

Econophysics: statistical physics of interacting agents

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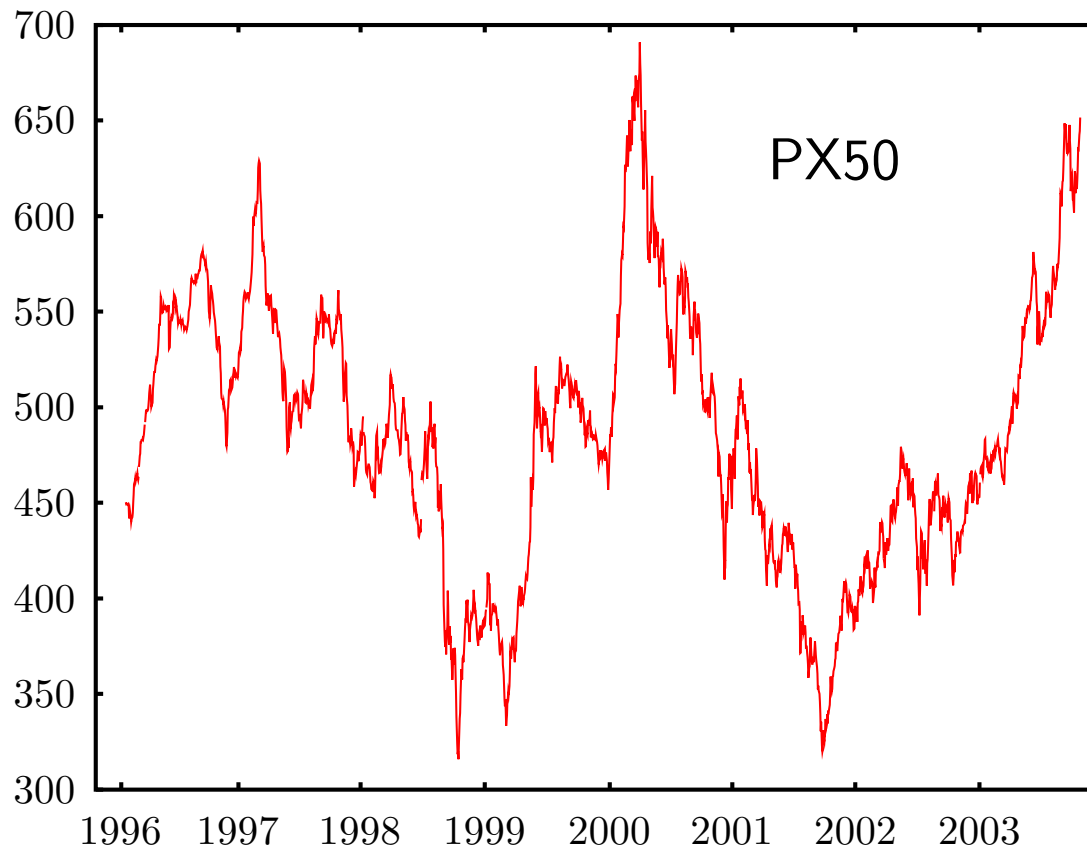
- Scaling, criticality and power laws
- Price fluctuations and book of orders
- Wealth distribution
- Imitation in Minority Game
- Sznajd model
- Thanks to GAČR 202/01/1091



Stock market crashes

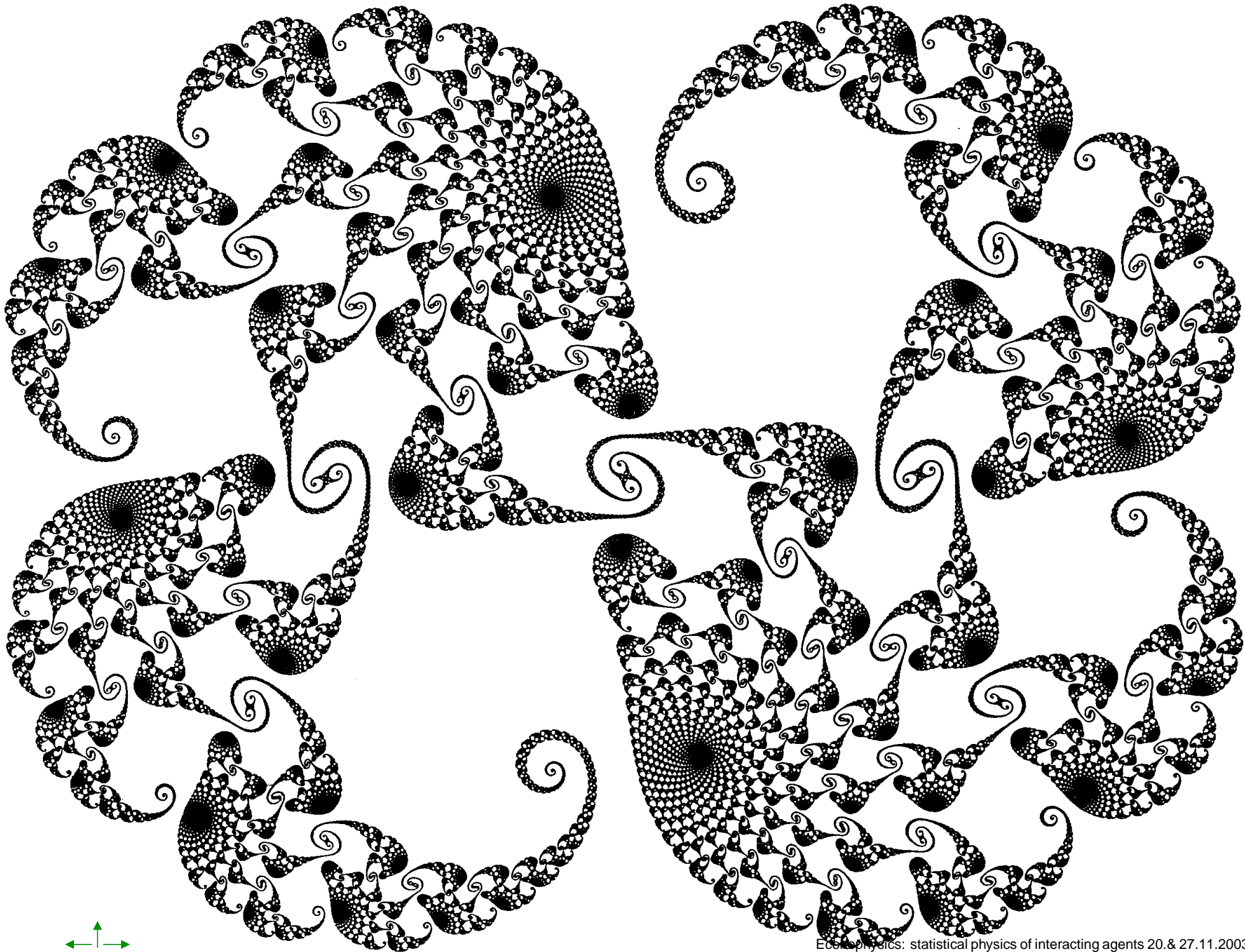


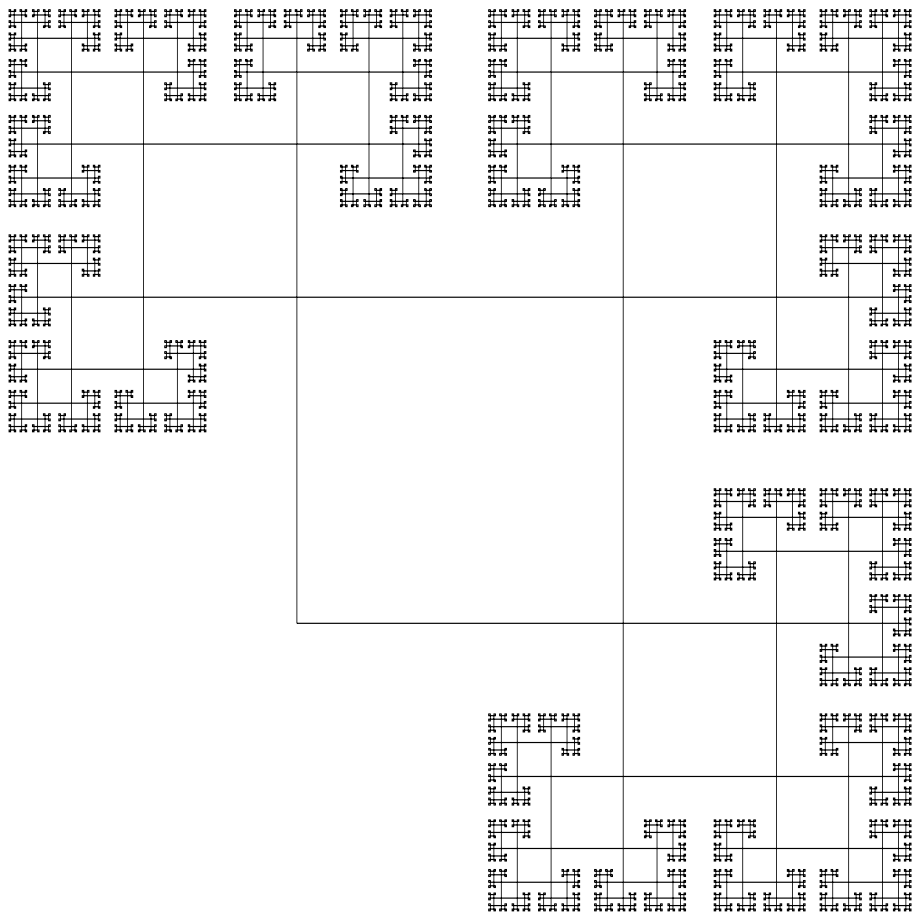
Stock market crashes



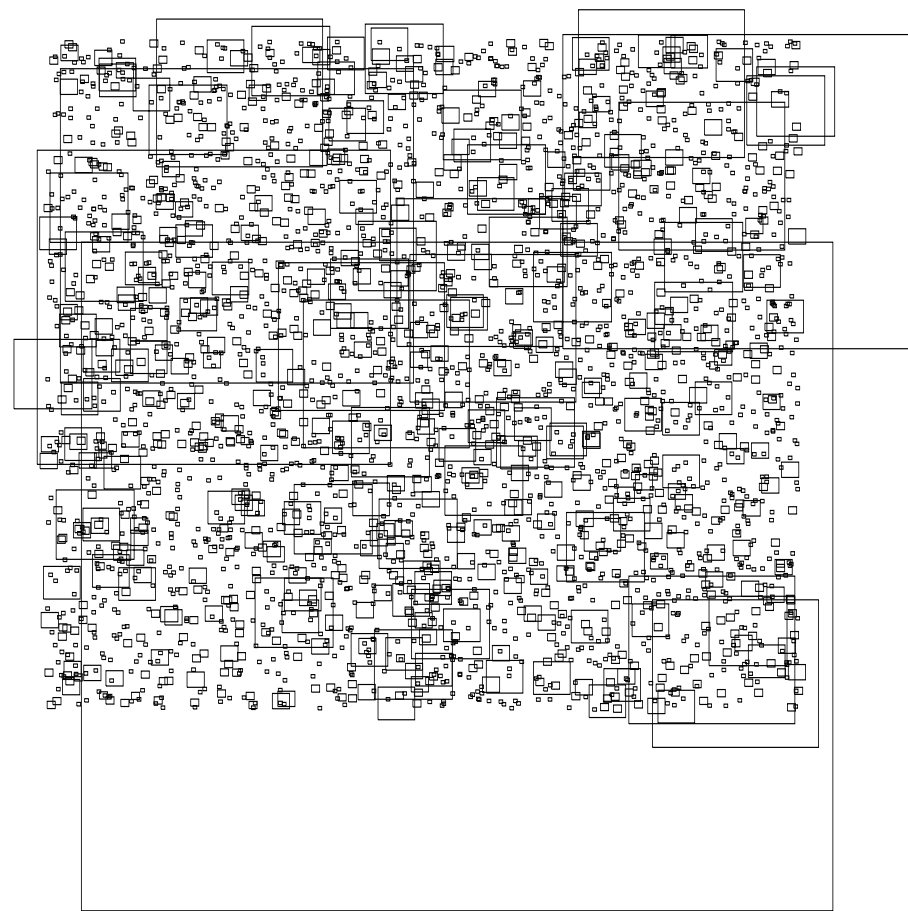
Prague Stock market index PX50.







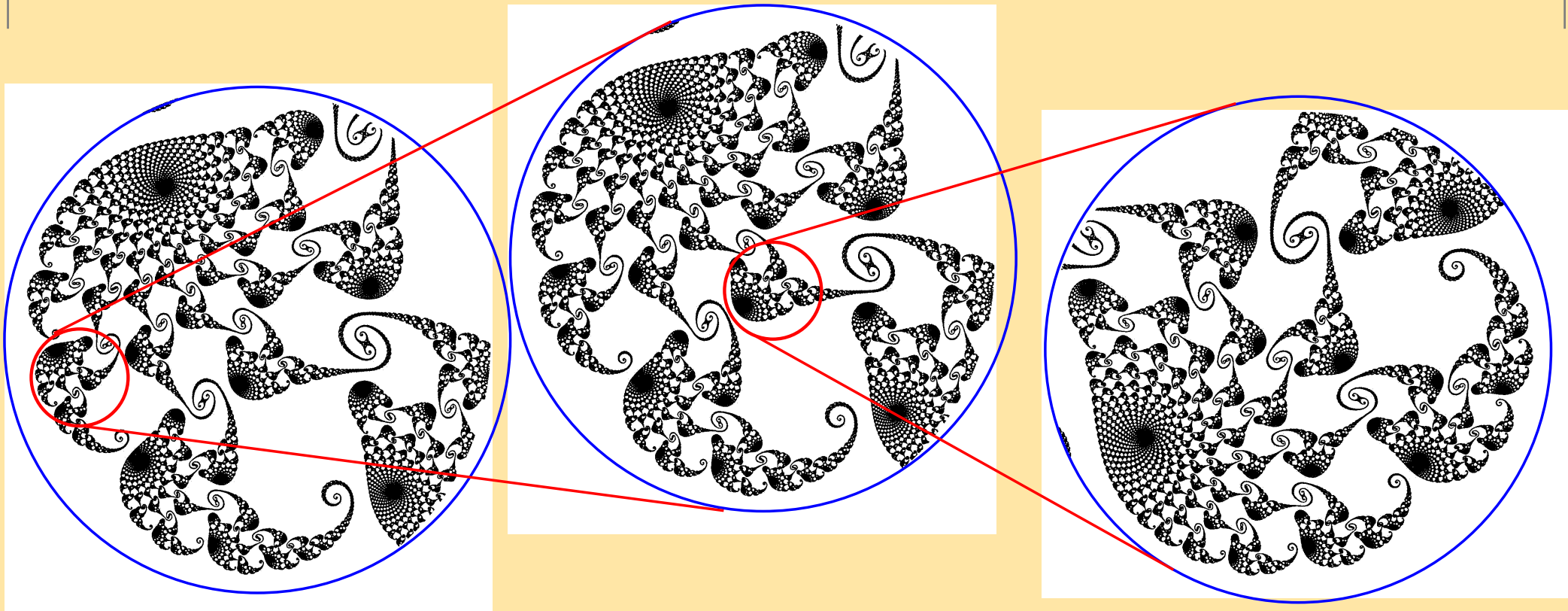
Regular fractal

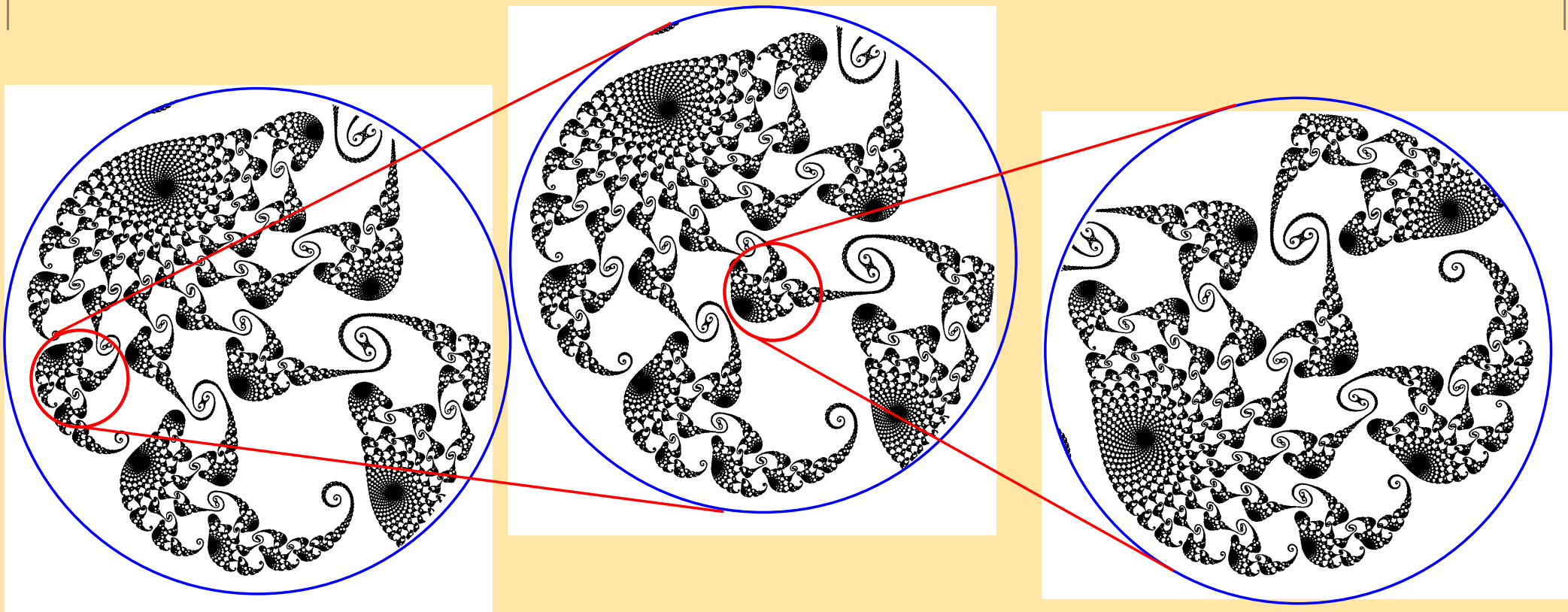


Random fractal

$$P(s) \sim s^{-\tau}, \quad \tau = -\frac{\ln 3}{\ln 0.47} = 1.455072\dots$$







Change of scale:

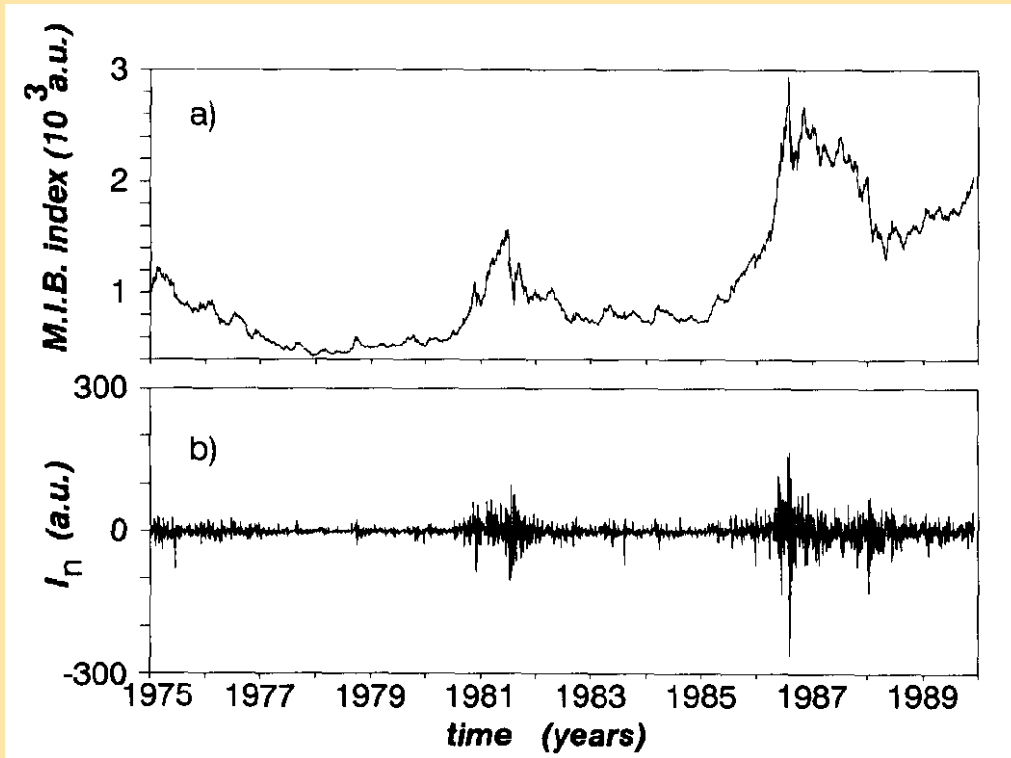
$$s \rightarrow bs \Rightarrow P(s) \propto s^{-\tau} \rightarrow b^{-\tau} s^{-\tau} \propto s^{-\tau}$$

...power-law unchanged!



Econophysical phenomenology

[R. N. Mantegna, Physica A 179, 232 (1991)]

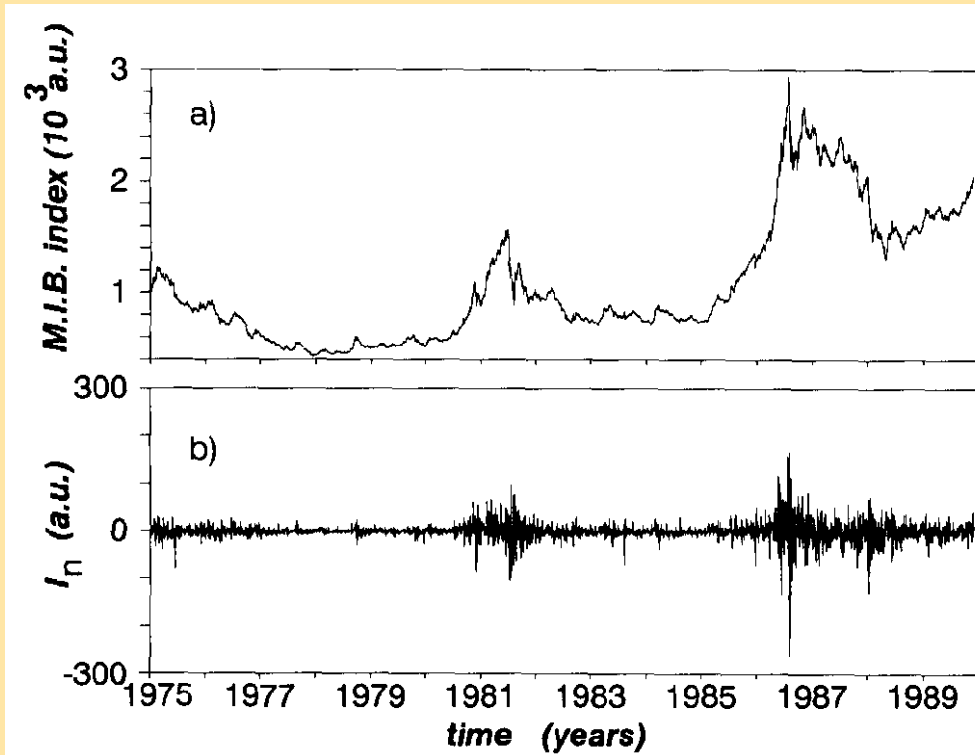


Time evolution of Milano Stock market index and returns.

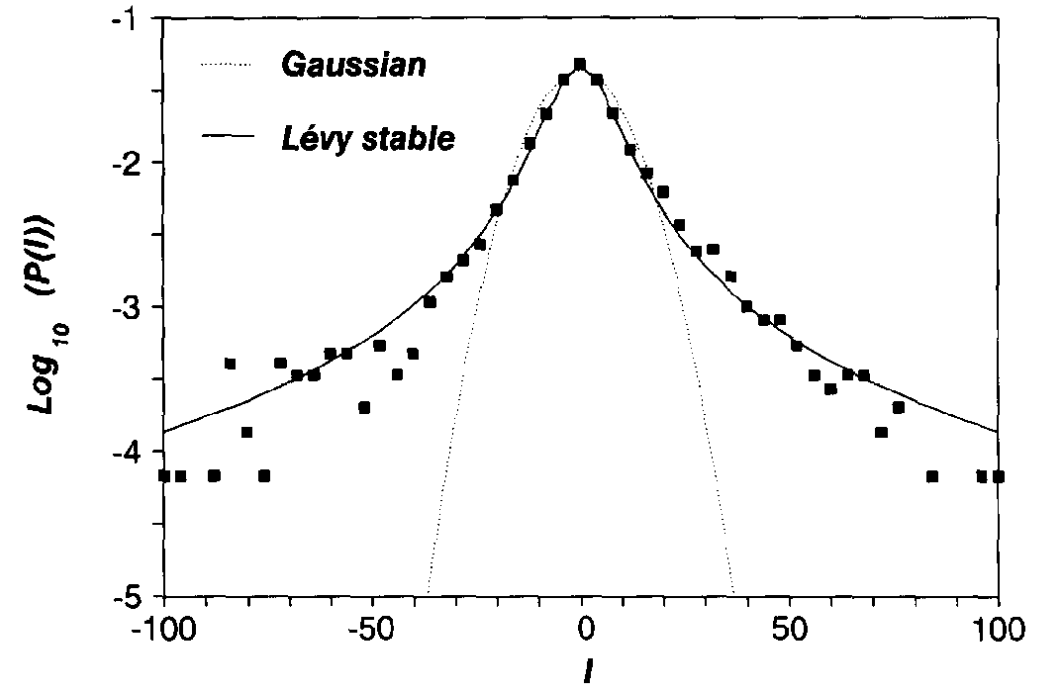


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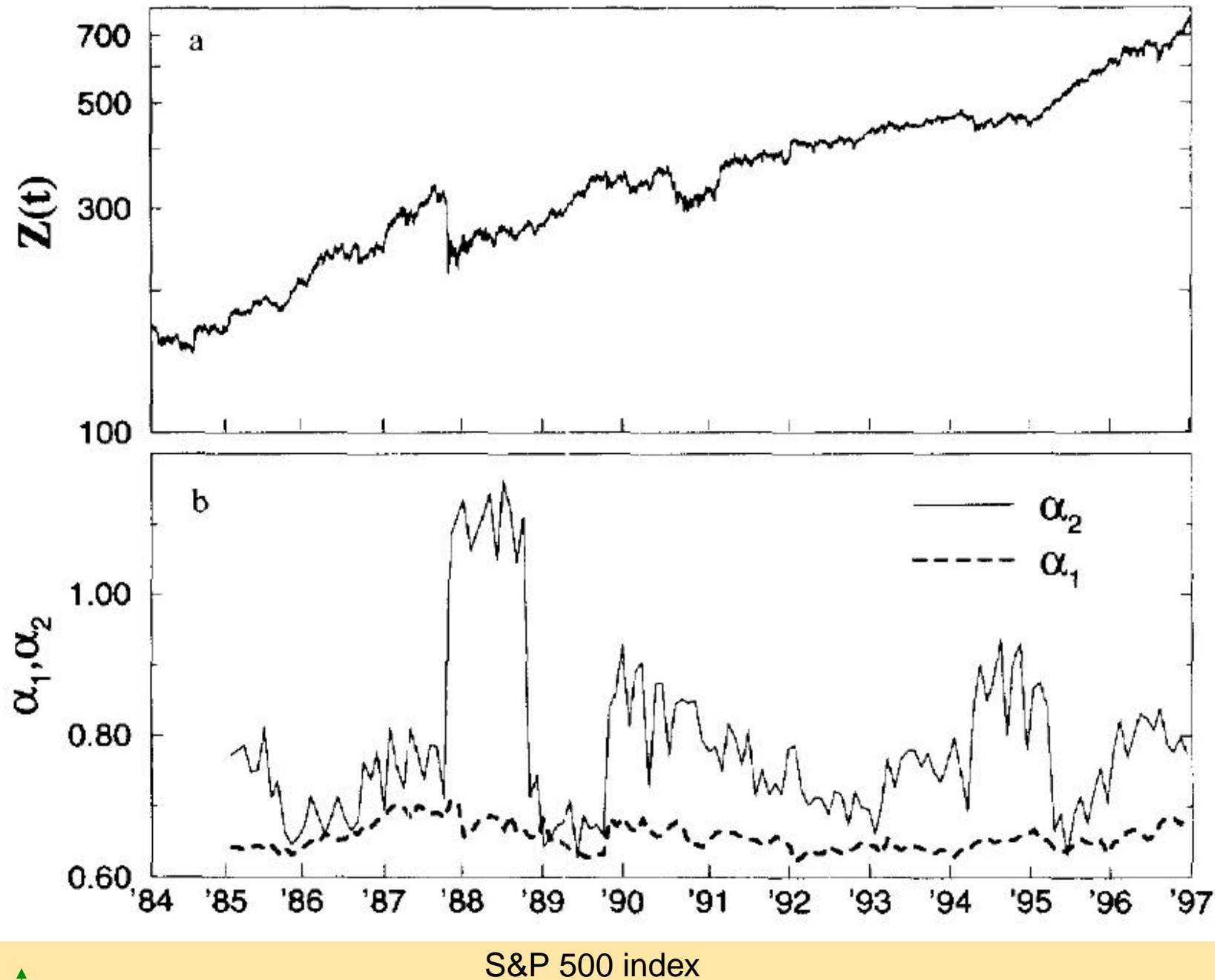
Histogram of time changes in Milano Stock market.

$$P(I) \propto I^{-\alpha}, \alpha \simeq 2.4.$$



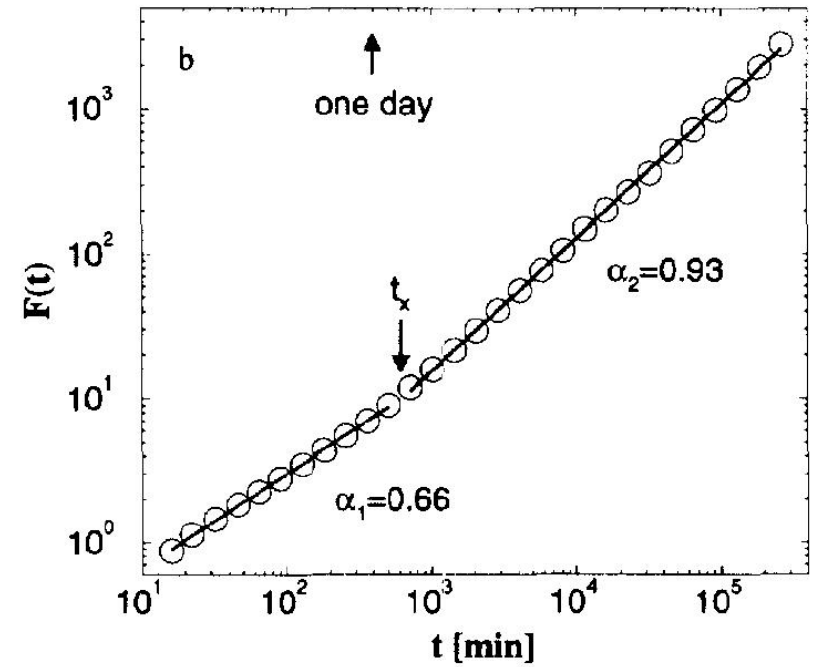
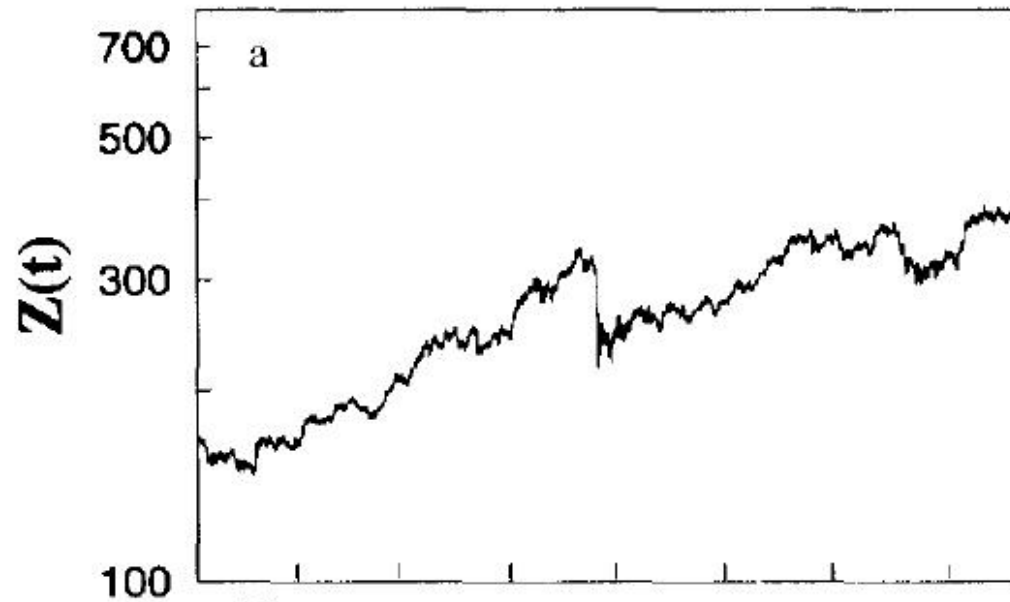
Price fluctuations : [R. N. Mantegna and H. E. Stanley, Nature 376, 46 (1995); Y. Liu, P. Cizeau, M. Meyer, C.-K. Peng and H. E. Stanley, Physica A 245, 437 (1997).]

Lévy walks

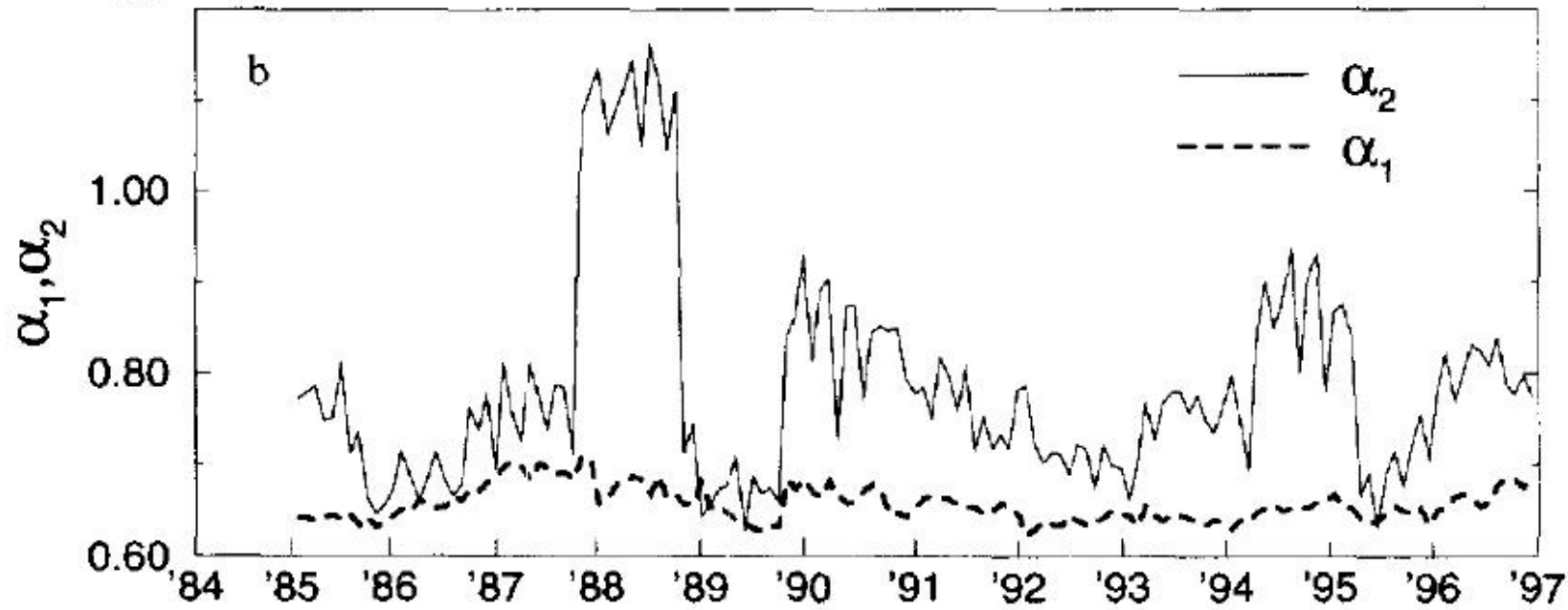


Price fluctuations : [R. N. Mantegna and H. E. S. Lévy walks

M. Meyer, C.-K. Peng and H.



Detrended fluctuation analysis

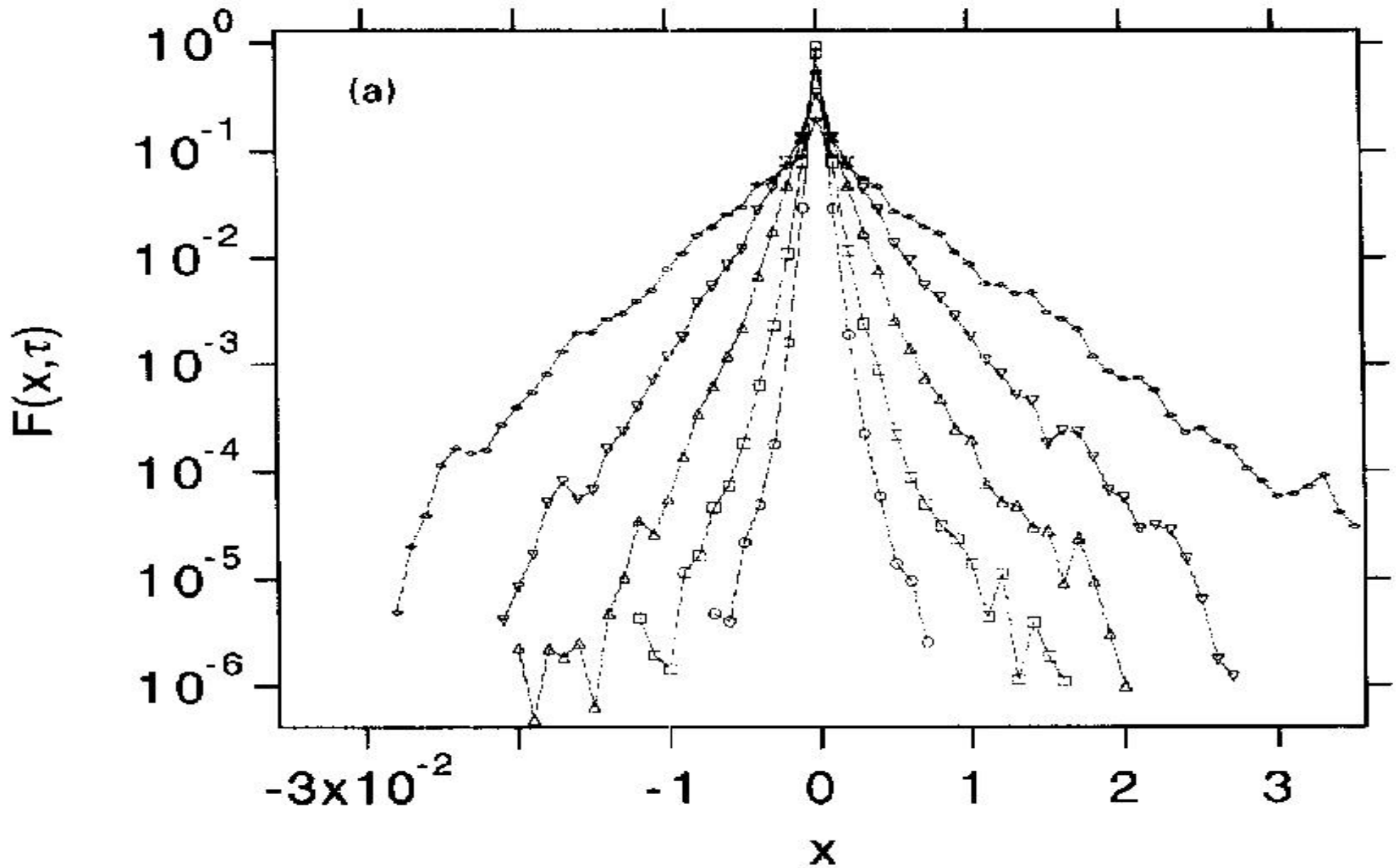


S&P 500 index



Scaling

[S. Galluccio, G. Caldarelli, M. Marsili and Y. -C. Zhang, Physica A 245, 423 (1997).]

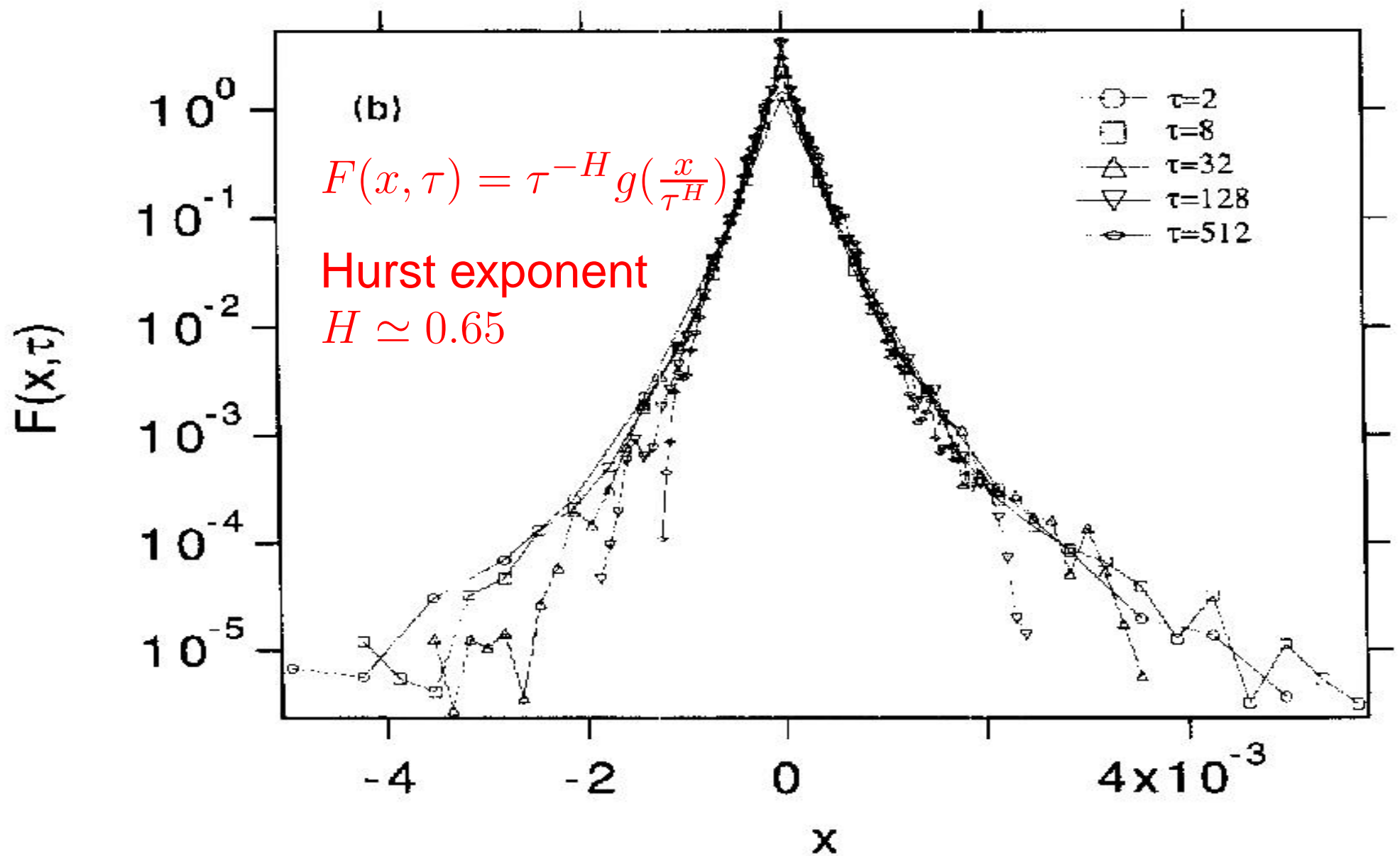


DEM \longrightarrow USD



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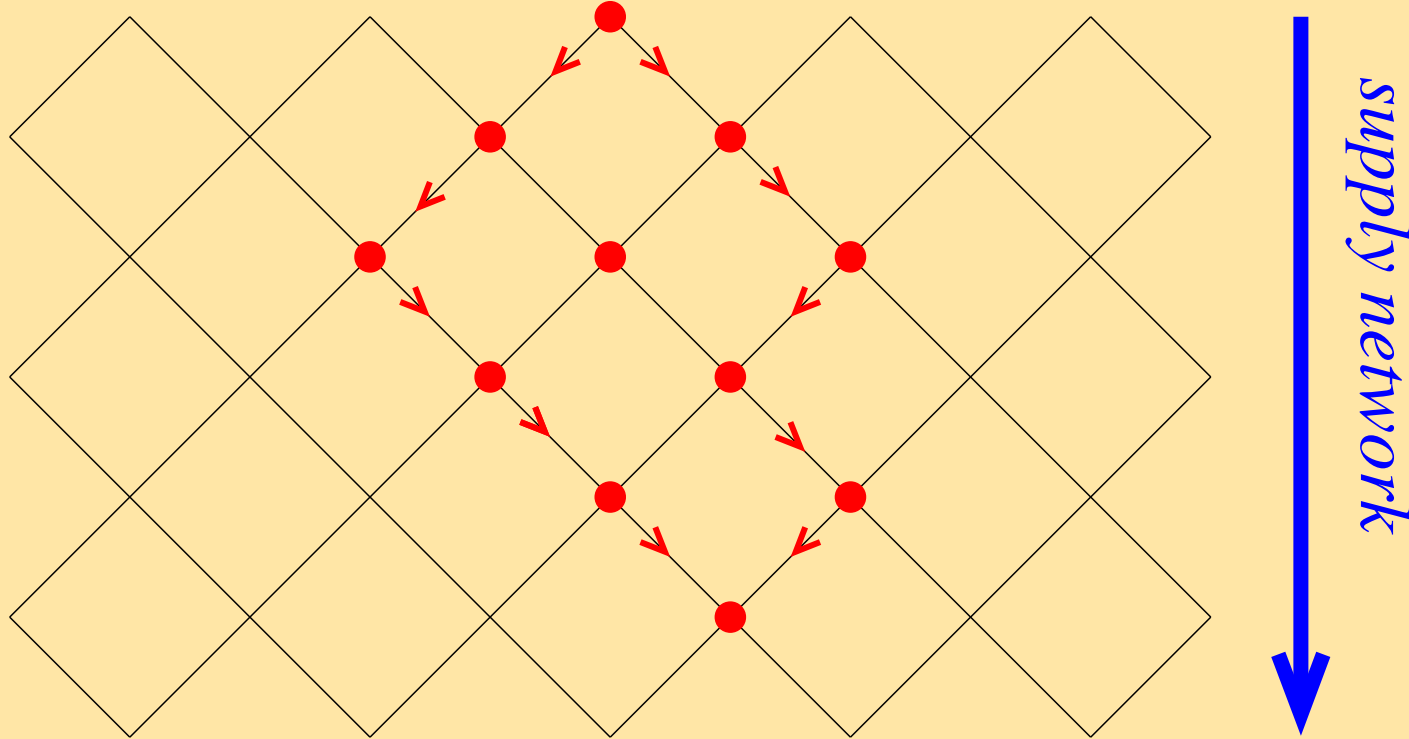


DEM \longrightarrow USD



Self-organized critical models

“Directed sandpile”, P. Bak et al.



Exactly soluble: avalanche = pair of annihilating random walkers

Distribution of durations: $P(\Delta t) \sim (\Delta t)^{-3/2}$.

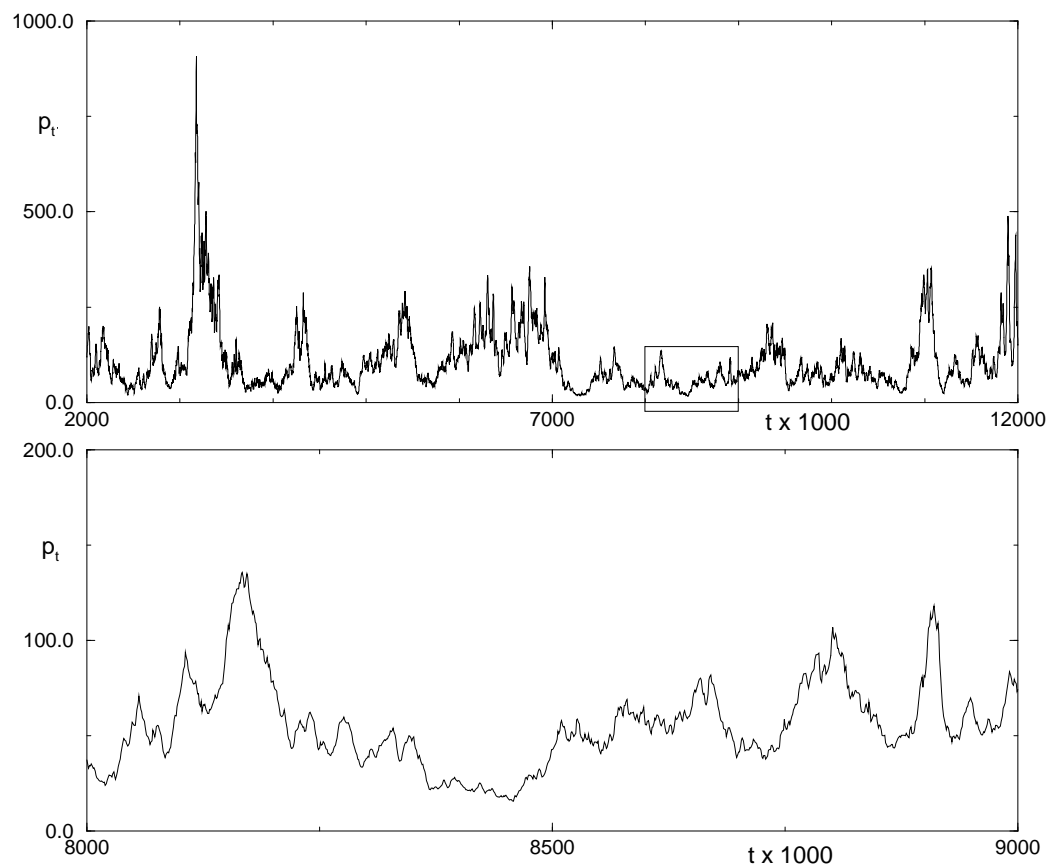
Cont-Bouchaud herding model: mean-field percolation

Distribution of cluster sizes: $P(s) \sim s^{-5/2}$

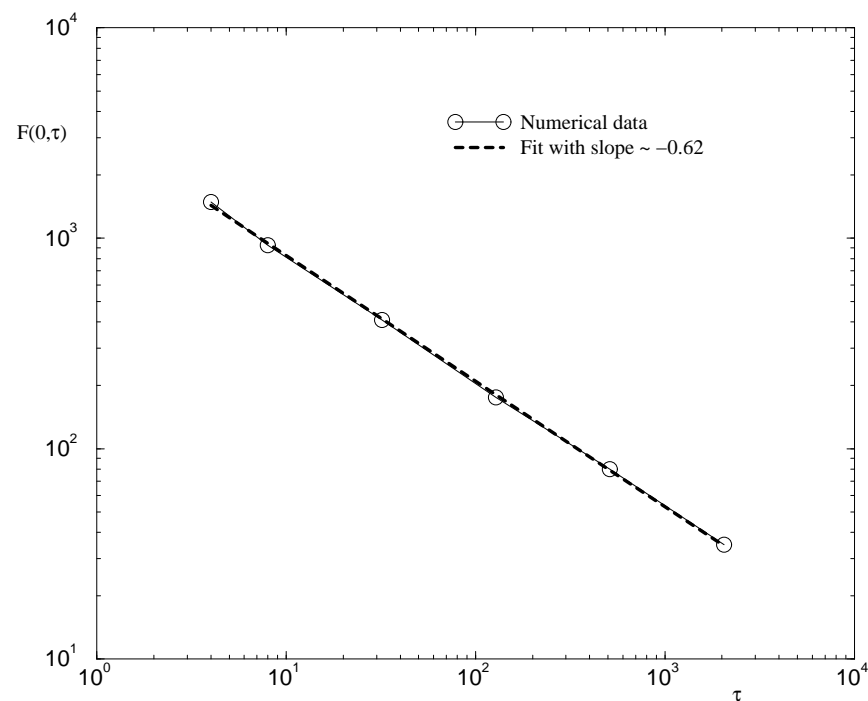


CMZ model

[Caldarelli G., Marsili M., Zhang Y.C., Europhys. Lett. 40, 479 (1997).]



Price history, 1000 agents.

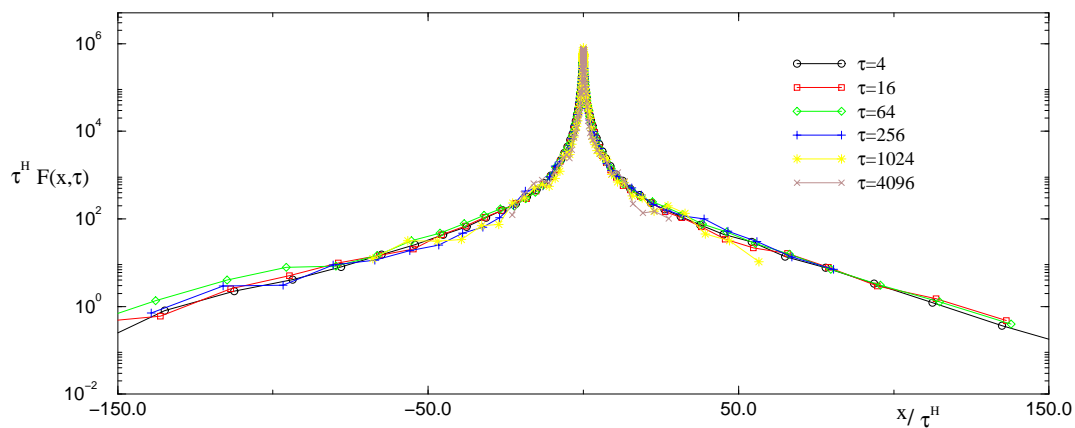
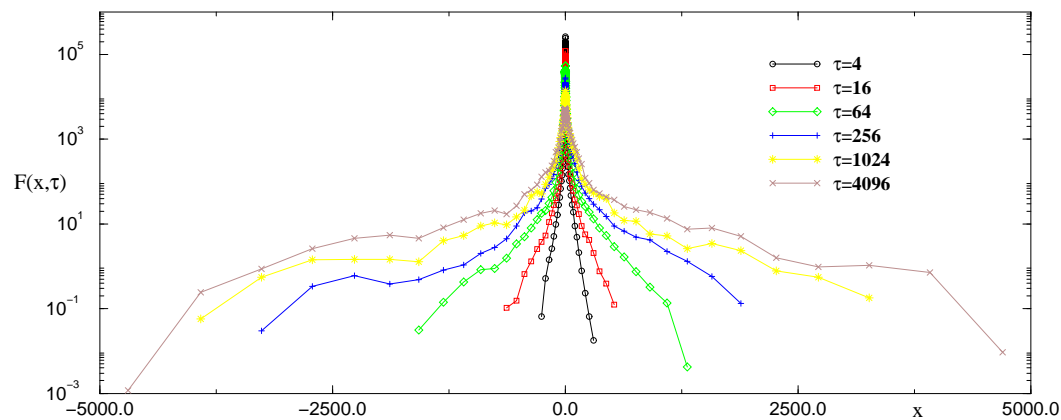


Probability of return to the original price, $H = 0.62$.

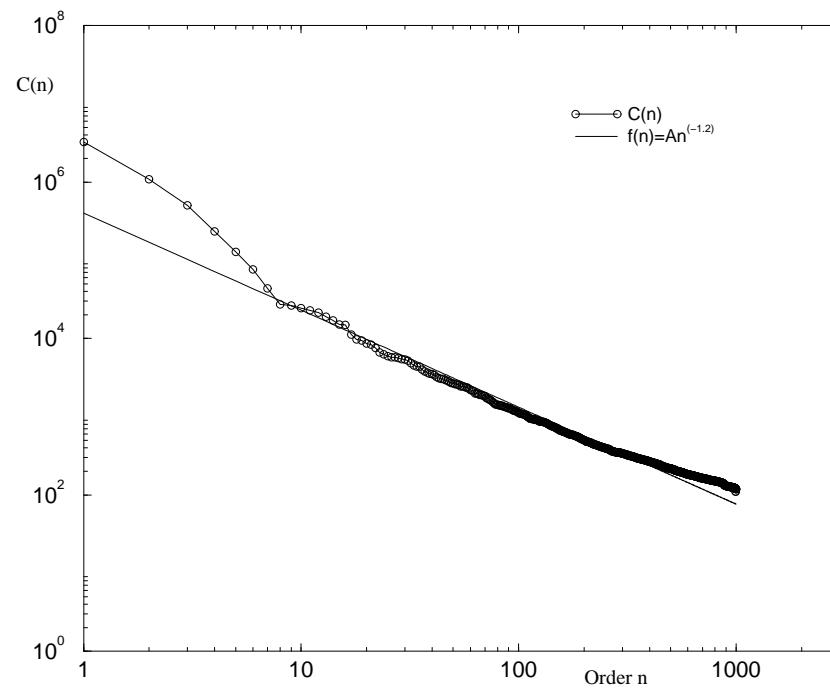


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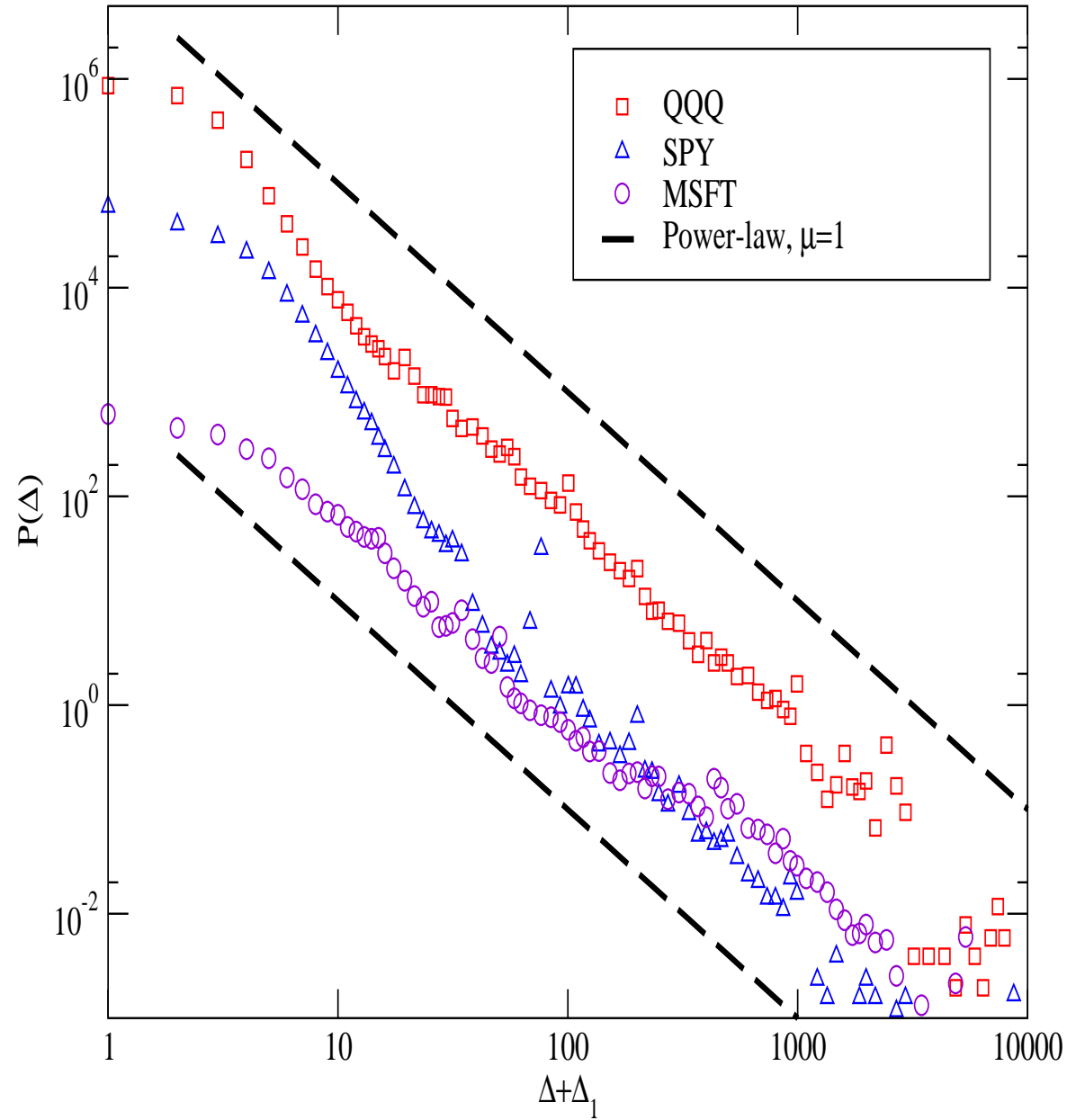
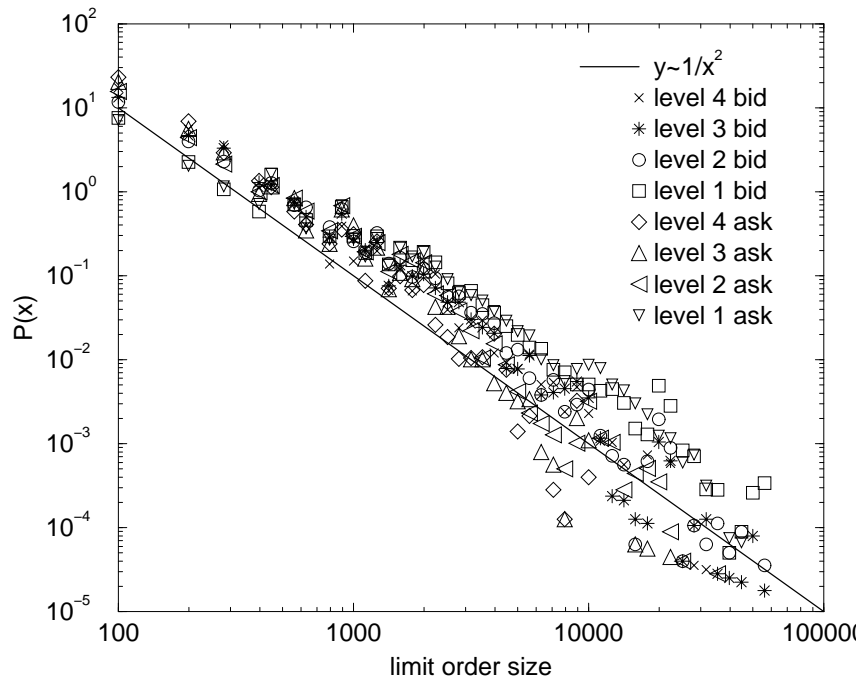
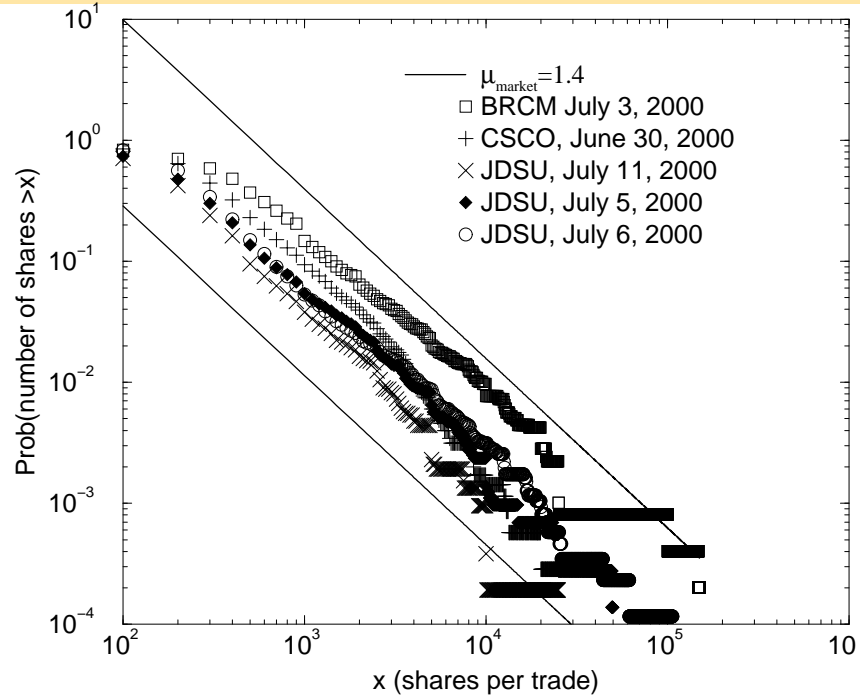
Price changes and scaling.



Wealth distribution (Zipf plot), exponent 1.2.



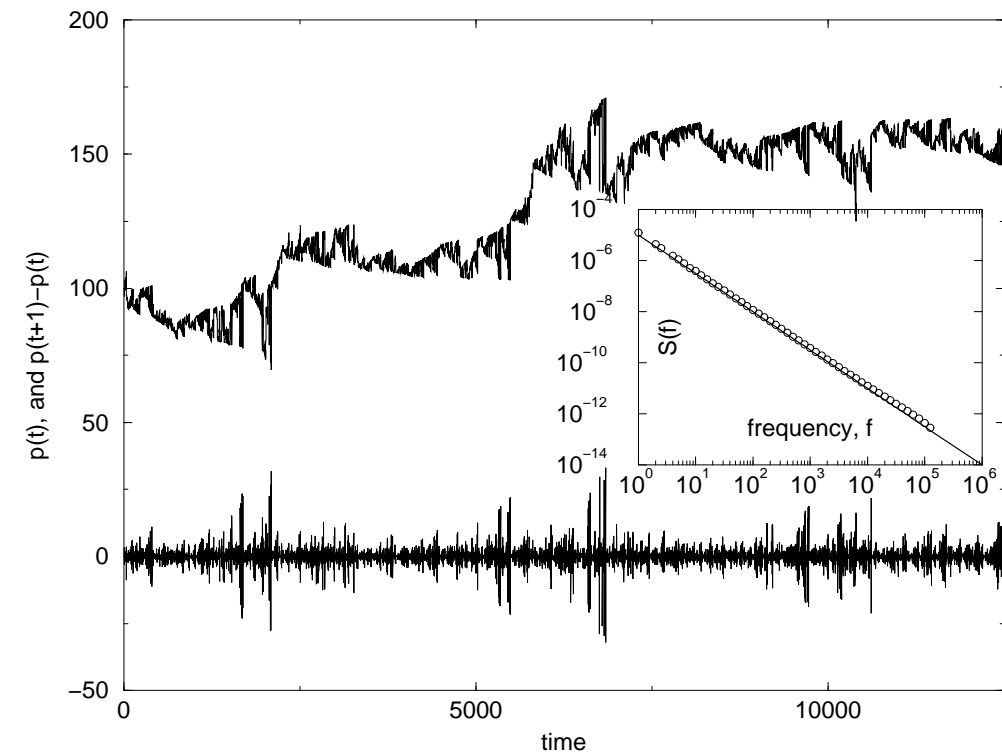
Order book statistics



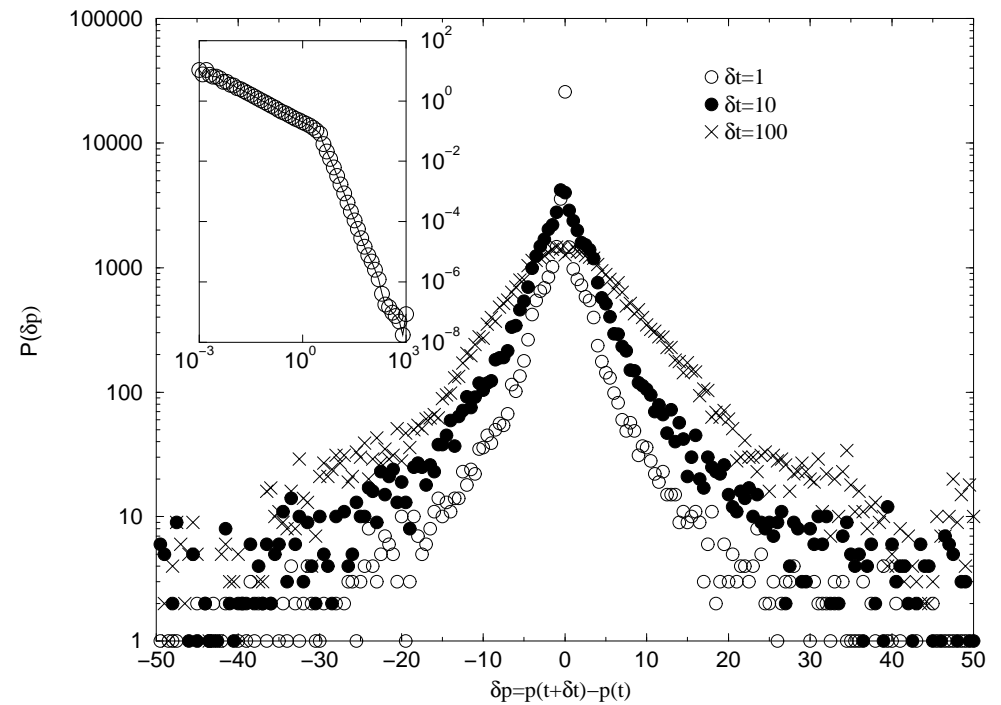
Distribution of volumes

Distribution of distances from current price



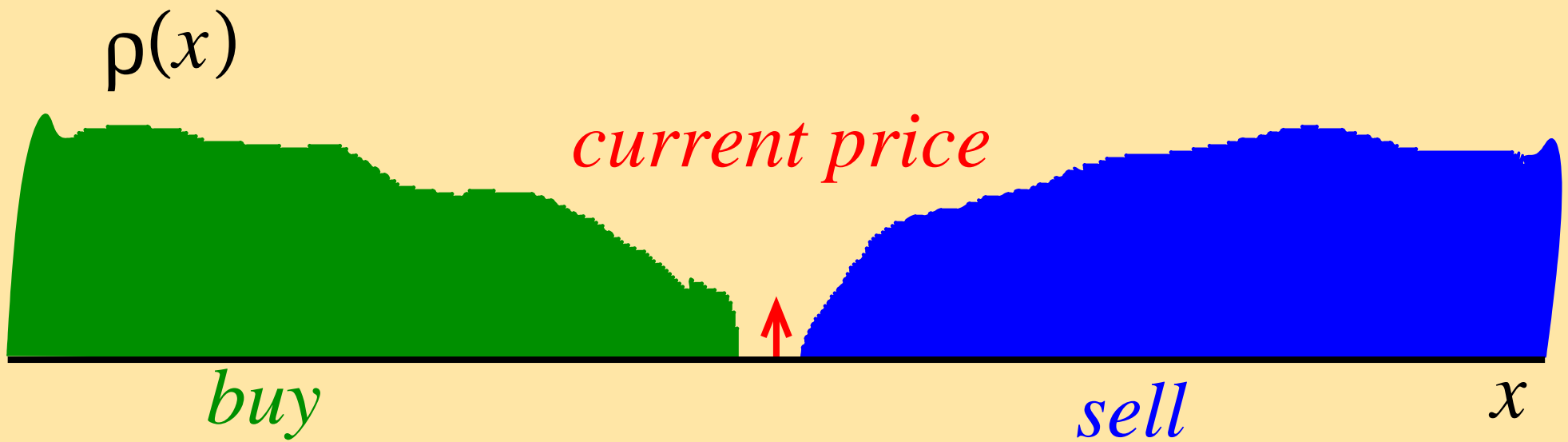


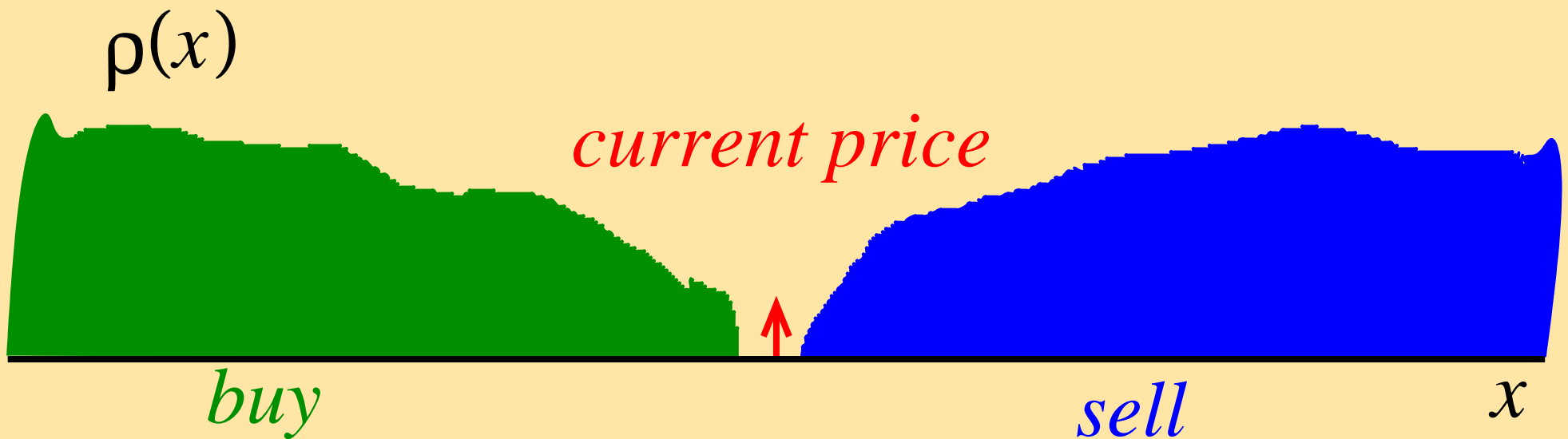
Price history, power spectrum ($H = 1/4$).



Price changes. Exponents 0.6 and 3 in the inset.







Mean-field approx.:

homogeneous upper ρ_+ , lower ρ_- ; order volume s .

potential price changes: $x_+ = s/\rho_+$, $x_- = s/\rho_-$

vector $X = \begin{pmatrix} x_+ \\ x_- \end{pmatrix}$ performs

a random matrix multiplicative process.

$$X \rightarrow X' = TX$$

$$T = \left\{ \begin{array}{l} \left(\begin{array}{cc} 1 & 0 \\ 1 & 1 \end{array} \right) \quad \text{buy order} \\ \left(\begin{array}{cc} 1 & 1 \\ 0 & 1 \end{array} \right) \quad \text{sell order} \\ \frac{1}{2}(3 - 1/p) \left(\begin{array}{cc} 1 & 0 \\ 0 & 1 \end{array} \right) \quad \text{limit order} \end{array} \right.$$



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Probability distribution of price changes (after m limit and one market order):

$$P(x) = \sum_{m=0}^{\infty} (1-p)p^m \int dx' P(x') \delta \left(x - \frac{3}{2} x' \left(\frac{3 - \frac{1}{p}}{2} \right)^m \right)$$



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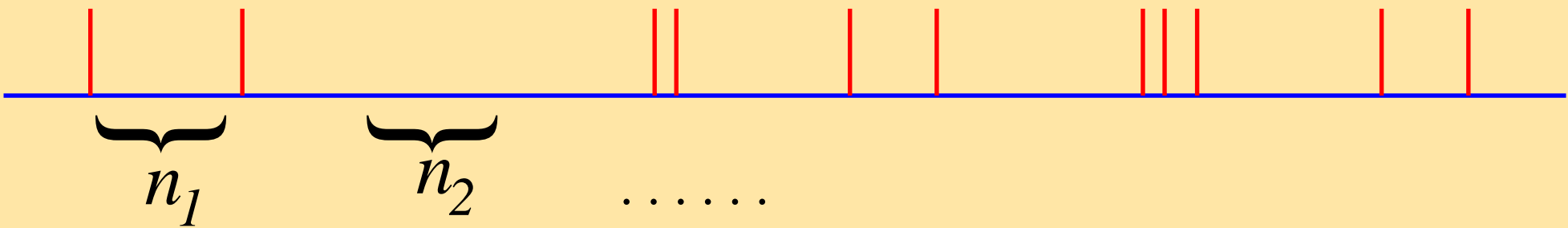
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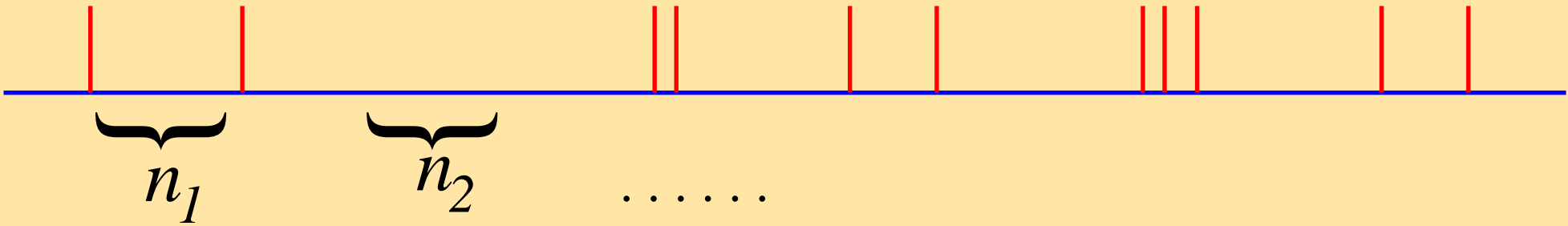
assuming power-law tail $P(x) \sim x^{-1-\alpha}$:

$$\sum_{m=0}^{\infty} (1-p)p^m \left(\frac{3}{2} \left(\frac{3 - \frac{1}{p}}{2} \right)^m \right)^{\alpha} = 1.$$

non-trivial solution: $\alpha = 1$

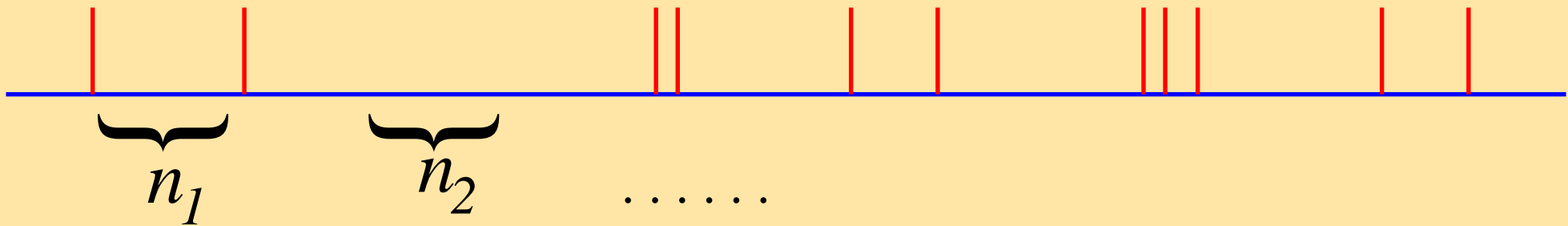






“collision” of a pair of intervals (n_i, n_j) :





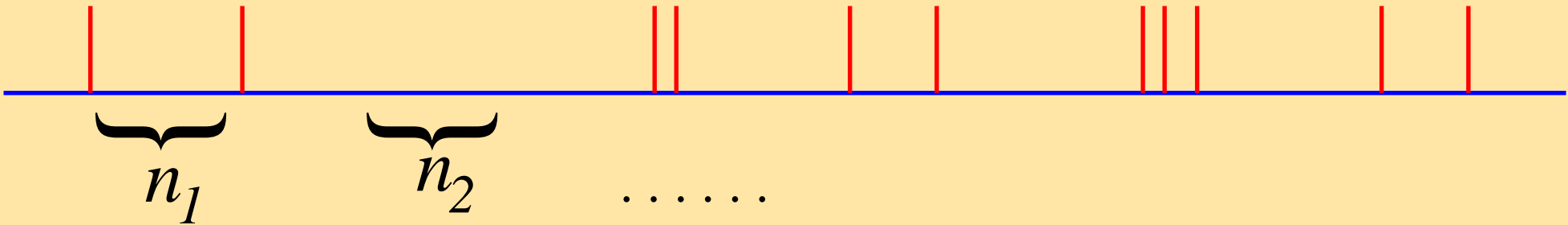
“collision” of a pair of intervals (n_i, n_j) :

1. a collapse with probability p :

$$n_i(t + 1) = n_i(t) + n_j(t) - 1$$

$$n_j(t + 1) = 1$$





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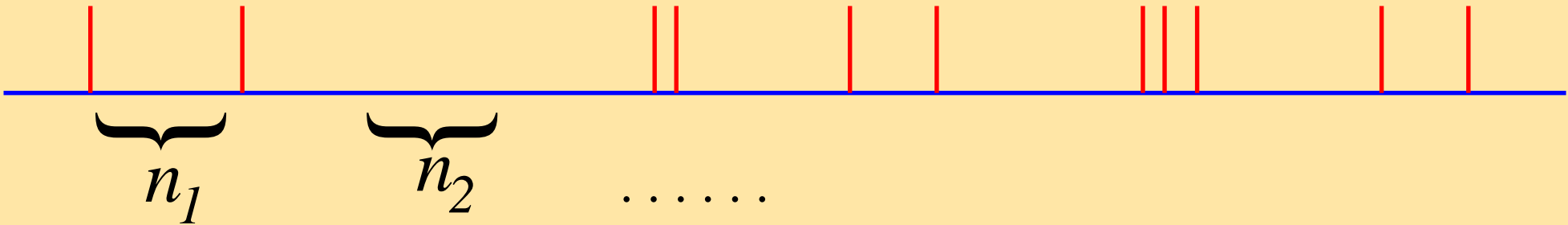
$$n_j(t + 1) = 1$$

2. a reaction with probability $1 - p$

$$n_i(t + 1) = n_i(t) - 1$$

$$n_j(t + 1) = n_j(t) + 1$$





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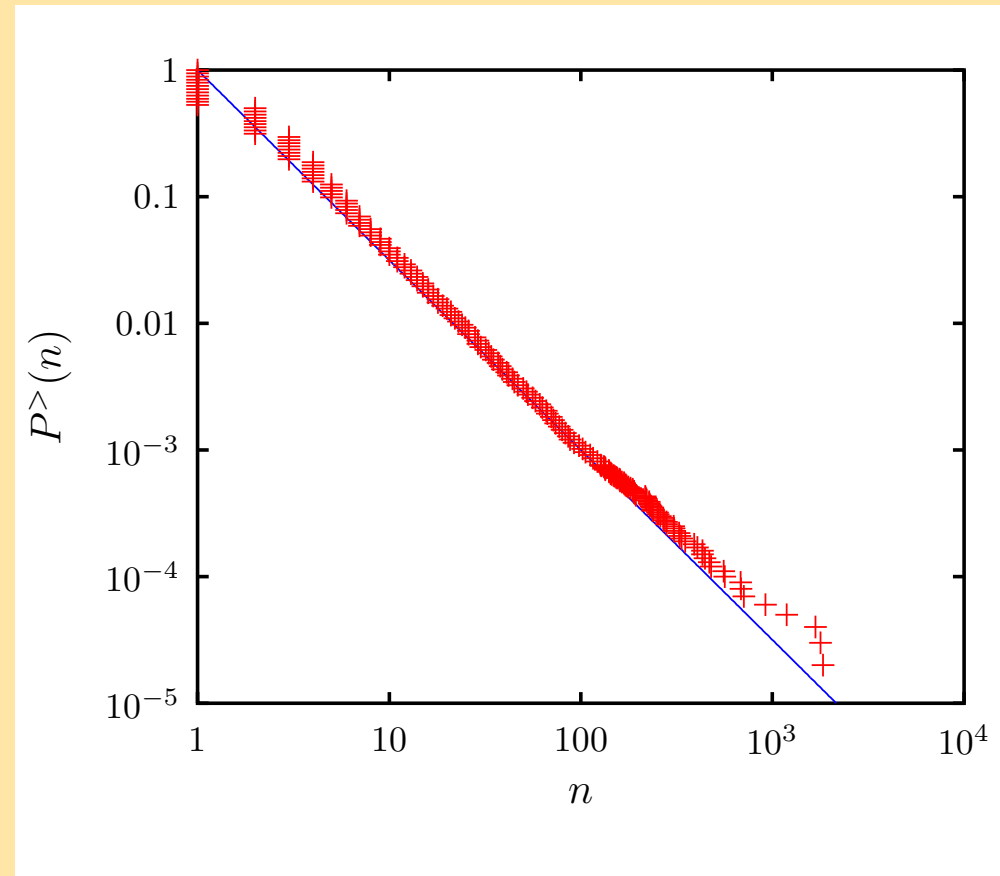
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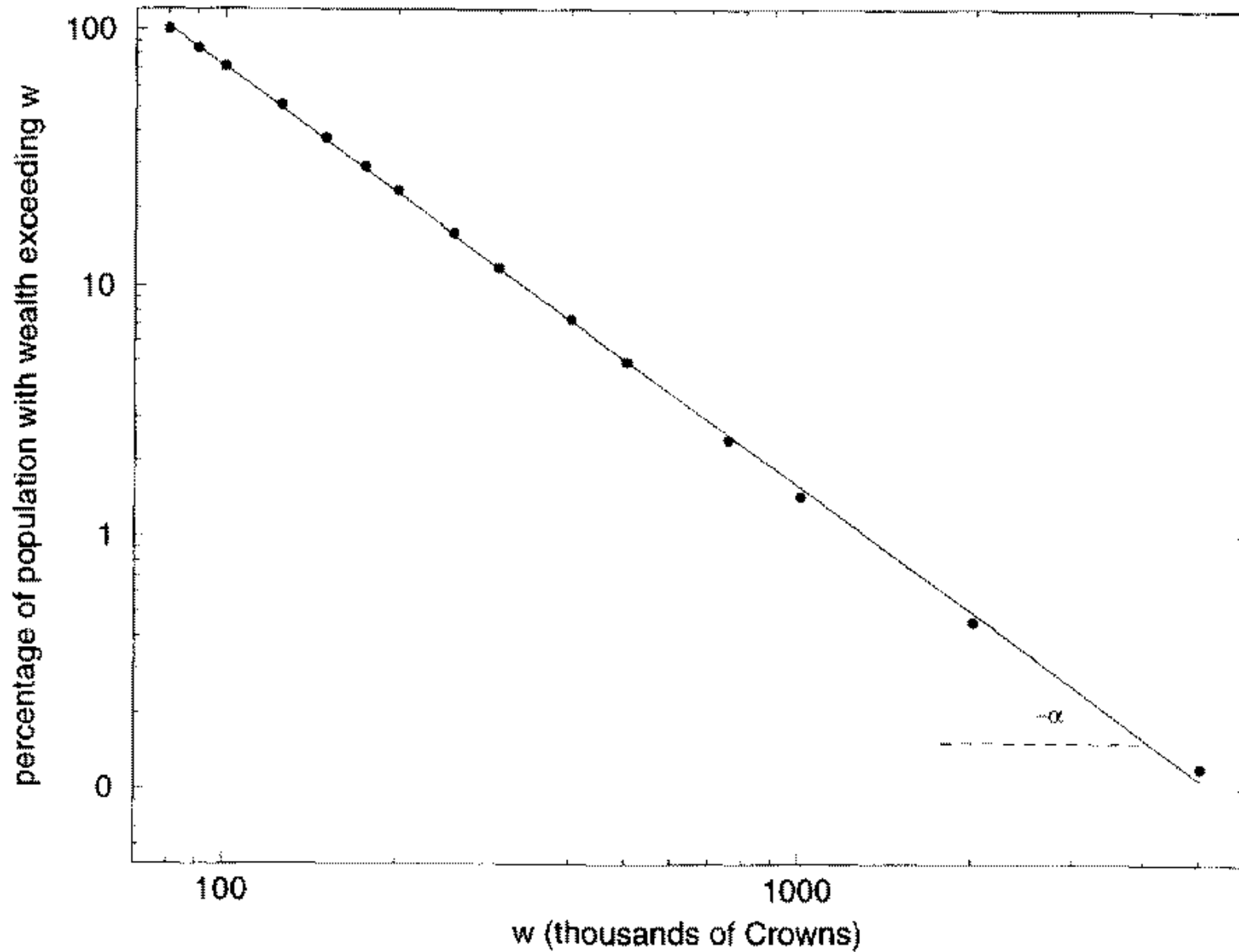


$$P^>(n) \sim n^{-\alpha}, \alpha = 3/2$$



Wealth distribution



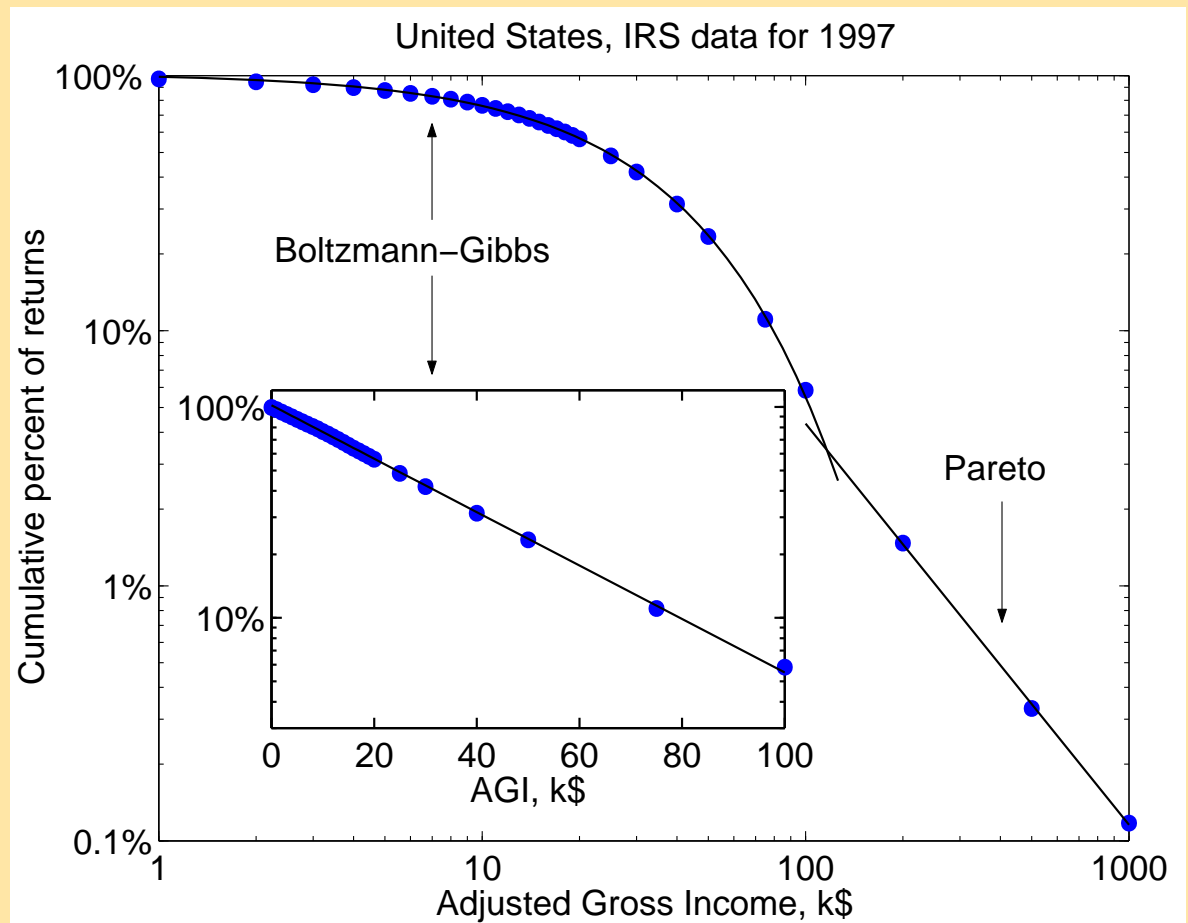
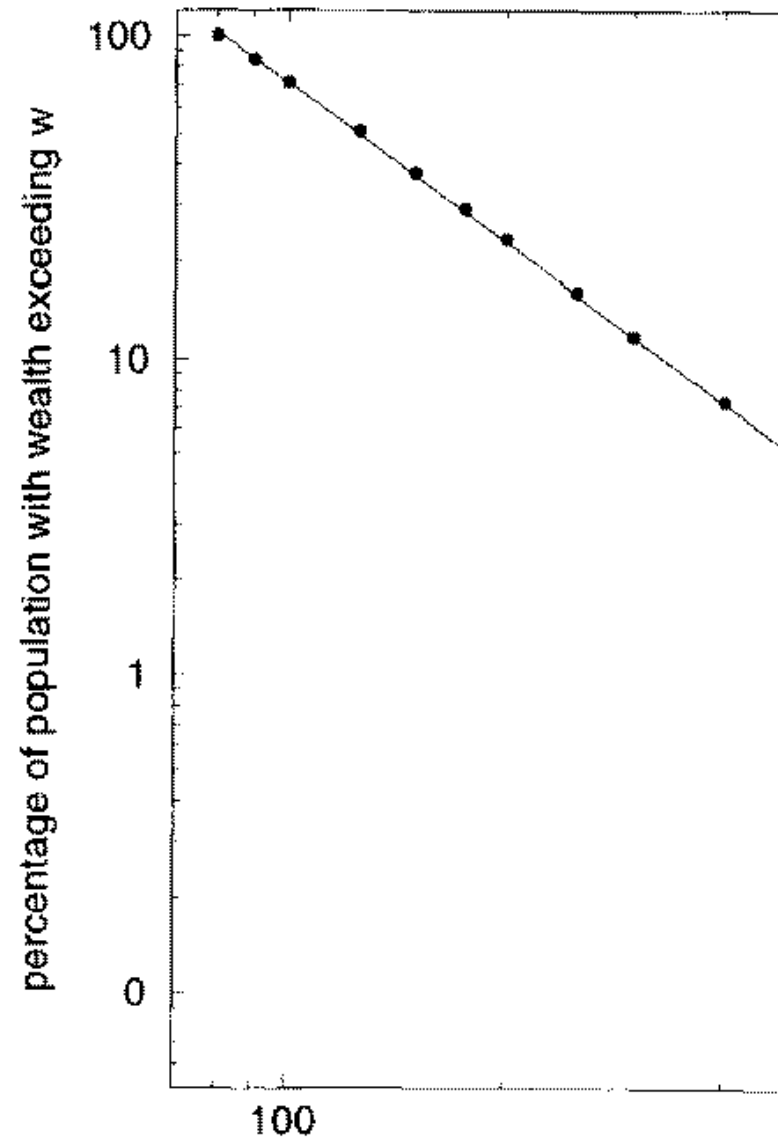


Pareto distribution $P(w) \sim w^{-\alpha-1}$, $\alpha \simeq 1.4$



Empirical wealth distribution

[M. Levy, S. Solomon Physica A 242, 90 (1997)]

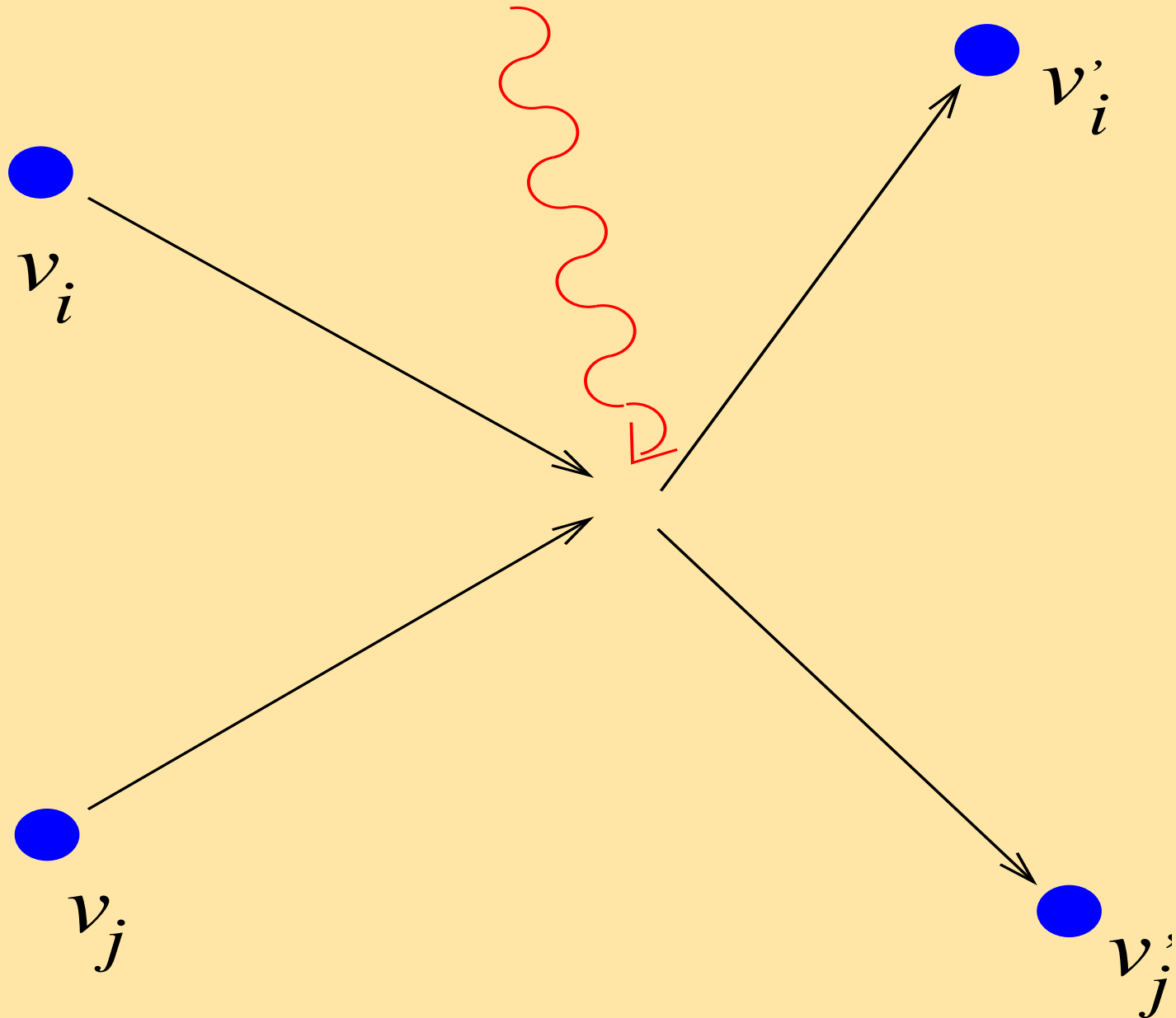


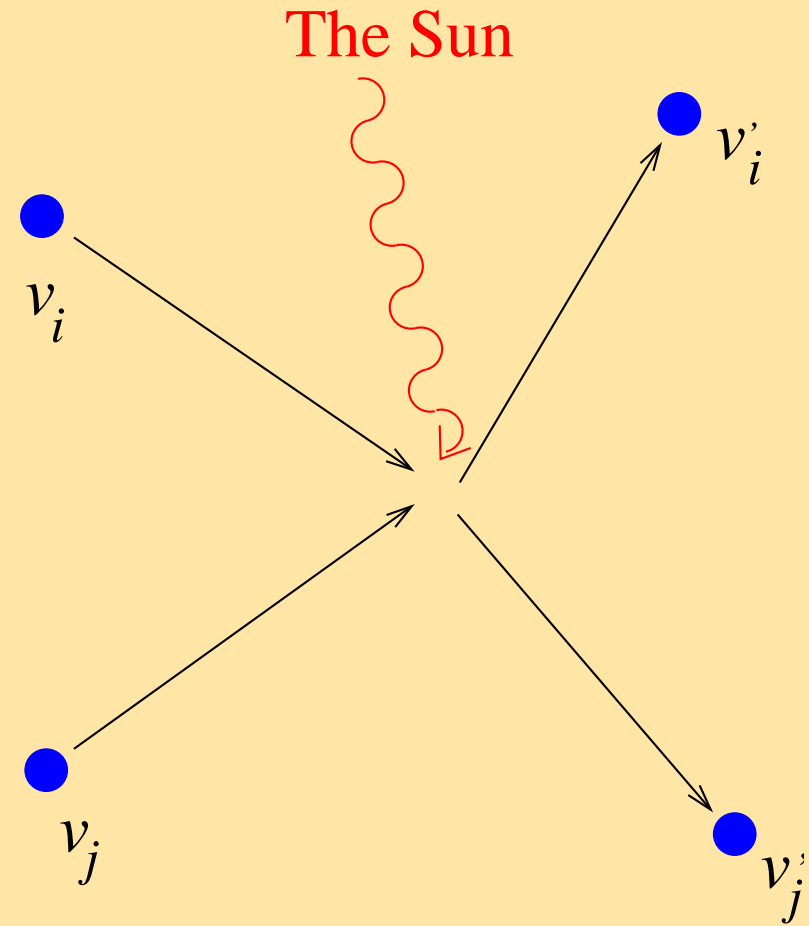
Exponential distribution at low incomes
 Pareto at high incomes (V.M. Yakovenko et al.)

Pareto distribution $P(w) \sim w^{-\alpha-1}$, $\alpha \simeq 1.4$



The Sun





$$\begin{pmatrix} v'_i \\ v'_j \end{pmatrix} = \begin{pmatrix} 1 + \varepsilon - \beta & \beta \\ \beta & 1 + \varepsilon - \beta \end{pmatrix} \begin{pmatrix} v_i \\ v_j \end{pmatrix}$$

Granular gas analogy

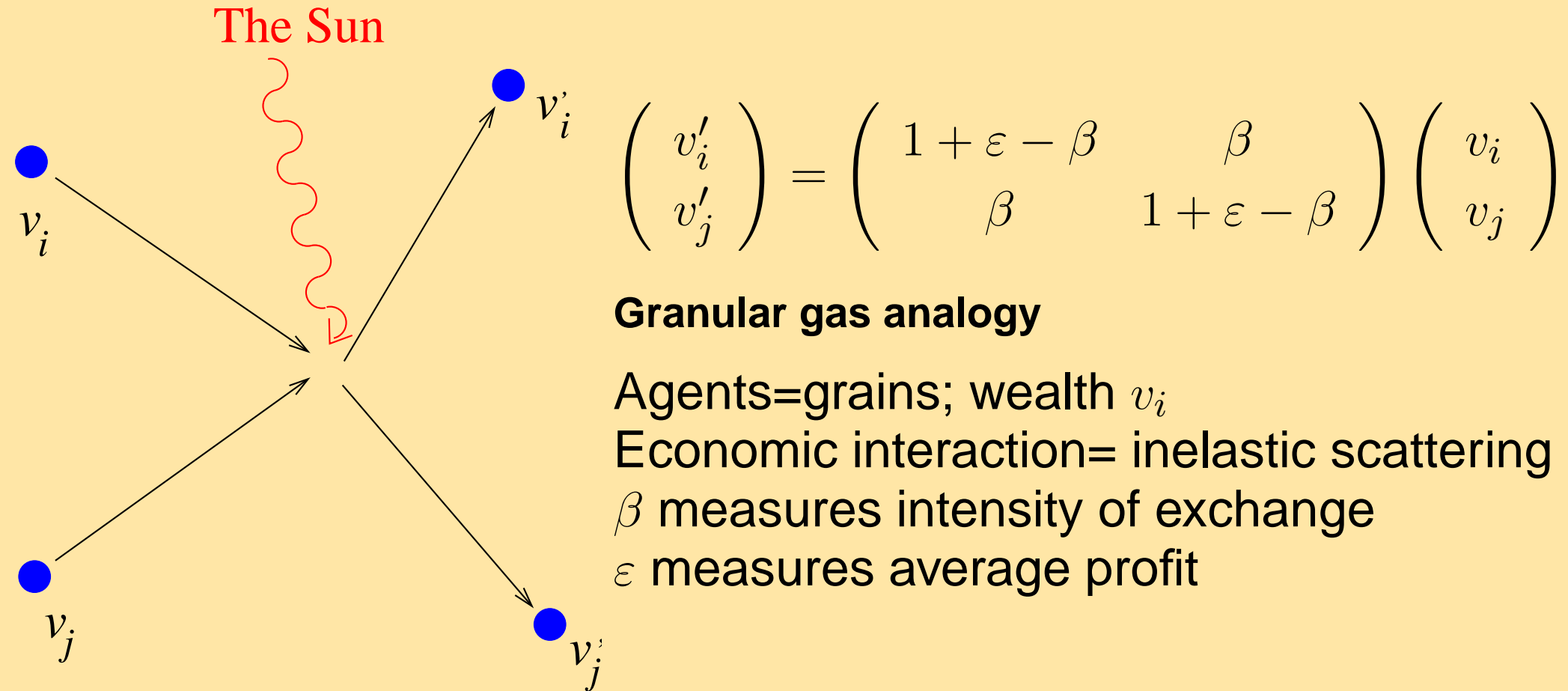
Agents=grains; wealth v_i

Economic interaction= inelastic scattering

β measures intensity of exchange

ε measures average profit





Probability density governed by a Boltzmann-like equation

$$\frac{\partial P(v)}{\partial t} + P(v) = \int P(v_1)P(v_2) \delta((1 - \beta + \varepsilon)v_1 + \beta v_2 - v) dv_1 dv_2$$



Average wealth grows exponentially: $\bar{v}(t) = \bar{v}(0) e^{\varepsilon t}$



Scaling solution: $P(v, t) = \frac{1}{\bar{v}(t)} \Phi\left(\frac{v}{\bar{v}(t)}\right)$



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Laplace transform: $\hat{\Phi}(x) = \int_0^\infty \Phi(w) e^{-xw} dw$

$$\varepsilon x \hat{\Phi}'(x) + \hat{\Phi}(x) = \hat{\Phi}((1 - \beta + \varepsilon)x) \hat{\Phi}(\beta x)$$

...non-local differential equation



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...non-local differential equation

Power-law tail \Rightarrow Looking for solution in the form

$$\hat{\Phi}(x) = 1 - x + A x^\alpha + \dots \quad \text{where } \alpha \in (1, 2)$$

$$\Rightarrow \Phi(w) \sim w^{-\alpha-1} \quad \text{for } w \rightarrow \infty.$$



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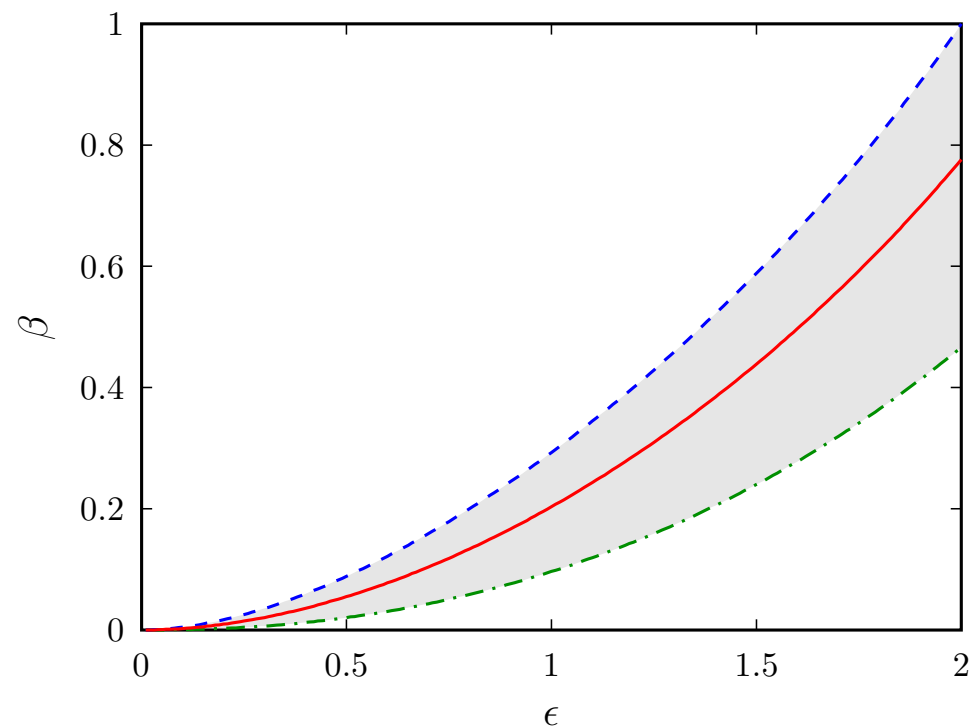
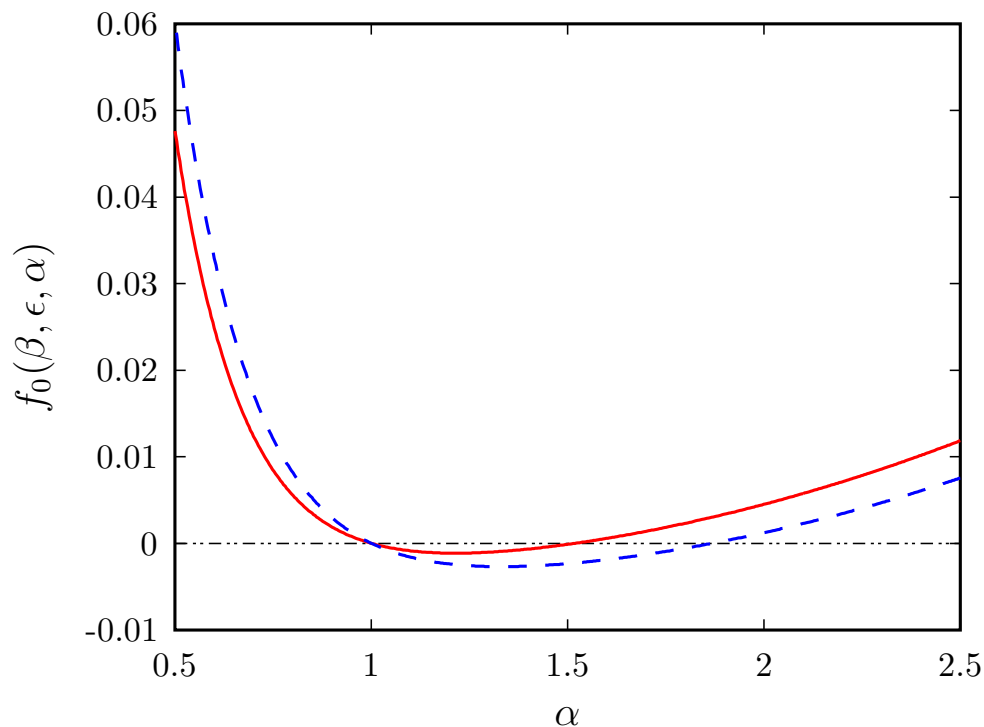
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$f_0(\beta, \varepsilon, \alpha) \equiv$

$$(1 + \varepsilon - \beta)^\alpha + \beta^\alpha - 1 - \varepsilon\alpha = 0$$



$$(1 + \varepsilon - \beta)^\alpha + \beta^\alpha - 1 - \varepsilon\alpha = 0$$



Solution of the equation for $\varepsilon = 0.1$ and $\beta = 0.0025$ (red) and $\beta = 0.004$ (blue).

Solution in the range $\alpha \in (1, 2)$ exists within the shaded region. Green line corresponds to $\alpha = 1$, blue line corresponds to $\alpha = 2$ and red line to the solution $\alpha = \frac{3}{2}$.



Limit of continuous trading: $\beta \rightarrow 0$, $\epsilon \rightarrow 0$, α fixed:

$$\beta = \frac{\alpha-1}{2} \epsilon^2 - \frac{(\alpha-1)(2\alpha-1)}{6} \epsilon^3 + \frac{1}{\alpha} \left(\frac{\alpha-1}{2}\right)^\alpha \epsilon^{2\alpha} + \dots$$

For $\alpha = \frac{3}{2}$:

$$\epsilon = \frac{1}{8} \frac{-3\sqrt{\beta} + 17\beta - 29\beta^{3/2} + 15\beta^2 + 4\beta^{5/2} - 4\beta^3 + \sqrt{3}\sqrt{(3-2\sqrt{\beta})\beta(2\sqrt{\beta}+1)^3(\sqrt{\beta}-1)^6}}{\sqrt{\beta} - 3\beta + 3\beta^{3/2} - \beta^2}$$

$$\beta = \frac{1}{4}\epsilon^2 - \frac{1}{12}\epsilon^3 + \frac{1}{16}\epsilon^4 - \frac{7}{144}\epsilon^5 + \frac{113}{2592}\epsilon^6 + \dots$$



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Solution with correct asymptotics $\hat{\Phi}(x) \rightarrow 0$ for $x \rightarrow +\infty$ is expressed through modified Bessel function

$$\hat{\Phi}(x) = C' x^{\alpha/2} K_\alpha(2\sqrt{\alpha-1}\sqrt{x})$$



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Inverting Laplace transform:

$$\Phi(w) = C w^{-\alpha-1} \exp\left(-\frac{\alpha-1}{w}\right)$$



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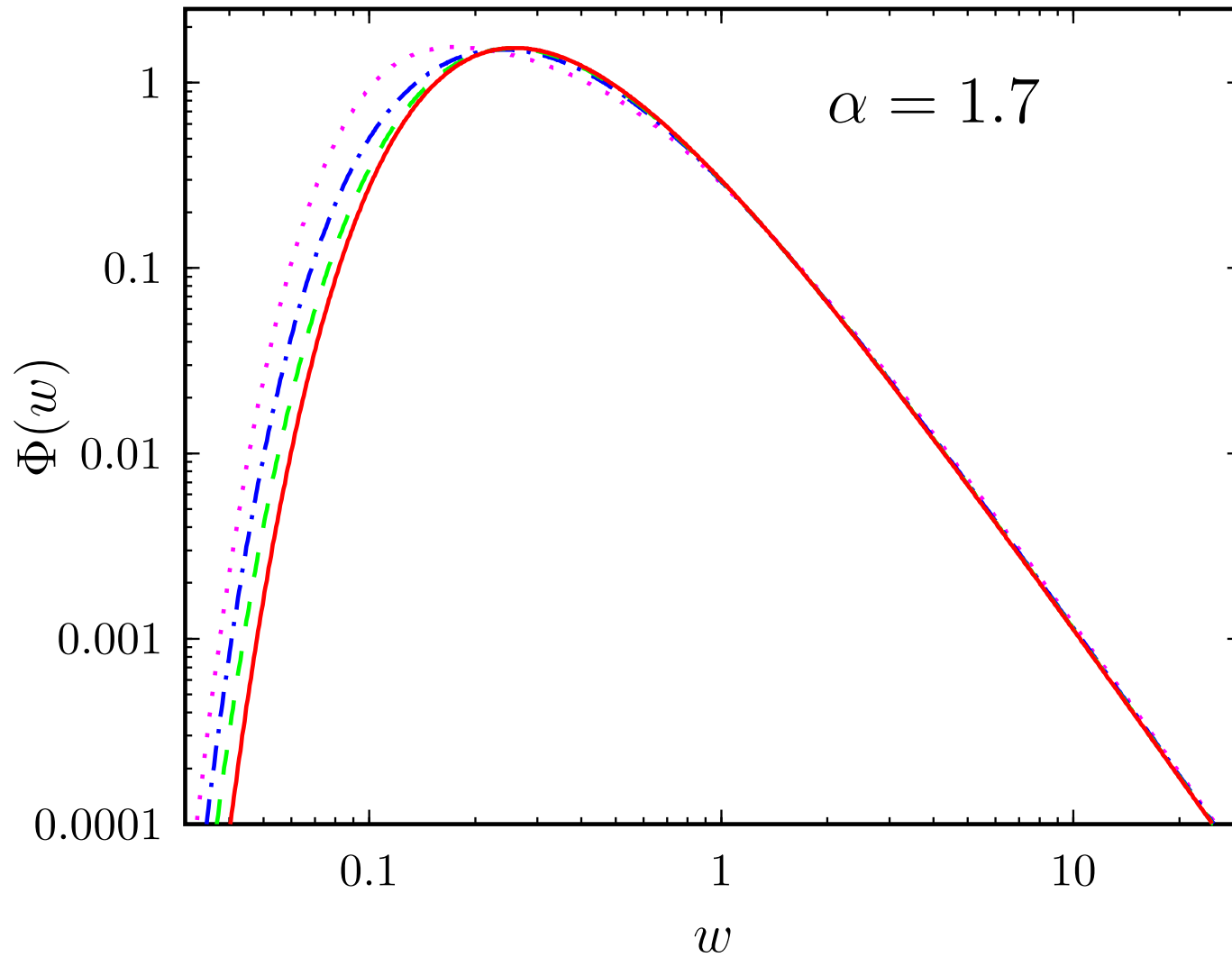
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$$\Phi(w) = C w^{-\alpha-1} \exp\left(-\frac{\alpha-1}{w}\right)$$

$$C = \frac{(\alpha-1)^\alpha}{\Gamma(\alpha)}$$



Systematic corrections: Expansion in ε



Wealth distribution for $\varepsilon \rightarrow 0$ (full line), $\varepsilon = 0.03$ (dashed line), $\varepsilon = 0.1$ (dash-dotted line), and $\varepsilon = 0.3$ (dotted line).

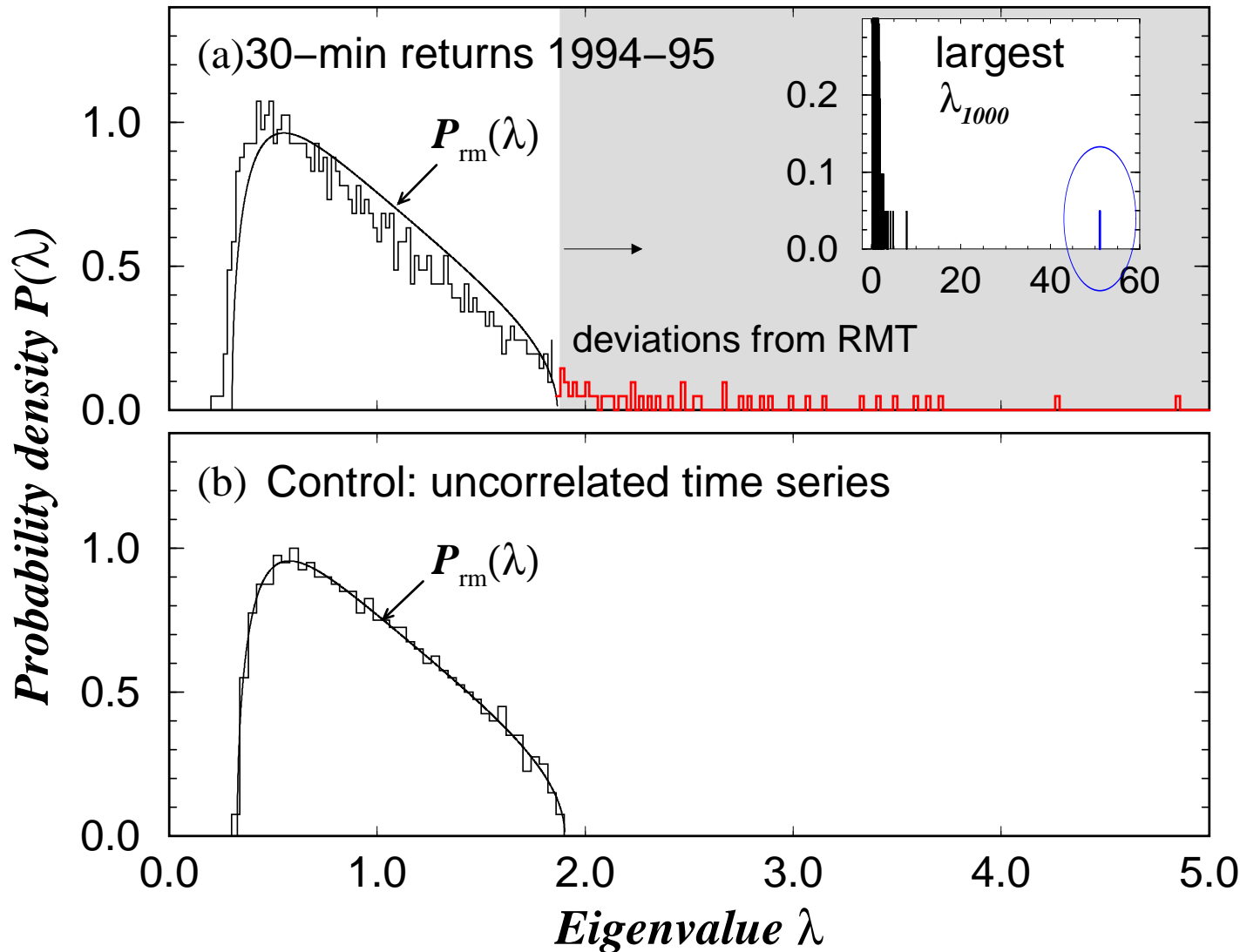


Imitation and herding



[L. Laloux, P. Cizeau, J.-P. Bouchaud, and M. Potters, Phys. Rev. Lett., 83, 1467 (1999); V. Plerou, P. Gopikrishnan, B. Rosenow, L. A. N. Amaral, and H. E. Stanley, Phys. Rev. Lett. 83, 1471 (1999).]

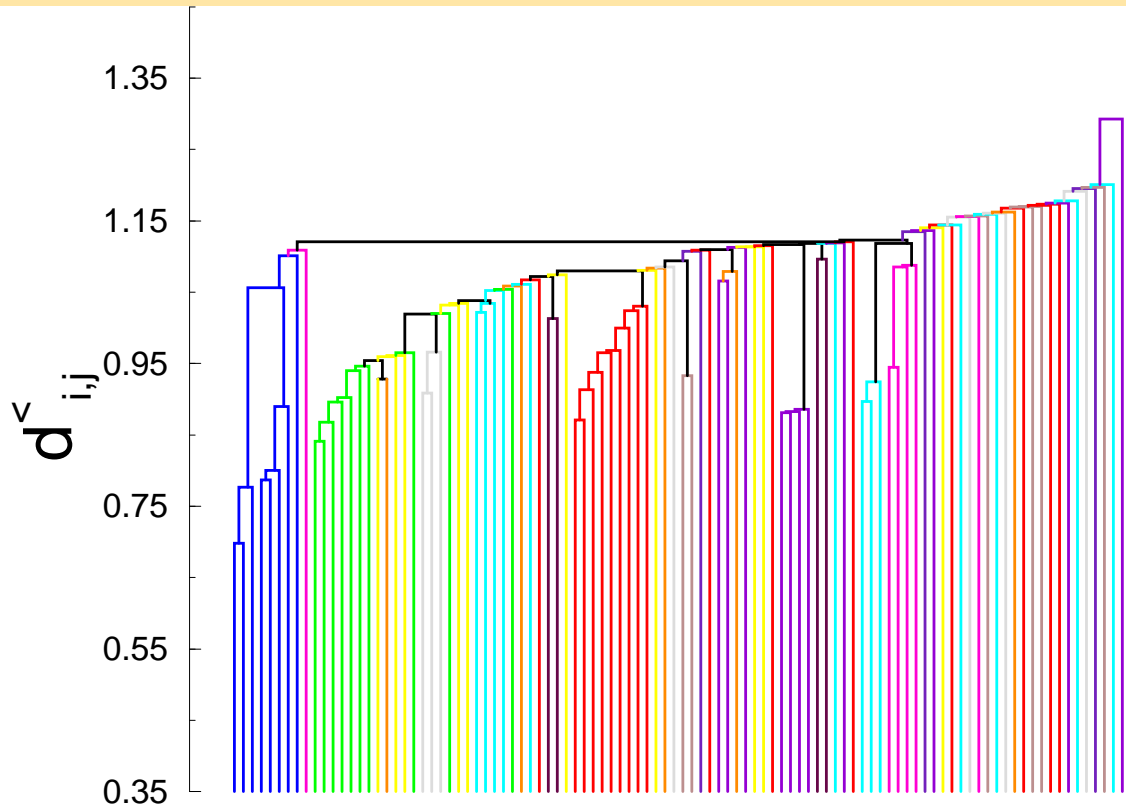
Random matrices



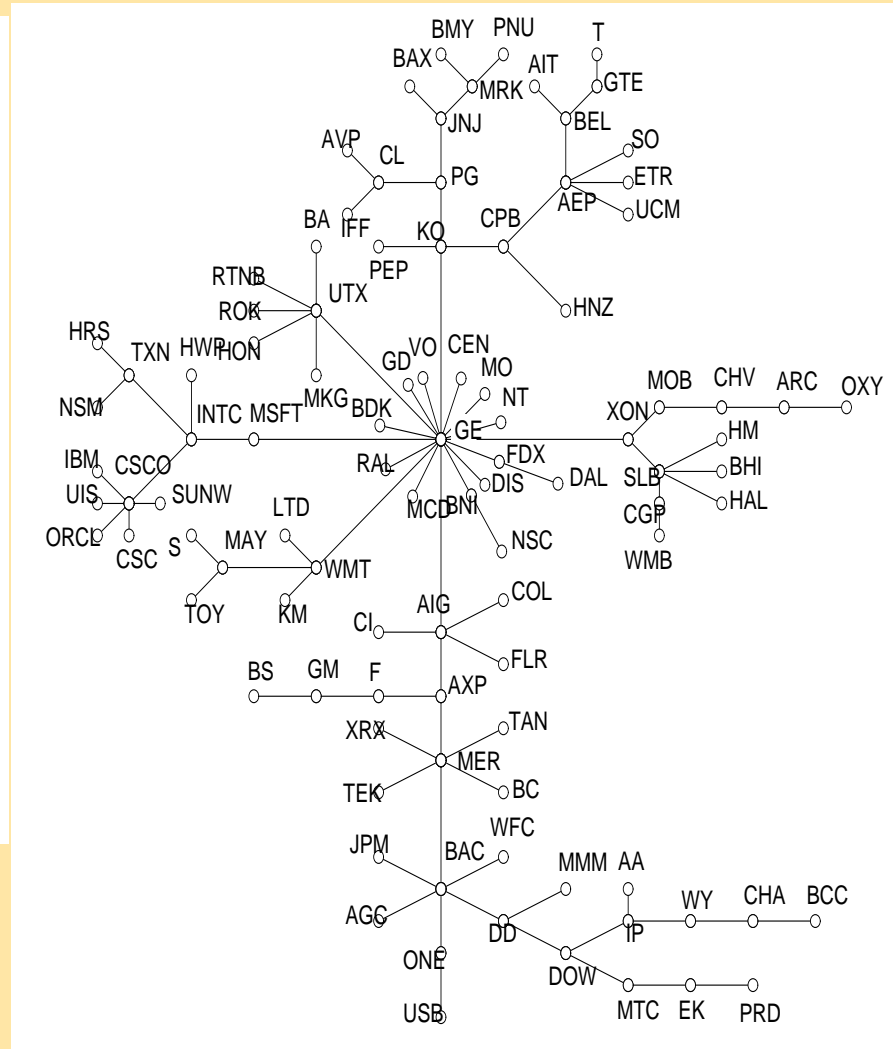
Industrial sectors can be attributed to each eigenvalue falling off the RMT spectrum.



Stock correlations [G. Bonanno, F. Lillo, R. N. Mantegna, Quantitative Finance 1, 96 (2001).]



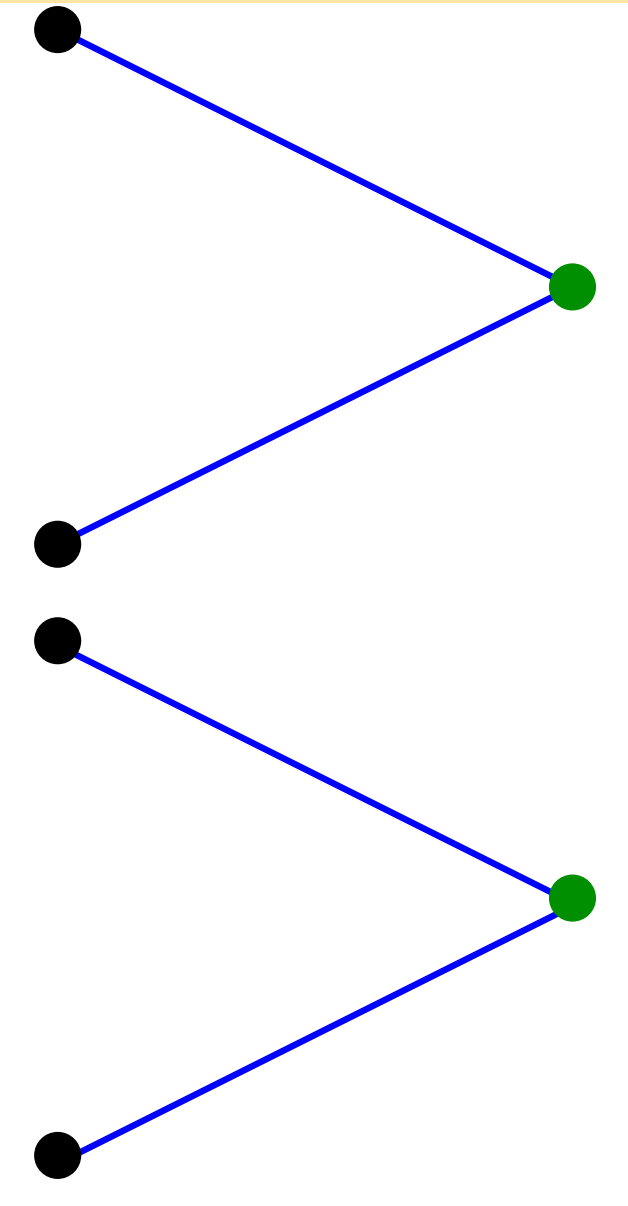
Ultrametric structure. Colors distinguish sectors, e.g. energy (blue), finance (green) etc. Time horizon 6h 30min.



Minimum spanning tree.



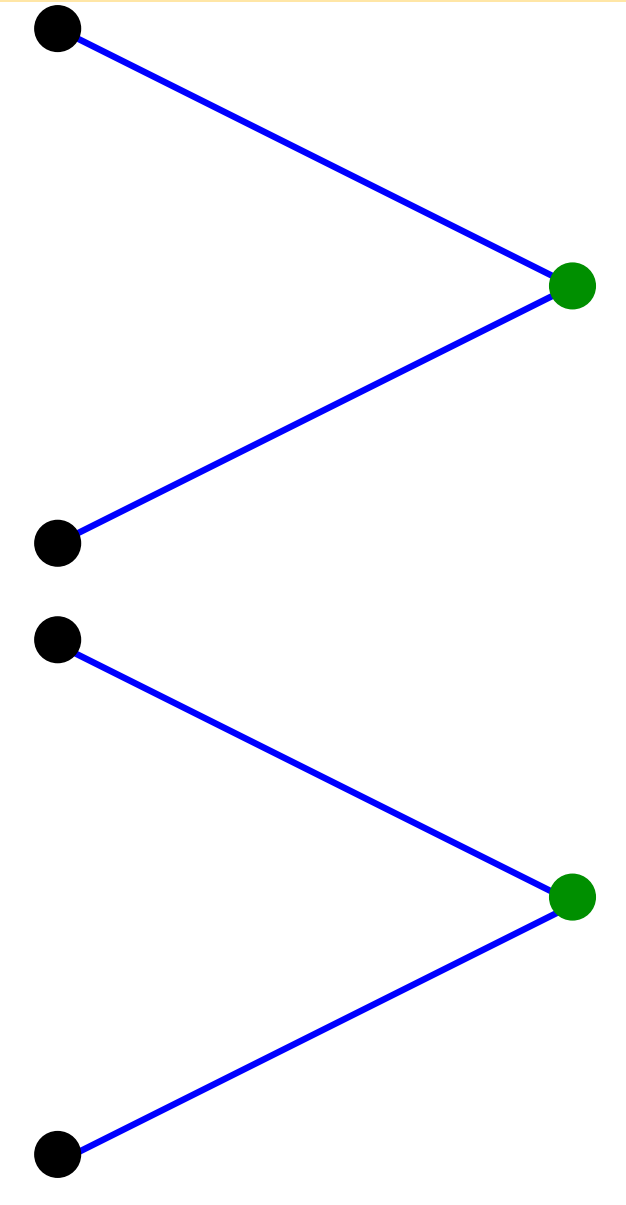
Imitation dilemma



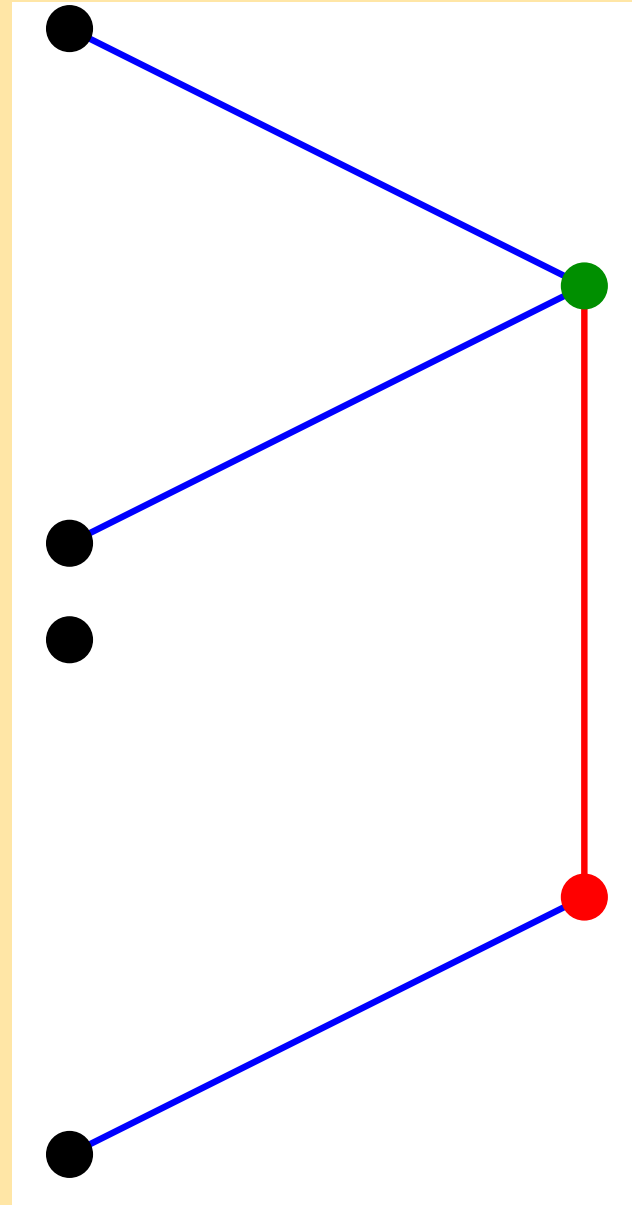
No imitation:
fair game.



Imitation dilemma



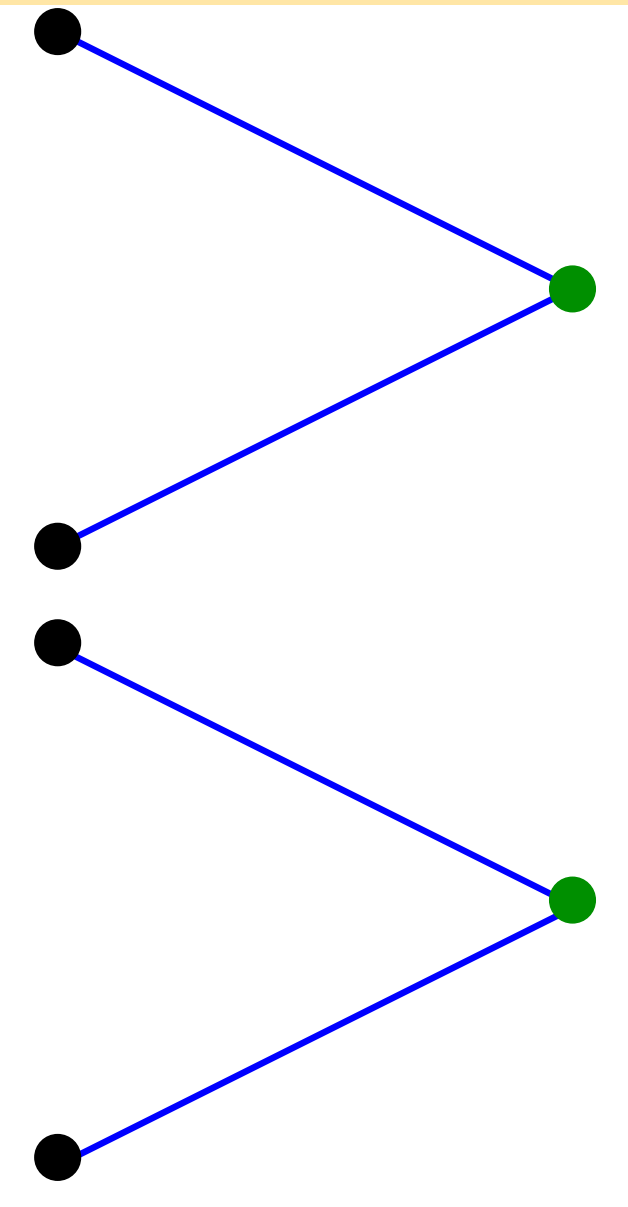
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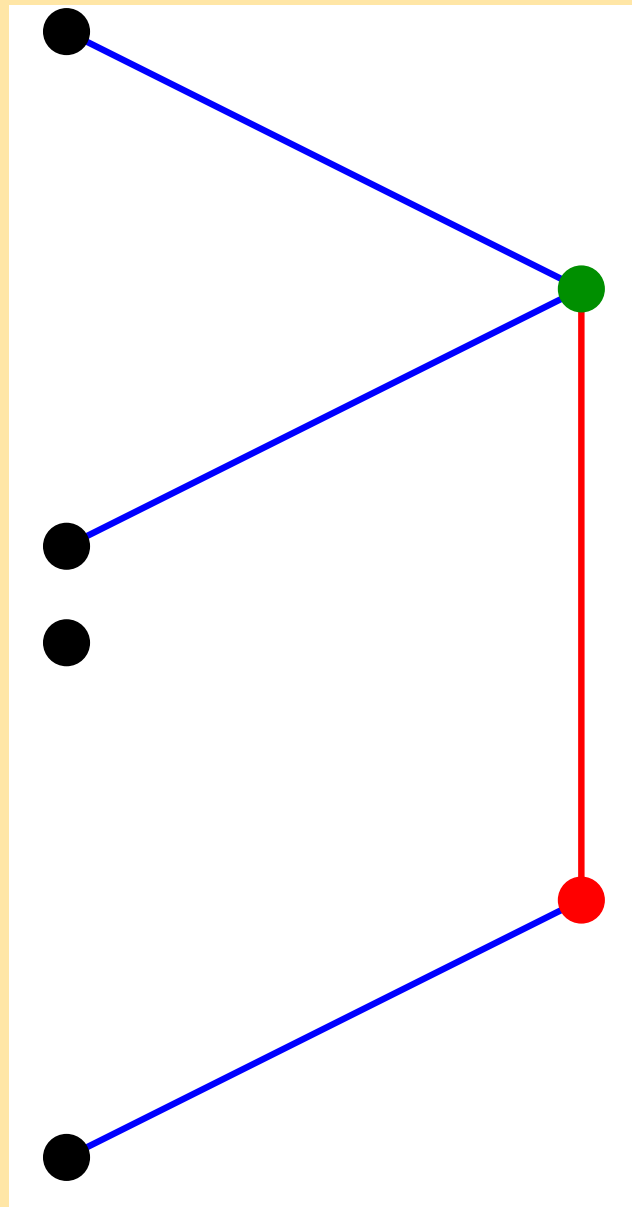
Imitation provides
comparative advantage.



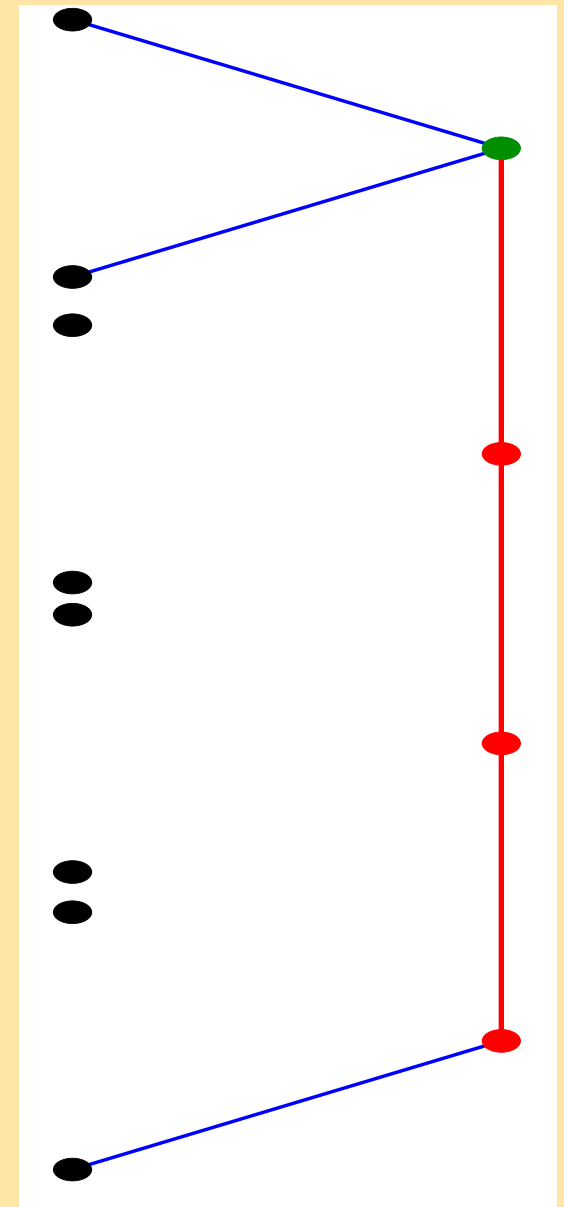
Imitation dilemma



No imitation:
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Imitation provides
comparative advantage.



Too much imitation
is dangerous.



Minority Game: [W. B. Arthur Amer. Econ. Review 84,406 (1994).
D. Challet and Y.-C. Zhang, Physica A 246, 407 (1997).]

**El Farol bar attendance problem:
go to bar (B) or stay at home (A)?**



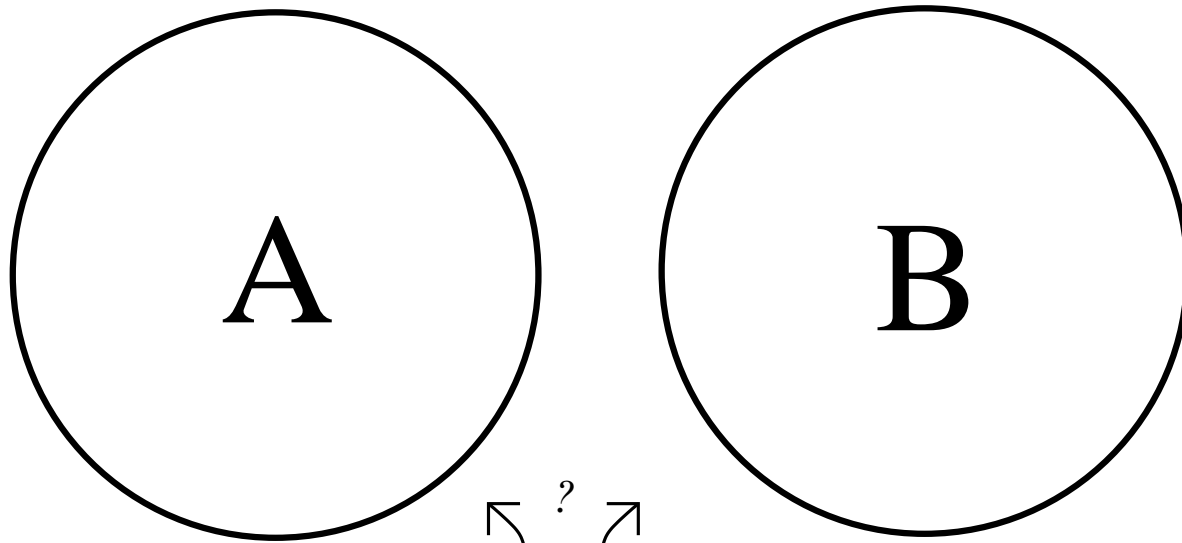
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Abstract formulation:



...AABABAABBABABBBAABAABBBAABBBABABA

winning group

memory

N players

S strategies,

memory length M .

Strategy with highest score is chosen.



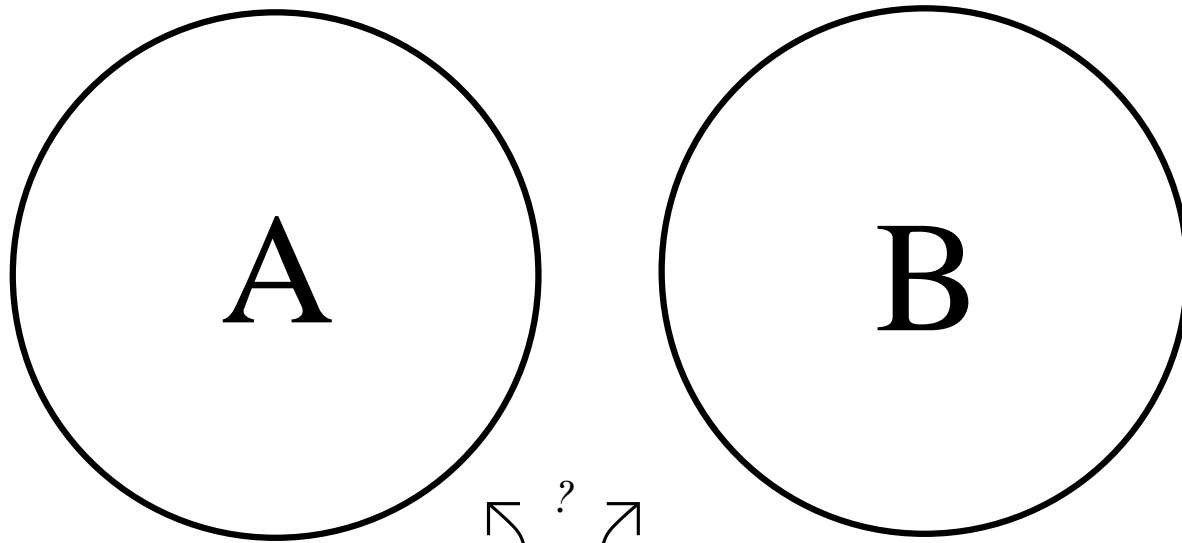
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Strategy with highest score is chosen.

Features: On-line adaptation. No optimal strategy possible.



Formalization:

Attendance: $A(t) = \sum_i a_i(t)$

Strategies' scores: $U_{j,s}(t+1) = U_{j,s}(t) - a_{j,s}^{\mu(t)} \text{sign}A(t)$

Action: $a_j(t) = a_{j,s_M(t)}^{\mu(t)}$, where $U_{j,s_M(t)}(t) = \max_s U_{j,s}(t)$

Measure of ineffectivity: $\sigma^2 = \frac{1}{T} \sum_{t'=t-T}^t A^2(t')$



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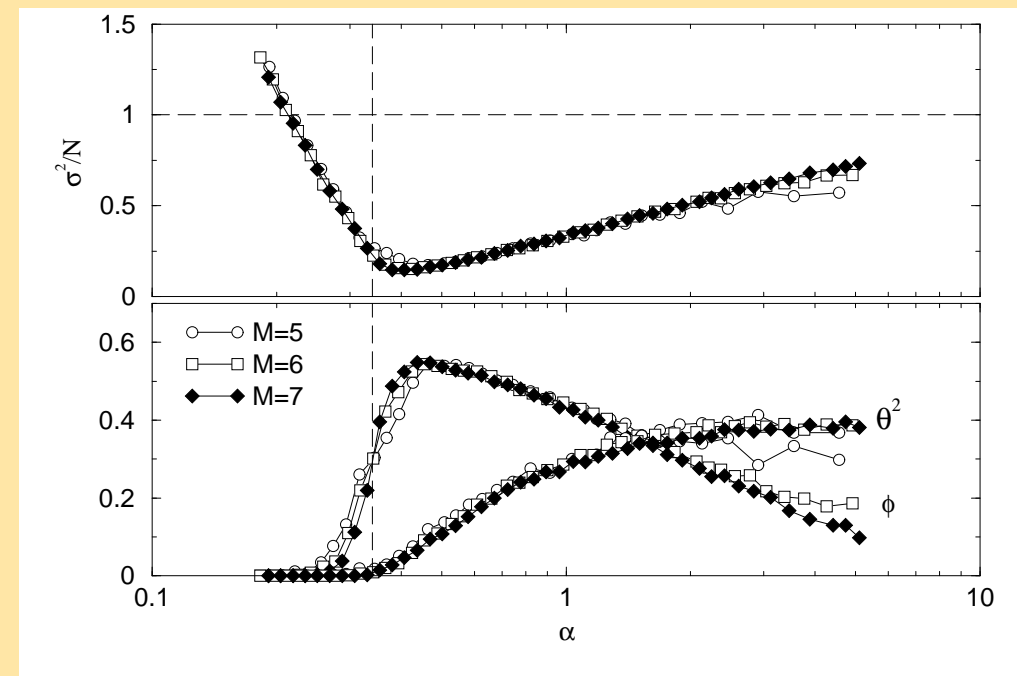
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Simulations:



Top: σ^2/N versus $\alpha = 2^M/N$

with $M = 5, 6$ and 7 .

Optimal value of the parameter

$\alpha = 2^M/N$ exists ($\alpha_c \simeq 0.34$)



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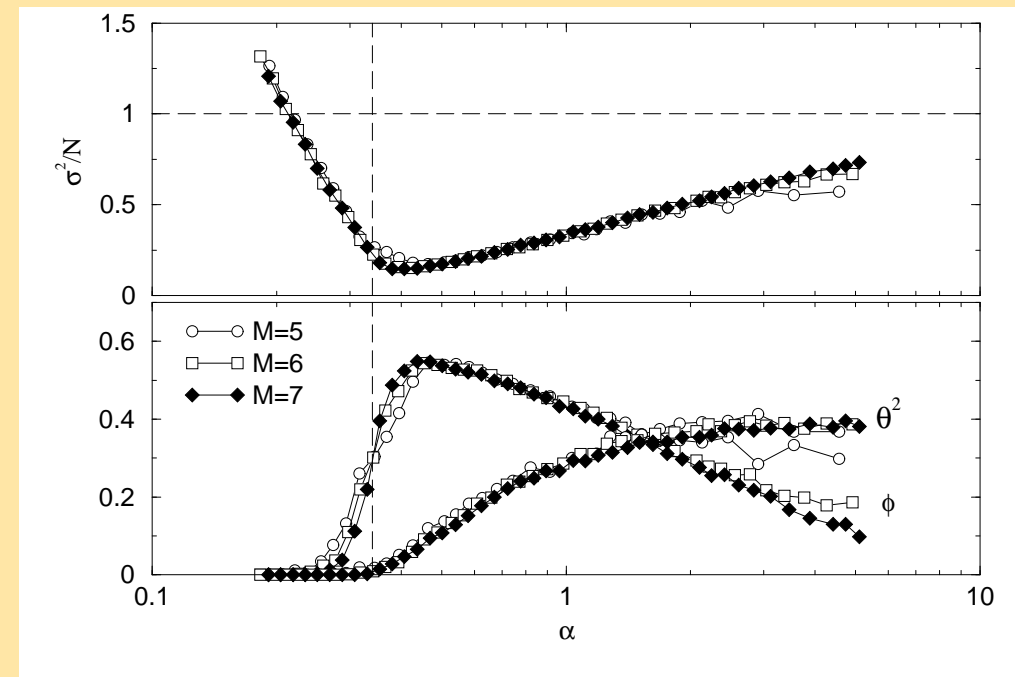
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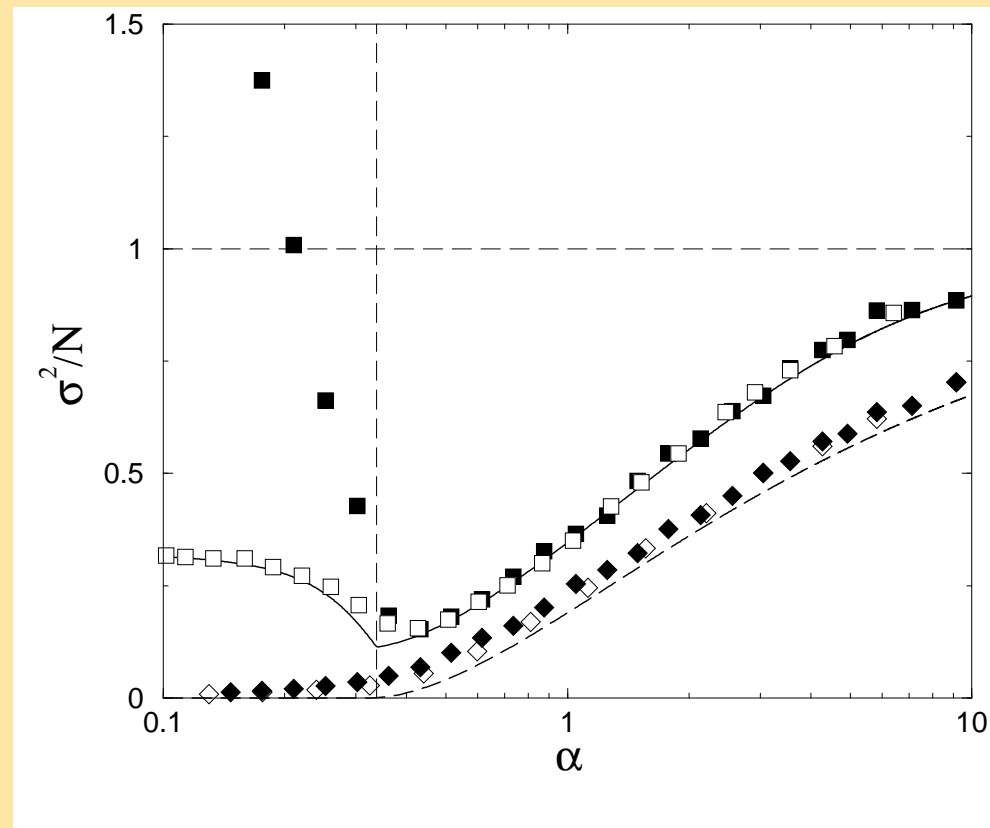
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Analytical solution: Replica method



Social organization [F. S., Physica A 286, 367 (2000); Physica A 299, 334 (2001).]

Agents on social network imitate more successful neighbors with probability p (and pay for it)



Agents are placed on linear chain. Imitation may occur along the link

- Leaders
- Imitators
- Potential imitators
- Information flow

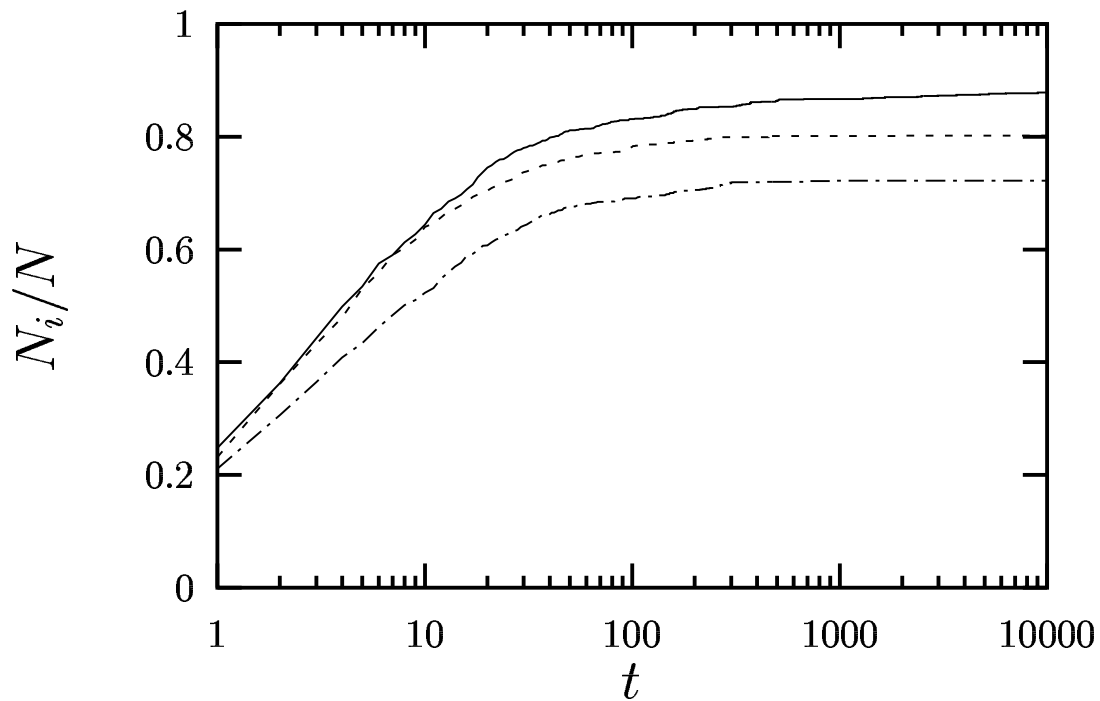


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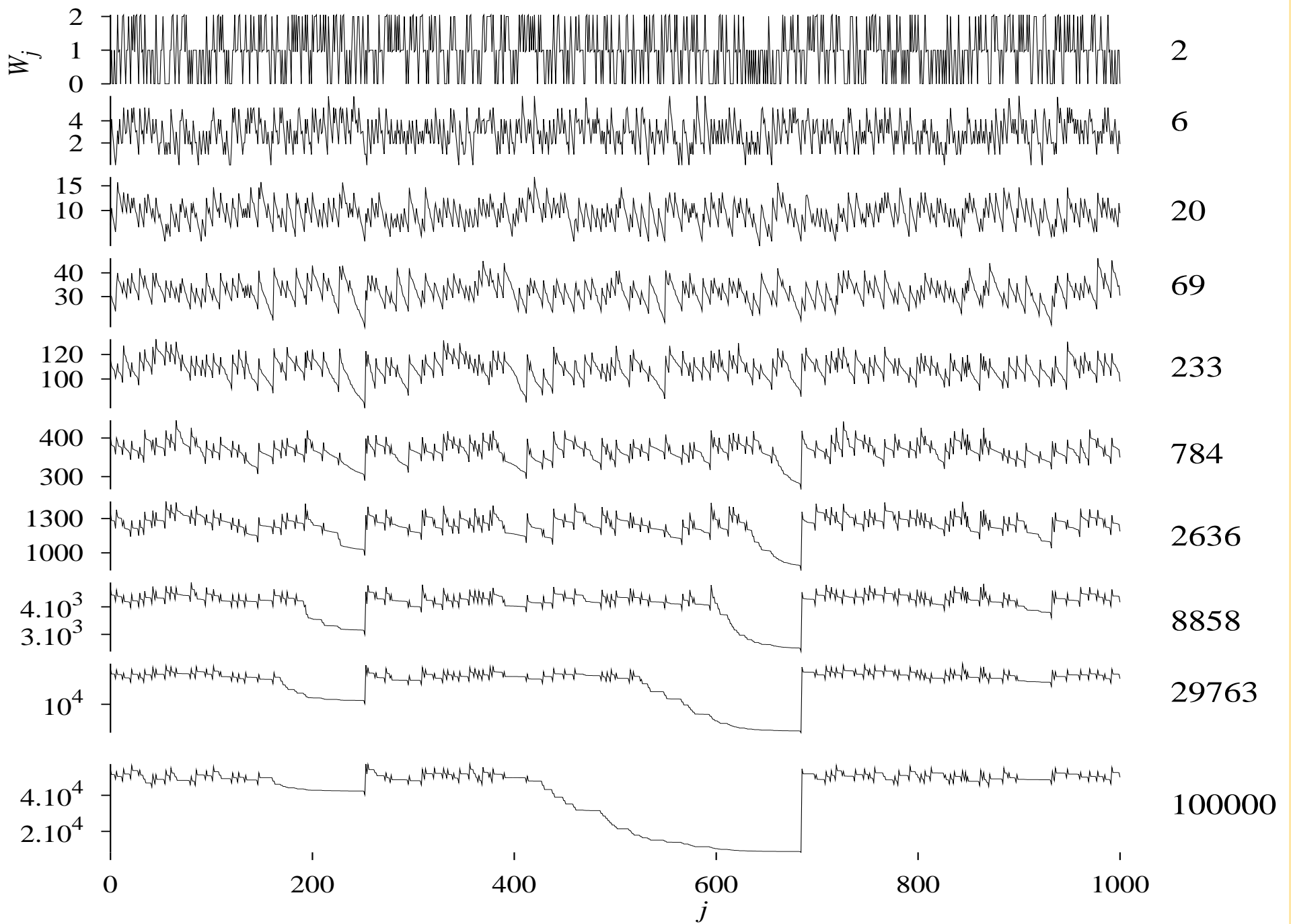
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Time dependence of imitation. $p = 0.99$ (full line)
0.95 (dashed), 0.8 (dash-dotted)

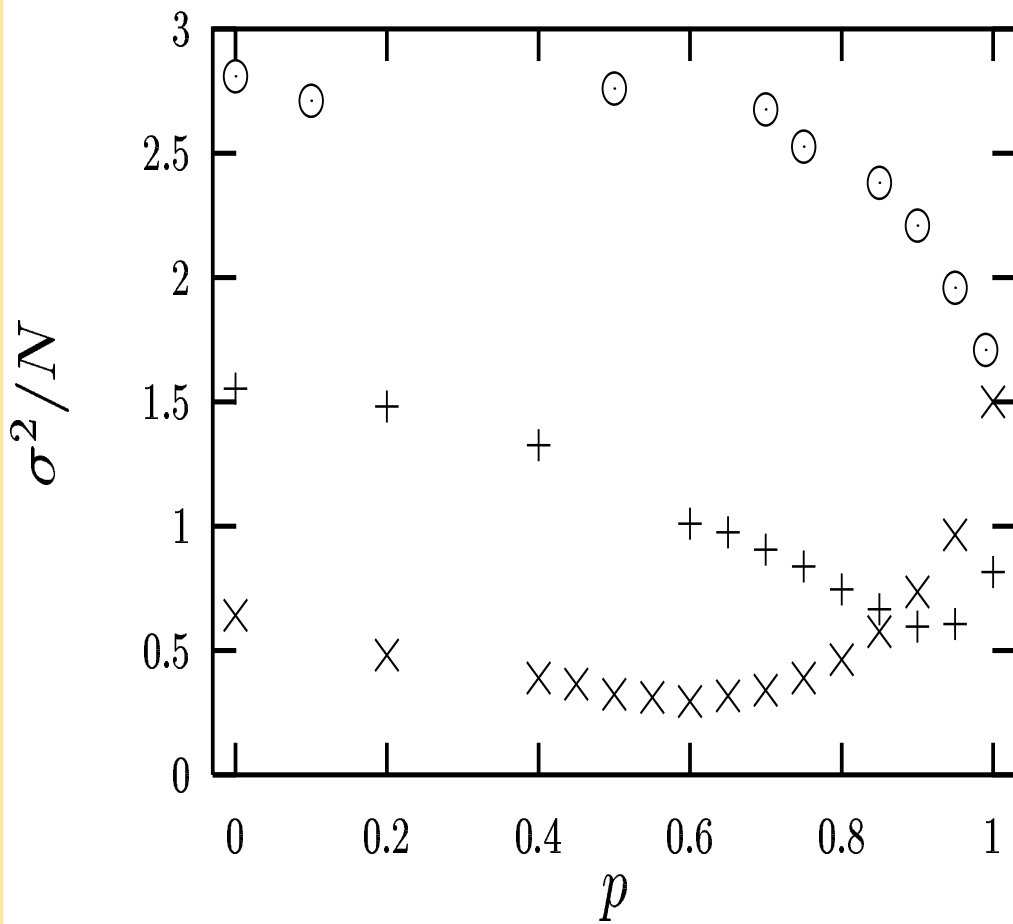
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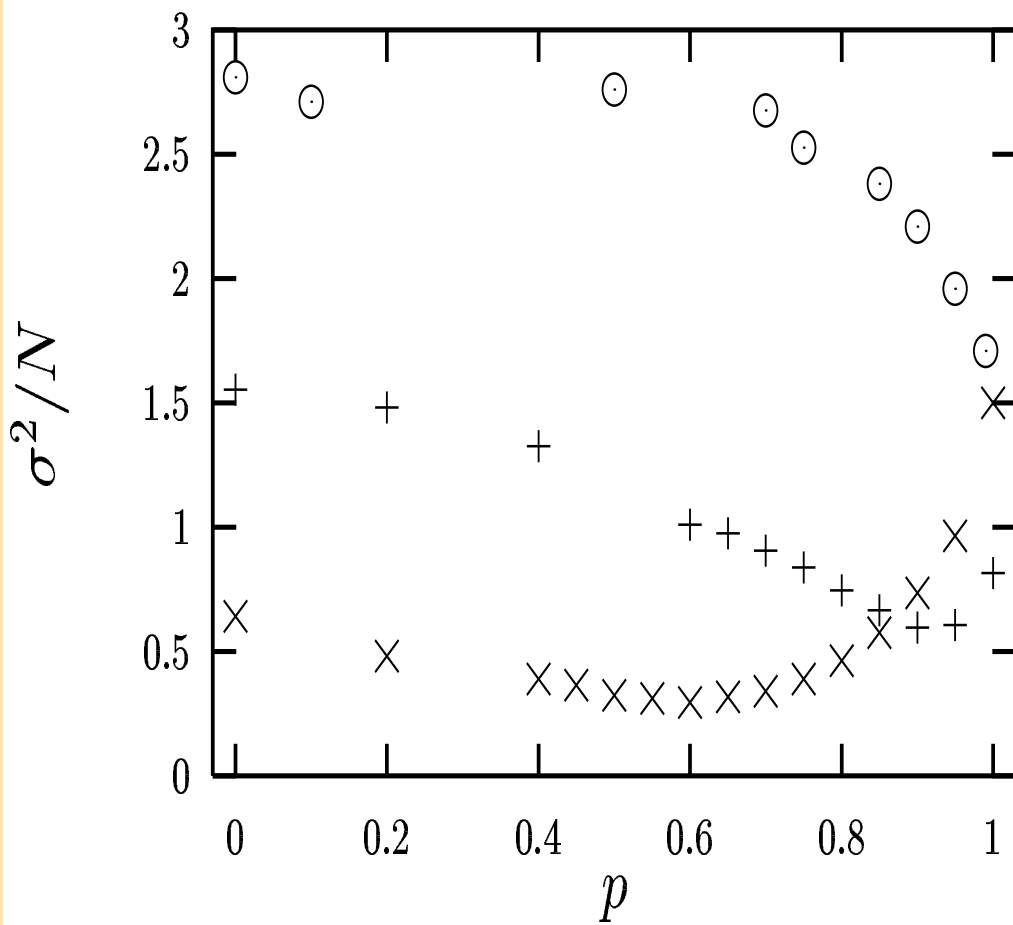
poverty islands created



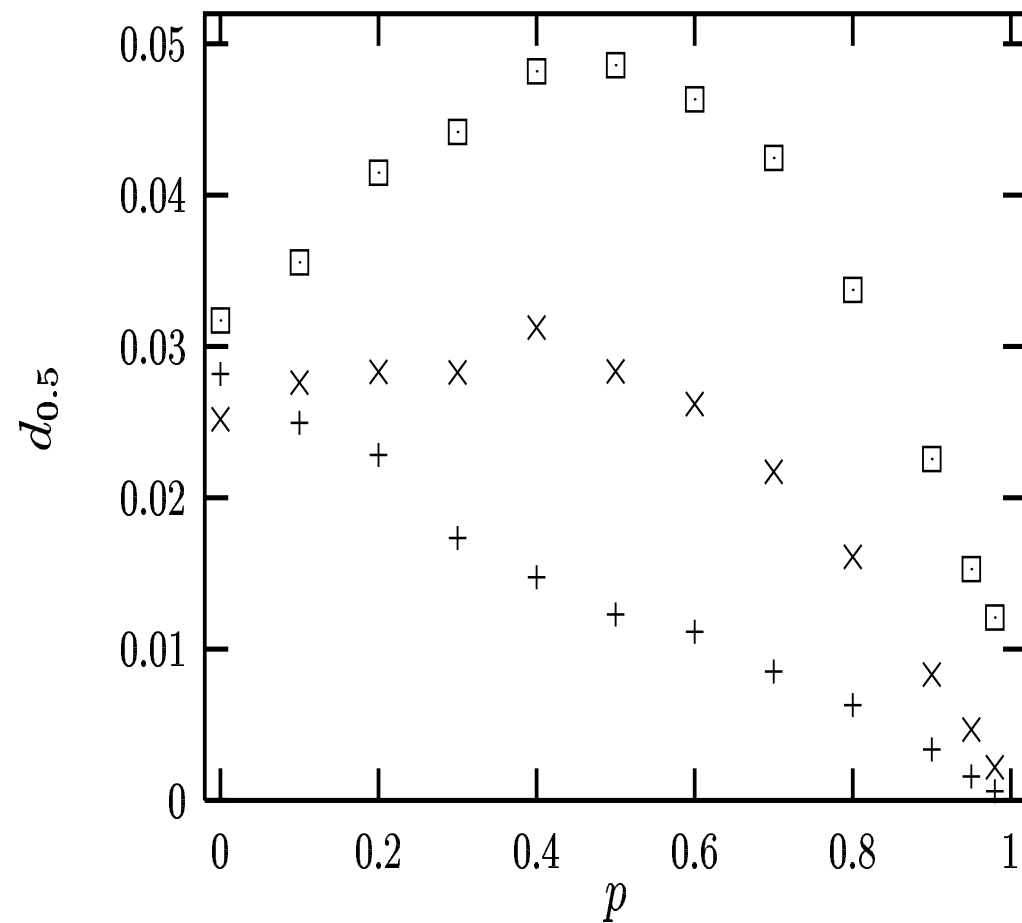


Effectivity optimized vs. imitation $N = 1001$, $M = 5$ (\odot),
 6 ($+$), 7 (\times).



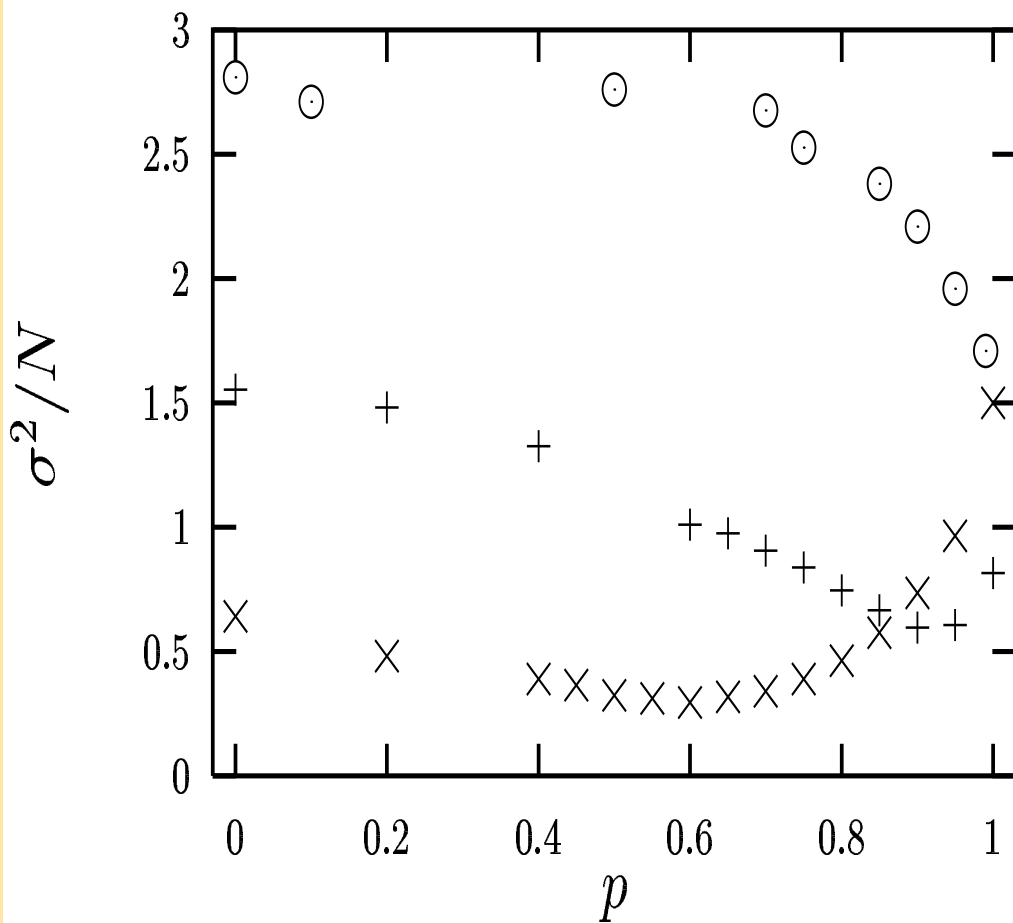


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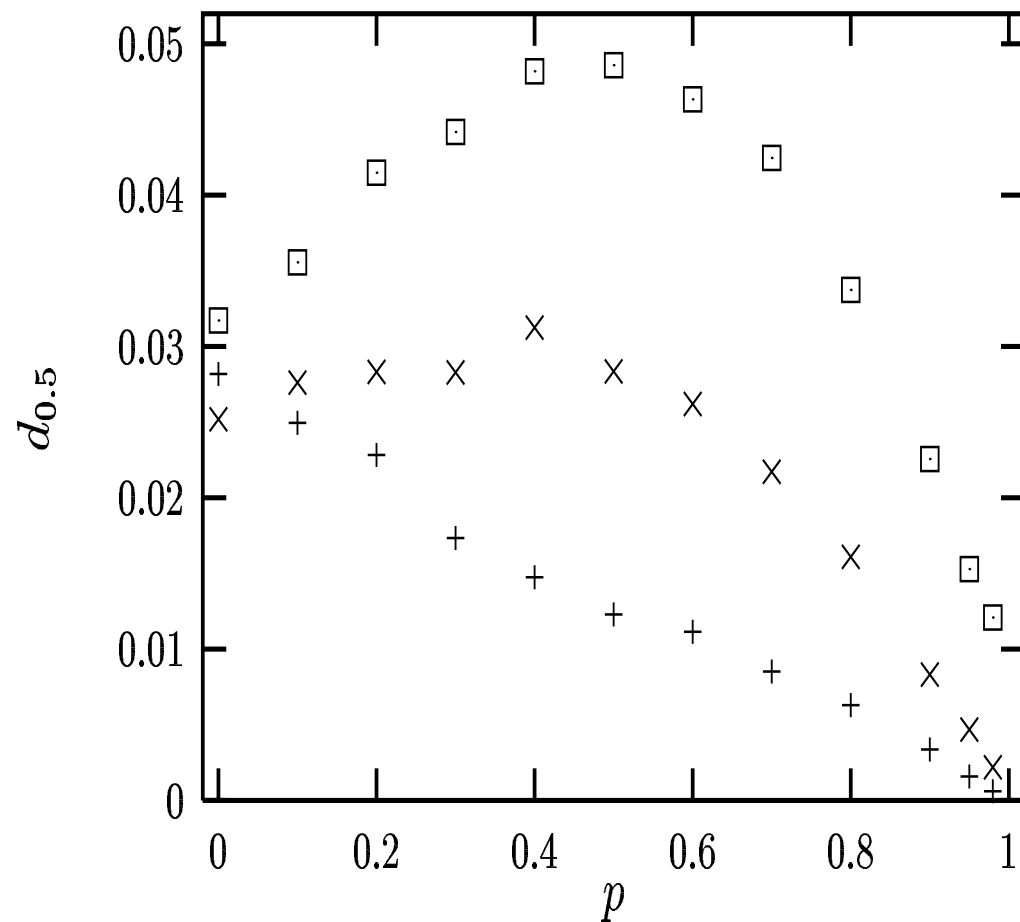


Tensions: information cost is essential. Commission $\varepsilon = 0.05$ (\square), 0.03 (\times), 0.01 ($+$).





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$$d_{0.5} = \frac{1}{\langle W \rangle} \left(\frac{1}{N} \sum_{j=1}^{N-1} |W_j - W_{j+1}|^{1/2} \right)^2 \quad \langle W \rangle = \frac{1}{N} \sum_{j=1}^N W_j$$



Sociophysics

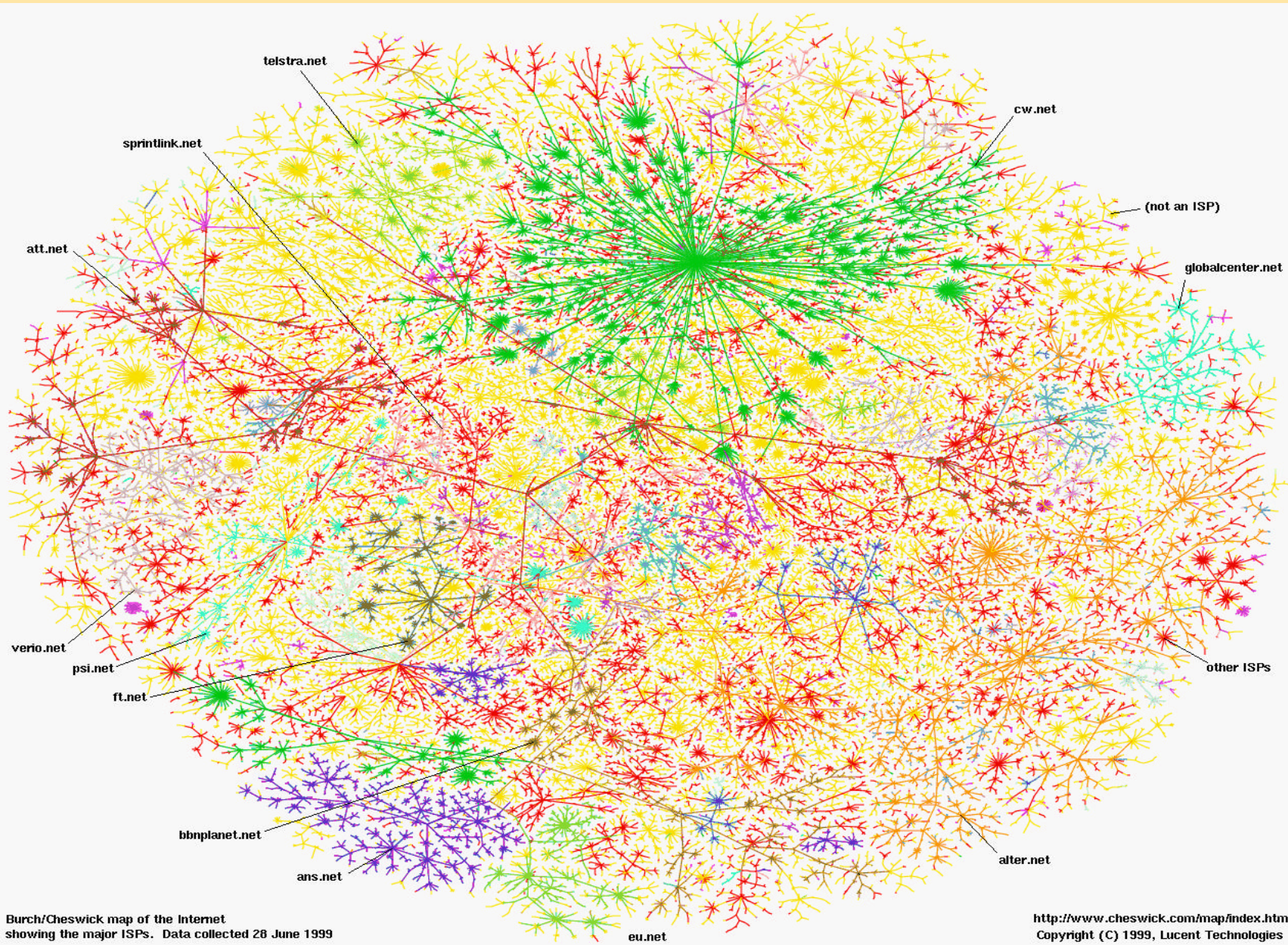
Thousands of Czechs in central Prague shout down their communist rulers in the non-violent "Velvet Revolution" of 1989



Opinion spreading: Sznajd model

[K. Sznajd-Weron and J. Sznajd, Int. J. Mod. Phys. C 11, 1157 (2000).]

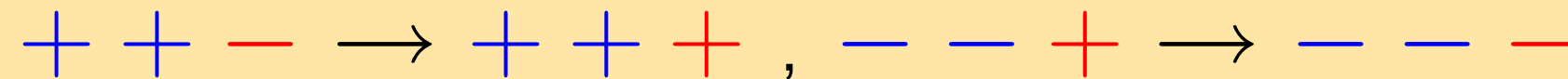
N agents on a social network



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Opinions $\sigma_i \in \{1, -1\}$. The state of the system $\Sigma = [\sigma_1, \sigma_2, \dots, \sigma_N]$ performs a discrete-time Markov process.

I. original model: two against one



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$+ + - \rightarrow + + +$, $- - + \rightarrow - - -$

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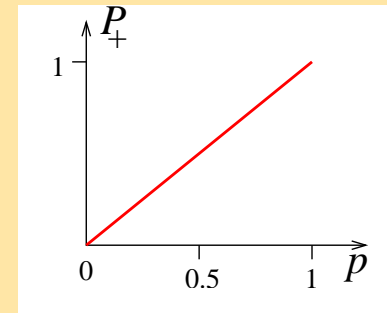
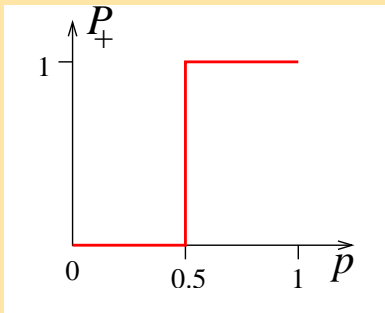
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Two absorbing states: uniform $\Sigma_+ = \{1\}^N$ and $\Sigma_- = \{-1\}^N$.

$P_+(p)$ probability of hitting Σ_+ for initial condition $p = N_+/N$:

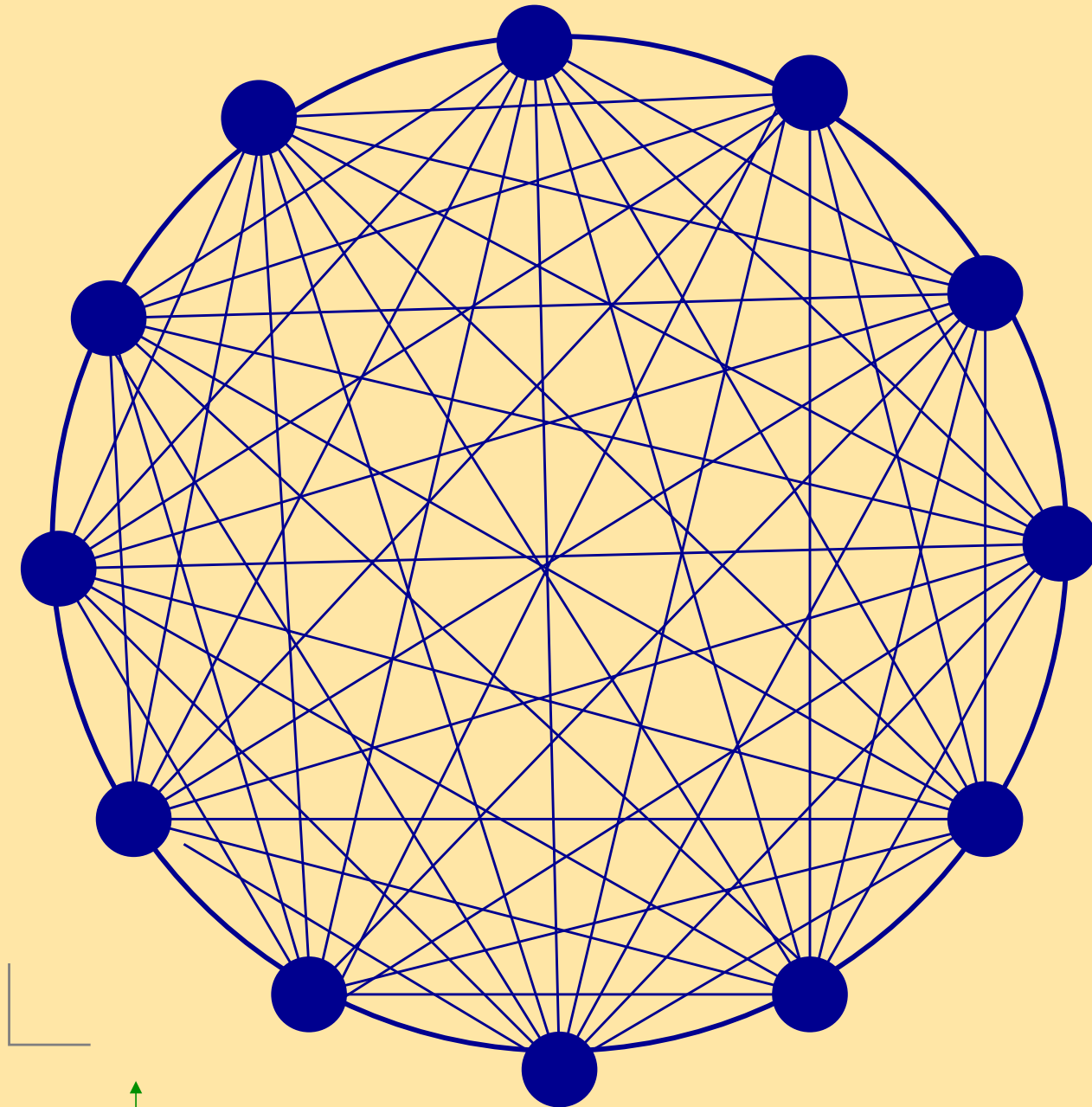
I. transition: $P_+(p) = \theta(p - 1/2)$

II. no transition $P_+(p) = p$



Solution of Sznajd model [F.S. and H. Lavička, Eur. Phys. J. B 35, 279 (2003).]

Approximation: complete graph (“mean-field”)



State fully described by “magnetization”,

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II. Gegenbauer polynomials:

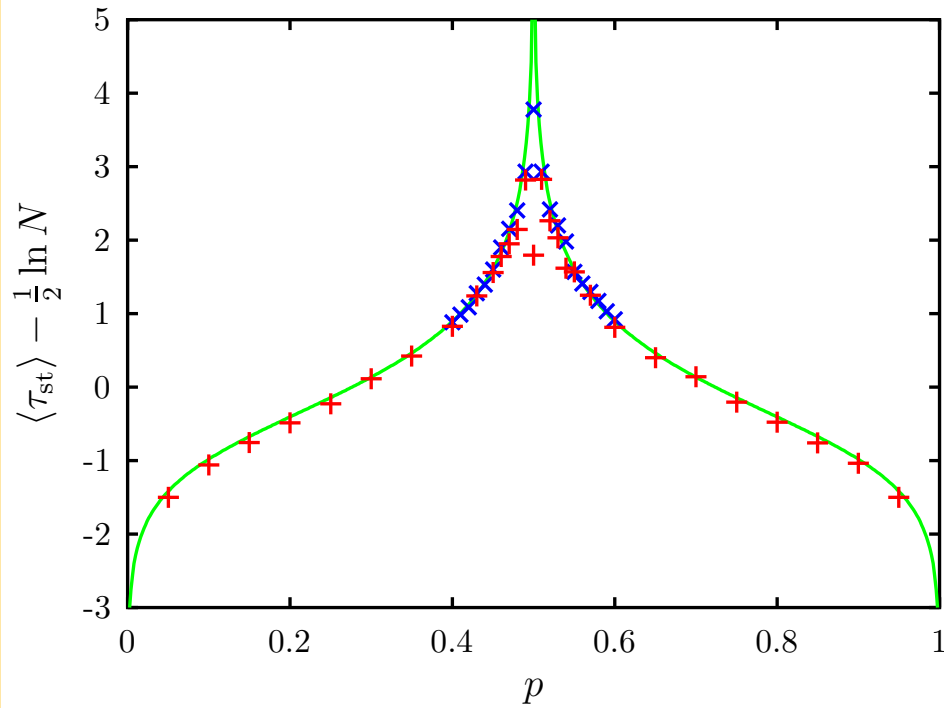
$$P(x, \tau) = \sum_c A_c e^{-c\tau} \Phi_c(x)$$

l	c_l	$\Phi_c(x)$
0	2	1
1	6	x
2	12	$1 - 5x^2$
3	20	$x - \frac{7}{3}x^3$
4	30	$1 - 14x^2 + 21x^4$
\vdots	\vdots	\vdots

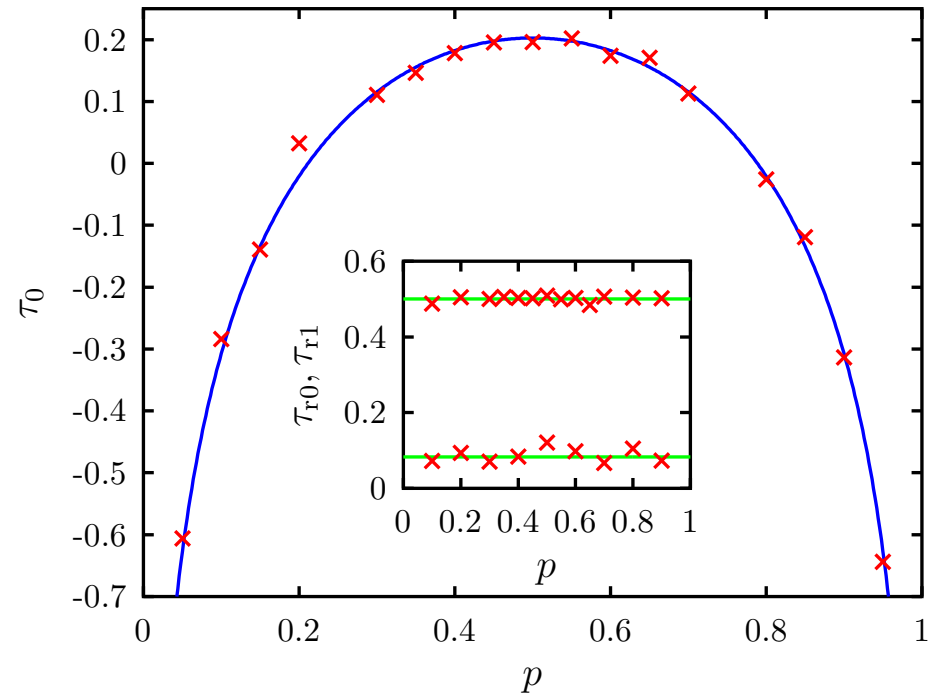


$$\langle \tau_{\text{st}} \rangle \simeq -\ln \left(\frac{|2p-1|}{\sqrt{p(1-p)}} \frac{1}{\sqrt{N}} \right)$$

$$\tau_0 \simeq \ln \sqrt{6p(1-p)}$$



Average time of reaching the absorbing state, case I.

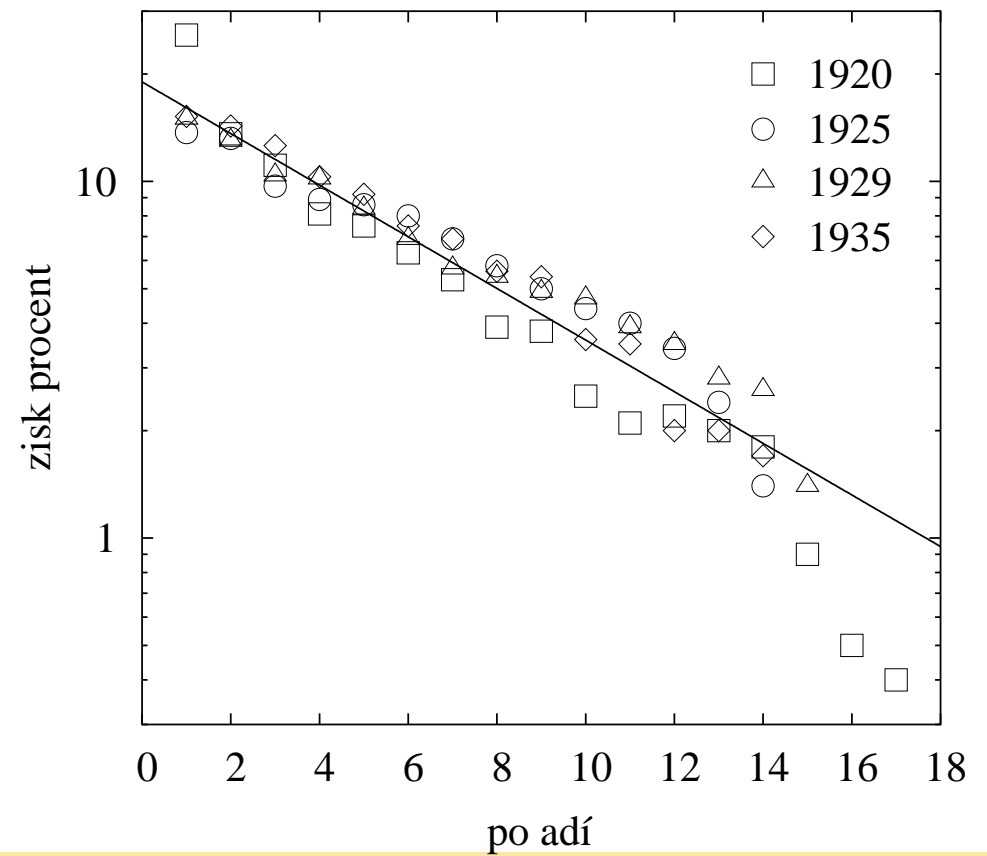
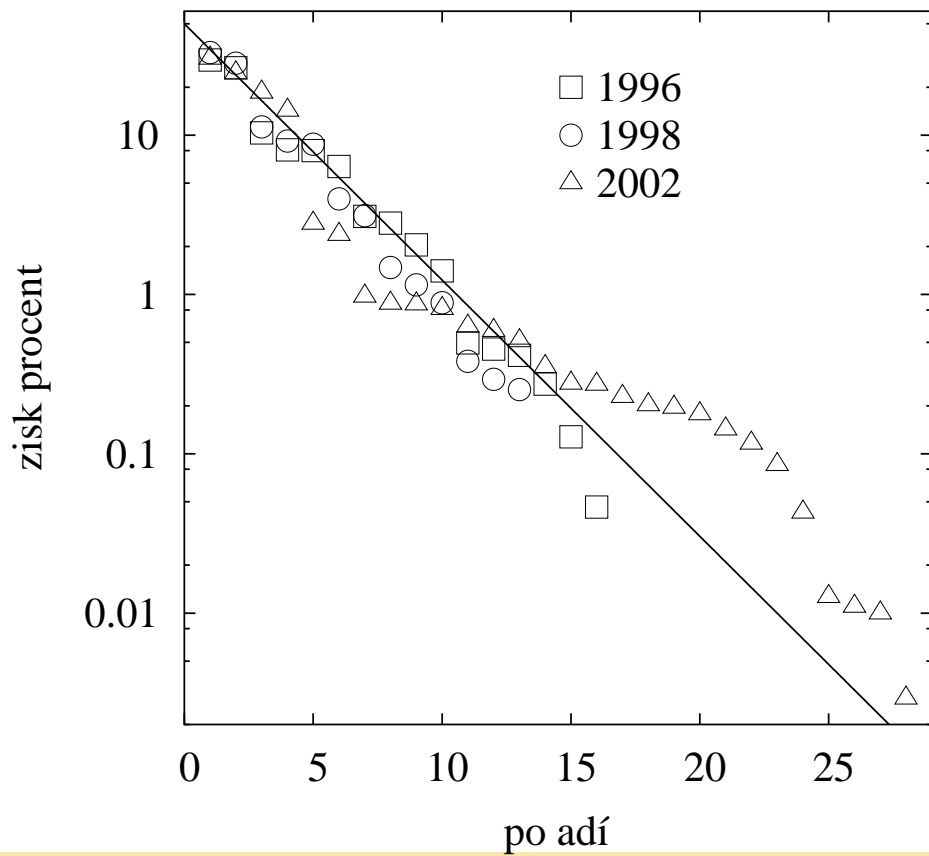


Average time to reach absorbing state, case II.



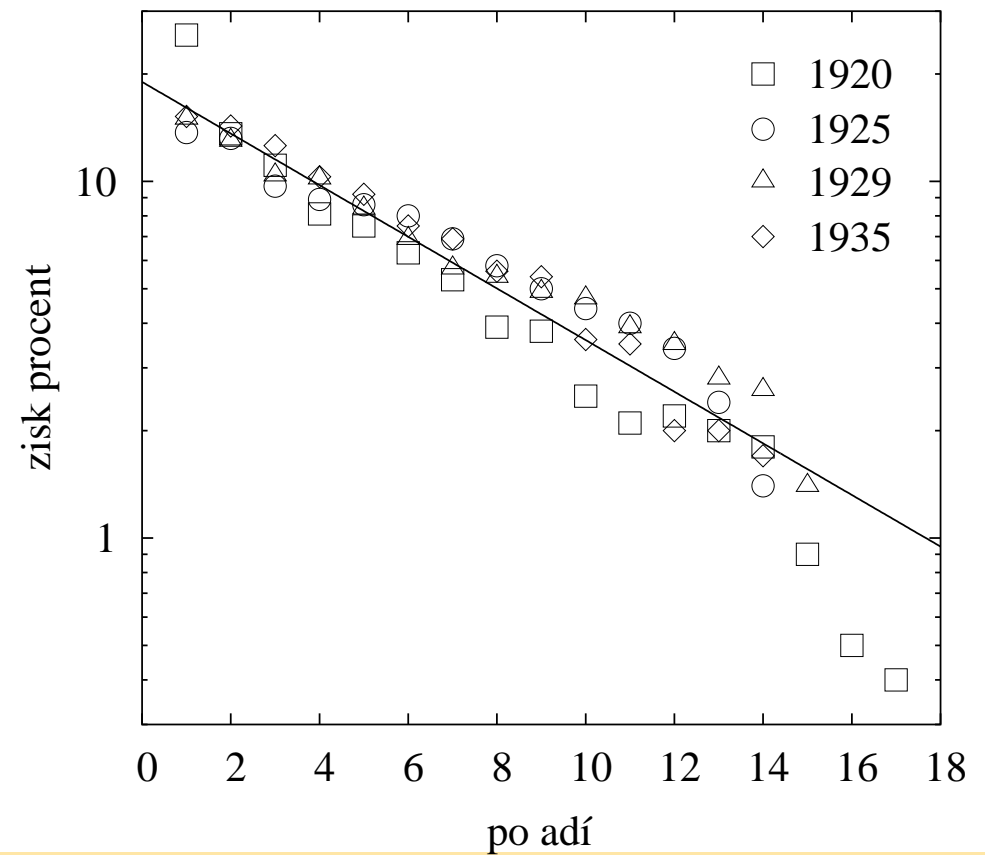
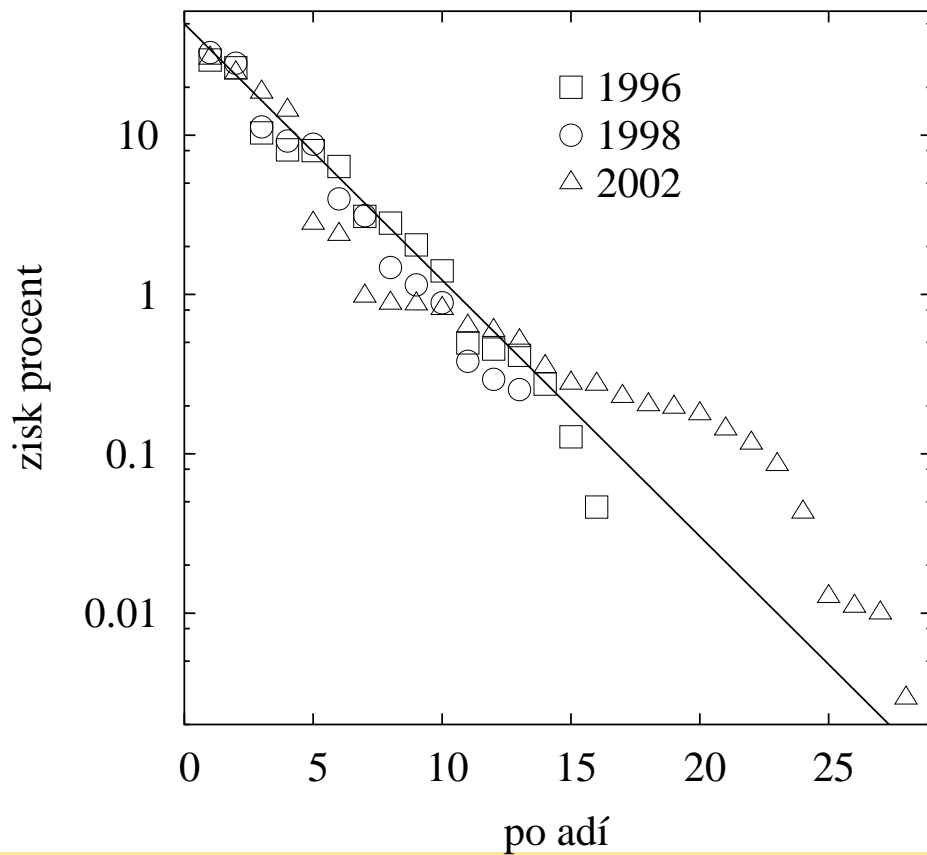
Elections

Stable patterns of election results:



Elections

Stable patterns of election results:



Distribution of votes: $P(n) \propto n^{-1}$



Sznajd model for elections

Choice from q parties: Potts variables $\sigma_i \in \{1, 2, \dots, q\}$

Distribution of votes: $D(n) = \frac{N}{q} \sum_{\sigma=1}^q \delta(n - n_{\sigma})$ $n_{\sigma} = \frac{1}{N} \sum_i \delta(\sigma_i - \sigma)$



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Neglect fluctuations: $D(n) \rightarrow P_n(n) \equiv \langle D(n) \rangle$

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Open system:

Non-normalizable stationary solutions:

$$\tilde{\Phi}(x) = \frac{1}{1 \pm x} \quad \Rightarrow \quad P_n(n) \simeq \frac{1}{n}$$

...as in Brazil or Czech Republic...

...let us tune election system now!



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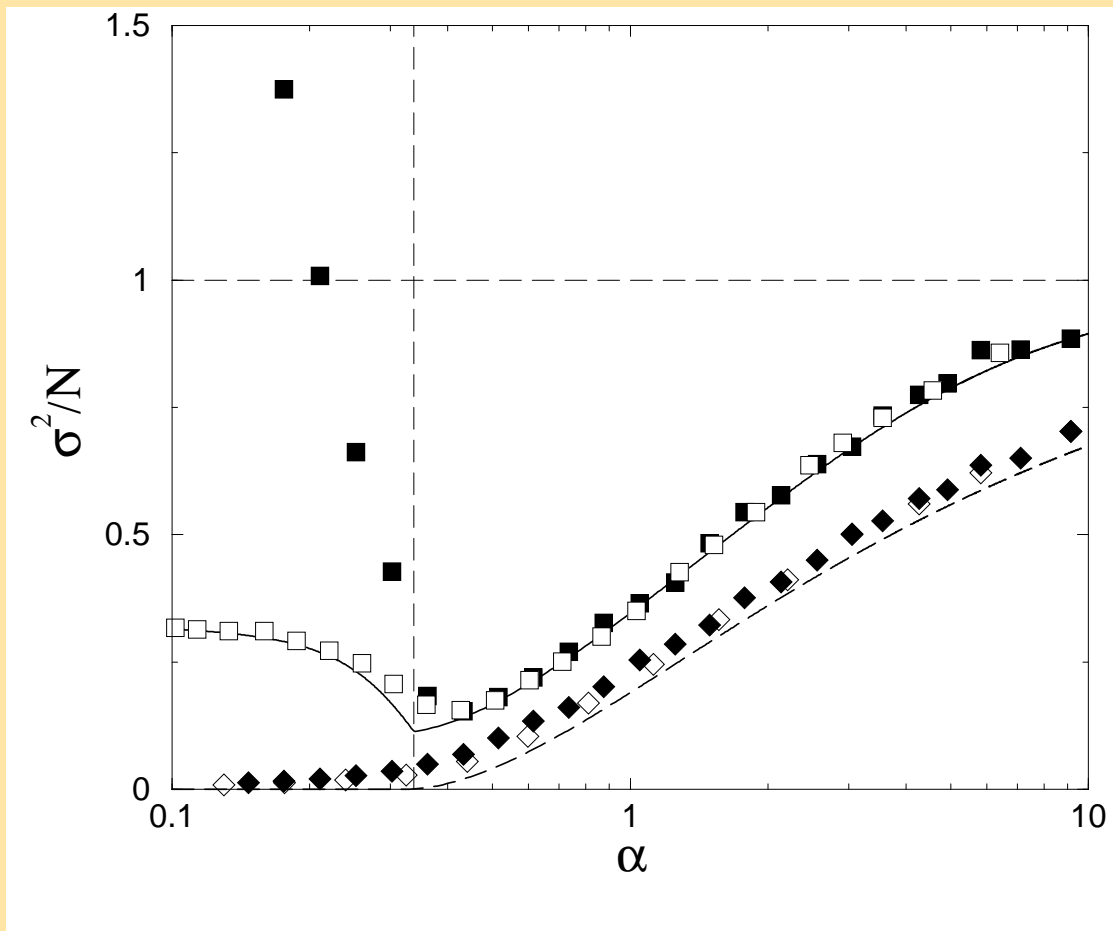
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- Supported by GACR (202/01/1091). Thanks to collaborators: Y.-C. Zhang, A. Capocci, P. Laureti,

Y.-K. Yu, M. Kotrla, J. Steiner, S. Solomon, L. Muchnik, M. Marsili, F. Vega-Redondo, H. Lavička



Analytical solution:

- Irrelevance of memory: one of P randomly chosen states ($P = 2^M$) labelled by an integer $\mu = 1, \dots, P$. $\bar{\bullet} = \frac{1}{P} \sum_{\mu} \bullet$
- Strategies $a_{i,s}^{\mu} = \omega_i^{\mu} + s \xi_i^{\mu}$, $s \in \{-1, 1\}$, $m_i = \langle s_i \rangle$
- Hamiltonian: $H = \overline{\Omega^2} + 2 \sum_i \overline{\Omega \xi_i} m_i + \sum_{ij} \overline{\xi_i \xi_j} m_i m_j$
- **Replica method** [D. Challet, M. Marsili, and R. Zecchina, Phys. Rev. Lett. 84, 1824 (2000).]



Go back

