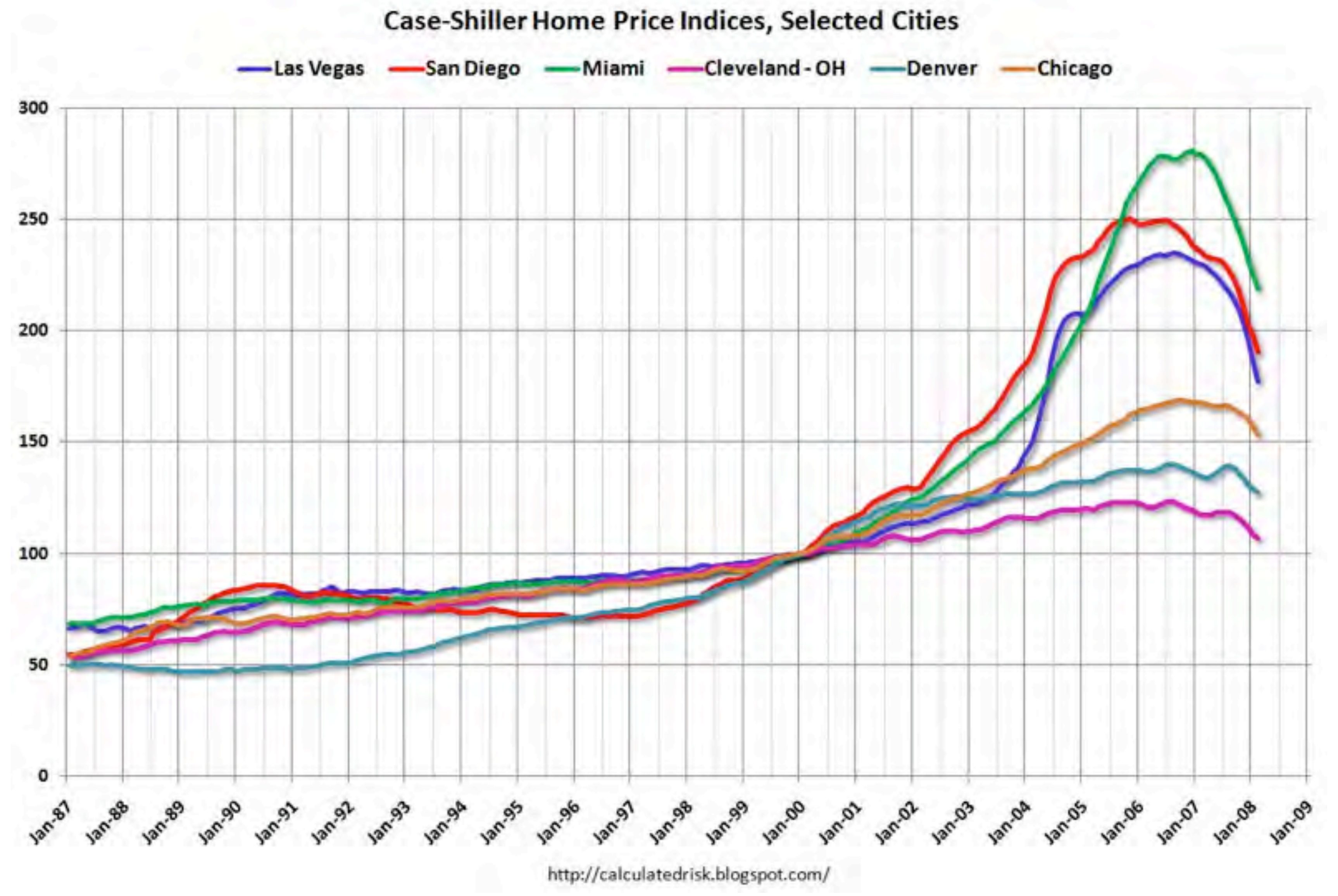
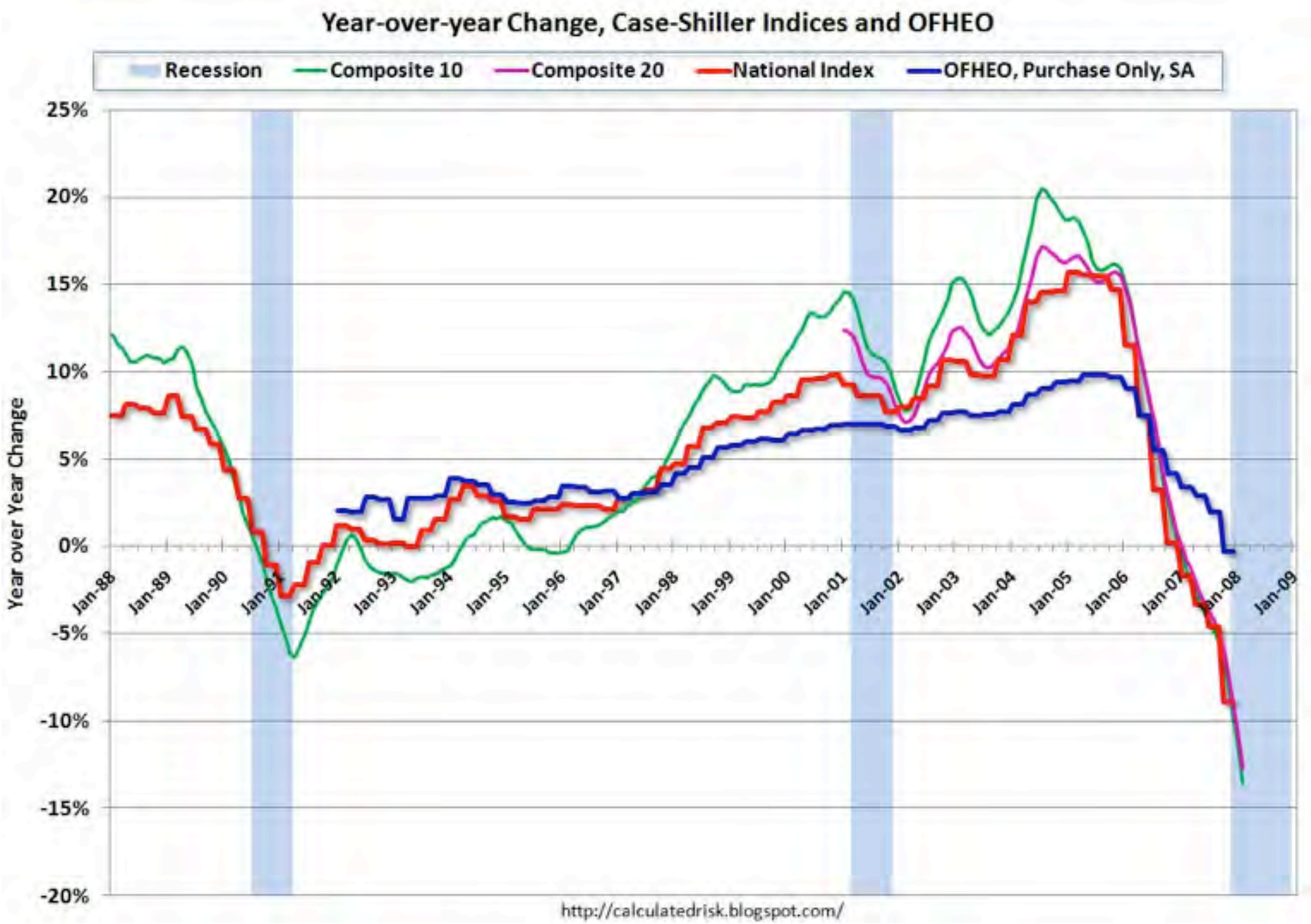


Figure 18: Predicting regional CSW indexes one year ahead. Red lines: Prediction using average growth rate obtained from all 27 indexes; Magenta lines: Prediction using average growth rate obtained from the individual index under investigation.



This graph shows the year-over-year price changes for the Case-Shiller composite 10 and 20 indices (through February), and the Case-Shiller and OFHEO National price indices (through Q4 2007).



The Case-Shiller national index will probably be off close to 12% YoY (will be released in late May).
Currently (as of Q4) the national index is off 10.1% from the peak.
The OFHEO index is barely negative YoY as of Q4 2007, and prices are only off 1.6% from the peak.

Does knowledge of all this change the future? Forecasts?

Learning from the Oct. 1987 Crash: implied volatility has changed dramatically, and in Bates' opinion permanently, since the 1987 crash.

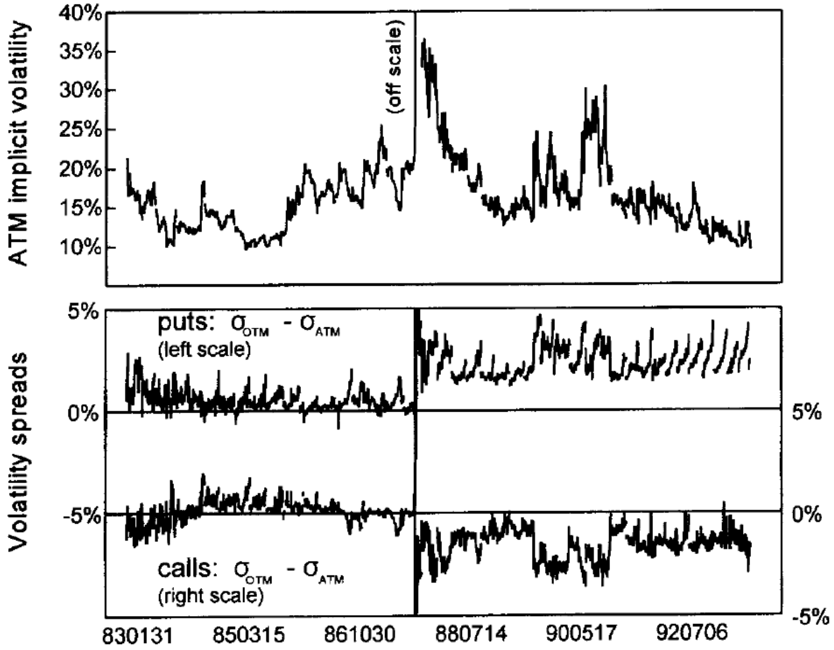


Fig. 2. Upper panel: implicit volatilities from at-the-money S&P 500 futures options, 1983–93. Lower panel: Volatility spreads for calls and puts.

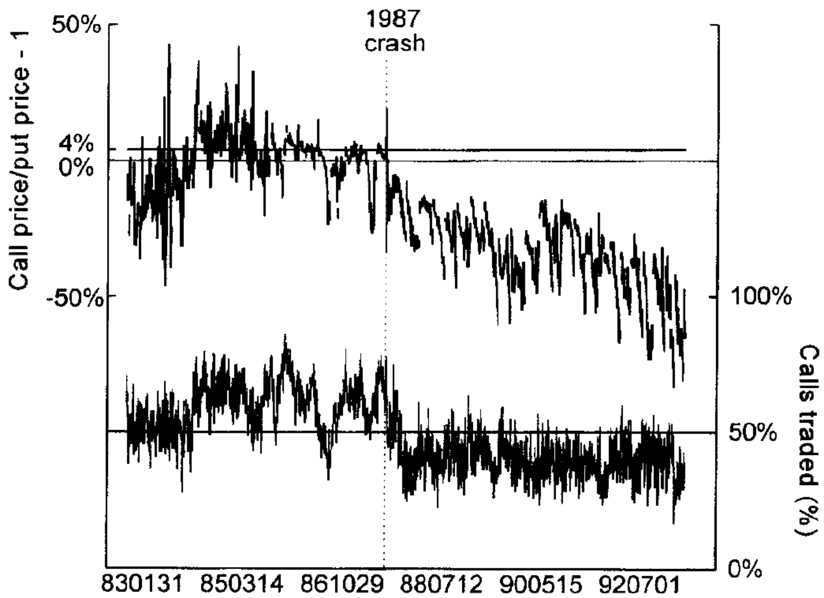
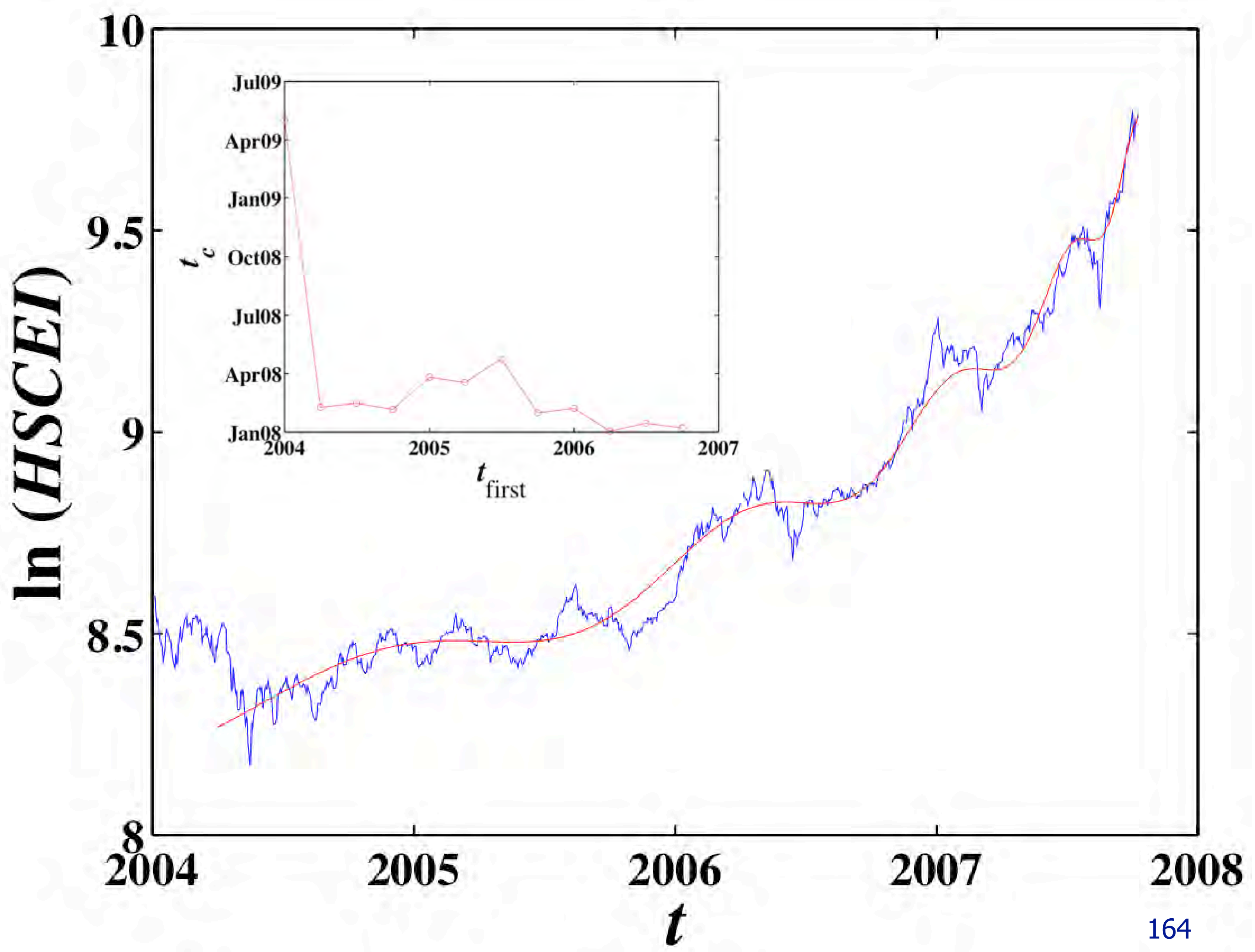
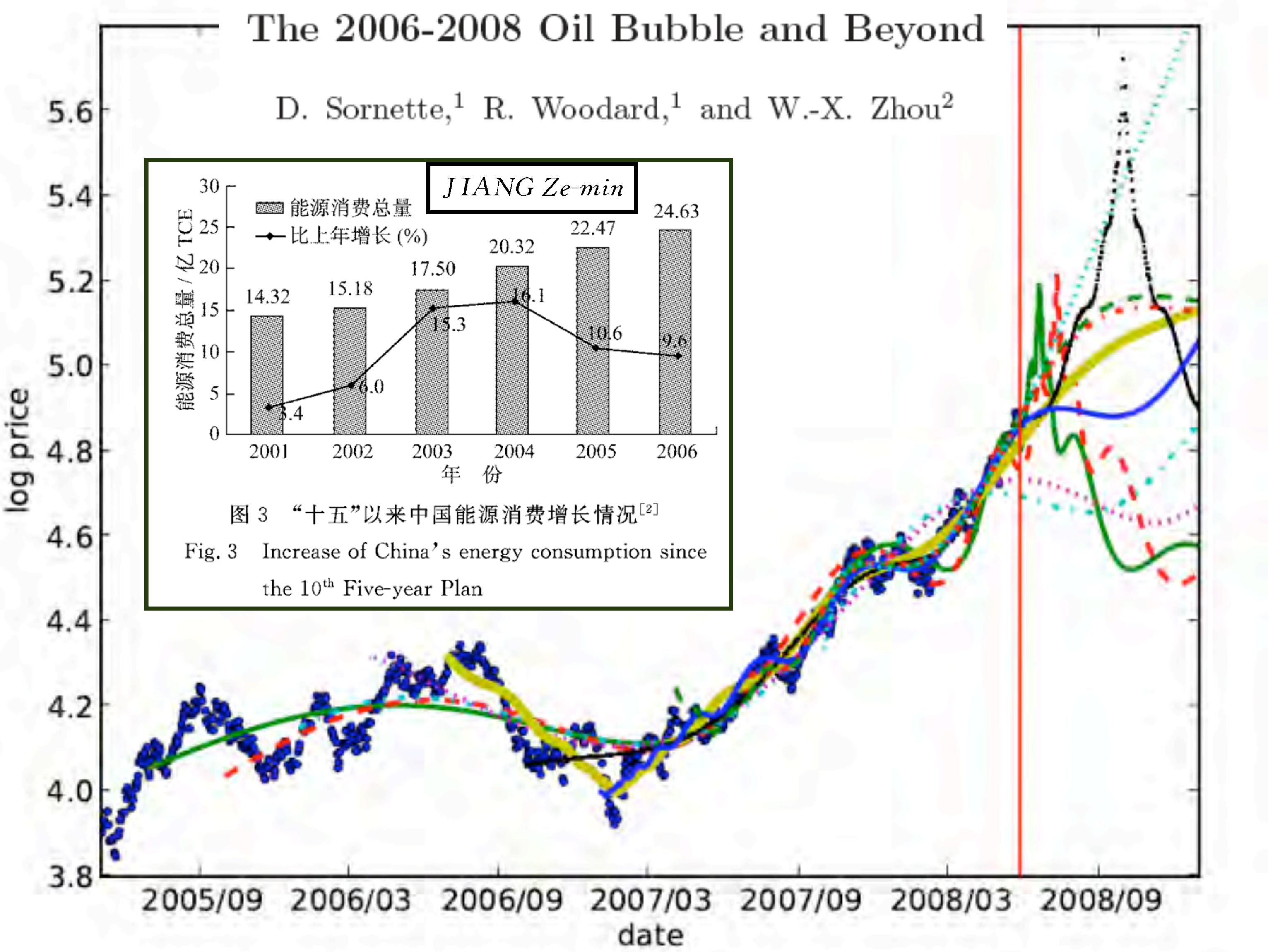


Fig. 3. 4% OTM skewness premium (upper line), and call transactions as a percentage of total reported call and put transactions (lower line).

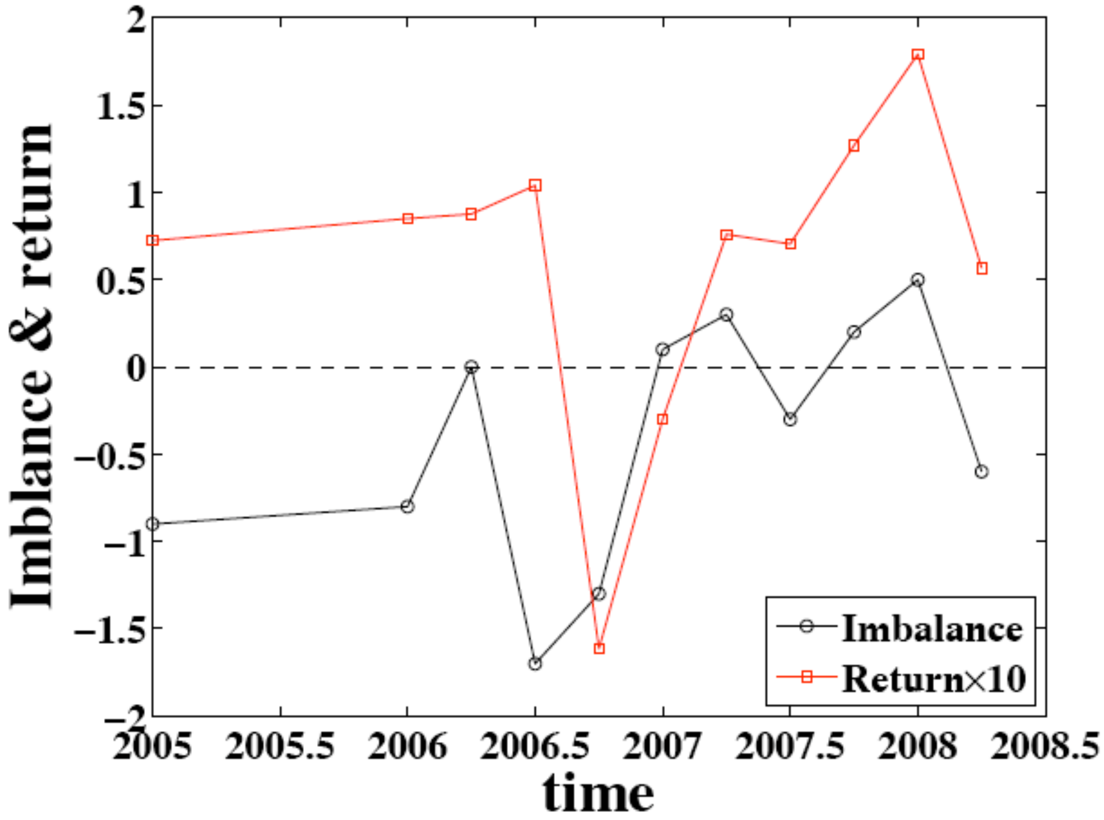
Bates, D., 2000, Post-'87 crash fears in S&P500 futures options. Journal of Econometrics, 94, 181-238.

Hang Seng China Entreprises Index (HSCEI)





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.



Time series from 2004 to the first quarter of 2008 of the total World oil demand minus supply (positive values mean that the demand is larger than the supply). For comParison, the relative price variation (return r(t)) of Oil (West Texas Intermediate) is also shown over the same period. The first data point of DS (demand minus supply) is for the whole year of 2004 and the second data point is for 2005. The other DS values are quarterly, according to the IEA. The returns are also calculated on the quarterly time scale.

$$r(t) = r_0 + a_1 r(t-1) + b_0 DS(t) + b_1 DS(t-1)$$

The coefficient r_0 is estimated at the level of 9.8% over this period with a p-value of 0.03, making it significant at the 97% level. Both coefficients $a_1 = 0.11$ and $b_0 = 0.04$ are found insignificant with p-values of 0.75 and 0.32 respectively. The small value of a_1 confirms the absence of reactivity of the oil prices to short-term shocks in the demand-supply variable over this time scale, due to the probable dominance of speculation that we argue here. The coefficient $b_1 = 0.077$ has a p-value of 0.097, making it significant at the 90% confidence level.

14 factors to propel a market bubble

1. the capitalist explosion and the ownership society,
2. cultural and political changes favoring business success,
3. new information technology,
4. supportive monetary policy and the Greenspan put,
5. the baby boom and their perceived effects on the markets,
6. an expansion in media reporting of business news,
7. analysts' optimistic forecasts,
8. the expansion of defined contribution pension plans,
9. the growth of mutual funds,
10. the decline of inflation and the effects of money illusion,
11. the expansion of the volume of trade due to discount brokers,
12. day traders,
13. twenty-four-hour trading,
14. the rise of gambling opportunities.

Why bubbles are not arbitraged away?

1. limits to arbitrage caused by noise traders (DeLong et, 1990)
2. limits to arbitrage caused by synchronization risk (Abreu and Brunnermeier, 2002 and 2003)
3. short-sale constraints (many papers)
4. lack of close substitutes for hedging (many papers)
5. heterogenous beliefs (many papers)
6. lack of higher-order mutual knowledge (Allen, Morris and Postlewaite, 1993)
7. delegated investments (Allen and Gorton, 1993)
8. psychological biases (observed in many experiments)
9. positive feedback bubbles

Securitization of credit risks

- Securitization of credit risks leads to smaller risks
- But more inter-connected

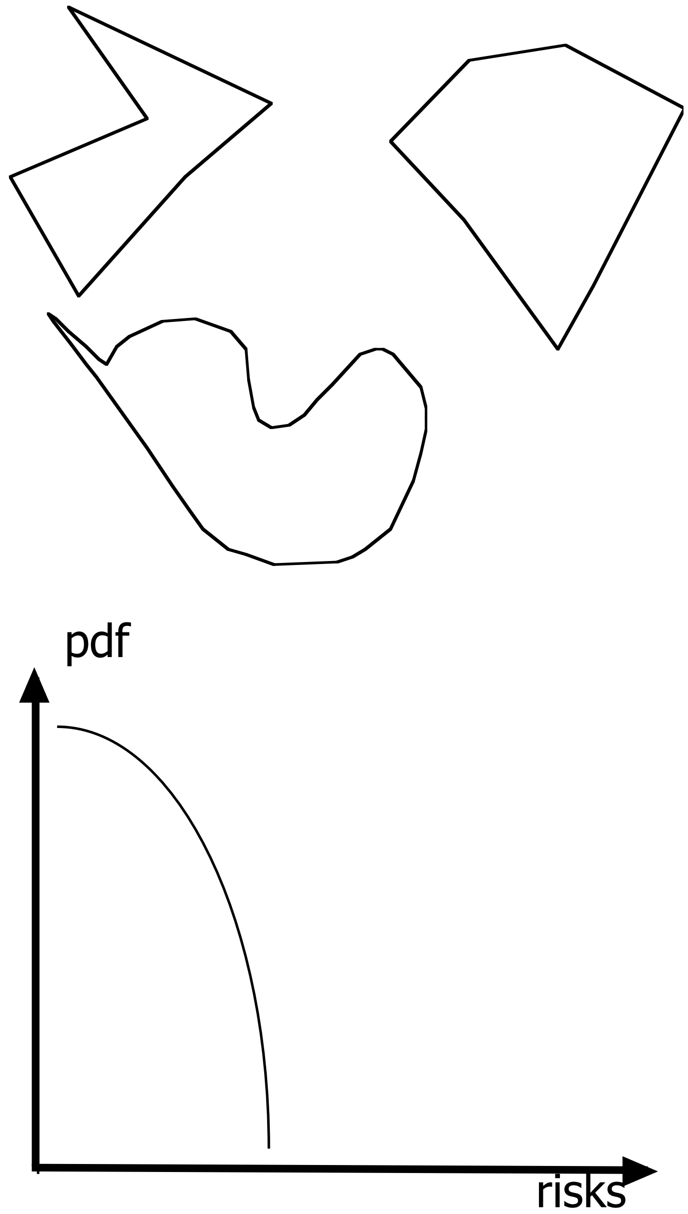
  $\Rightarrow$ global risk?

CDS and CDO: form of insurance contracts linked to underlying debt that protects the buyer in case of default.

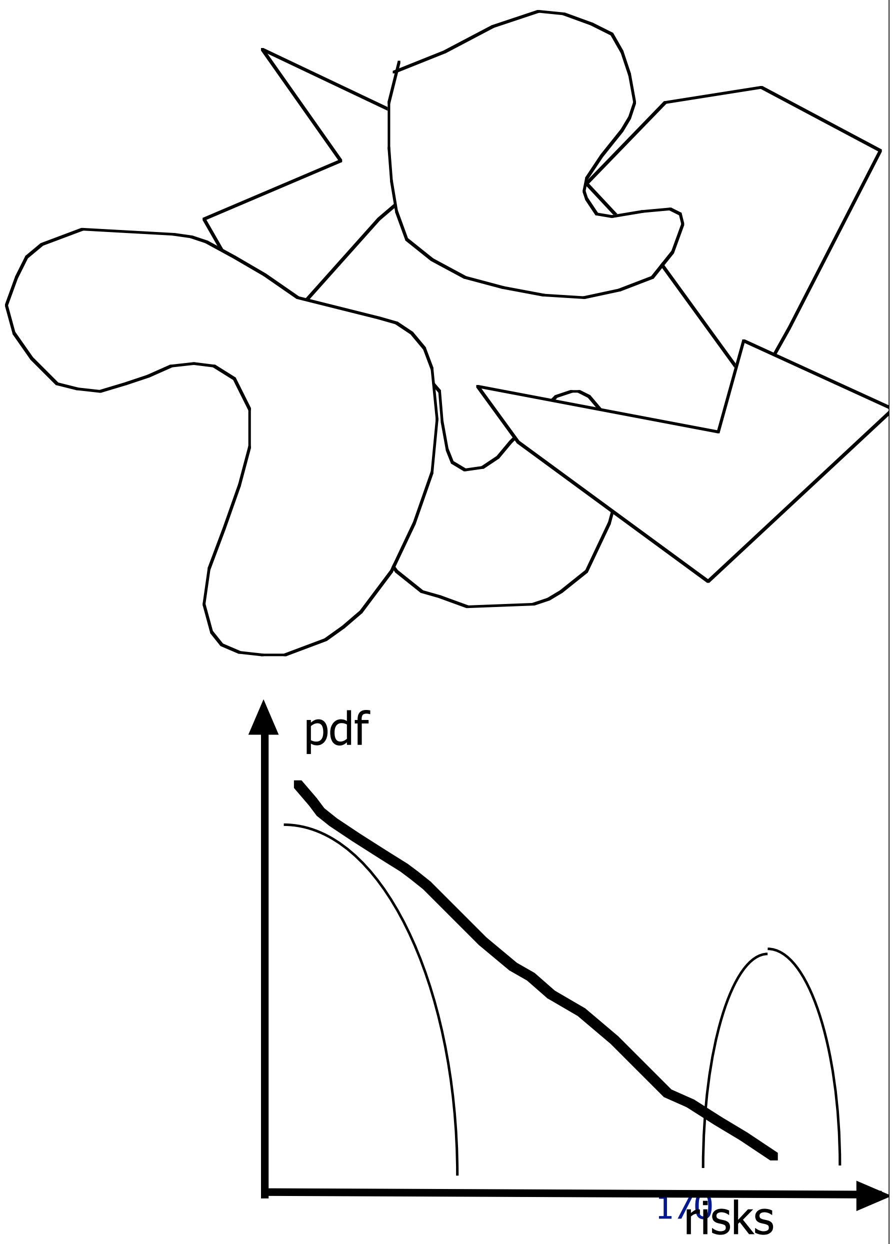
The market has almost doubled in size every year for the past five years, reaching $20 trillion in notional amounts outstanding last June 2007, according to the Bank for International Settlements.

Bundling of indexes of CDSs together and slicing them into trenches, based on riskiness and return. The most toxic trench at the bottom exposes the holder to the first 3% of losses but also gives him a large portion of the returns. At the top, the risks and returns are much smaller-unless there is a systemic failure.

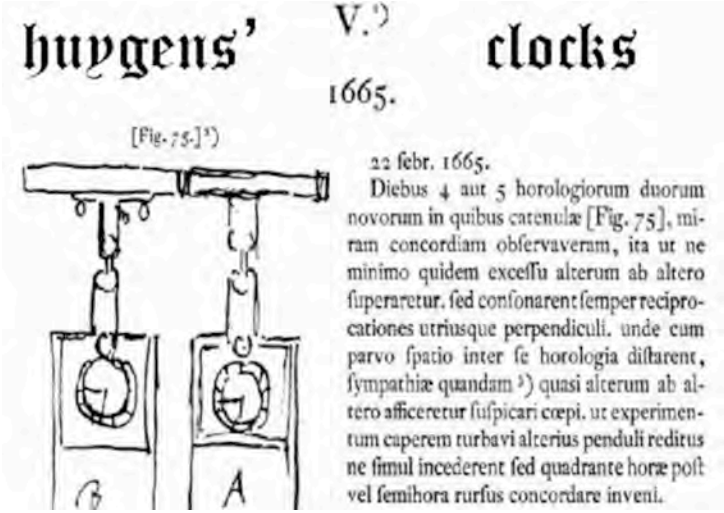
Separation of financial and credit risks



Securitization leads to larger inter-connectivity



SYNCHRONISATION AND COLLECTIVE EFFECTS IN EXTENDED STOCHASTIC SYSTEMS


Huygens' clocks

V.[1]

1665.

[Fig. 75.][2]

22 febr. 1665.

Diebus 4 aut 5 horologiorum duorum novorum in quibus catenulæ [Fig. 75], miram concordiam obſervaveram, ita ut ne minimo quidem exceſſu alterum ab altero ſuperaretur, ſed conſonarent ſemper reciprocationes utriusque perpendiculi. unde cum parvo ſpatio inter ſe horologia diſtarent, ſympathiæ quandam [3]) quasi alterum ab altero afficeretur ſuſpicari cœpi. ut experimentum caperem turbavi alterius penduli reditus ne ſimul incederent ſed quadrante horæ poſt vel ſemihora rurſus concordare inveni.

Fireflies

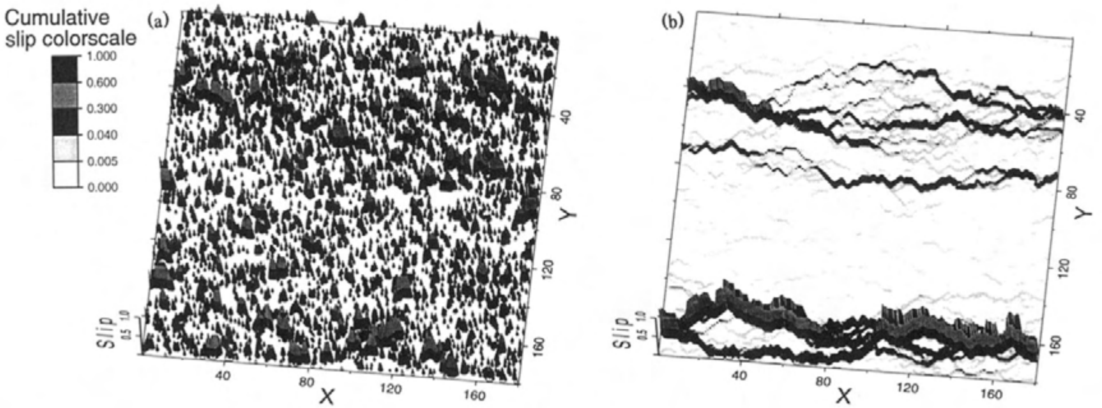


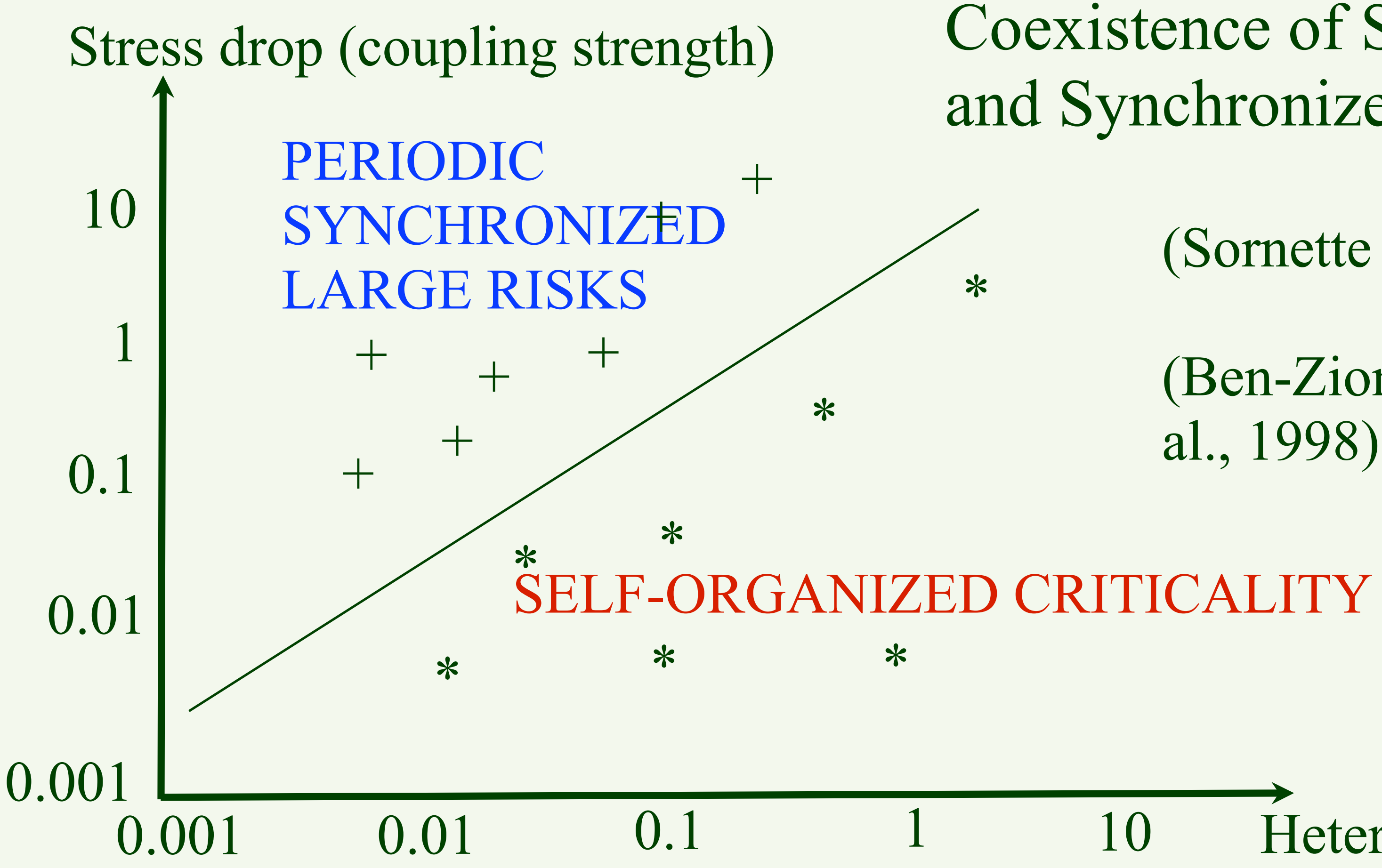
FIG. 1. Evolution of the cumulative earthquake slip, represented along the vertical axis in the white to black color code shown above the picture, at two different times: (a) early time and (b) long time, in a system of size $L=90$ by $L=90$, where $\Delta\sigma=1.9$ and $\beta=0.1$.

Miltenberger et al. (1993)

Coexistence of SOC and Synchronized behavior

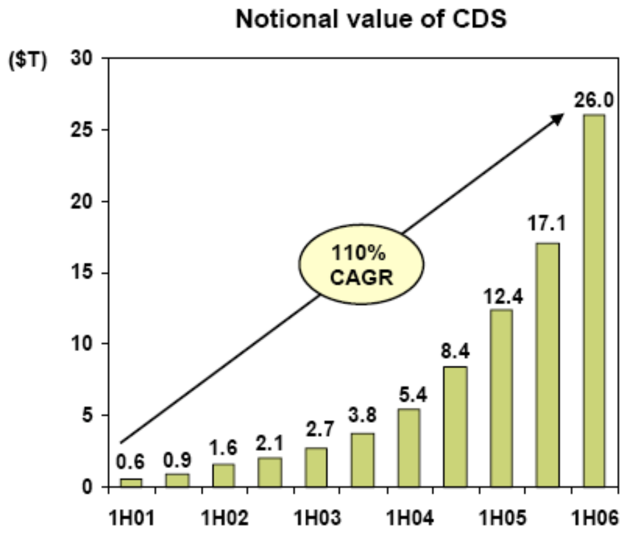
(Sornette et al., 1994)

(Ben-Zion, Dahmen et al., 1998)



“Phase diagram” for the model in the space (heterogeneity, stress drop). Crosses (+) correspond to systems which exhibit a periodic time evolution. Stars * corresponds to systems that are self-organized critical, with a Gutenberg-Richter earthquake size distribution and fault localization whose geometry is well-described by the geometry of random directed polymers.

Risks?



Source UBS (March 07)

Securitization of non-financial assets (commodities, real-estate, credit)

-US global imbalances

-Yen carry trades which could be unwound massively

-Commodity prices jumping leading to inflationary pressures and liquidity tightening

-Low risk premia on emerging market bonds and High yield bonds which could lead to a global credit repricing

-What are possible scenarios with regard to the development of global financial markets?

+Monetary union in Asia

+Continuation of the massive development of derivatives in all risk sectors

-Principle-agency-theory shows:

-information asymmetries and strategic behavior of agents lead to moral hazard and cannot be corrected by incentive alone

-cooperation needs transparency and the possibility to retaliate/punish (feedback).

Conclusion

- Regularities in bubbles and crashes
- Kings and black swans
- Positive and negative feedbacks
- RE bubble models and imitation/herding
- Empirical case studies
- Endogenous versus Exogenous
- Foreign capital flows, Fed's feedback and macroeconomic feedbacks (not shown here)
- Anti-bubbles and the recent 2000-05 phase (not shown here)
- Towards routine predictions

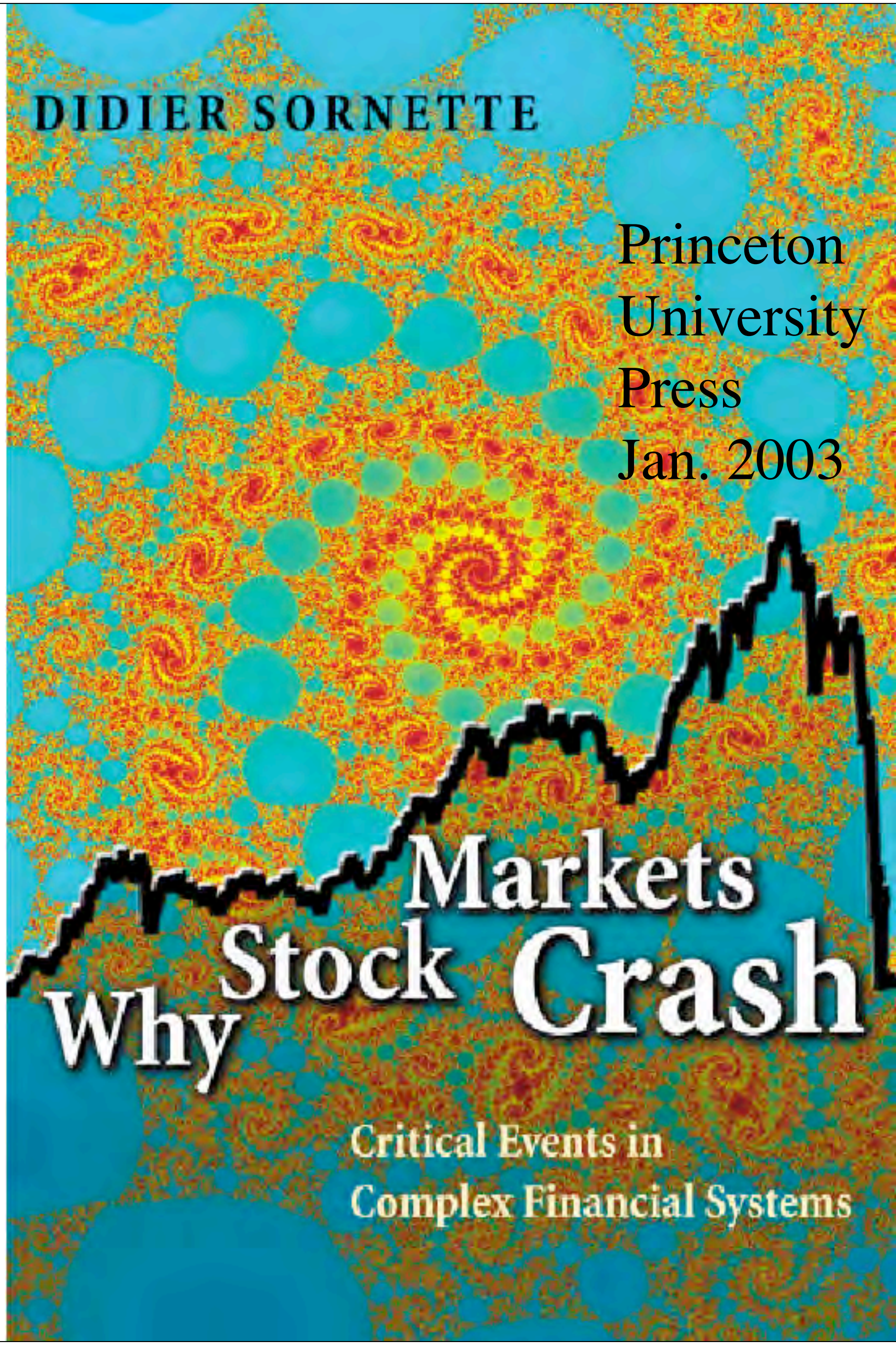
All papers and much more at http://www.ess.ucla.edu/faculty/sornette/

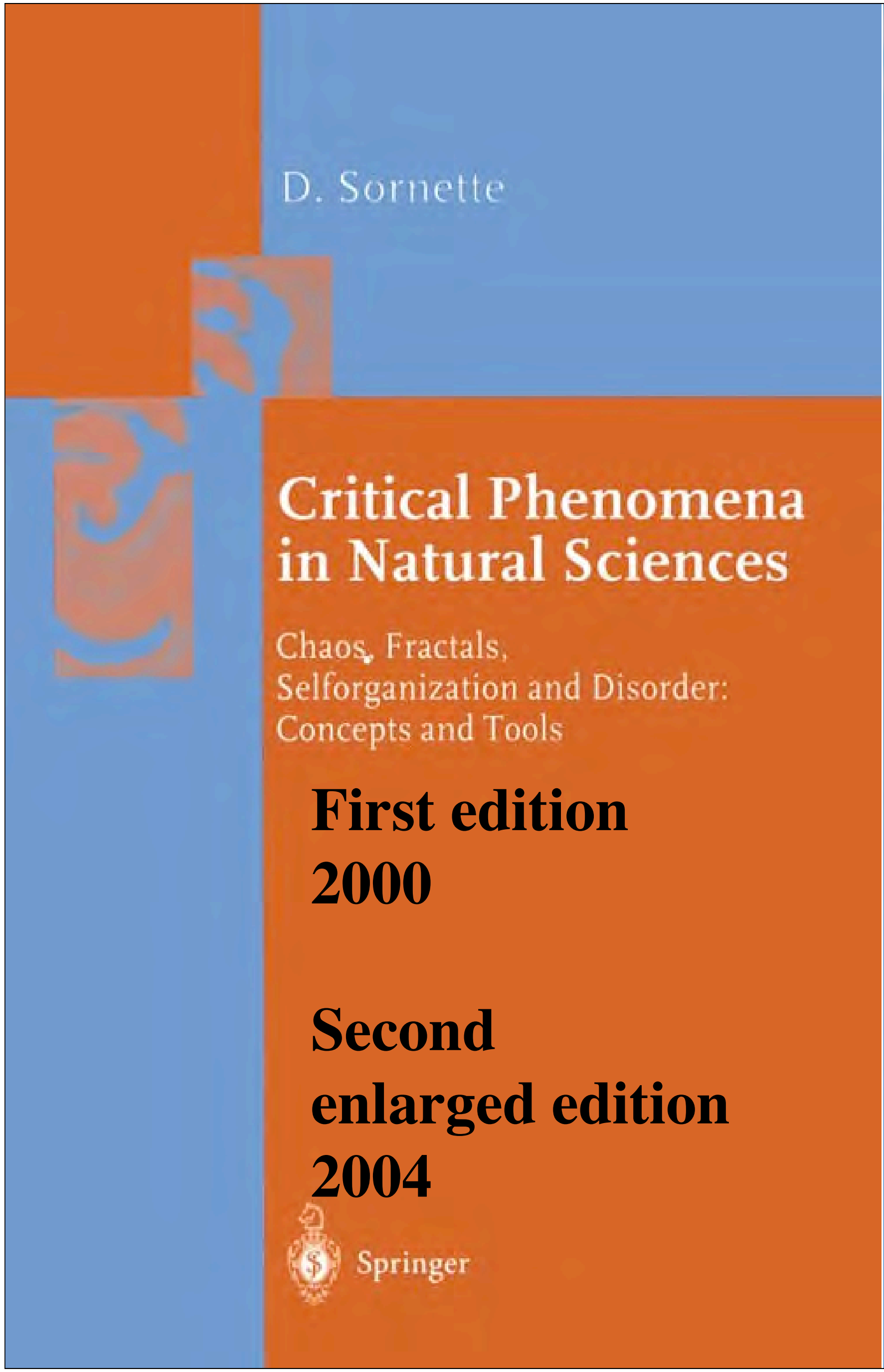
Main Messages

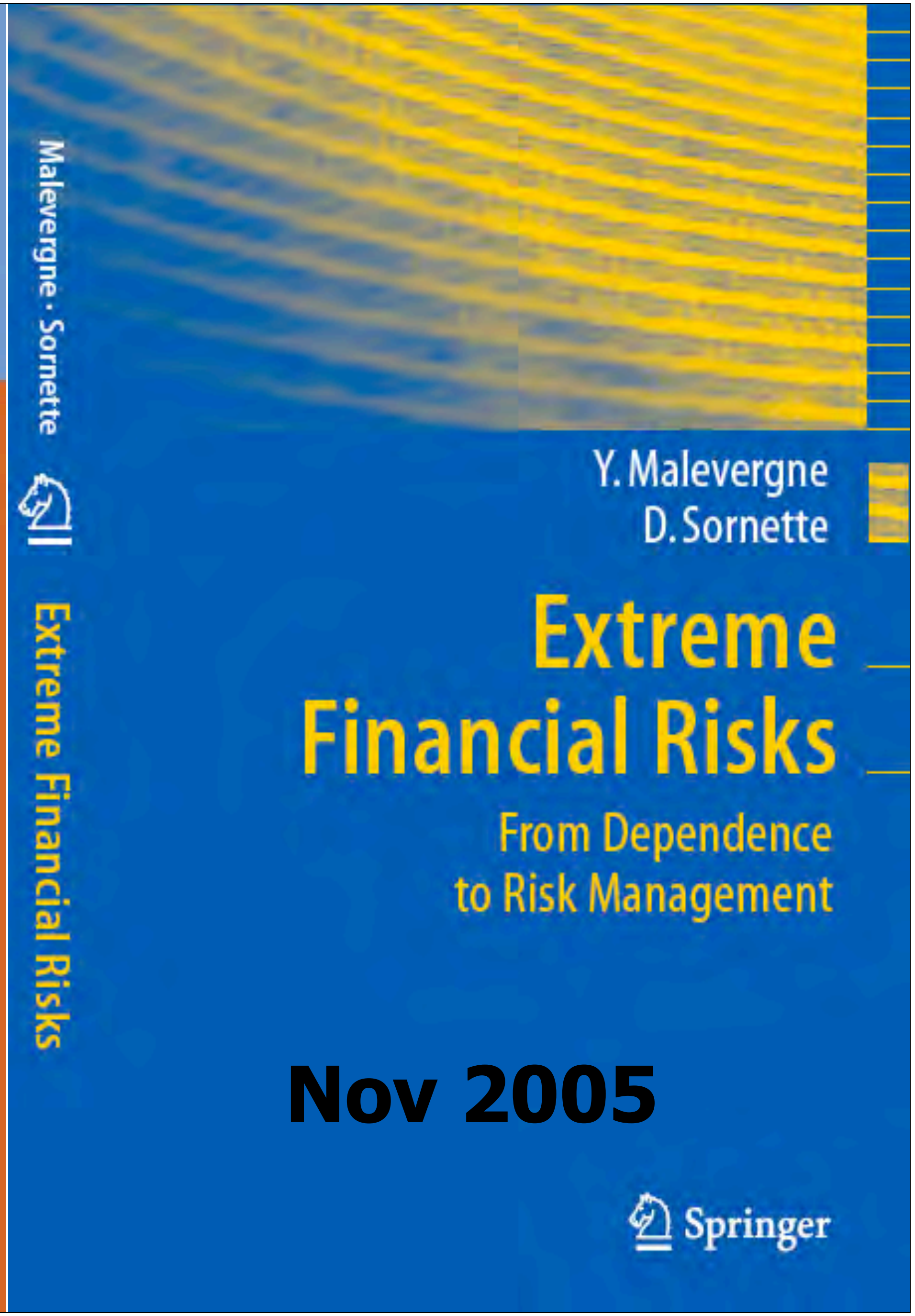
Investors, stock market regulators and macro-economic policy cannot ignore COLLECTIVE BEHAVIOR between AGENTS (with negative and positive feedbacks).

Imitation and herding behaviors lead to Positive and negative feedbacks AND vice-versa : the stock markets and the economy have never been more a CONFIDENCE "game".

Predictions and Preparation: complexity theory applied to such collective processes provides clues for precursors and suggests steps for precaution and preparation.

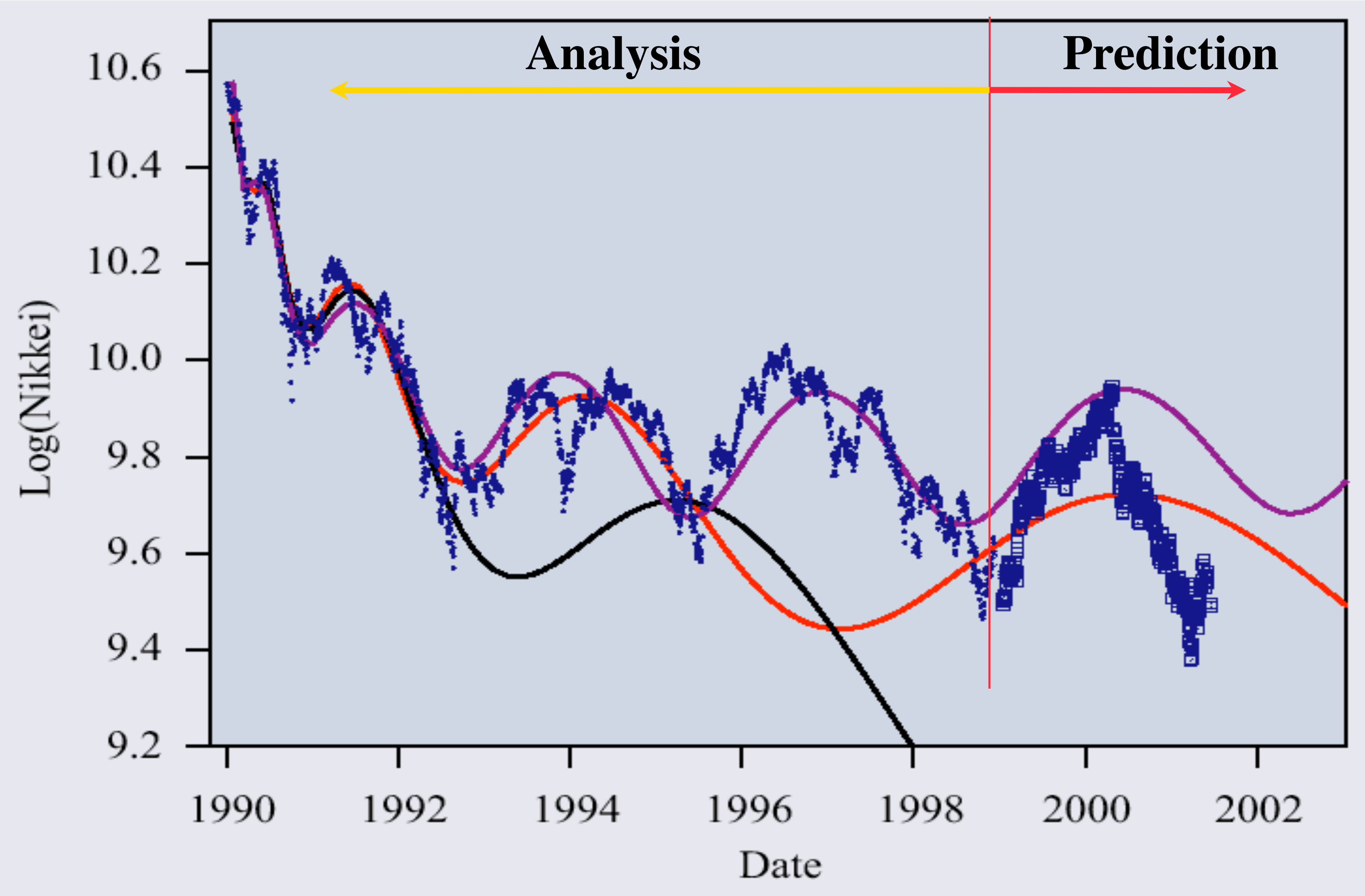

DIDIER SORNETTE
Princeton
University
Press
Jan. 2003
Why Stock Markets Crash
Critical Events in
Complex Financial Systems


D. Sornette
Critical Phenomena in Natural Sciences
Chaos, Fractals, Selforganization and Disorder: Concepts and Tools
First edition 2000
Second enlarged edition 2004
Springer

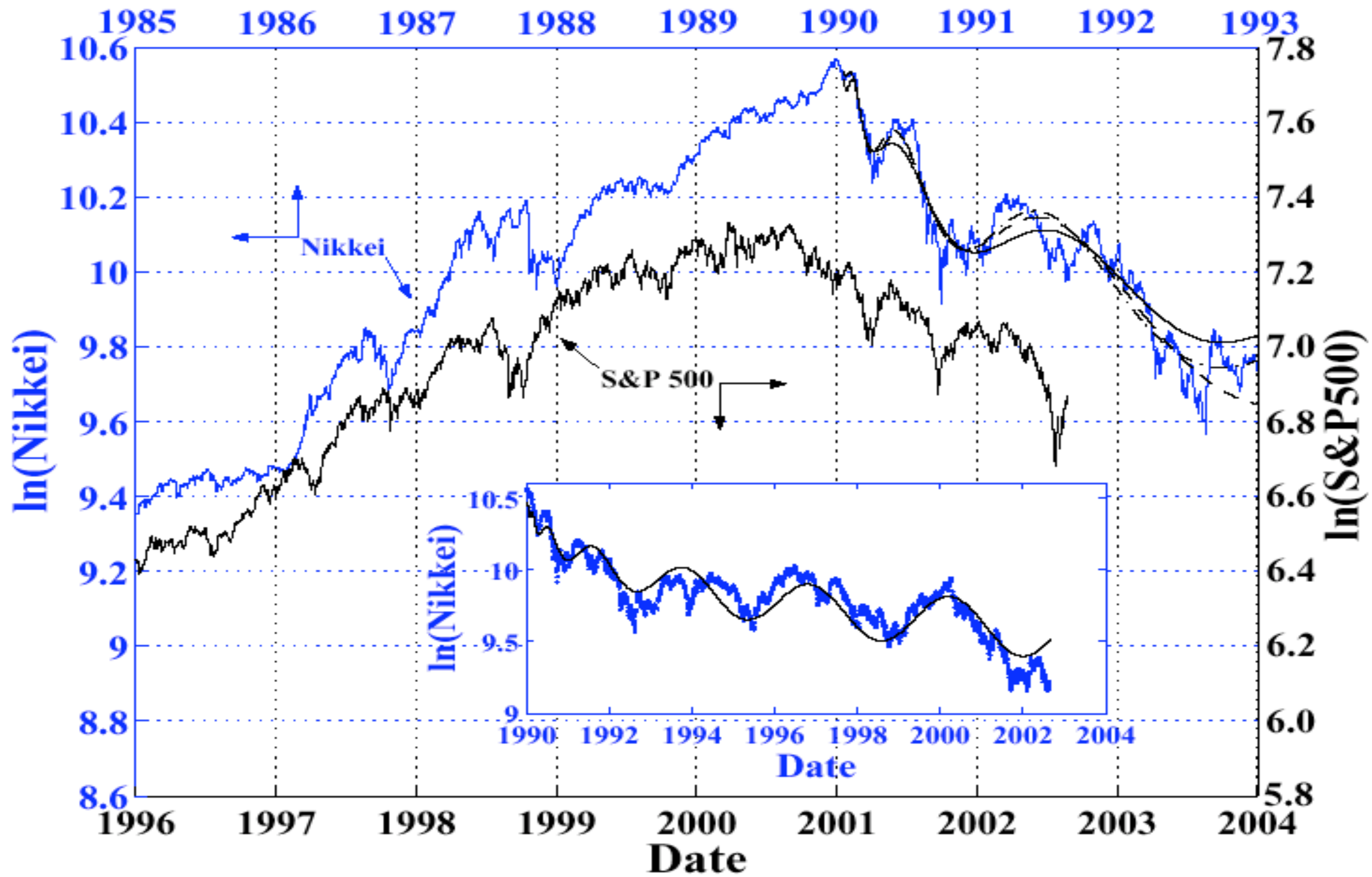

Malevergne · Sornette
Extreme Financial Risks
Y. Malevergne
D. Sornette
Extreme Financial Risks
From Dependence to Risk Management
Nov 2005
Springer

ANTIBUBBLES

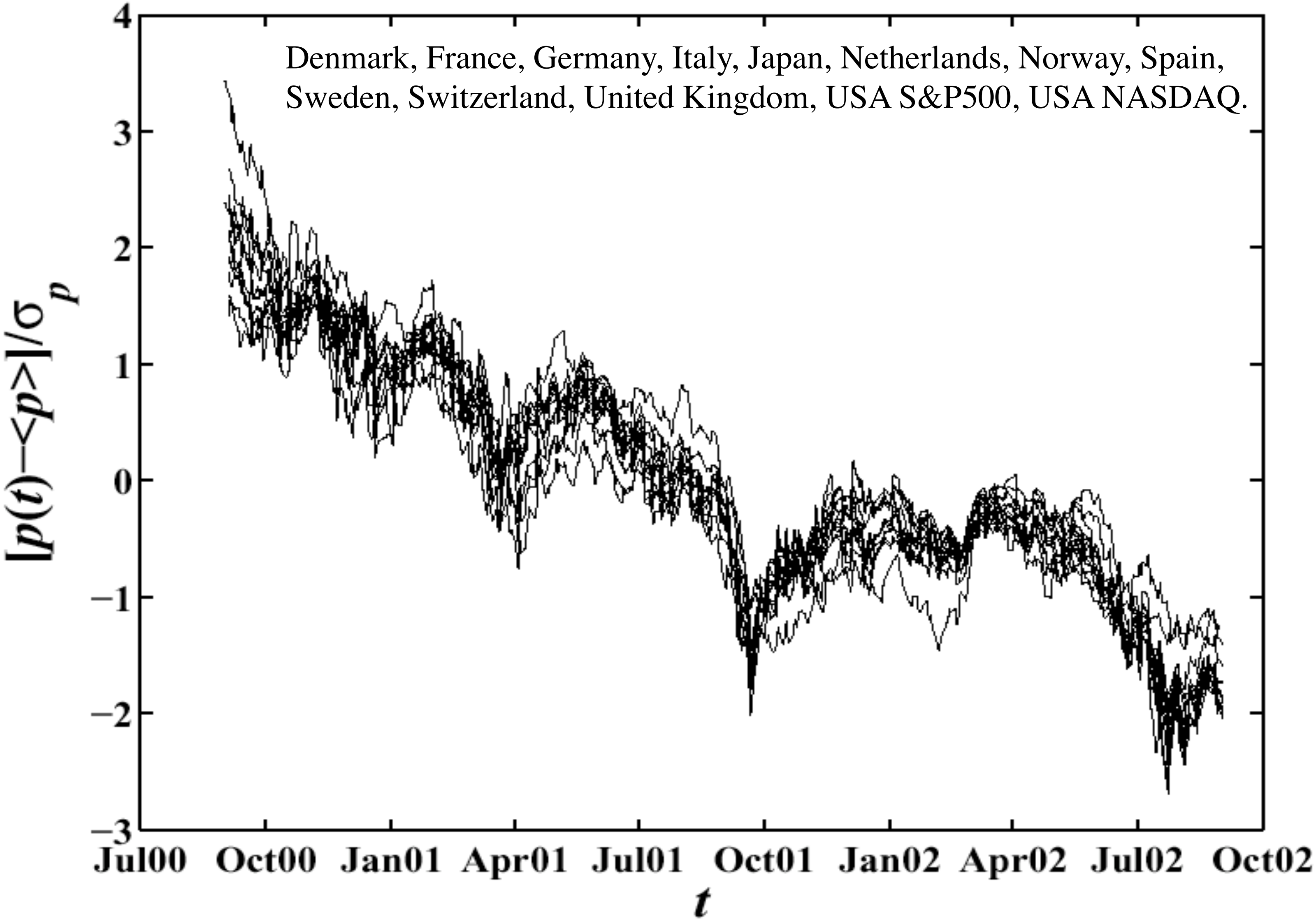
Japanese Index: model and prediction

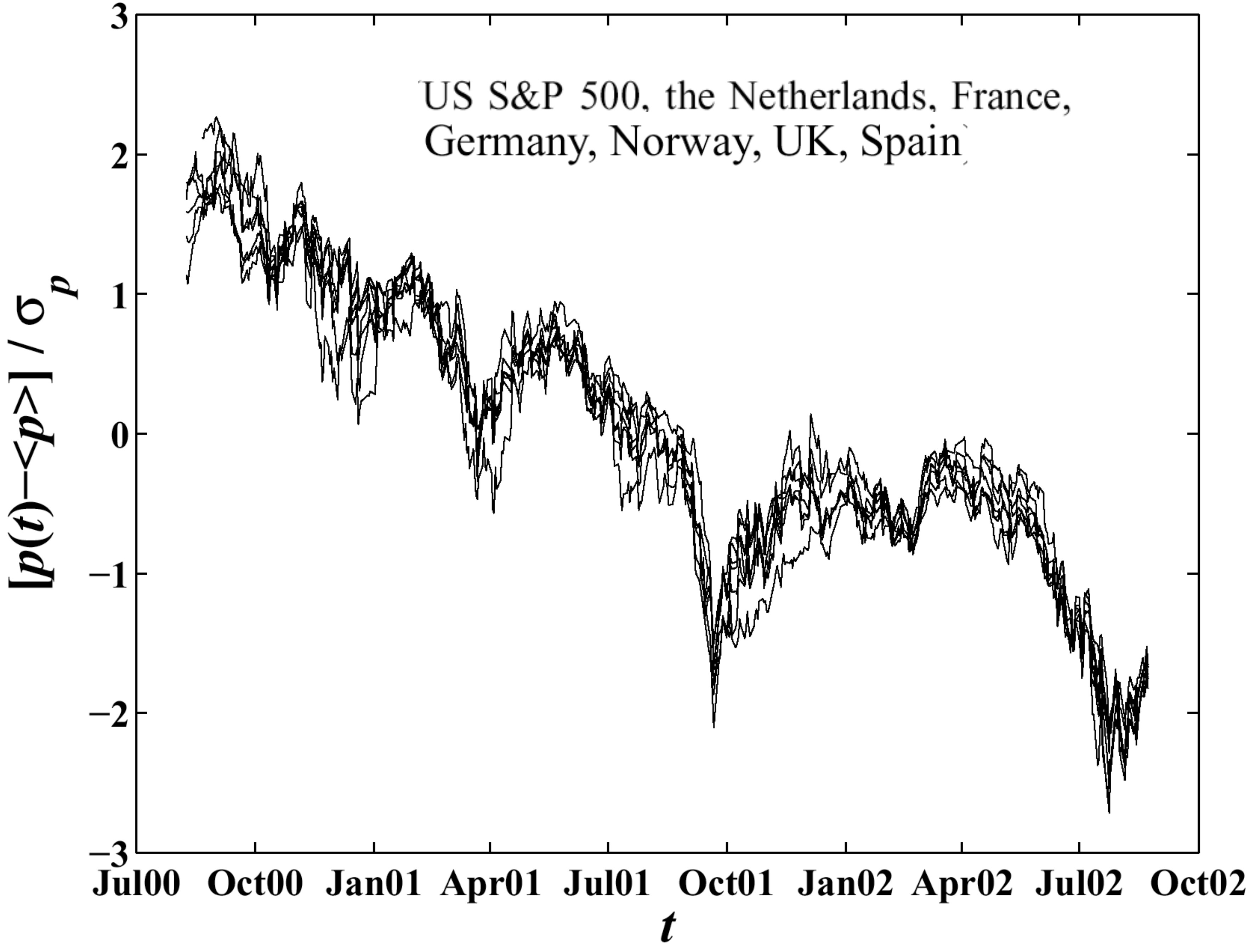


S&P vs Nikkei

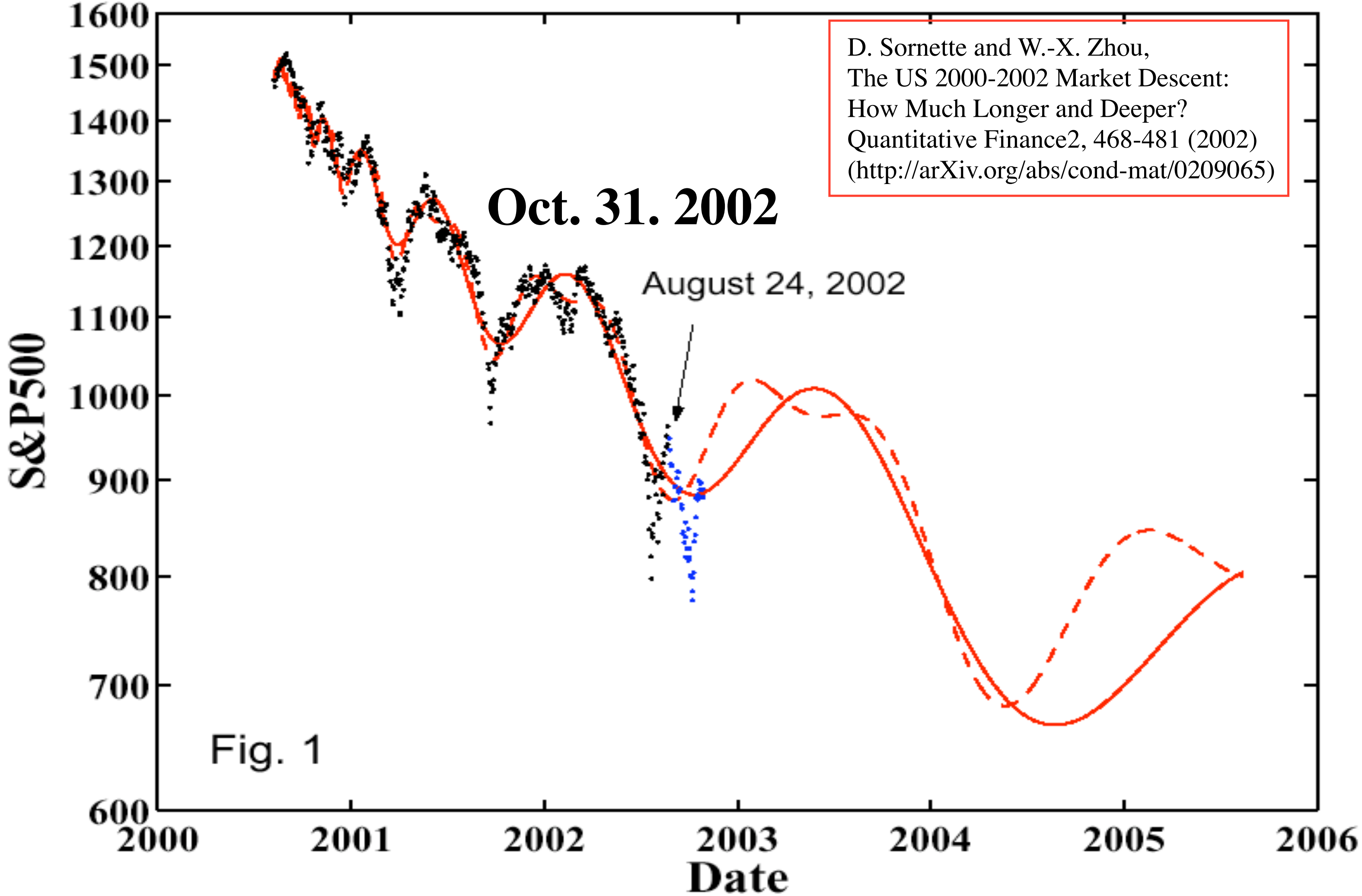

1985
1986
1987
1988
1989
1990
1991
1992
1993
10.6
10.4
10.2
10
9.8
9.6
9.4
9.2
9
8.8
8.6
ln(Nikkei)
7.8
7.6
7.4
7.2
7.0
6.8
6.6
6.4
6.2
6.0
5.8
ln(S&P500)
Nikkei
S&P 500
1996
1997
1998
1999
2000
2001
2002
2003
2004
Date
10.5
10
9.5
9
ln(Nikkei)
1990
1992
1994
1996
1998
2000
2002
2004
Date

Inter-market Correlations

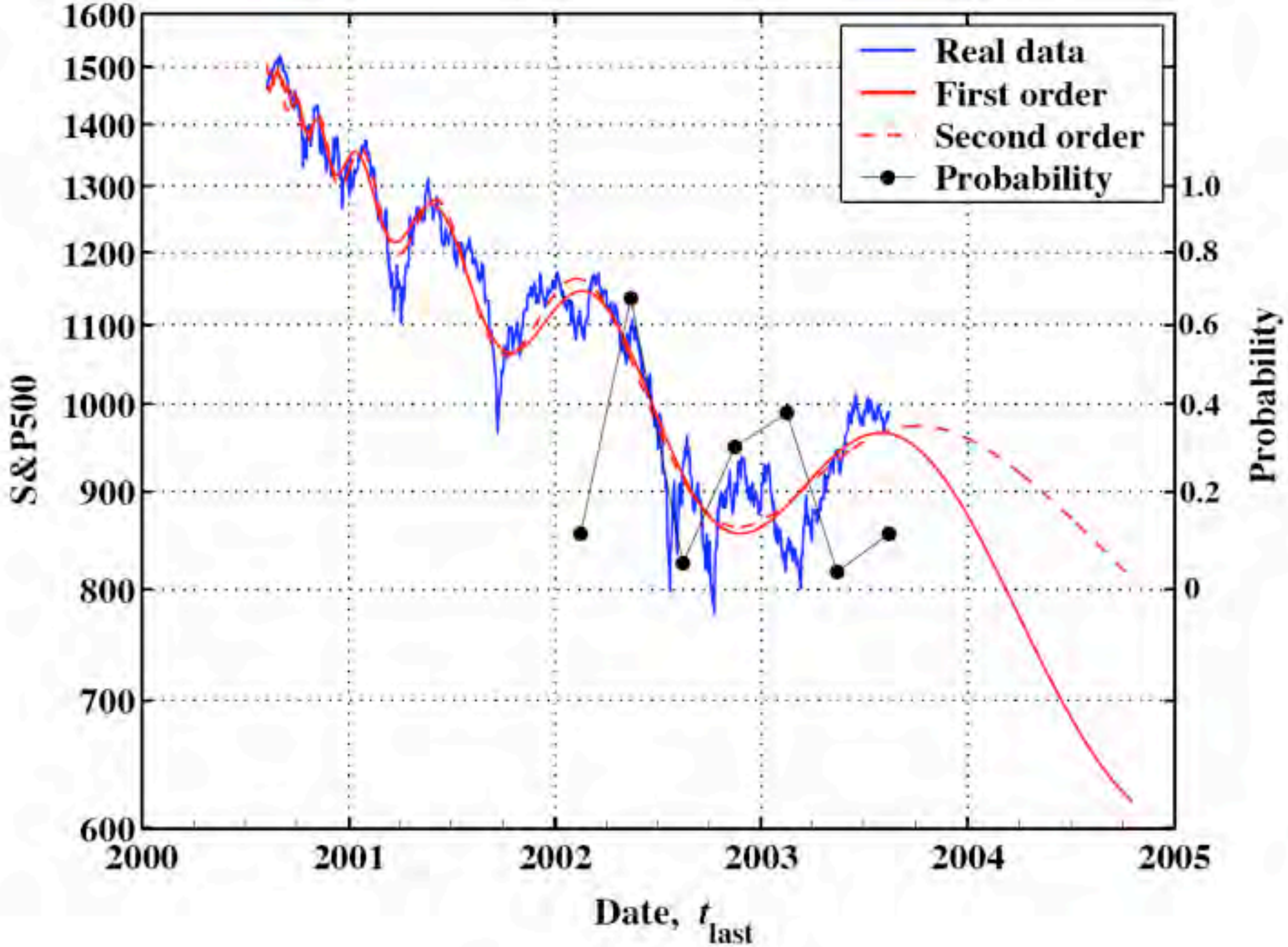



US S&P 500, the Netherlands, France,
Germany, Norway, UK, Spain
[p(t)−<p>] / σ_p
t
3
2
1
0
−1
−2
−3
Jul00
Oct00
Jan01
Apr01
Jul01
Oct01
Jan02
Apr02
Jul02
Oct02

The US Market Descent   Prediction

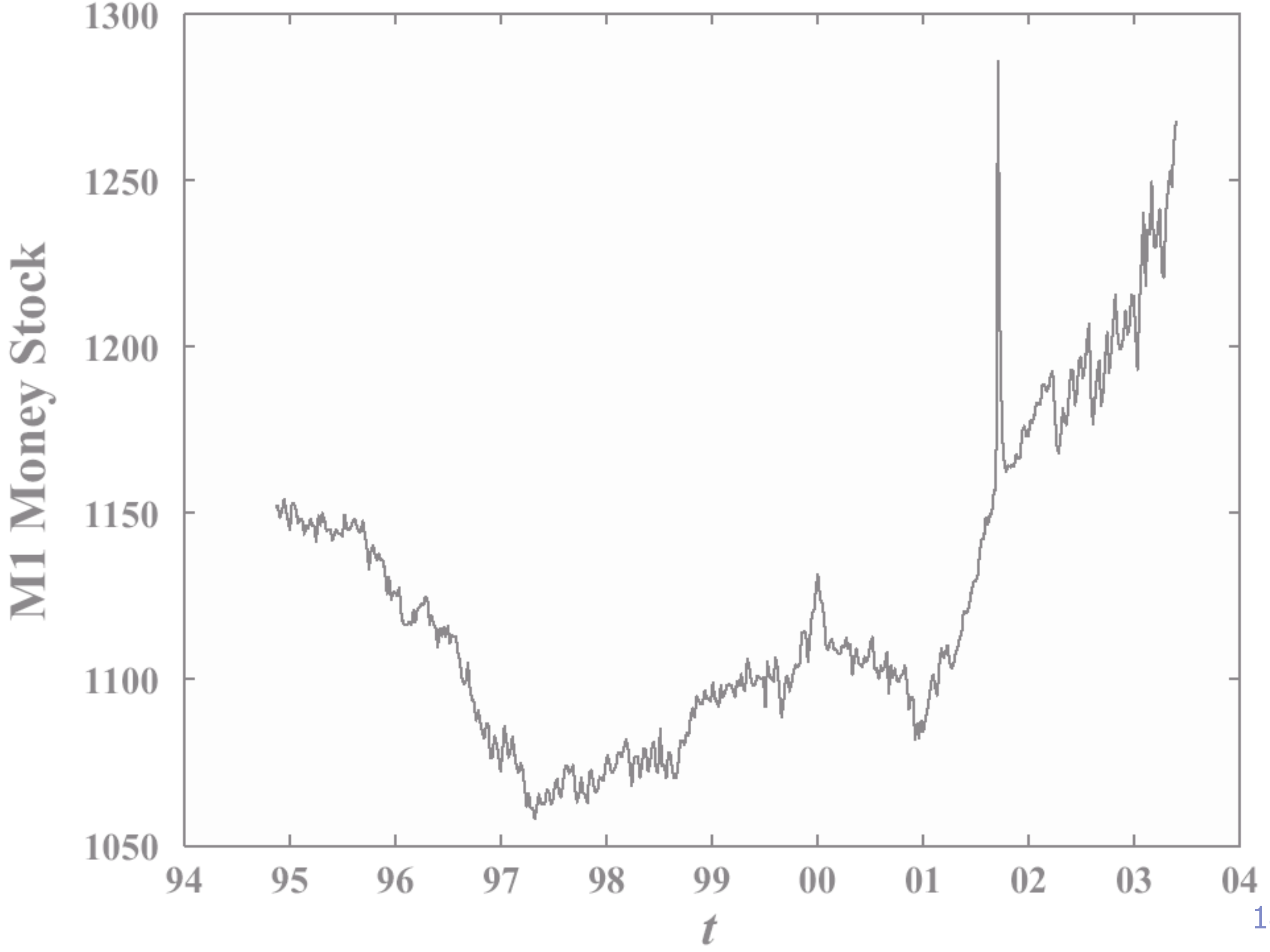


- In December 2004, we decided to discontinue the update, concluding that, after more than two years, our projections for the US market have not been verified.
- In contrast, our projections for the US market translated in foreign currencies (in particular in euro) have been rather accurate.

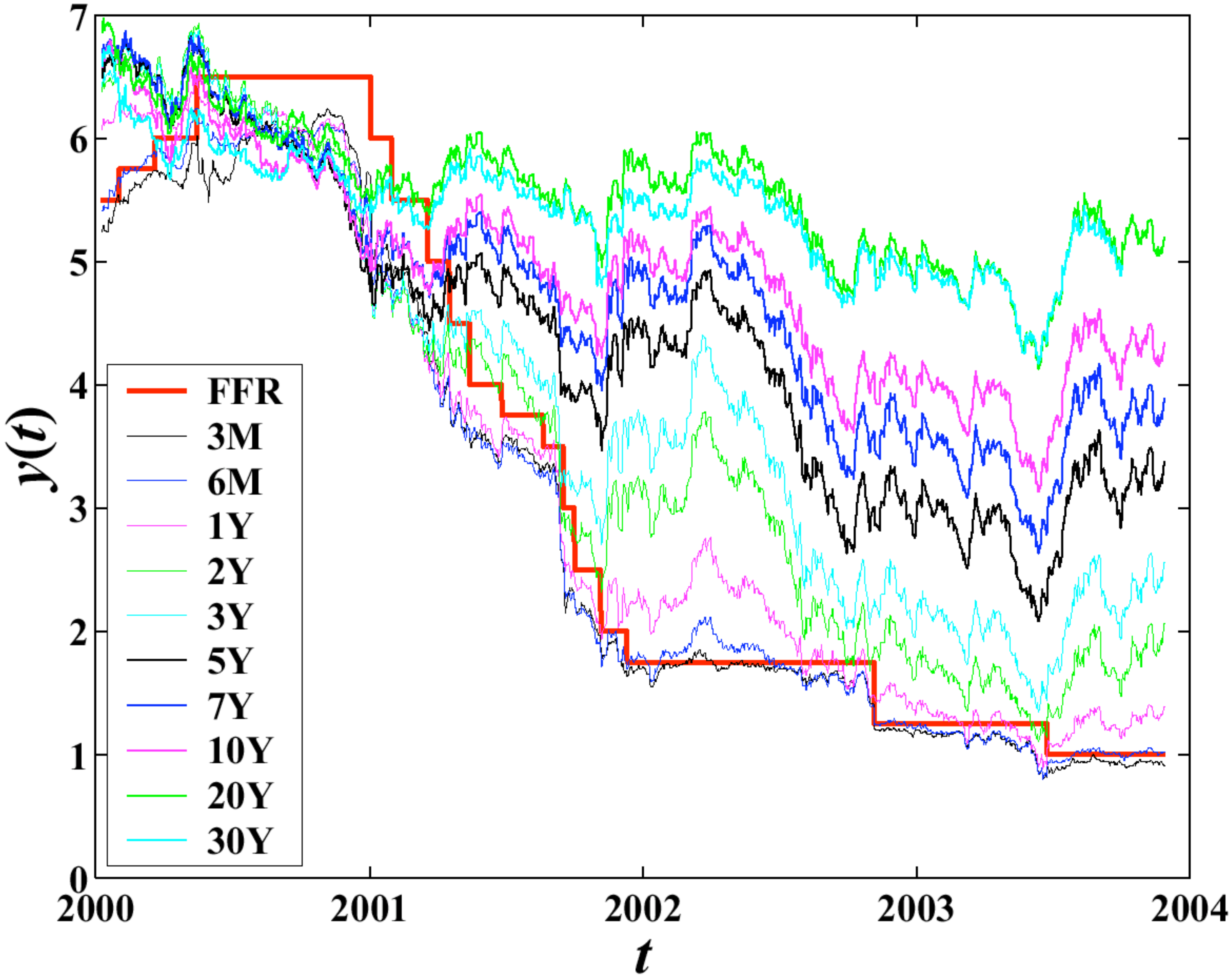


Left ordinate: Fits of the S&P 500 index over a time interval of three years with a daily sampling rate using the first-order LPPL formulae (1) and the second-order LPPL formulae (3). The parameters are the following: $t_c = 2000/08/27$, $m = 0.72$, $\omega = 9.2$, $\phi = 4.62$, $A = 7.3123$, $B = -0.0037$, $C = -0.0008$, and the r.m.s. of fit residuals is $\chi_1 = 0.03859$ for the first order formula; and $t_c = 2000/08/06$, $m = 0.76$, $\omega = 11.4$, $\phi = 1.03$, $\Delta_t = 2778$, $\Delta_\omega = -22.6$, $A = 7.3245$, $B = -0.0031$, $C = -0.0007$, and the r.m.s. of fit residuals is $\chi_2 = 0.03729$ for the second order formula. **Right ordinate**: The probability that the simulated log-likelihood-ratio exceeds the realized ratio as a function of t_{last}.

Growth of Money supply (M1)



Causal slaving of the US Treasury Bond yields to the stock market



W.-X. Zhou, D. Sornette / Physica A 337 (2004) 586–608

S&P 500 in other currencies

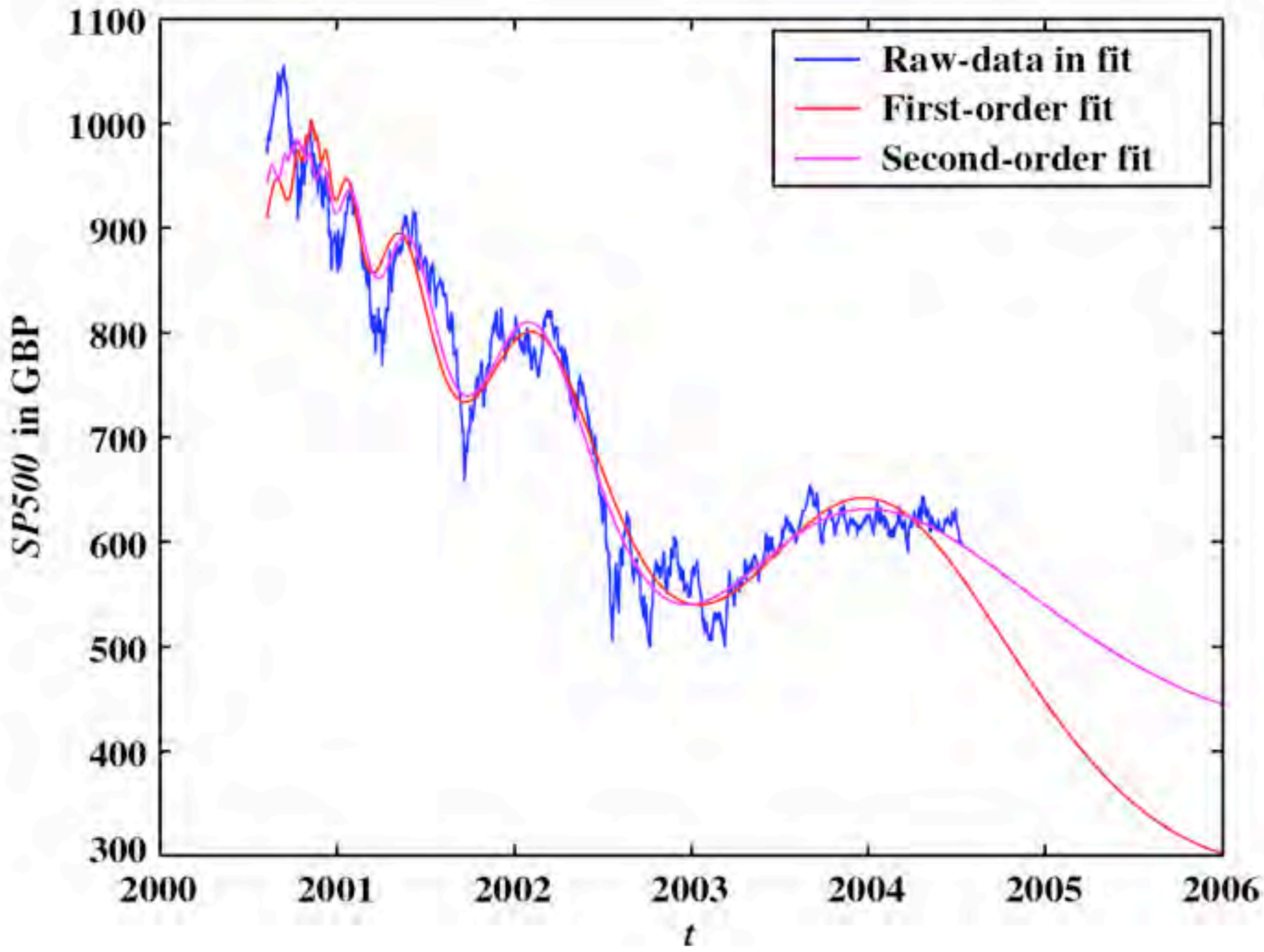
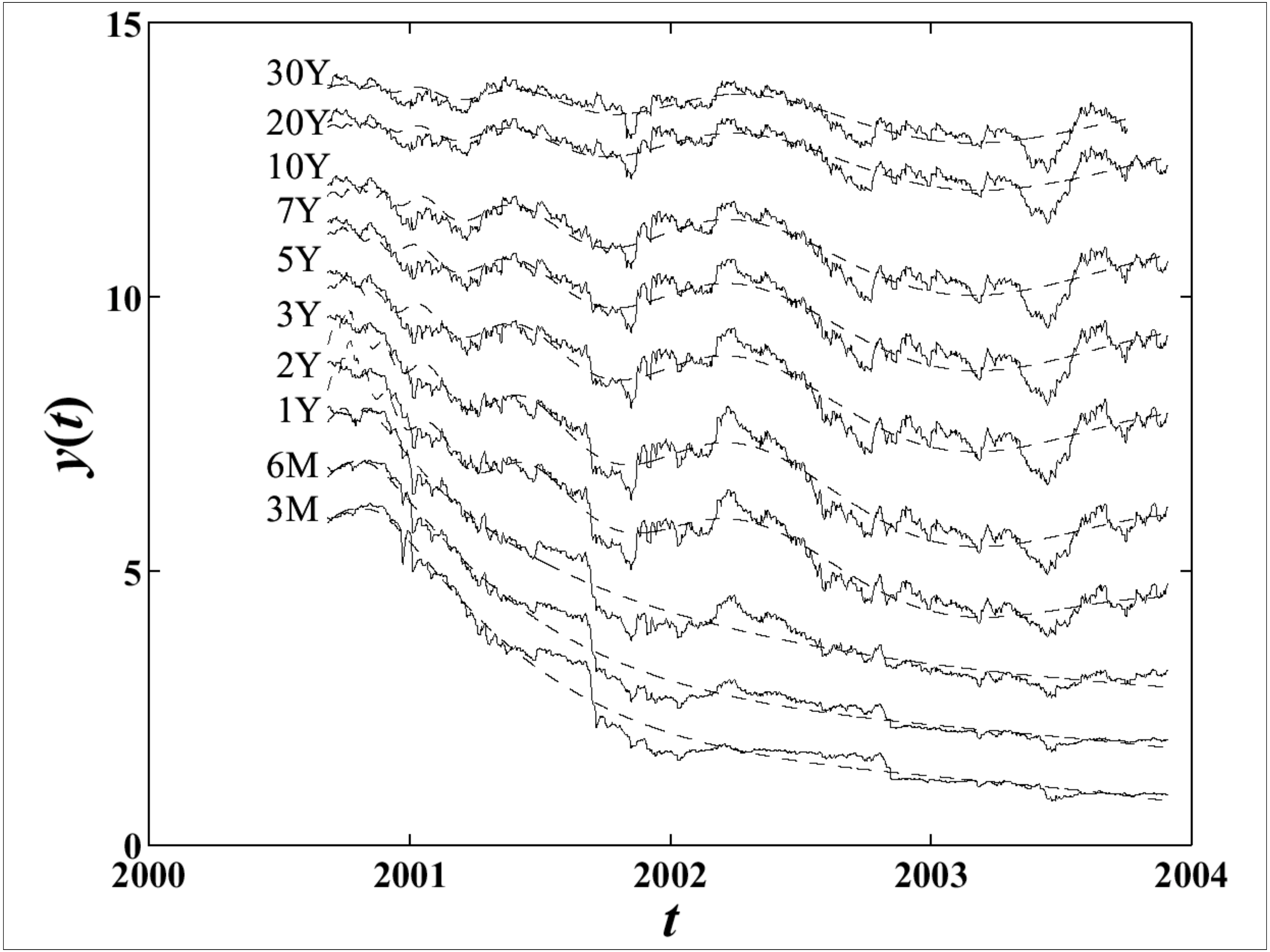
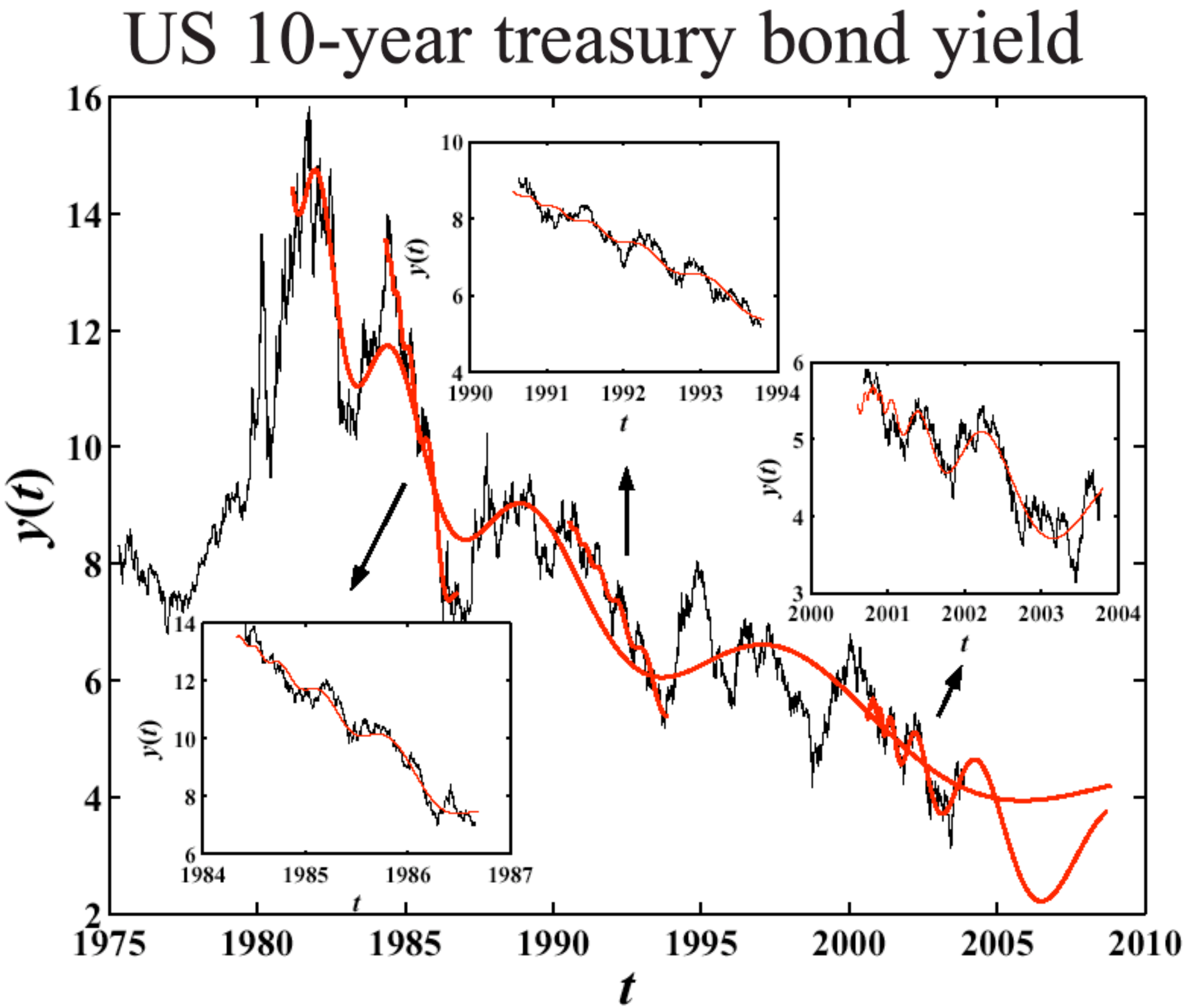


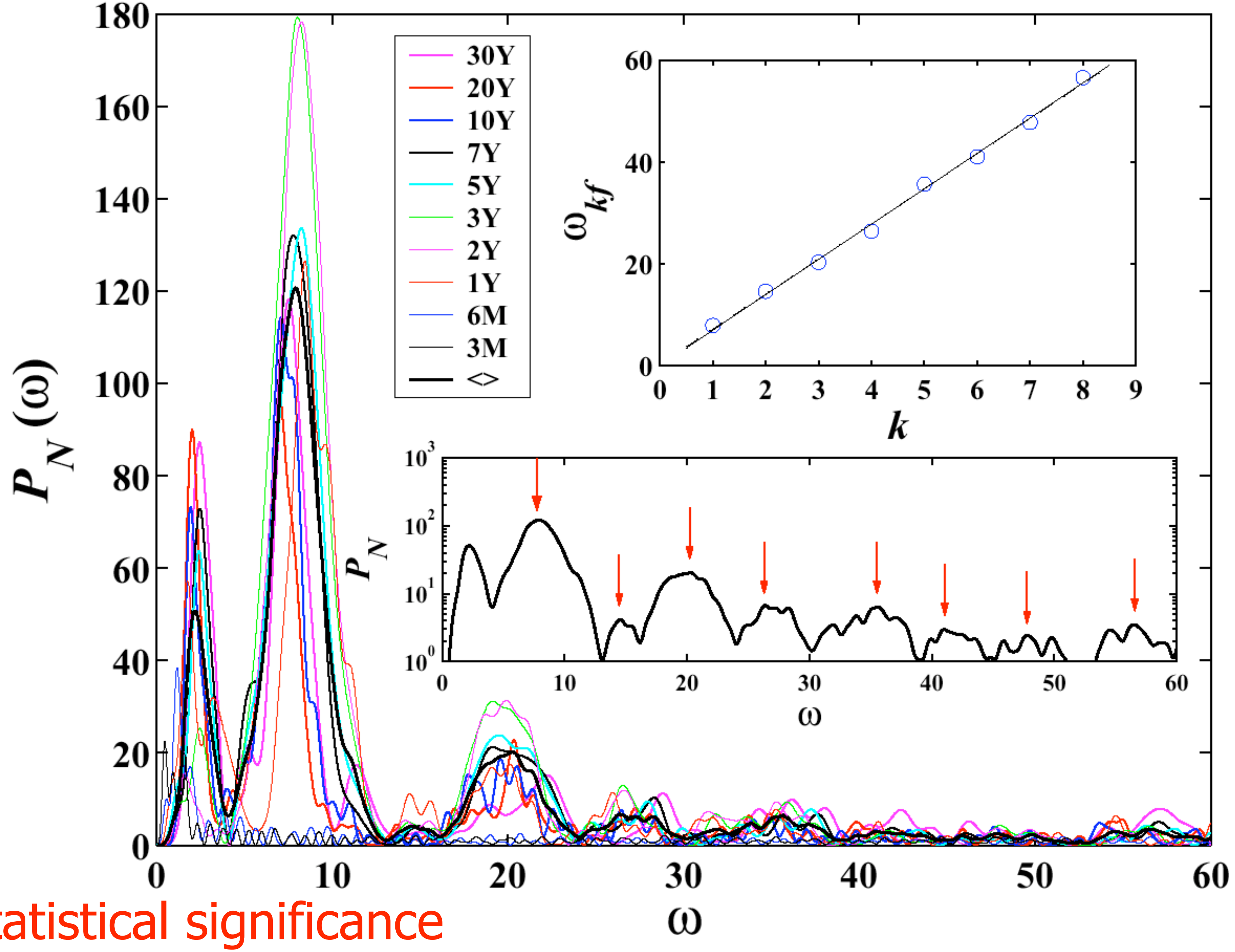
Fig. 9. The S&P 500 index denominated in GBP from 2000/08/09 to 2004/07/16 and its fits using the first-order and second-order Landau formulas. The values of the fit parameters are listed in Table 3. The fits are extrapolated to the end of 2005.



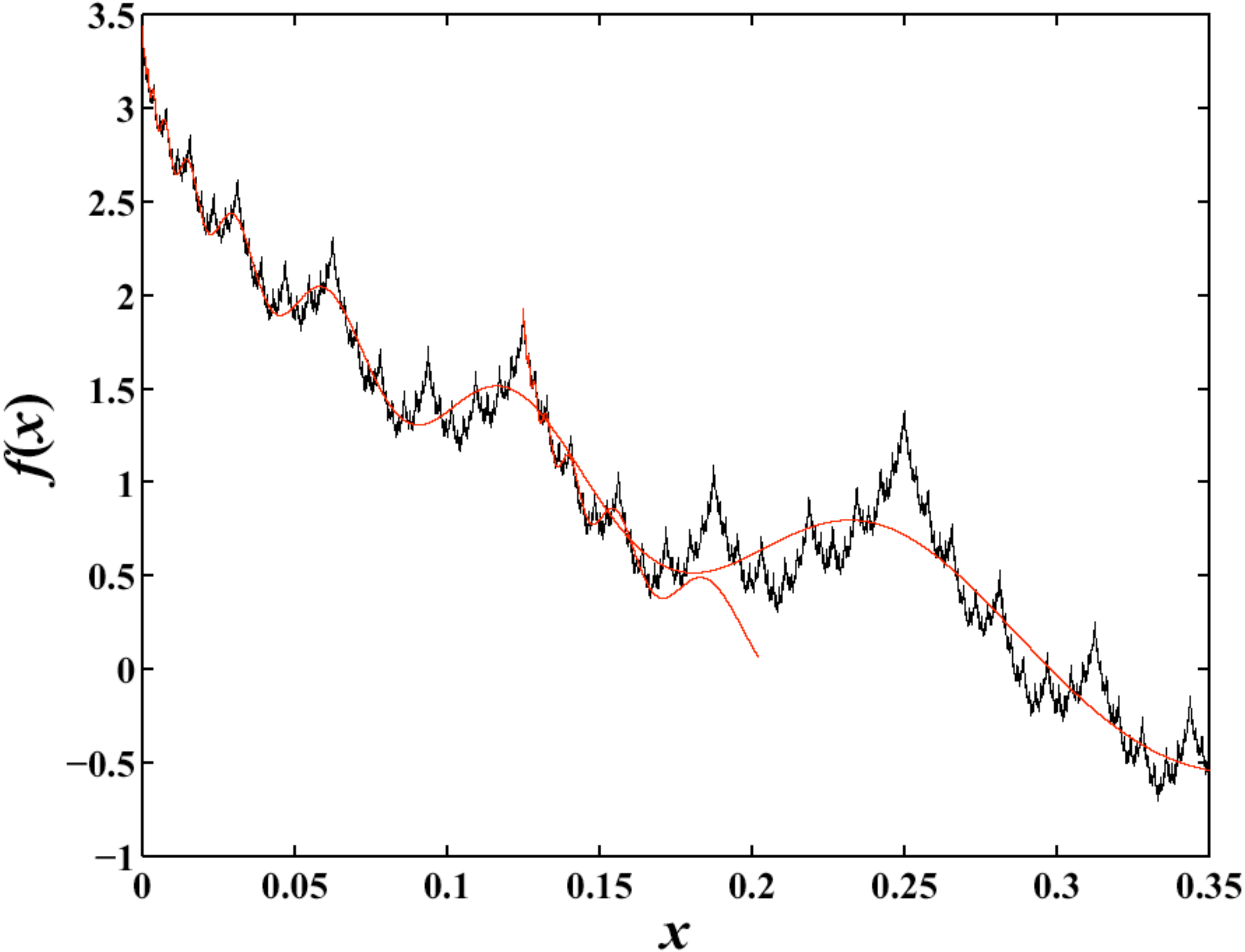
15
10
5
0
2000
2001
2002
2003
2004
y(t)
t
30Y
20Y
10Y
7Y
5Y
3Y
2Y
1Y
6M
3M

A hierarchy of antibubbles

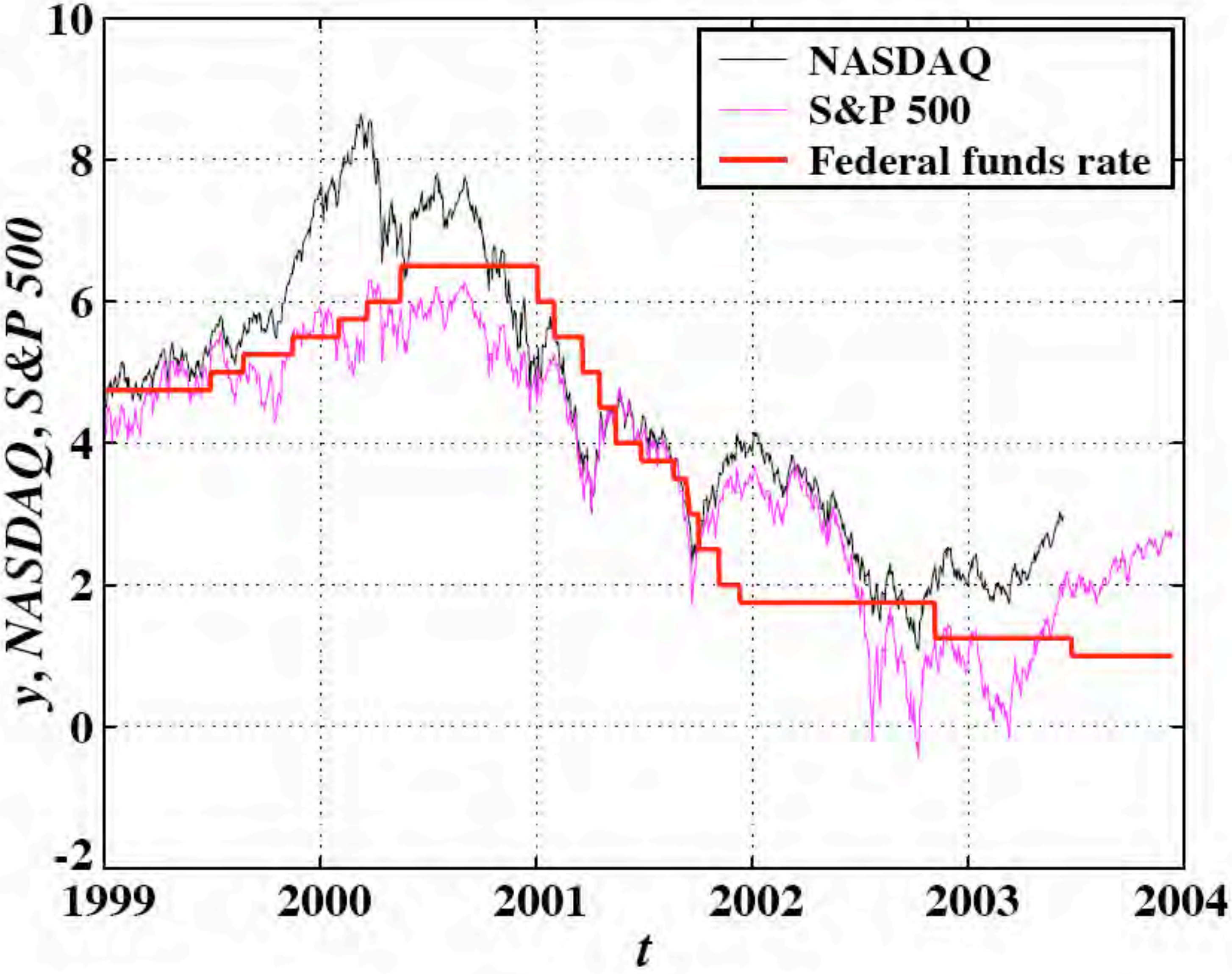




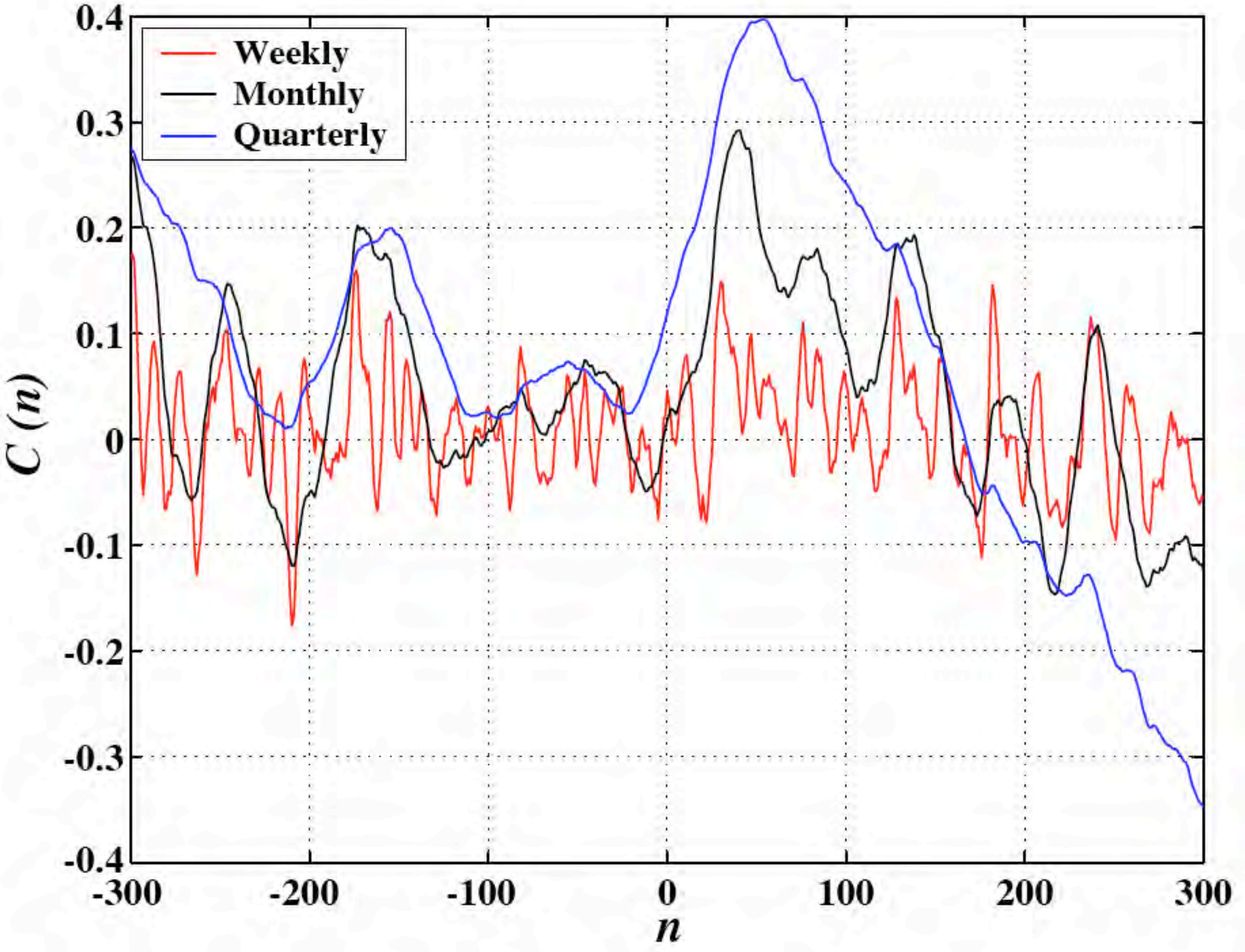
Statistical significance



3.5
3
2.5
2
1.5
1
0.5
0
−0.5
−1
f(x)
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
x



Comparison of the Federal funds rate, the S&P 500 Index x(t), and the NASDAQ composite z(t), from 1999 to mid-2003. To allow a illustrative visual comparison, the indices have been translated and scaled as follows: $x \rightarrow 5x - 34$ and $z \rightarrow 10z - 67$.



Cross-correlation coefficient C(n) between the increments of the logarithm of the S&P 500 Index and the increments of the Federal funds rate as a function of time lag n in days. The three curves corresponds to three different time steps used to calculate the increments: weekly, monthly and quarterly. A positive lag n corresponds to having the Federal funds rate posterior to the stock market.