

Departmental Seminar, March 2005

Andreas Penckwitt

Intelligent Finance

A Convergence of Mathematical
Finance with
Technical and Fundamental Analysis

First International Workshop on Intelligent Finance
held in Melbourne, December 13-14, 2004

Session 1: Social Economic Perspectives of Finance

- **Intelligent Finance - An Introduction**
Heping Pan, Didier Sornette and Kenneth Kortanek
- **The Financial/Economic Dichotomy**
Robert R. Prechter and Wayne D. Parker, The Socionomics Foundation, USA

Session 2: Fundamental Analysis and Econometrics

- **Warren Buffett: Investment Genius or Statistical Anomaly?**
John Price, The Conscious Investor, Australia, and Edward Kelly, University of Dublin, Trinity College, Ireland
- **Credit Risk Evaluation Through Stock Price Fluctuations and Their Correlations**
Naoto Oshiro and Yasufumi Saruwatari, University of Tsukuba, Financial Technology Research Institute, Japan
- **How Long Is the Long Run? Evidence from the Foreign Exchange Market**
Kenneth Clements, Yihui Lan, University of Western Australia

Session 3: Technical Analysis and Trading Strategies

- A Test of Momentum Trading Strategies in Foreign Exchange Markets: Evidence from the G7

Robert J. Bianchi, Michael E. Drew and John Polichronis, Queensland University of Technology, Australia

- Simulating Profitable Stock Trading Strategies with an Evolutionary Artificial Neural Network

Serge Hayward, Ecole Supérieure de Commerce de Dijon, France

Session 3 ... continued

- **On the Representation of Trading Strategies and Financial Products**
Stefan Dirnstorfer, Technical University Munich, Germany
- **The Predictive Ability of Simple Technical Indicators: Australian Evidence**
Maurice Peat, Max Stevenson and Daniel Maroney, University of Sydney, Australia

Session 4: Stochastic Process Models

- Non-stochastic Uncertainty Approaches to Prediction in Finance
Kenneth Kortanek, University of Pittsburgh, USA
- Pricing Barrier Options with Local Volatility Surface for Advantage
Zili Zhu, CSIRO Mathematical & Information Sciences, Australia
- ~~Dynamic Optimal Recovery to Credit Risk~~
~~Jianhui Huang, University of Alberta, Canada~~
- Karhunen-Loève Approximations of Wiener Processes and Solutions of SDEs
Deborah Downes and Stephen Lucas, University of South Australia

Session 7: Game Theory and Intelligent Agents

- **A Mechanism for Pockets of Predictability in Complex Adaptive Systems**
Jørgen Vitting Andersen and Didier Sornette, CNRS, France, UCLA, USA
- **Minority Games in Financial Markets**
Damien Challet, Oxford University, UK (presentation only)
- **Strategic Updating of Threshold Response in An Agent-based Market Model**
François Ghoulmie, University of Paris, France
- **Phase Transition of Dynamical Herd Behaviors in Financial Markets**
Kyungsik Kim and Seong-Min Yoon, Pukyong National University, Korea
- **Strategic Alliance: Absorptive Capacity and Search**
Julian Lowe and Munirul Haque Nabin

Session 8: Chaos Theory and Econophysics

- Dependence Structures in Financial Time Series: A Chaos-Theoretic Approach
Rodney C Wol, Queensland University of Technology, Australia
- A Mean-Field Approach of Predicting the Future of the Income Distributions of Companies
Hideki Takayasu, Takayuki Mizuno and Misako Takayasu, Sony Computer Science Laboratories, Japan
- Characterization of Temporal Behavior of Foreign Exchange Markets
Misako Takayasu, Takaaki Ohnishi, Takayuki Mizuno and Hideki Takayasu, Tokyo Institute of Technology, Japan
- ~~Statistical Analysis of Detrended Stock Market Indices~~
~~Boon Leong Lan, Monash University, Malaysia~~

Session 9: Quantitative Analysis and Portfolio Management

- Calculating the Optimal Exercise
Boundary of American Put Options with An
Approximation Formula
Song-Ping Zhu, University of Wollongong, Australia
- Phase Transitions in an Equity-Ranking
Predictor
Jerrey Satinover, University of Nice, France

Session 9 ... continued

- **Compound Models of High-Low Speculative Prices: A Cointegration-based Approach**
Nagaratnam Jeyasreedharan, University of Tasmania, Australia
- **Relationships between Different Term Structures of Australian Interest Rate Swap Market**
Musa Mammadov and John Yearwood, University of Ballarat

Session 10: Computational Intelligent Finance Systems

- **Algorithmic Trade Execution and Market Impact**
Richard Coggins, Marcus Lim and Kevin Lo, University of Sydney, Australia
- **The Components of the Bid-Ask Spread: An Ability-Based Model**
Paochung Hsu, Providence University, Taiwan, Republic of China
- **An Investigation of the Uses of Depth of Field and Stochastic Concepts in Fine Tuning Strategic Plays in the Australian Stock Market and Its Impact on Systems Development**
Barry O'Gray, Curtin University of Technology, Australia

Session 11: Intelligent Finance Theories

- ~~Why Stock Markets Crash - Critical Events in Complex Financial Systems~~

~~Didier Sornette, University of California LA and CNRS,
University of Nice, France~~

- A Swingtum Theory of Finance for Swing Trading and Momentum Trading

Heping Pan, University of Ballarat

Intelligent Finance - An Introduction

Heping Pan

Intelligent finance emerging convergence of several distinct disciplines:

- Fundamental Analysis
- Technical Analysis
- Quantitative Analysis
- Strategic Analysis
 - Art of trading and active speculation either passively exploiting market-inequilibria or actively with conscious intention to affect market
 - Game theory and intelligent agents

Characteristics of Intelligent Finance

- **Objective:** gain consistently absolute positive and nontrivial returns of investing and trading in selected financial markets
- **Approach:** exploit complete information about the selected markets
- **Methodology:** manage the very last risk - the incompleteness of a standalone trading system

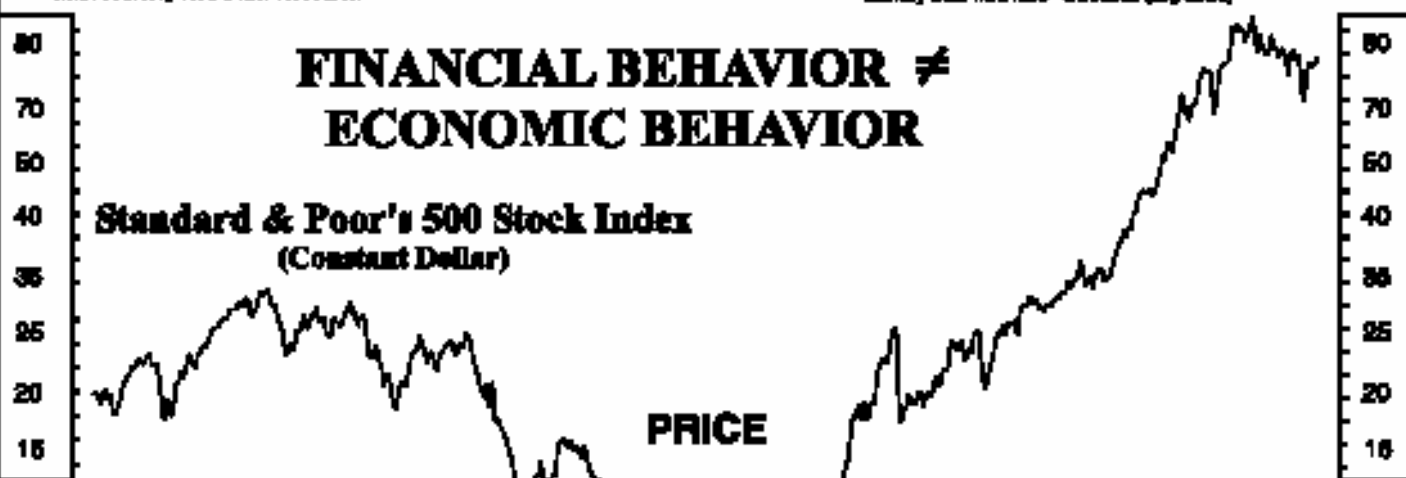
The Financial/Economic Dichotomy

Robert R. Prechter

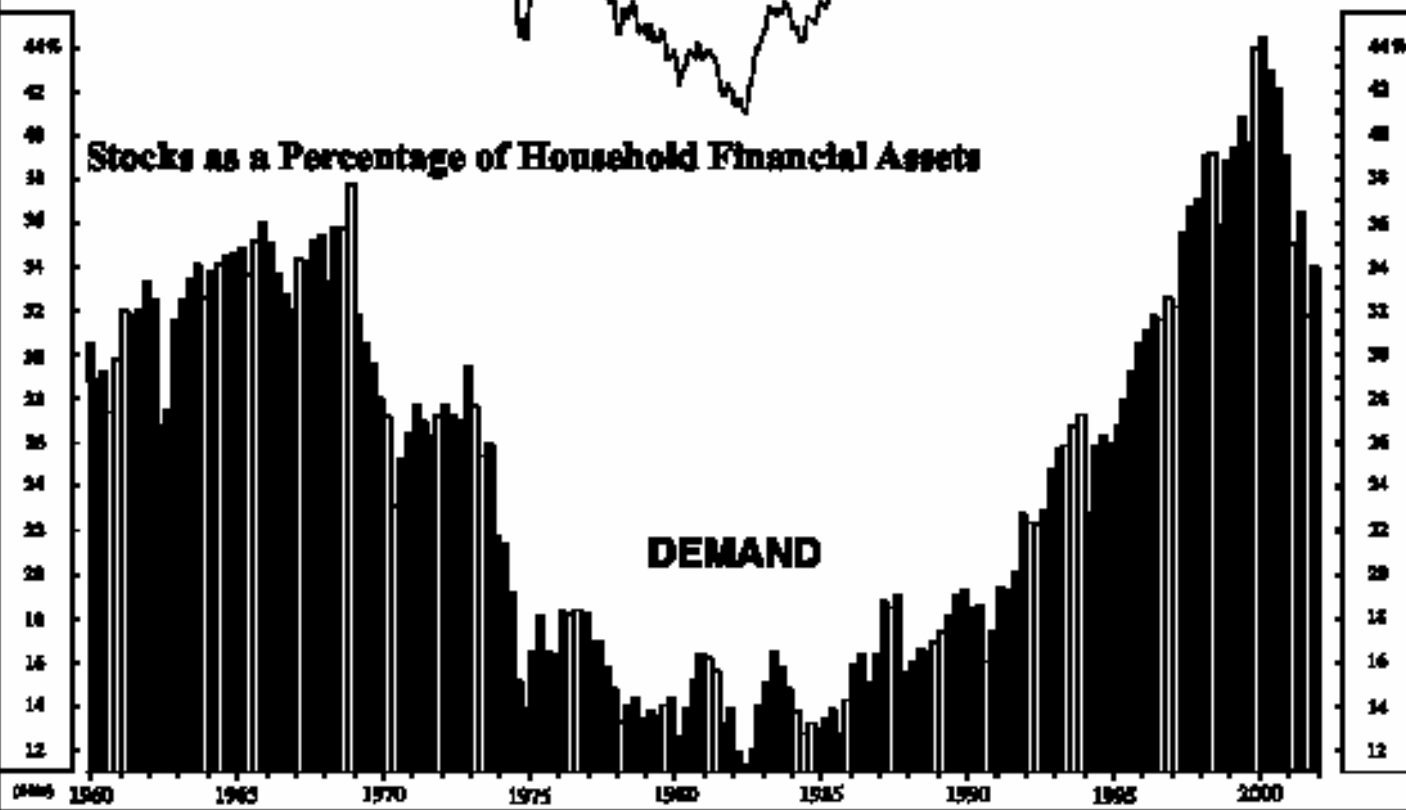
- Dramatic Anomalies:
 - 1976-1980: quaterly GPD growth, but stock market went down
 - 1980-now: Inflation leads to money supply tripled, but gold prize went down
 - 9/11: market closed for 6 days, slight drop for six days, but went up following six month
 - etc.
- Knowing news one day ahead does not help to predict financial markets

FINANCIAL BEHAVIOR \neq ECONOMIC BEHAVIOR

Standard & Poor's 500 Stock Index (Constant Dollar)

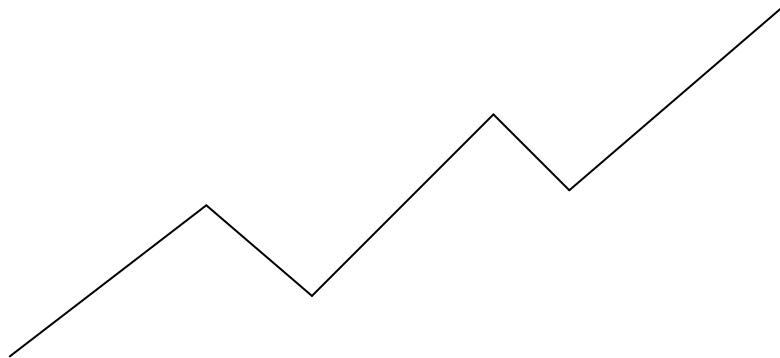


Stocks as a Percentage of Household Financial Assets



Elliot Waves

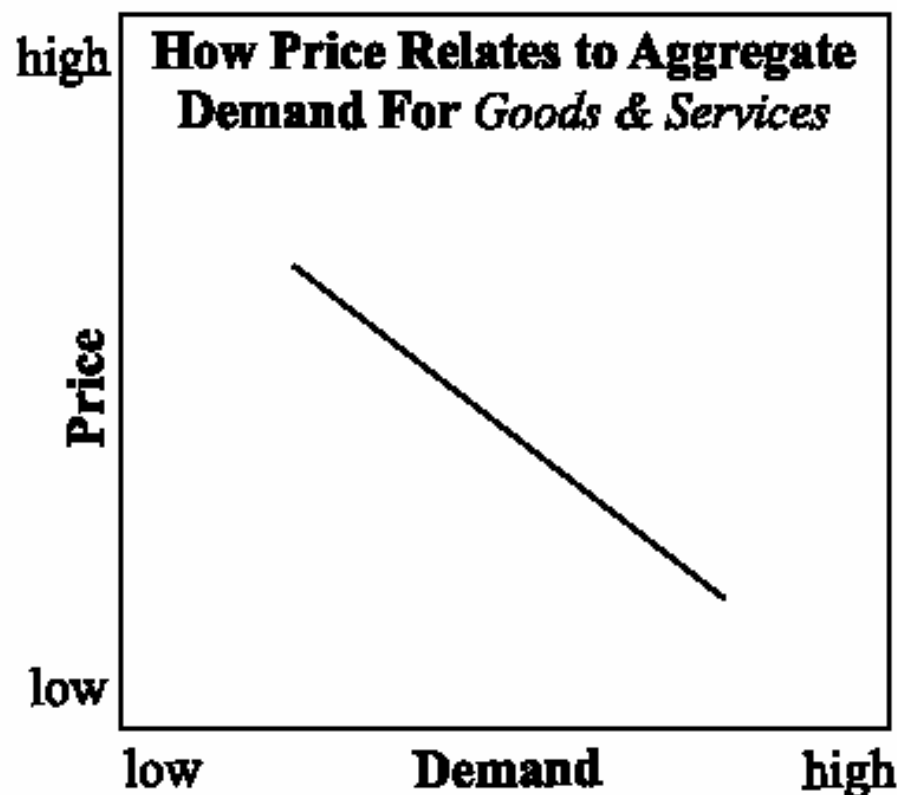
- Stock market highly correlated to itself
- Natural growth pattern
- Simplest one is a basic Elliot Wave (1940)



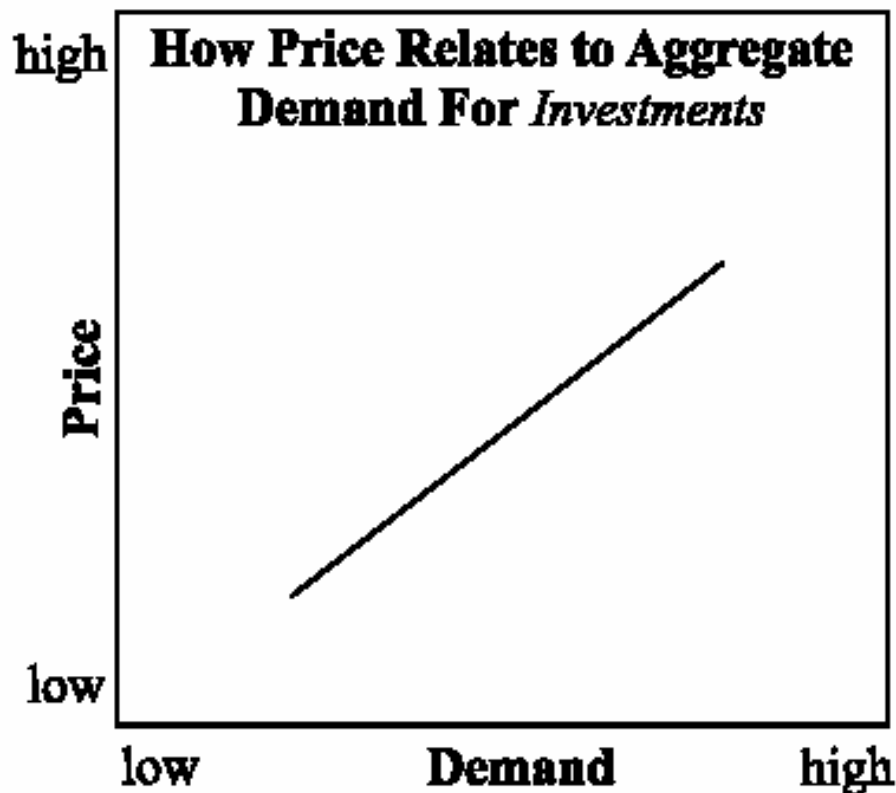
Herding

- Herding when faced with uncertainty
- Notion that following the herd decreases risk (while risk actually increases)
- Herding creates patterns
- Rationalizing, not reasoning

ECONOMICS



FINANCE

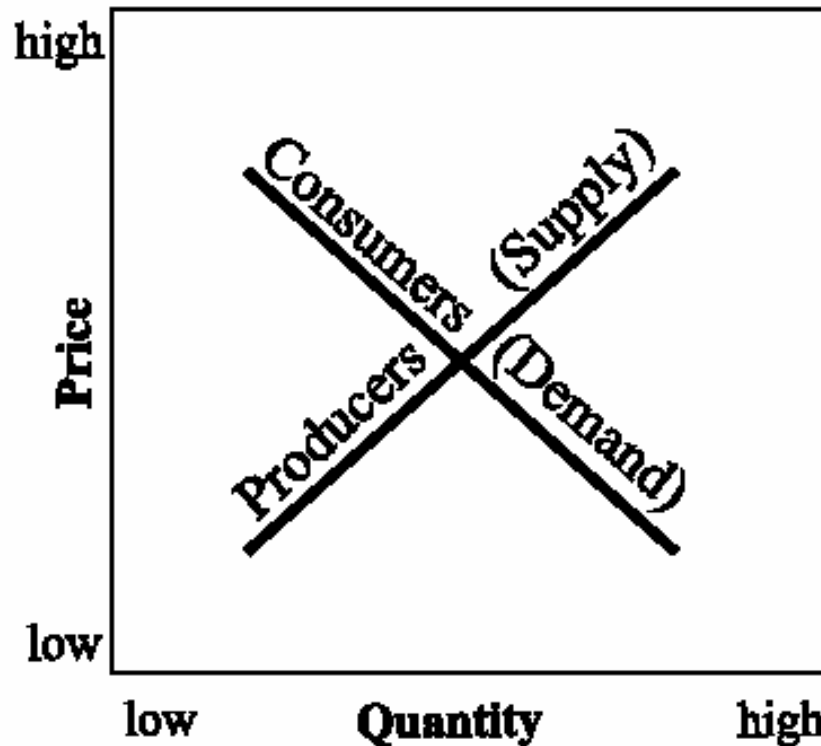


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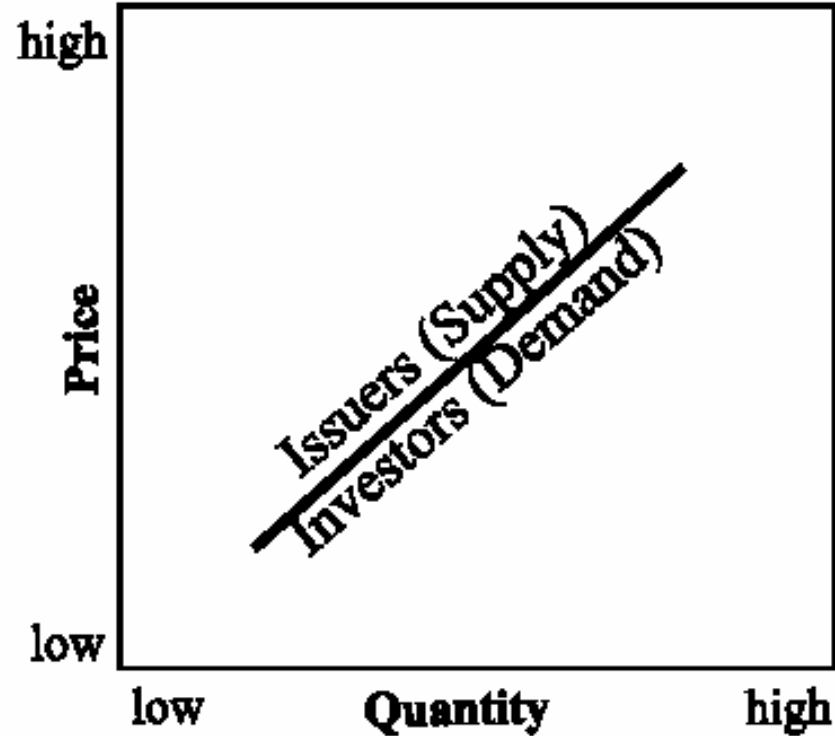
Motivation (goal): Survive and Thrive
Means: Maximizing Utility
Mechanism: Conscious Reason
Result: Survive and Thrive

Motivation (goal): Survive and Thrive
Means: Herding
Mechanism: Unconscious Reason
(Ultimate Result) Result: Losses

The Law of Supply & Demand in Utilitarian Economics



Herding Impulse in Finance



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Features: Rational Valuation
Equilibrium
Objective Values
Aggregate Governor: The Invisible Hand

Features: Pre-Rational (Impulsive) Valuation
Dynamism
Subjective Values
Aggregate Governor: The Wave Principle

Socionomics

- Economic behaviour results from major mood trends
- Stock market is leading, not lagging
- Stock market as major sociometer
- Elliot waves of social mood

Contrasting Models of Finance

EMH (Economic) Model

1. Objective, conscious, rational decisions to maximize utility determine financial values.
2. Financial markets are random.
3. Financial markets are unpredictable.
4. Financial markets "tend toward equilibrium" and "revert to the mean."
5. Investors in financial markets typically use information to reason.
6. Investors' decisions are based on knowledge and certainty.
7. Changing events presage changes in the values of associated financial instruments.
8. Economic principles govern finance.

WP (Sociomic) Model

1. Subjective, unconscious, pre-rational impulses to herd determine financial values.
2. Financial markets are patterned.
3. Financial markets are probabilistically predictable.
4. Financial markets are dynamic and do not revert to anything.
5. Investors in financial markets typically use information to rationalize emotional imperatives.
6. Investors' decisions are fraught with ignorance and uncertainty.
7. Changing values of financial instruments presage changes in associated events.
8. Sociomic principles govern finance.

Minority Game (MG)

- Multi-agent system
- Addresses interaction between agents and information
- No optimal strategy
- Inductive reasoning
- Cooperation without direct interaction
- Critical transition (collective behaviour qualitatively different from single agent)

Minority Game

- N agents with memory length m and a set of s strategies (randomly assigned)
- At each time step, agents take action

$$a_i^{\mu m}(t) = \pm 1$$

based on common information

$$\mu_m(t) = \left\{ \frac{1 + \text{sign}[A^\mu(k)]}{2}; k = t - m + 1, \dots, t \right\}$$

where $A^\mu(k) = \sum_i a_i^\mu(k)$ excess demand

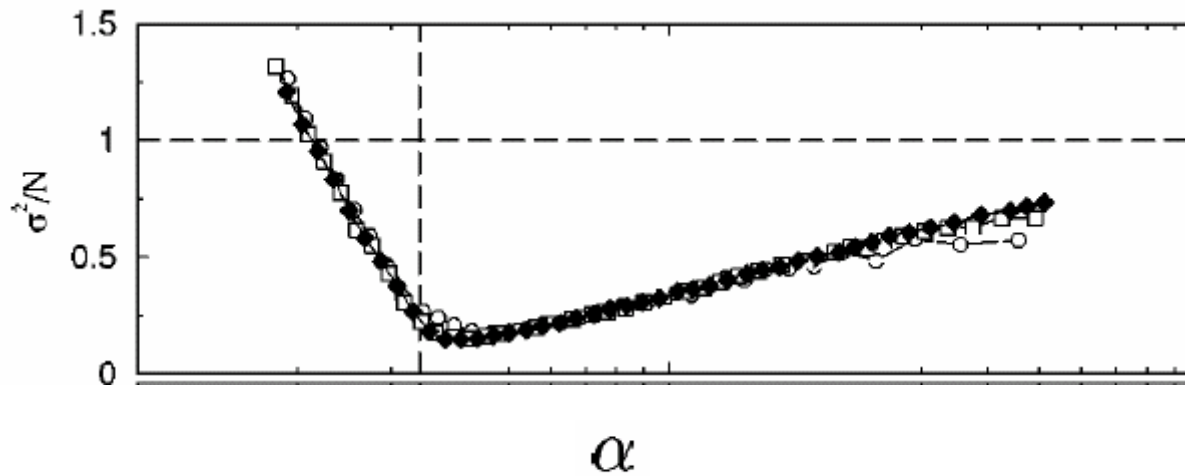
Minority Game

- Action based on best strategy, where a strategy is a mapping of 2^m possible histories onto two possible decisions
- In standard minority game $s = 2$
- Payoff $g_j(t) = -a_j(t)A(t)$ (standard MG)
- Other payoff functions lead to different mechanisms, e.g. $g_j(t) = a_j(t-1)A(t)$ (\$ game)

Phase transition

- Fluctuations of $A(t)$ depend only on ratio

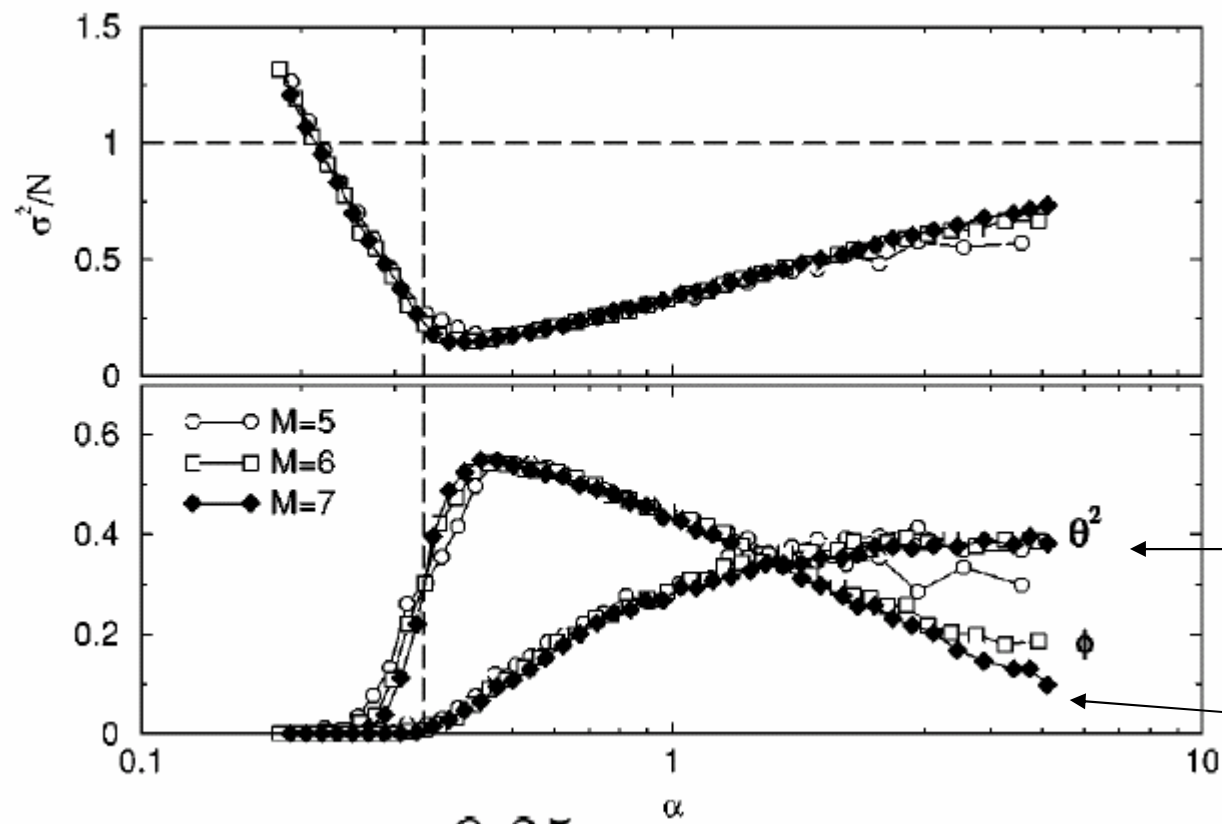
$$\alpha \equiv 2^m / N$$



Crowded

Coordination

Random



$$\alpha_c \approx 0.35$$

Measure of predictability

Ratio of agents with frozen strategy

symmetric phase

asymmetric phase

unpredictable

predictable

Other interesting results

- Possibility to extract sufficient information on strategies from collective action $A(t)$
- Behaviour becomes very predictable just before a crash
- Only if agents account for their market impact, Nash equilibrium is reached (in standard MG agents play against $A(t)$, not each other)

A Mechanism for Pockets of Predictability in Complex Adaptive Systems

Jørgen Vitting

- Found pockets of predictability in MG
- Some strategies might be decoupled
For example

$$\{000 \rightarrow 0; 001 \rightarrow 0; 010 \rightarrow 1; 011 \rightarrow 0;$$
$$100 \rightarrow 1; 101 \rightarrow 0; 110 \rightarrow 1; 111 \rightarrow 0\}$$

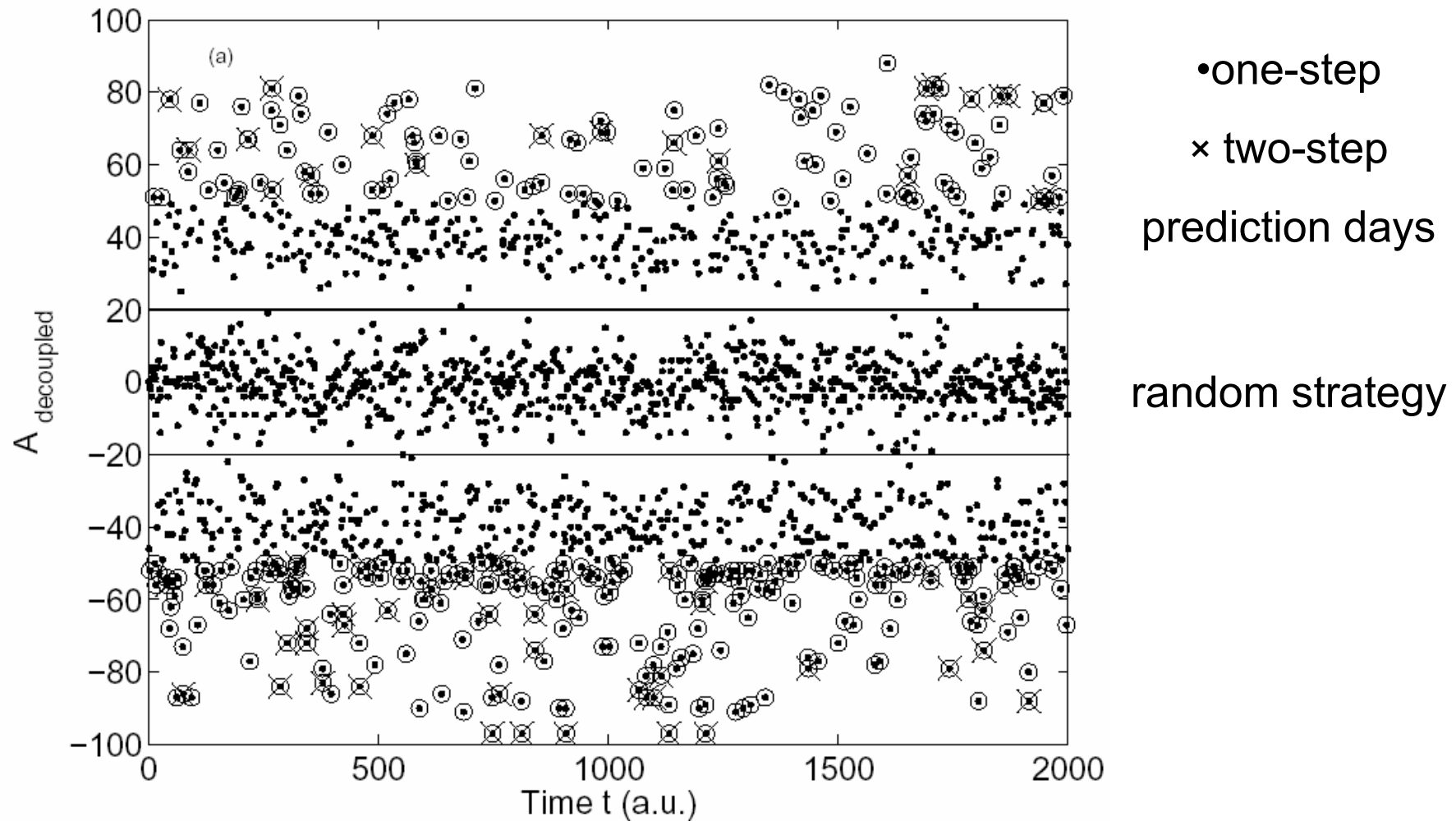
one time-step decoupled conditioned on

$$\mu_3(t) = 100 \text{ or } \mu_3(t) = 000$$

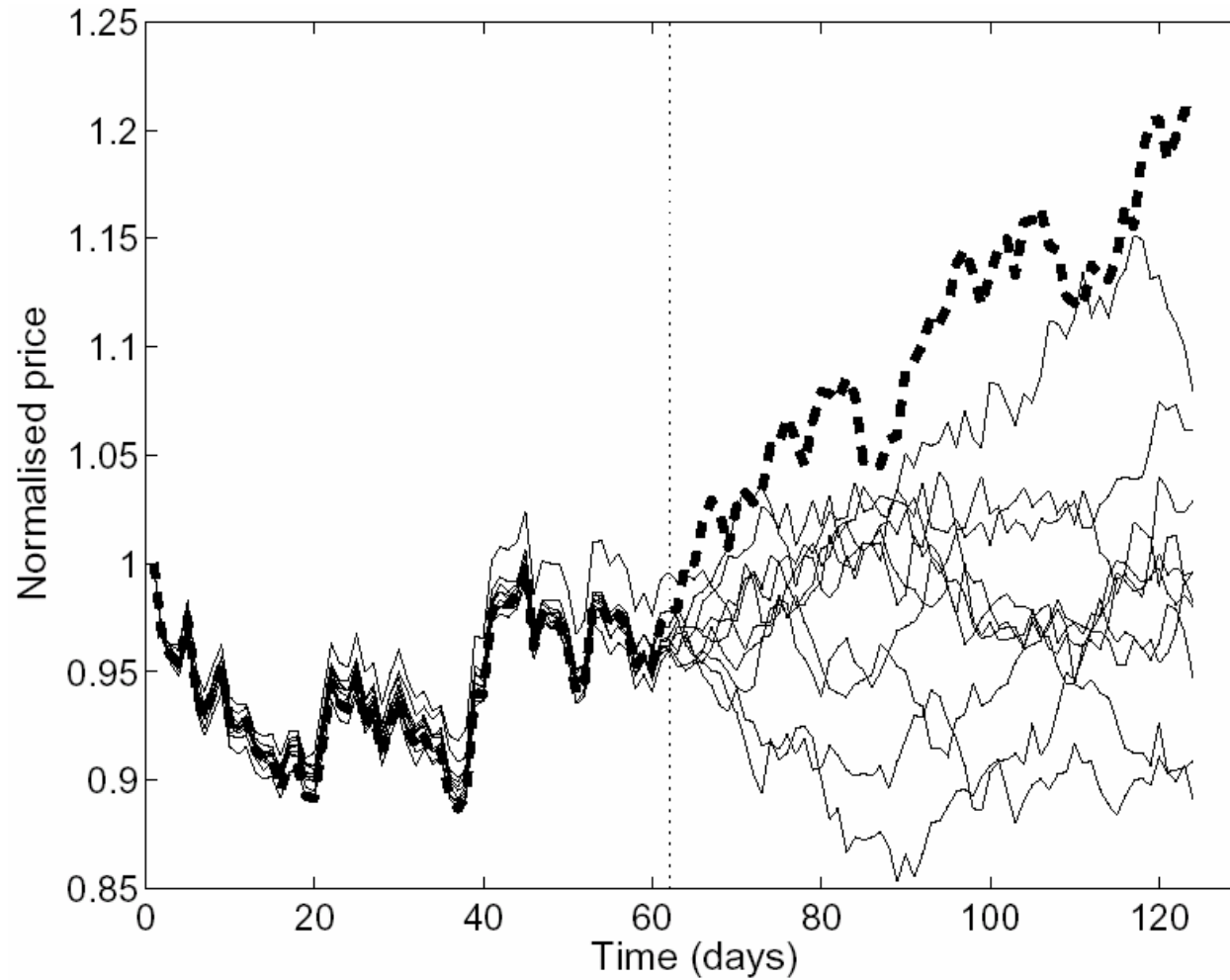
Prediction days

- Possibility to predict with *certainty* future of global action if majority of agents use decoupled strategies which combine to a majority action
- Prediction days more frequent in statistically unpredictable regime ($\alpha < \alpha_c$)

Frequency of prediction days



Comparison to Nasdaq



Poor job predicting prices

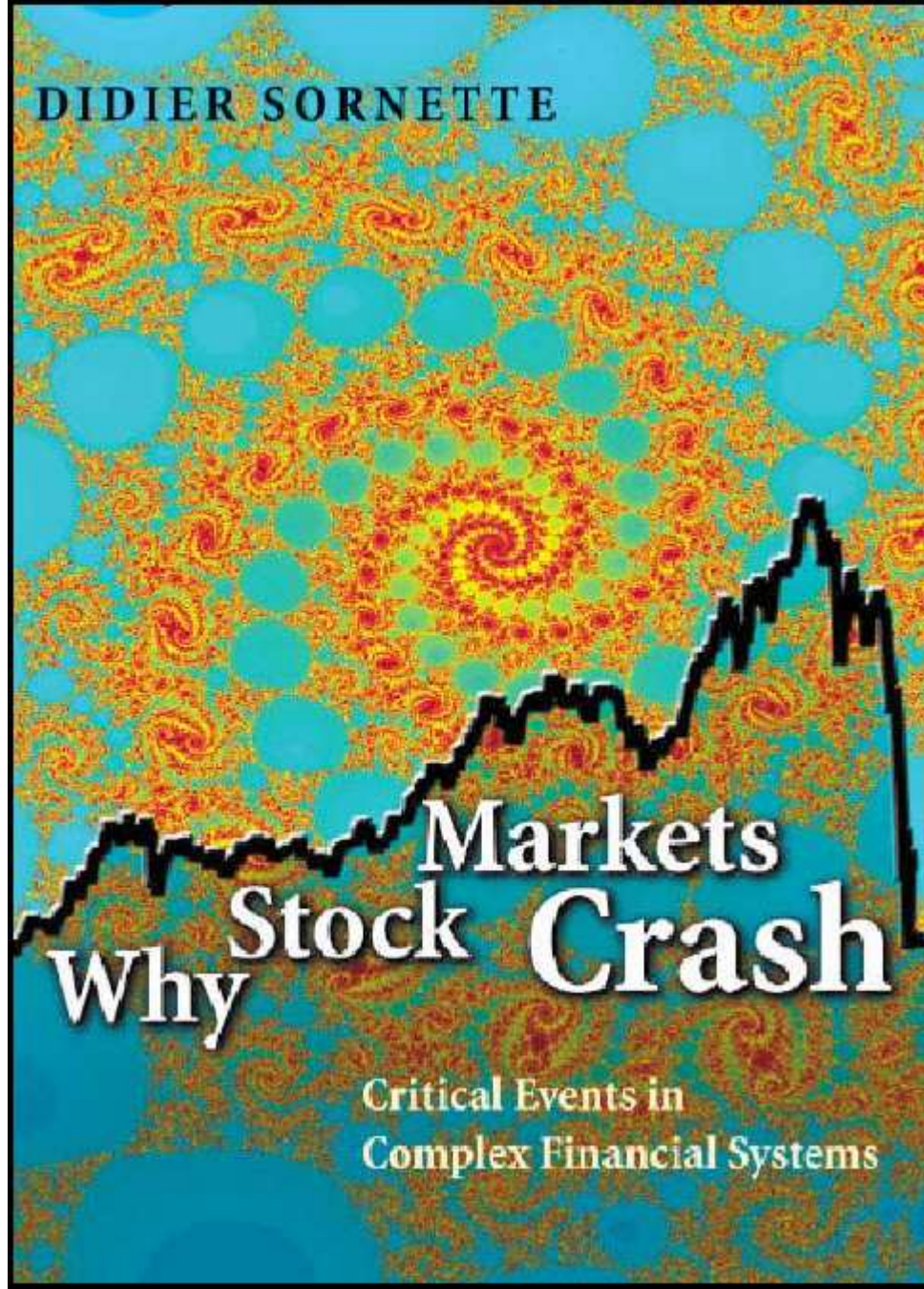
Comparison to Nasdaq

- However, very good in predicting sign of change on prediction days

$ A $	0	0.5	1	1.5	2	2.5	3	3.5	4	4.5
%	53	61	67	65	82	70	67	67	100	100
Nb	62	49	39	23	17	10	6	3	2	1

- On non-prediction days success rate not above 50%

DIDIER SORNETTE



Why Markets Stock Crash

**Critical Events in
Complex Financial Systems**

D. SORNETTE

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D. Darcet (Insight Finance, France)

K. Ide (UCLA)

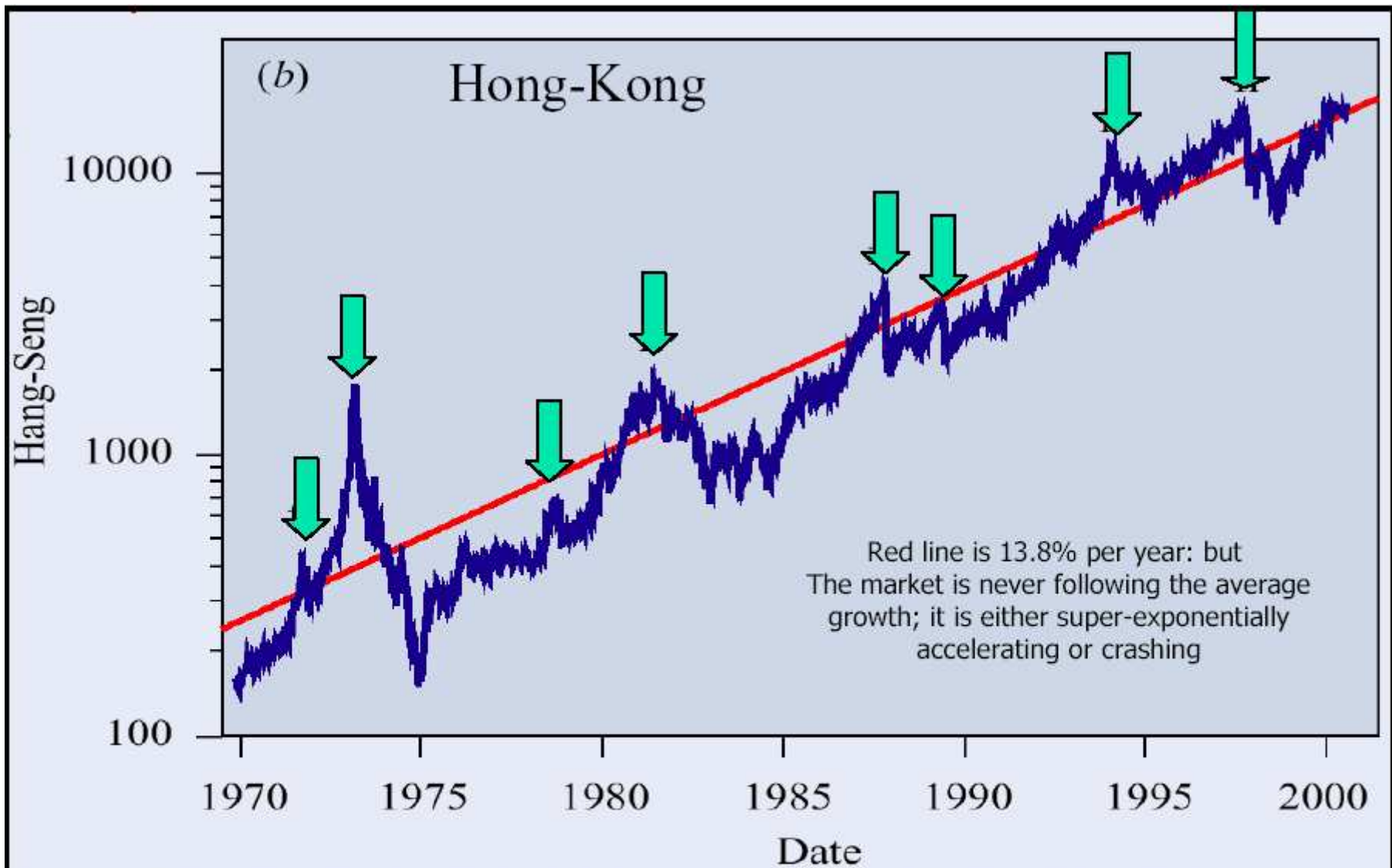
A. Johansen (Risø Nat. Lab, Denmark)

Y. Malevergne (Univ. Nice, France)

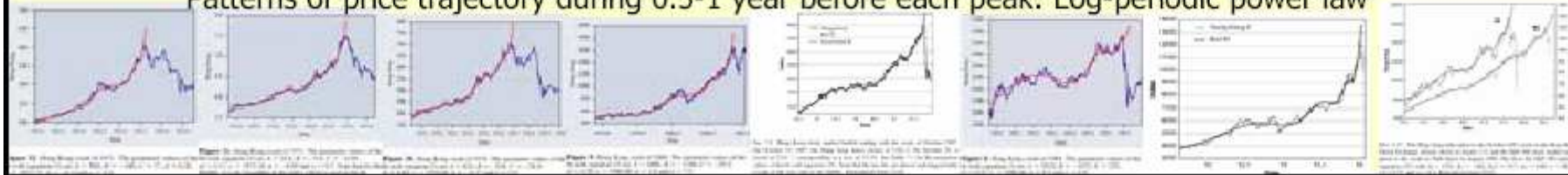
V. Pisarenko (Acad. Sci. Moscow, Russia)

W.-X. Zhou (UCLA)

<http://www.ess.ucla.edu/faculty/sornette/>



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.

Complex Systems

-positive feedbacks

-non sustainable regimes

-rupture

Mechanisms for positive feedbacks in the stock market

- Technical mechanisms
 1. Option hedging
 2. Insurance portfolio strategies
 3. Trend following investment strategies

- Behavioral mechanisms
 1. It is rational to imitate
 2. It is the highest cognitive task to imitate
 3. We mostly learn by imitation

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

Kal

CARTOONISTS & WRITERS SYNDICATE <http://CartoonWeb.com>



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

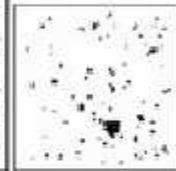
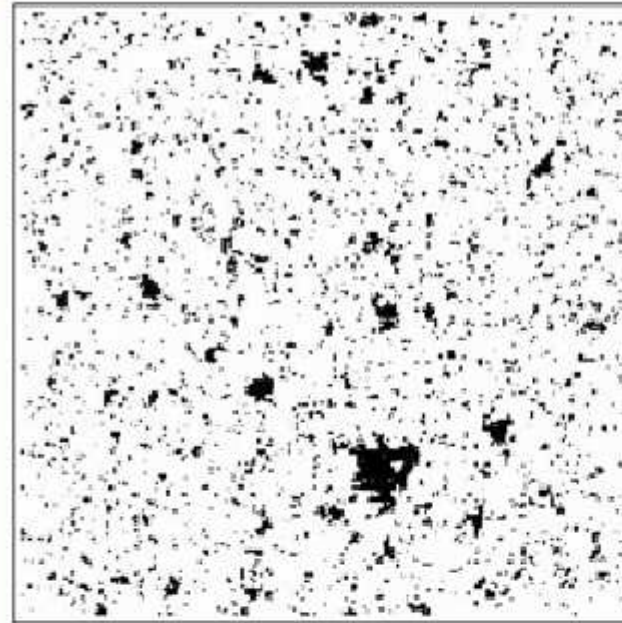
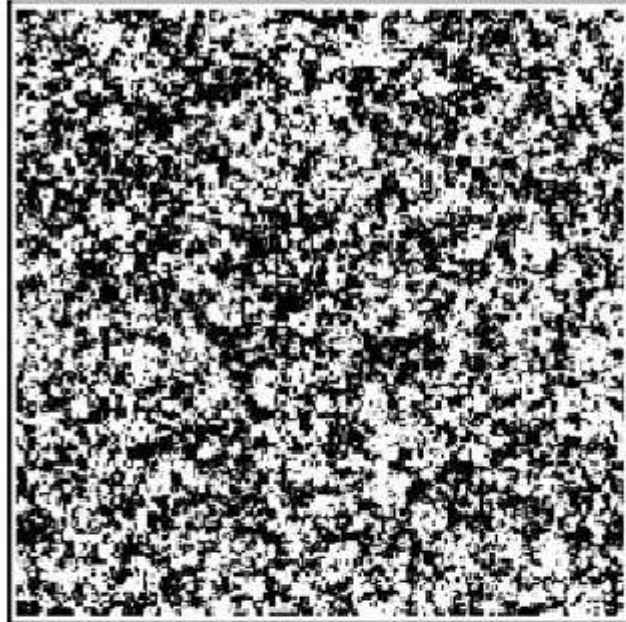
- Crash = coordinated sell-off of a large number of investors
- single cluster of connected investors to set the market off-balance
- Crash if 1) large cluster $s > s^*$ and 2) active

-Proba(1) = $n(s)$

-Proba(2) $\sim s^a$ with $1 < a < 2$ (coupling between decisions)

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

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

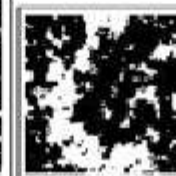
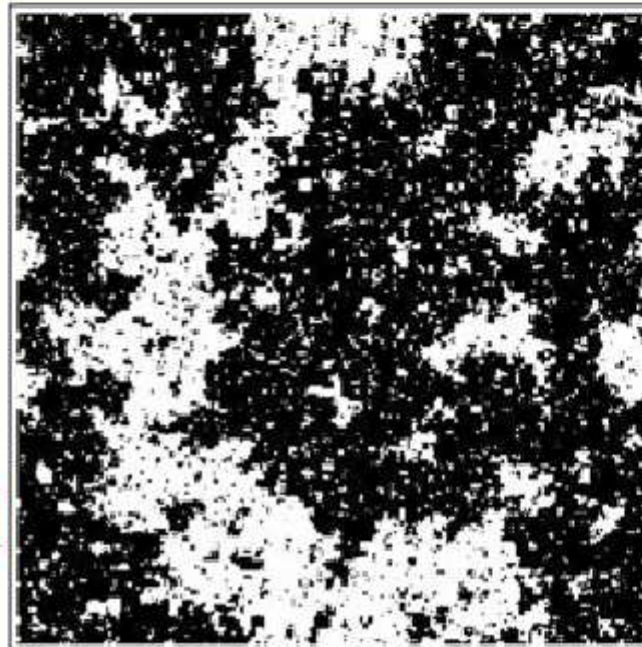


Order
K large

Disorder : K small

Renormalization group:
Organization of the
description scale by scale

Critical:
K=critical
value



DISCRETE HIERARCHY OF THE AGENT NETWORK

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

- • Why do we have a big Brain?
 - • Co-evolution of brain size and group size
- • Interplay between **nonlinear positive** and **negative feedbacks** and **inertia**
- • Discrete scale invariance
Complex fractal dimension
Log-periodicity

FRACTALS

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

2) $d \in \mathbb{R}$ Mandelbrot (1960-1980)
(Weierstrass, Hausdorff, Holder, ...)

3) $d \in \mathbb{C}$

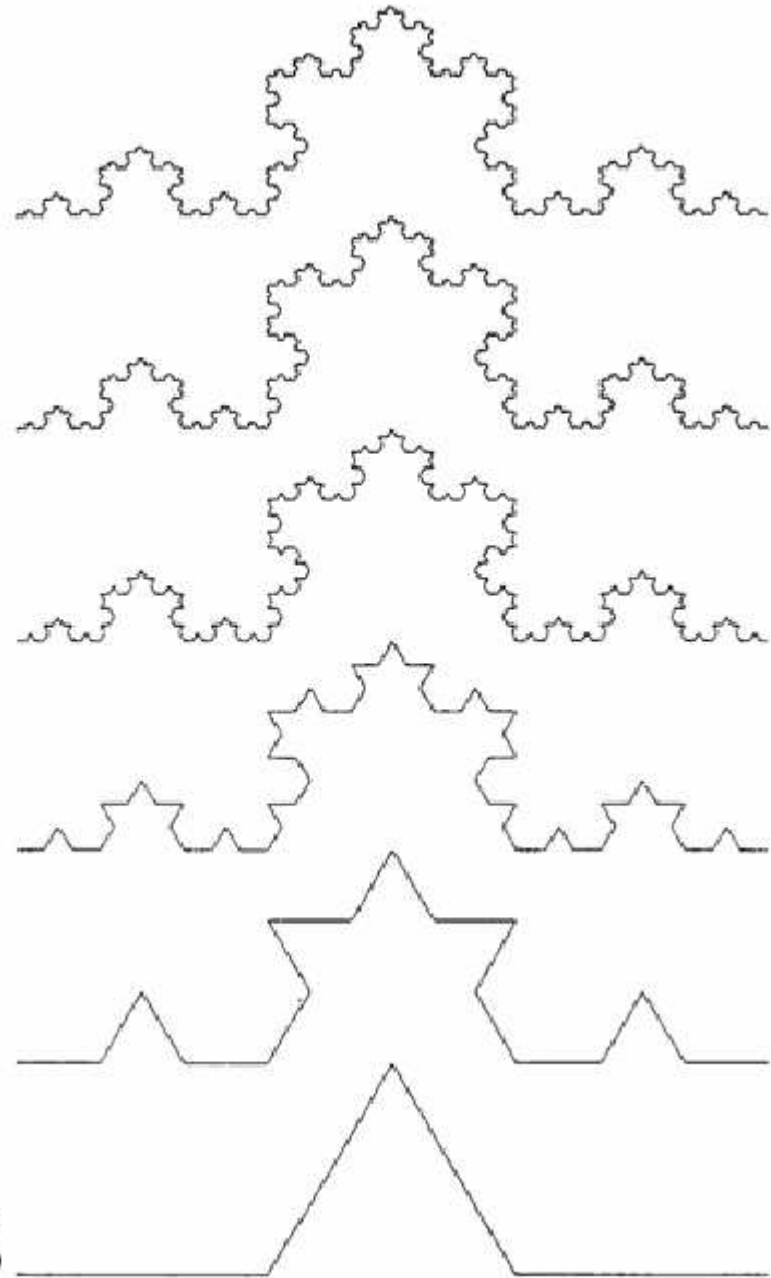
Discrete scale invariance

Complex fractal dimension

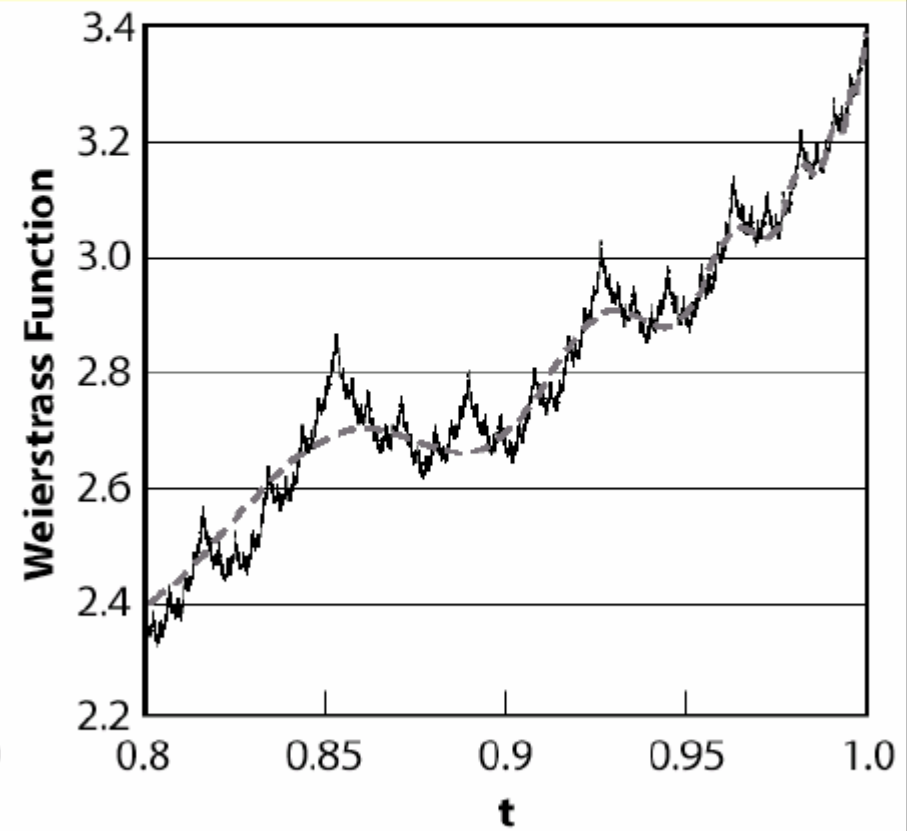
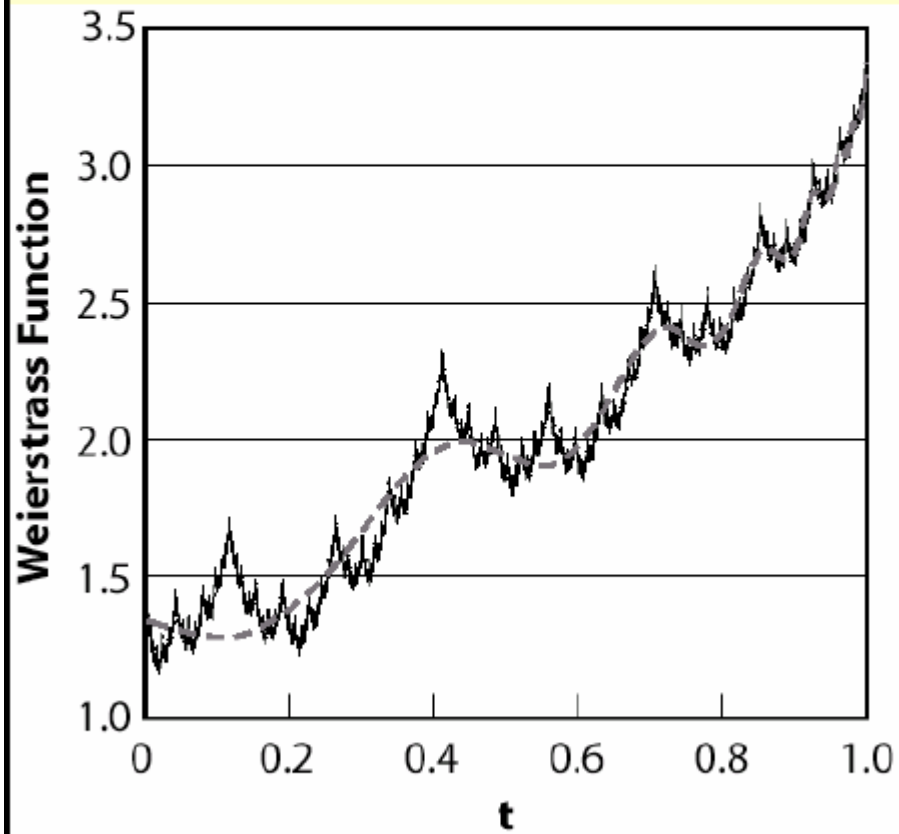
Log-periodicity

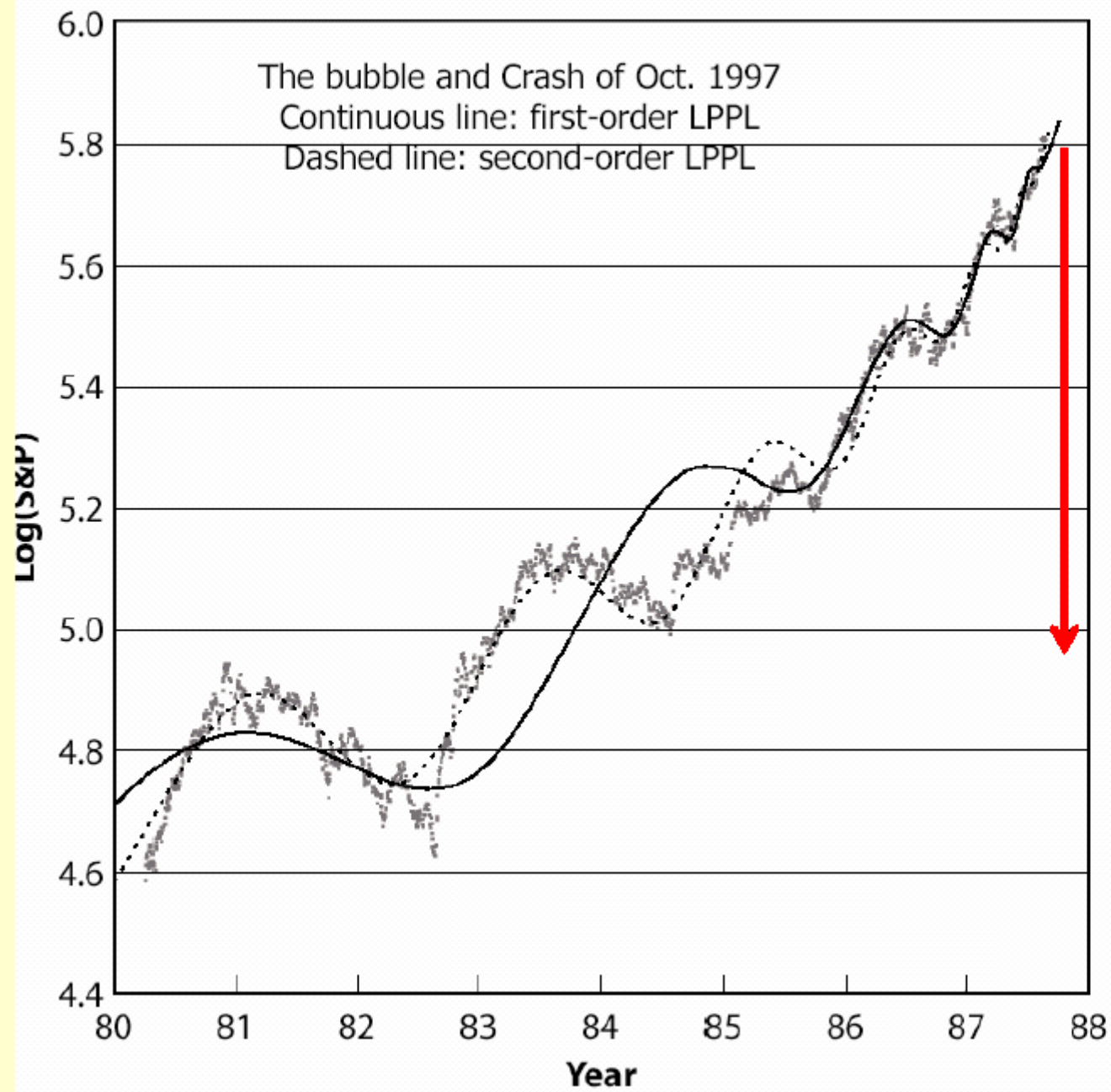
Preferred scaling ratio is **3**

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



Fractal function





Conclusion

- Interesting and stimulating workshop
- Financial markets are complex systems of interacting agents
- Collective behaviour in complex systems leads to new phenomena (phase transitions, extreme events)
- Emergence of universal patterns in complex systems
- Computer cluster allows computational study of complex systems