ETH
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EXTREME FINANCIAL RISKS

Power laws and scaling in finance

Practical implications for risk control and management

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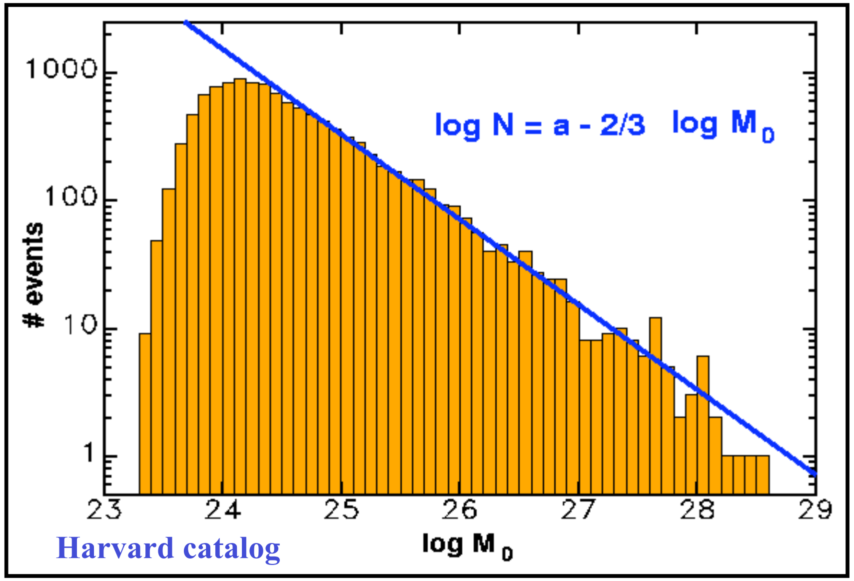
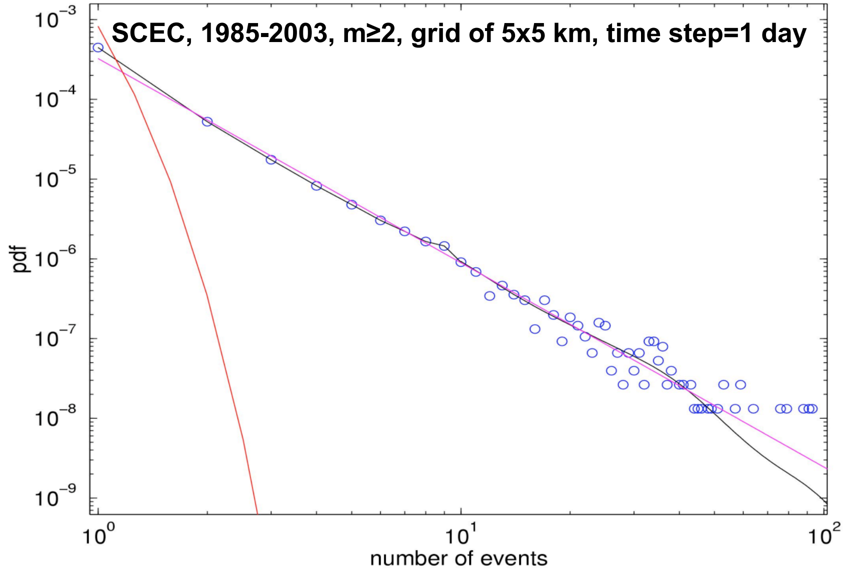
- What tail risks? Power law vs Stretched exponentials
- Heavy-tail of PDF of firm sizes and new risk factors
- Power laws? No! Better measures of risks = "kings"
- Imitation, herding, conventions: bubbles and crashes
- Illusion of control

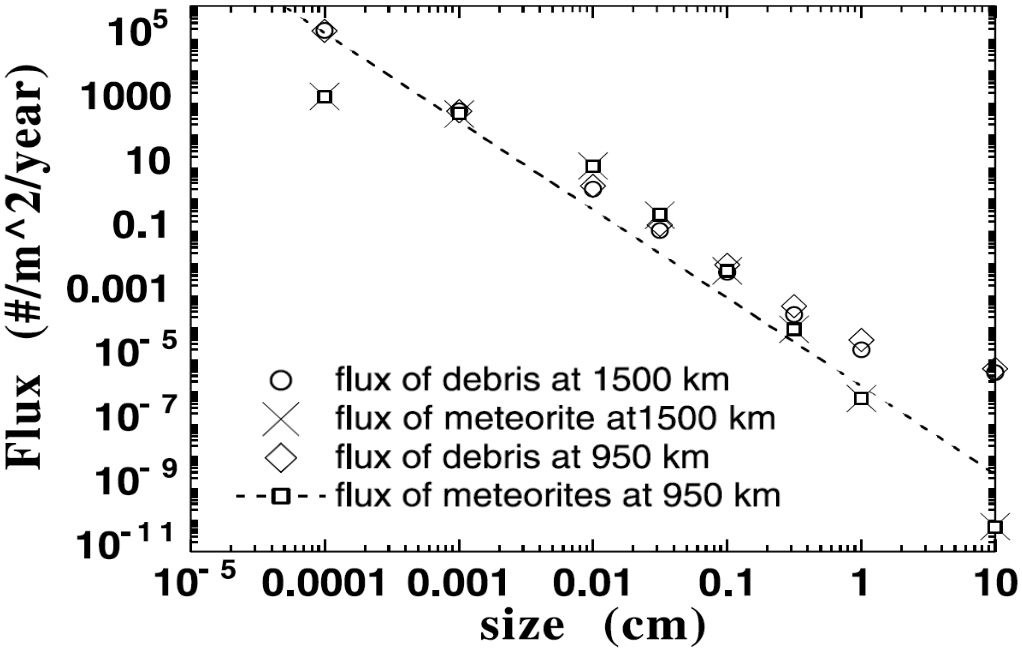
Heavy tails in pdf of earthquakes



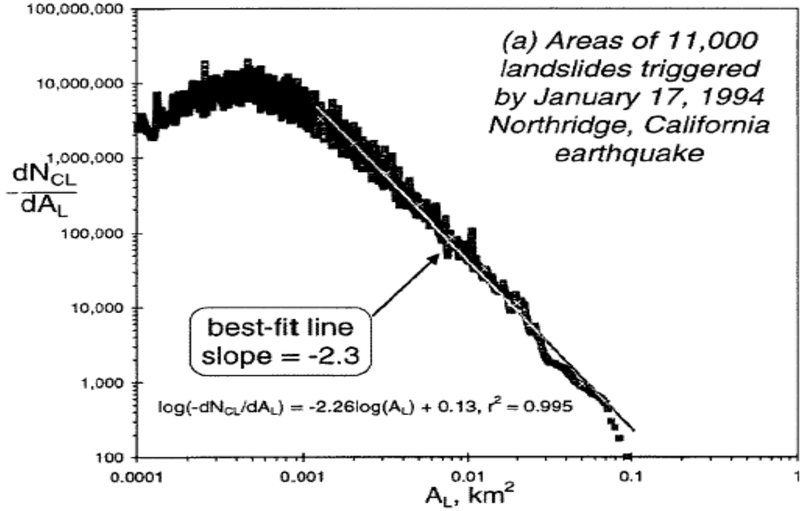
Heavy tails in pdf of seismic rates



Heavy tails in ruptures



Heavy tails in pdf of rock falls, Landslides, mountain collapses



Heavy tails in pdf of forest fires

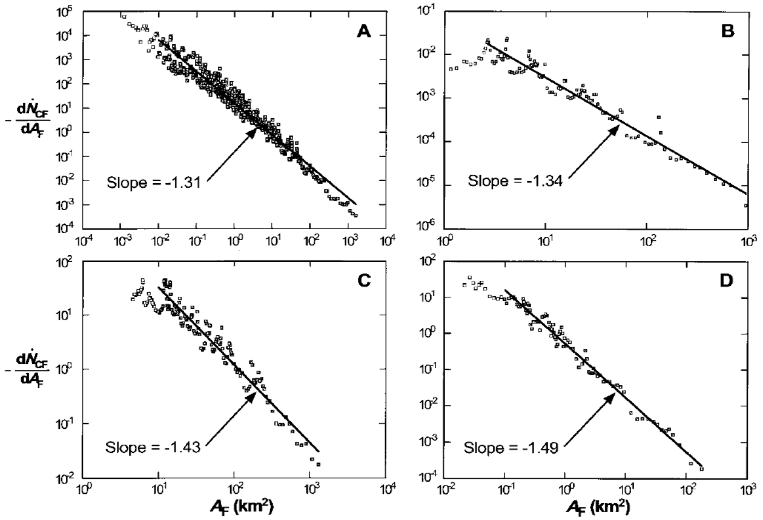
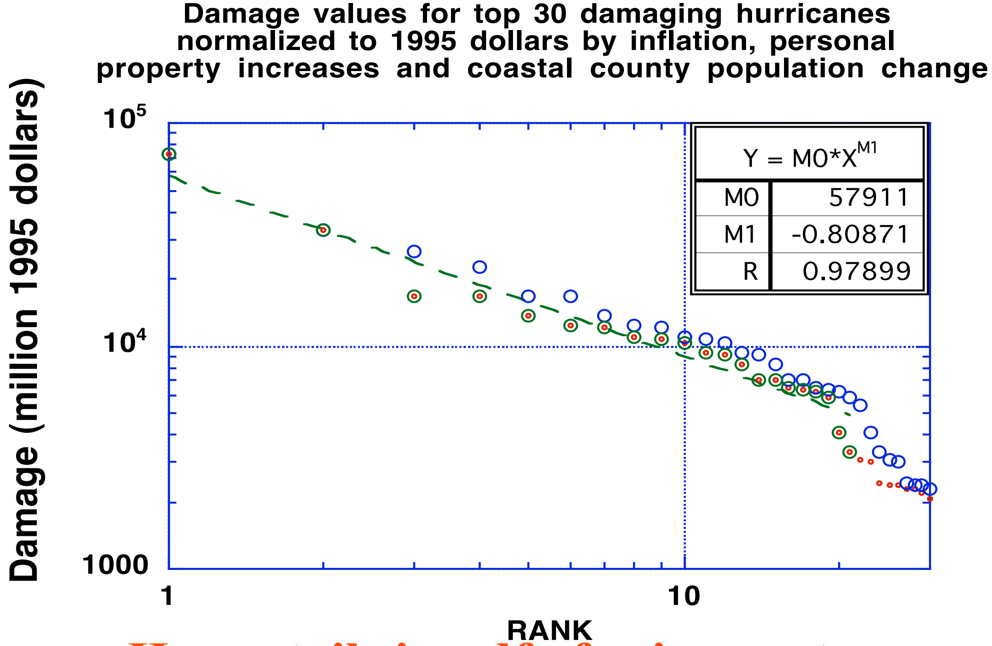
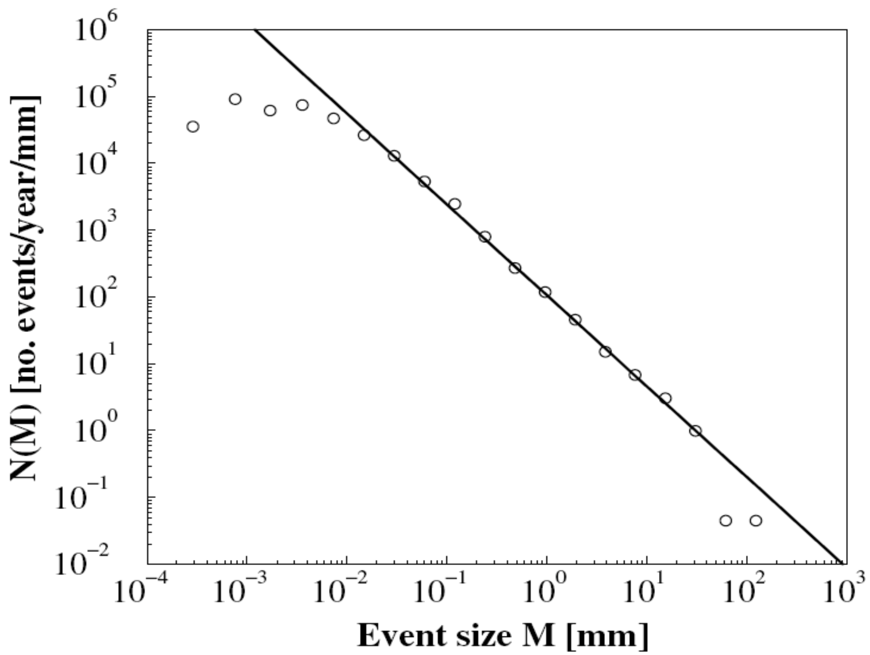


Fig. 2. Noncumulative frequency-area distributions for actual forest fires and wildfires in the United States and Australia: (**A**) 4284 fires on U.S. Fish and Wildlife Service lands (1986–1995) (*9*), (**B**) 120 fires in the western United States (1150–1960) (*10*), (**C**) 164 fires in Alaskan boreal forests (1990–1991) (*11*), and (**D**) 298 fires in the ACT (1926–1991) (*12*). For each data set, the noncumulative number of fires per year ($-d\dot{N}_{CF}/dA_F$) with area (A_F) is given as a function of A_F (*13*). In each case, a reasonably good correlation over many decades of A_F is obtained by using the power-law relation (Eq. 1) with α = 1.31 to 1.49; $-\alpha$ is the slope of the best-fit line in log-log space and is shown for each data set.

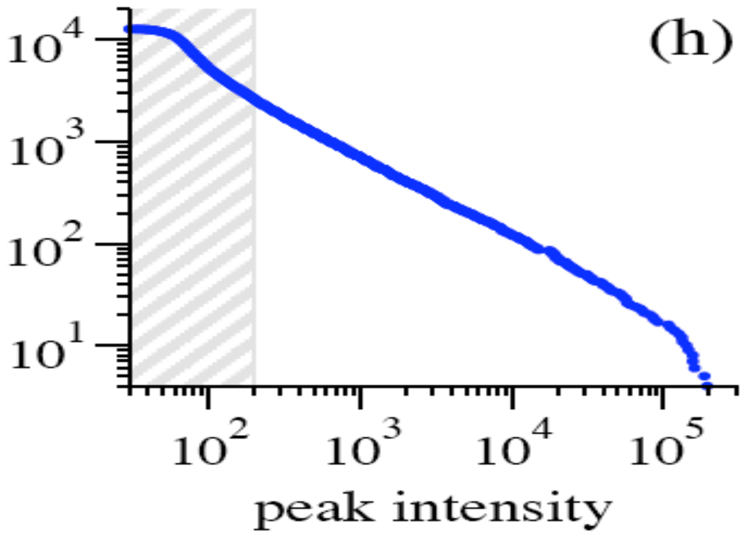
Heavy tails in pdf of Hurricane losses

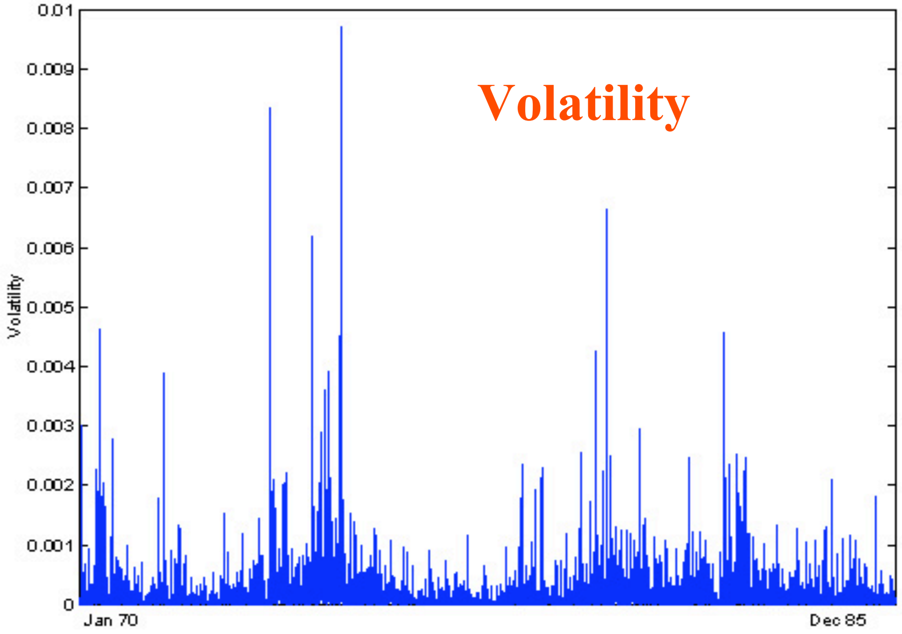


Heavy tails in pdf of rain events

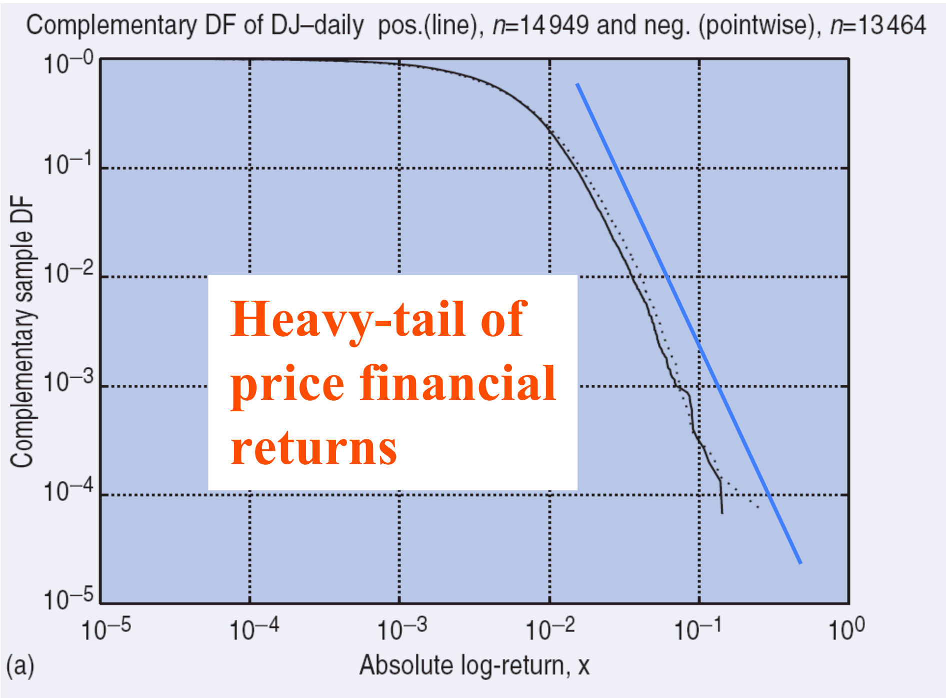


Heavy tails in pdf of Solar flares

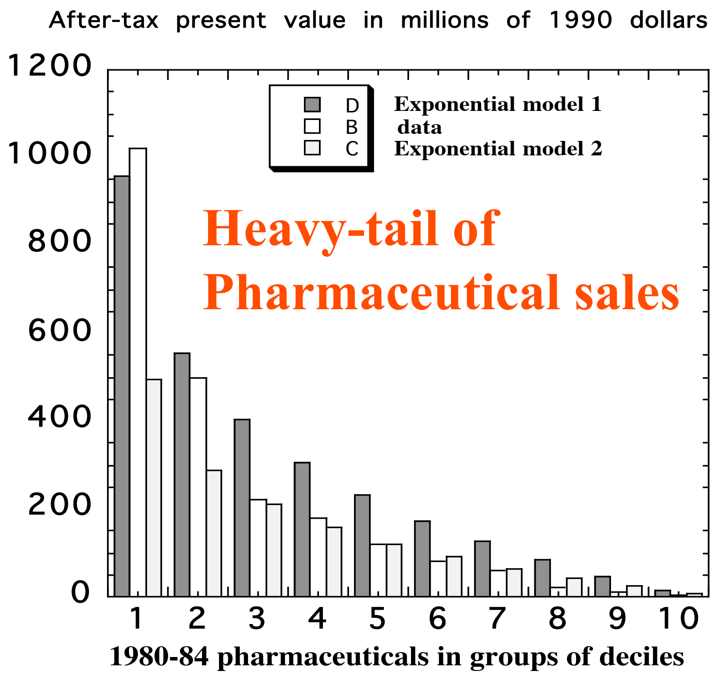




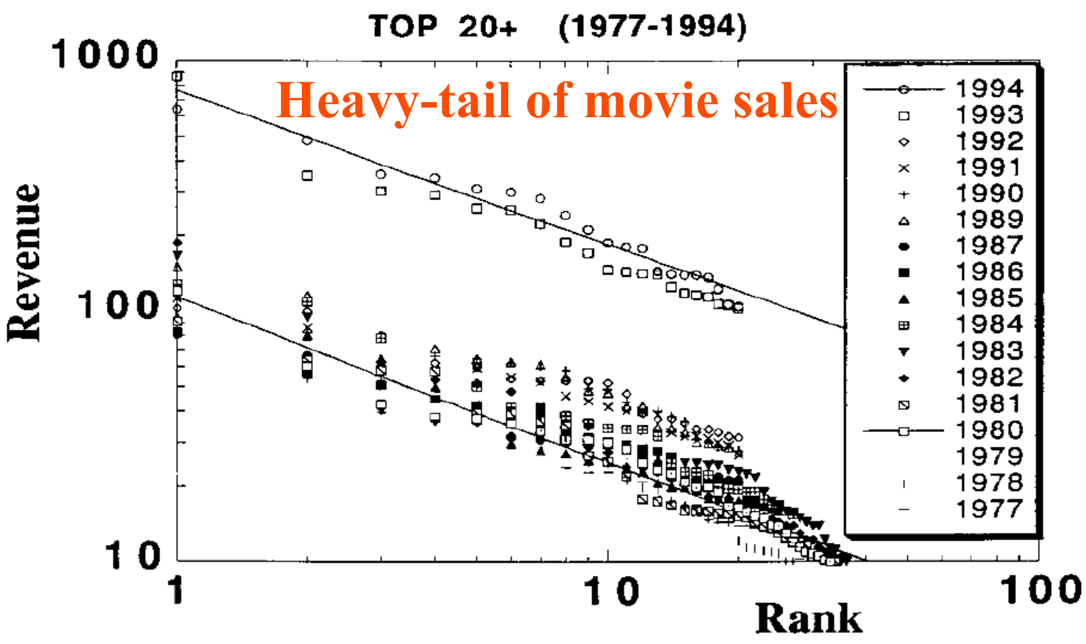
Volatility
0.01
0.009
0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0
Volatility
Jan 70
Dec 85



Complementary DF of DJ–daily pos.(line), n=14949 and neg. (pointwise), n=13464
Heavy-tail of price financial returns
Complementary sample DF
Absolute log-return, x
(a)

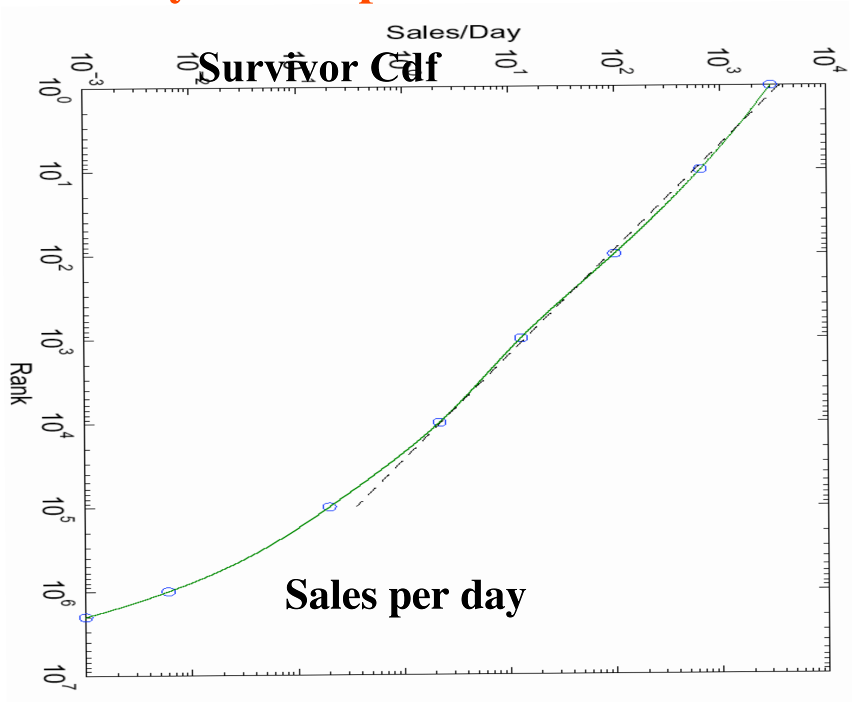


After-tax present value in millions of 1990 dollars
1200
1000
800
600
400
200
0
D Exponential model 1
B data
C Exponential model 2
Heavy-tail of Pharmaceutical sales
1 2 3 4 5 6 7 8 9 10
1980-84 pharmaceuticals in groups of deciles

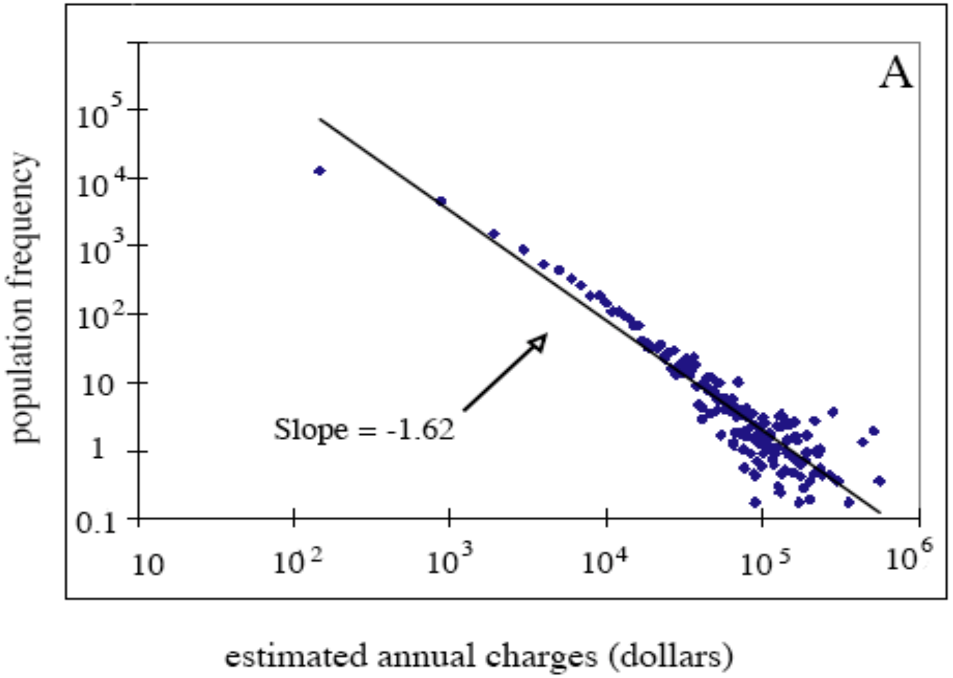


TOP 20+ (1977-1994)
Heavy-tail of movie sales
Revenue
Rank
1000
100
10
1
10
100
1994
1993
1992
1991
1990
1989
1987
1986
1985
1984
1983
1982
1981
1980
1979
1978
1977

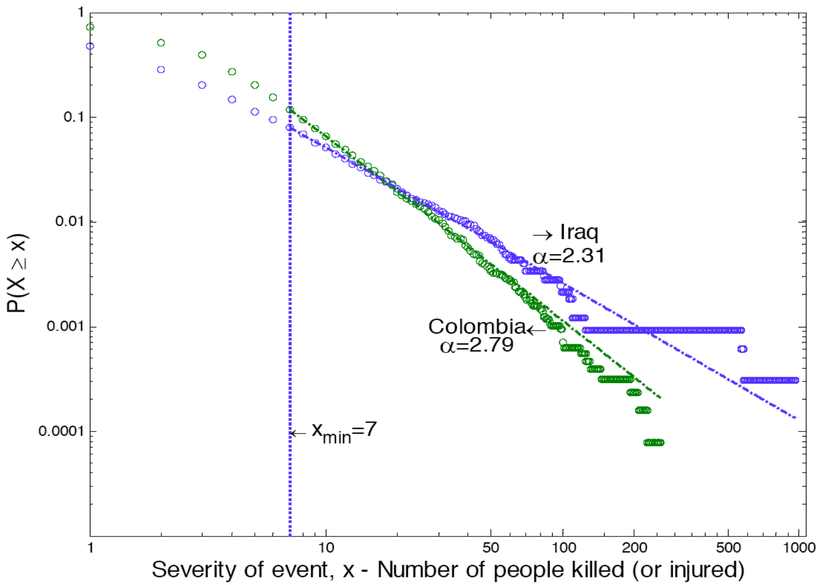
Heavy-tail of pdf of book sales



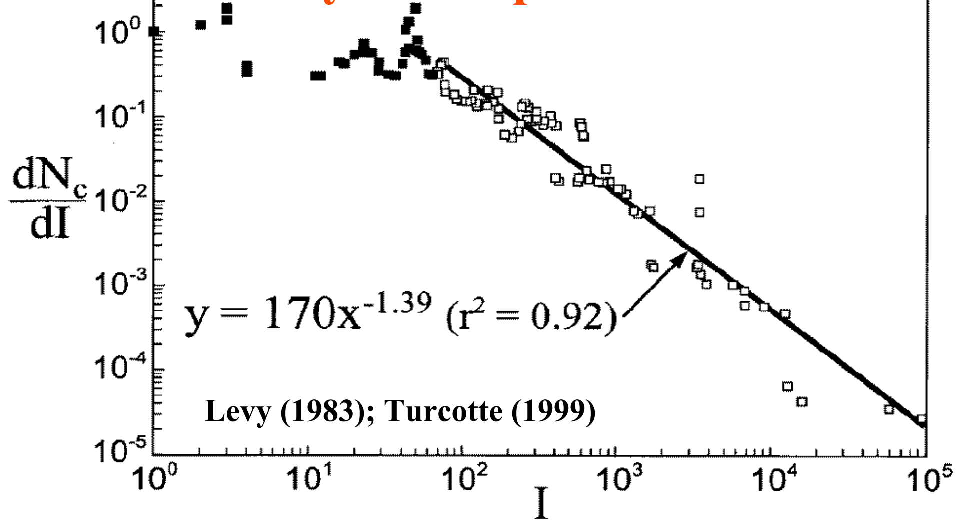
Heavy-tail of pdf of health care costs



Heavy-tail of pdf of terrorist intensity



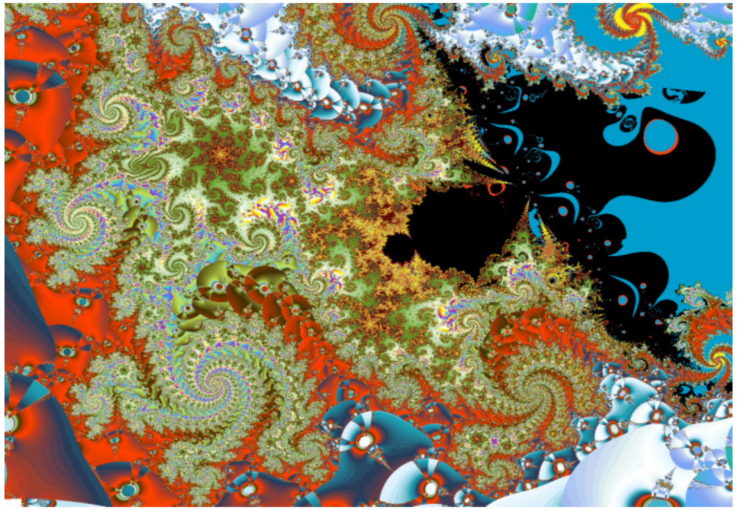
Heavy-tail of pdf of war sizes



Power laws and large risks

- Power laws are ubiquitous
- They express scale invariance
- Large and extreme events

  -example of height vs wealth
- Gaussian approach inappropriate: underestimation of the real risks
  - Markowitz mean-variance portfolio
  - Black-Scholes option pricing and hedging
  - Asset valuation (CAPM, APT, factor models)
  - Financial crashes



TWO PROBLEMS

✓What tail?

✓What risks?

What model(s) for the Distributions of Returns?

- Models in terms of Regularly varying distributions:

$$\Pr[r_t \geq x] = \mathcal{L}(x) \cdot x^{-\mu} \qquad (\mu \approx 3-4)$$

Longin (1996) , Lux (1996-2000), Pagan (1996), Gopikrishnan et *al.* (1998)…

- Models in terms of Weibull-like distributions:

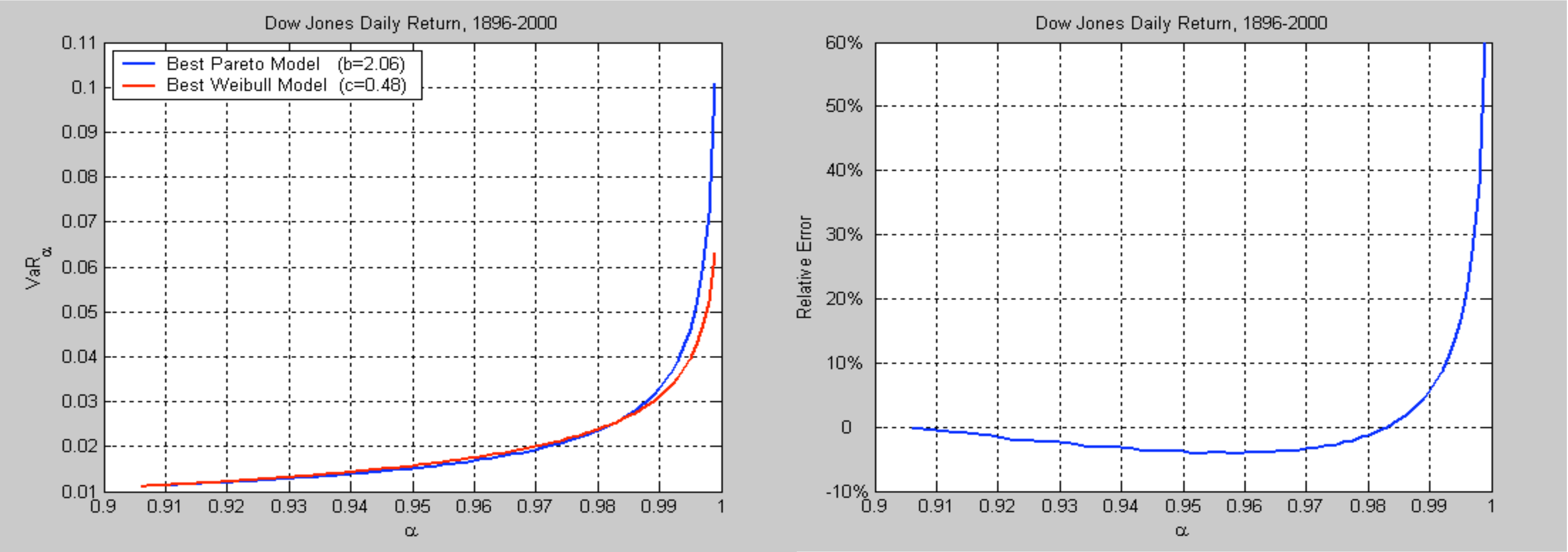
$$\Pr[r_t \geq x] = \exp[-\mathcal{L}(x) \cdot x^{c}] \qquad (c < 1)$$

Mantegna and Stanley (1994), Ebernlein et *al.*(1998), Gouriéroux and Jasiak (1998), Laherrère and Sornette (1999)…

Implications of the two models

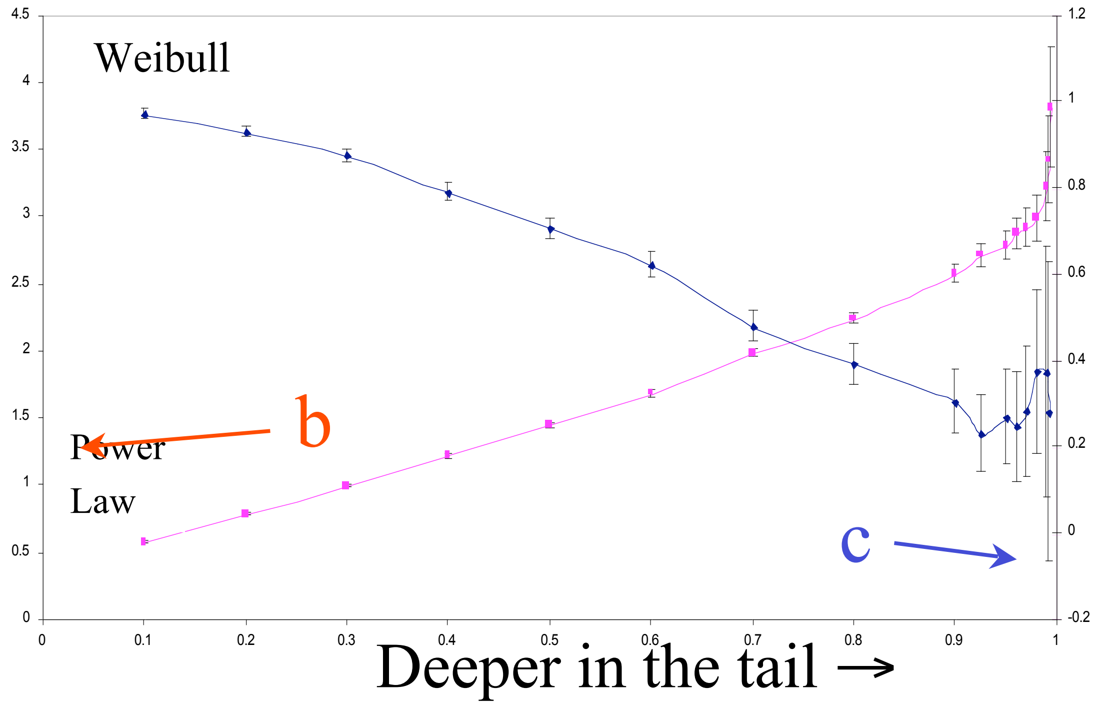
Practical consequences :

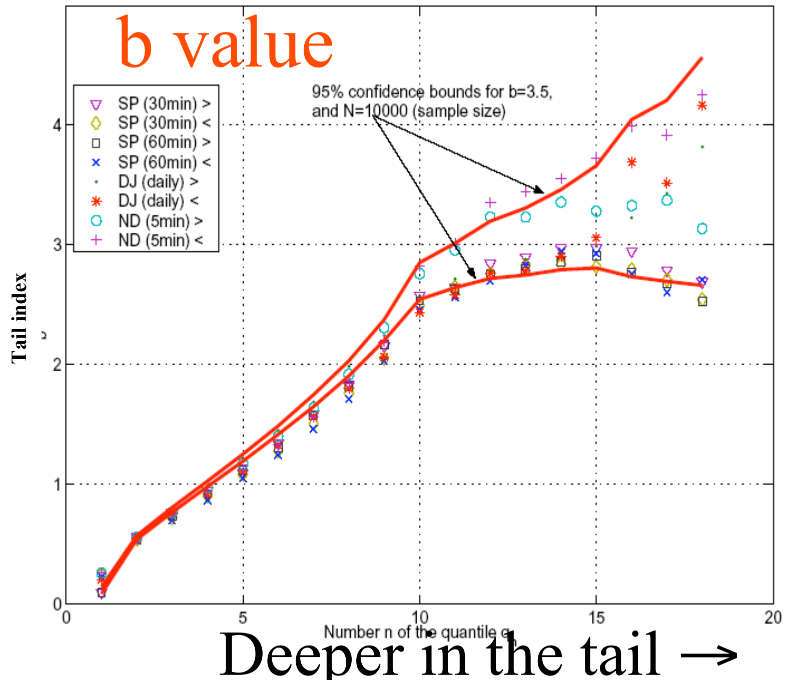
- Extreme risk assessment,
- Multi-moment asset pricing methods.



Main Results

- Power law model asymptotically embedded in SE model
- The SE model describes a much larger quantile domain
- For both models, the evolution of the parameters is not exhausted at the end of the range of available data.
- Different predictions for large risks (under- and over-estimation?)





$q_1=0$
$q_2=0.1$
$q_3=0.2$
$q_4=0.3$
$q_5=0.4$
$q_6=0.5$
$q_7=0.6$
$q_8=0.7$
$q_9=0.8$
$q_{10}=0.9$
$q_{11}=0.925$
$q_{12}=0.95$
$q_{13}=0.96$
$q_{14}=0.97$
$q_{15}=0.98$
$q_{16}=0.99$
$q_{17}=0.9925$
$q_{18}=0.995$
$q_{19}=0.999$
$q_{20}=0.9995$
$q_{21}=0.9999$

Y. Malevergne, V.F. Pisarenko and D. Sornette, Empirical Distributions of Log-Returns: between the Stretched Exponential and the Power Law? Quantitative Finance 5 (4), 379–401 (2005)

Value@Risk confidence level = 1%

Monthly Data		Realised losses <-VaR
>3 years	2528 Hedge funds (126100 mths)	**0.97%**
	5000 simulated portfolios of 100 funds	0.96%
	5000 simulated portfolios of 25 funds	0.97%
2 years	3067 Hedged Funds (156912 mths)	1.17%
1 year	3067 Hedged Funds (156912 mths)	1.53%

Track Value™

Software for funds of funds risk management

INSIGHT RESEARCH

Value@Risk confidence level = 5%

Monthly Data		Realised losses <-VaR
>3 years	2528 Hedge funds (126100 mths)	**4.86%**
	5000 simulated portfolios of 100 funds	4.86%
	5000 simulated portfolios of 25 funds	4.87%
2 years	3067 Hedged Funds (156912 mths)	5.09%
1 year	3067 Hedged Funds (156912 mths)	5.79%

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Heavy distribution of firm's capitalizations, lack of diversification and the pricing anomalies

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(2006)
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For arbitrary large economies, there may exist a new source of significant systematic risk, which has been totally neglected up to now but must be priced by the market. This is due to

(i) The "self-consistency" condition that the market portfolio (or factors) is constituted of the assets whose returns it is supposed to explain

(ii) the distribution of the capitalization of firms is sufficiently heavy-tailed.

New risks in CAPM, APT and other factor models (size effect and book-to-market effect)

Hypotheses

- N risky assets and one risk-free asset,
- the excess returns on the risky assets over the risk-free rate write :

$$\vec{r}_t = \vec{\beta} \cdot r_m(t) + \vec{\varepsilon}(t),$$

- r_m and $\vec{\varepsilon}$ uncorrelated, and $\mathrm{E}\left[\vec{\varepsilon}\right] = 0$,
- complete market :

$$r_m(t) = \sum_{i=1}^{N} w_{m,i}(t) \cdot r_i(t) = \vec{w}_m(t)' \cdot \vec{r}(t).$$

The internal consistency condition

$$\vec{r}_t = \vec{\beta} \cdot r_m(t) + \vec{\varepsilon}(t)$$

$$\Downarrow$$

$$r_m(t) \left[1 - \vec{w}_m(t)' \cdot \vec{\beta} \right] = \vec{w}_m(t)' \cdot \vec{\varepsilon}(t)$$

$$\Downarrow$$

$$\boxed{\vec{w}_m(t)' \cdot \vec{\beta} = 1 \quad \text{and} \quad \vec{w}_m(t)' \cdot \vec{\varepsilon} = 0}$$

There is a "self-consistency" factor f (Fama 1973)

- The condition $\vec{w}_m \cdot \vec{\varepsilon} = 0$ shows that the ε_i's are *correlated*.
- Fama (1973), Sharpe (1992) : these correlations go to zero in the limit of an infinite number of assets.

Is it always true ???

Proposition

The asymptotic behavior of the excess return over the risk free interest rate of the equally-weighted portfolio is as follows :

1. *provided that* $\mathrm{E}[S] < \infty$*, or that* S *is regularly varying with tail index* $\mu = 1$*,*

$$r_e = \beta_e \cdot r_m + o_p(1) \ ;$$

2. *provided that* S *admits a regularly varying distribution with tail index* $\mu \in (0, 1)$*,*

$$r_e = \beta_e \cdot r_m + \mathrm{E}[\gamma] \cdot \frac{\xi_N}{\zeta_N} + o_p(1) \ ,$$

where ξ_N *and* ζ_N *are two sequences of dependent random variables with distributions given by two stable laws with the same tail index* μ*.*

Concretely: well-diversified portfolios cannot be well-diversified

Variance of the equally weighted portfolio

It can be shown that

$$\mathrm{Var} r_e \simeq \beta_e{}^2 \cdot \mathrm{Var} r_m + K \cdot H_N$$

for some $K > 0$ that depends on the distributional properties of the η_i's and γ_i's.

Asymptotic behavior of H_N ? ? ?

Herfindahl index (participation ratio) of market portfolio

$H_N = \Sigma_{i-1}^{N} \ \omega_i^2 \quad \sim$ 1/N (well-diversified) to 1 (concentrated)

Proposition

The asymptotic behavior of H_N is as follows :

1. *provided that* $\mathrm{E}\left[S^2\right] < \infty$

$$H_N = O_p\left(1/N\right) \;,$$

2. *provided that* $\mathrm{E}\left[S\right] < \infty$ *and admits a regularly varying distribution with tail index* $\mu \in (1, 2)$,

$$H_N = O_p\left(1/N^{2(1-1/\mu)}\right) \;,$$

3. *provided that* $\mathrm{E}\left[S\right] = \infty$,

$$\boxed{H_N \nrightarrow 0.}$$

Concretely: H=0.04-0.05 $\Rightarrow$ N_{eff} = 20-25 (and not 10000)

Case μ=1

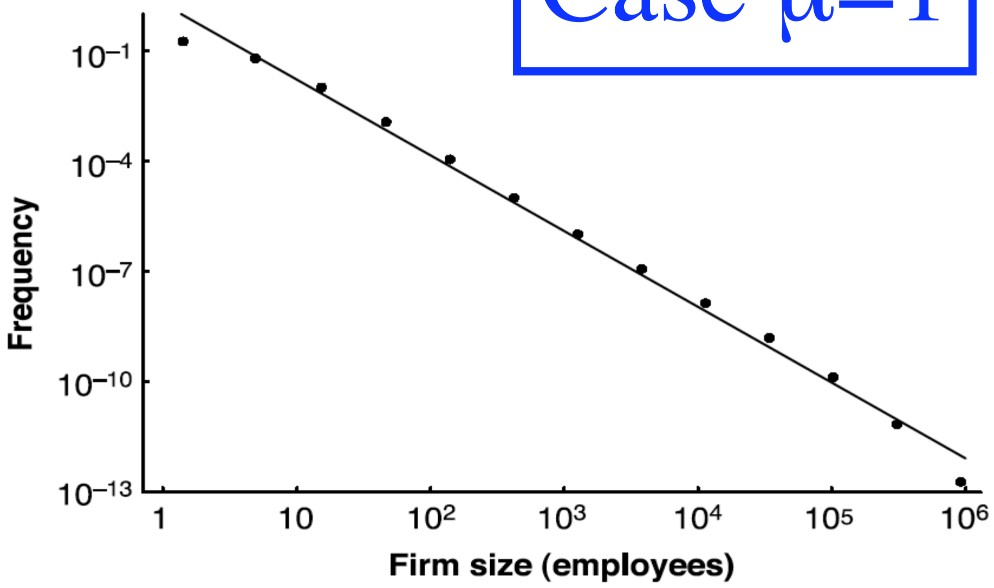


Fig. 1. Histogram of U.S. firm sizes, by employees. Data are for 1997 from the U.S. Census Bureau, tabulated in bins having width increasing in powers of three (*30*). The solid line is the OLS regression line through the data, and it has a slope of 2.059 (SE = 0.054; adjusted R^2 = 0.992), meaning that α = 1.059; maximum likelihood and nonparametric methods yield similar results. The data are slightly concave to the origin in log-log coordinates, reflecting finite size cutoffs at the limits of very small and very large firms.

Zipf, Gabaix *et al.*, Axtell, Simon *et al.* :

$$\Pr[S \geq s] \sim \frac{1}{s}, \qquad \text{for large } s.$$

- $r_e = \beta_e \cdot r_m + O_p(1/\ln N)$,
- $\mathrm{Var} r_e = {\beta_e}^2 \cdot \mathrm{Var} r_m + O_p\left(1/\ln^2 N\right)$,
- $H_N = O_p\left(1/\ln^2 N\right)$.

US stock market (Amex + Nasdaq + Nyse) : $N \sim 7000 - 8000$

Non-diversified risk : $\sim 10 - 20\%$ of the total risk

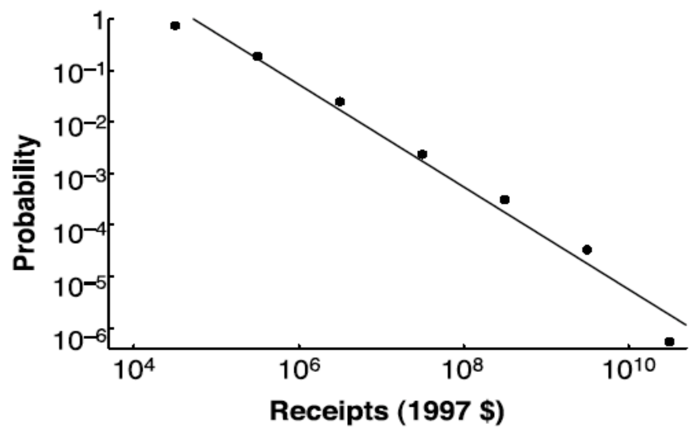


Fig. 2. Tail cumulative distribution function of U.S. firm sizes, by receipts in dollars. Data are for 1997 from the U.S. Census Bureau, tabulated in bins whose width increases in powers of 10. The solid line is the OLS regression line through the data and has slope of 0.994 (SE = 0.064; adjusted R^2 = 0.976).

Application to the APT (Arbitrage Pricing Theory)

$$\vec{r}_t = \sum_{i=1}^{q} \vec{\beta}_i \phi_i(t) + \vec{\varepsilon}_t$$

- provided that $\mathrm{E}[S] < \infty$, the correlation between the disturbance terms ε_i can be neglected

$$\Downarrow$$

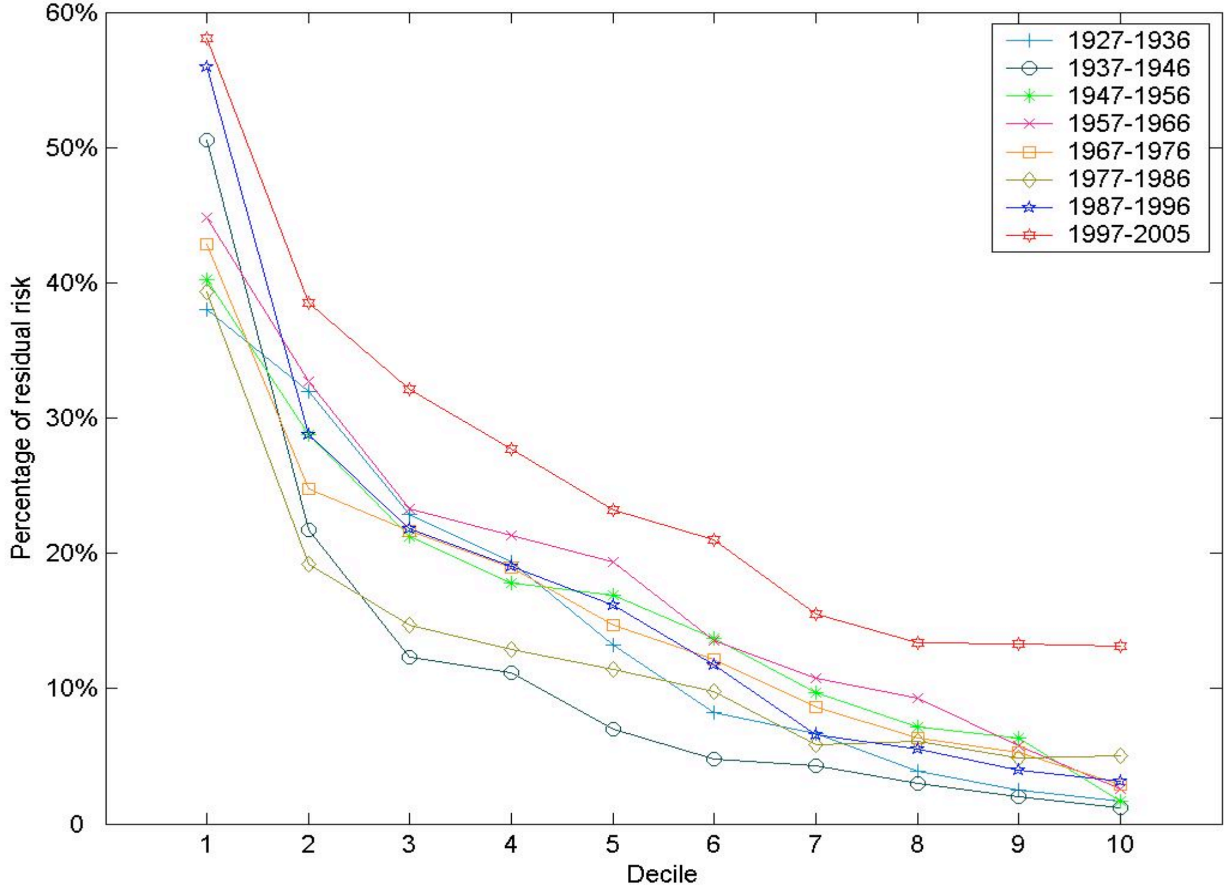
$$\text{APT applies : } \mathrm{E}\left[\vec{r}\right] = \vec{\beta} \cdot \mathrm{E}[r_m]$$

- when $\mathrm{E}[S] = \infty$, the "self-consistent" factor f introduces an additional risk that must be remunerated by the market :

$$\mathrm{E}\left[\vec{r}\right] \simeq \vec{\beta} \cdot \mathrm{E}[r_m] + \left[\vec{\gamma} - \left(\vec{w}'_m \cdot \vec{\gamma}\right) \cdot \vec{\beta}\right] \cdot \mathrm{E}[r_{ICC}]$$

$$\vec{\varepsilon}_t = \vec{\gamma} \cdot f_t + \vec{\eta}_t$$

Large book-to-market (value) firms have low beta's $\Rightarrow$ larger returns (larger risks?)



$$\vec{r}_t = \sum_{i=1}^{q} \vec{\beta}_i \phi_i(t) + \vec{\varepsilon}_t$$

$$\vec{\varepsilon}_t = \vec{\gamma} \cdot f_t + \vec{\eta}_t$$

Factor loading γ
indep. of
Firm size S

$\Downarrow$

No size effect

Assumption : Small caps are more sensitive to f than large caps

$\gamma (> 0)$ is *Stochastically Decreasing* in S $\Longrightarrow$ Size effect

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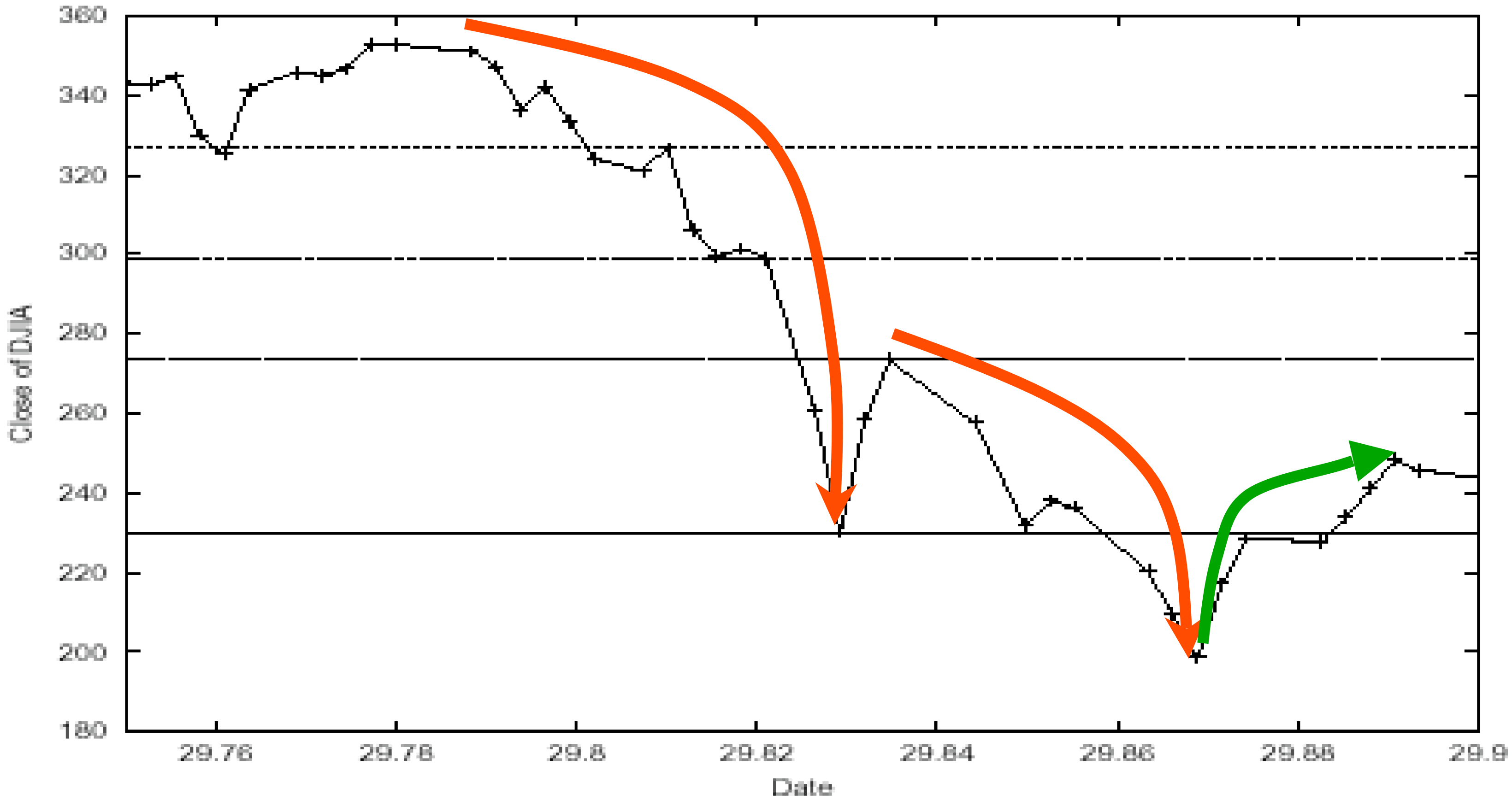
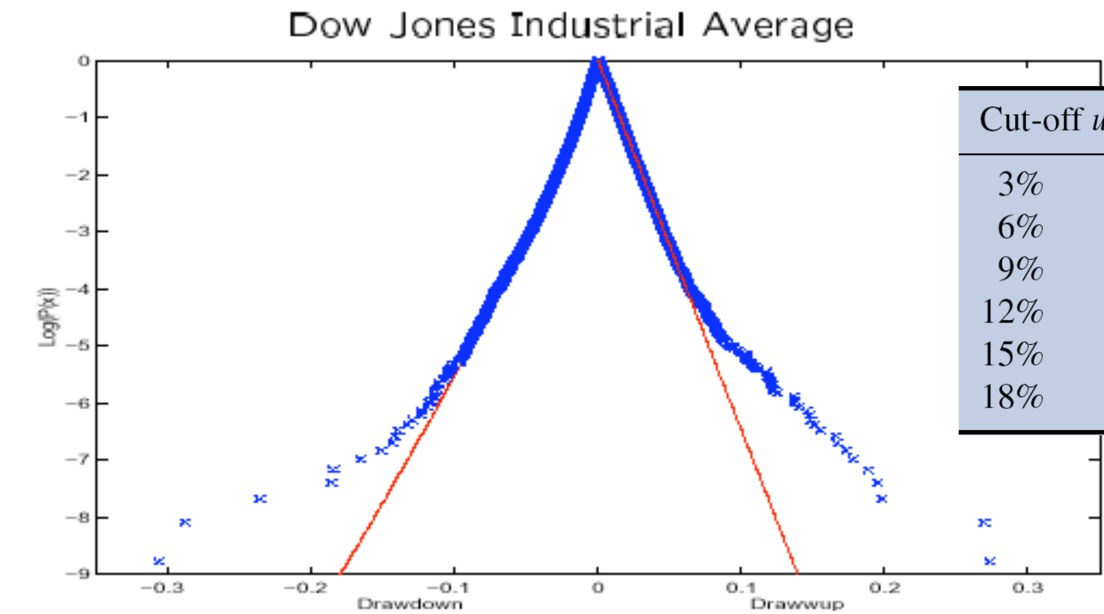
Better risk measure: drawdowns

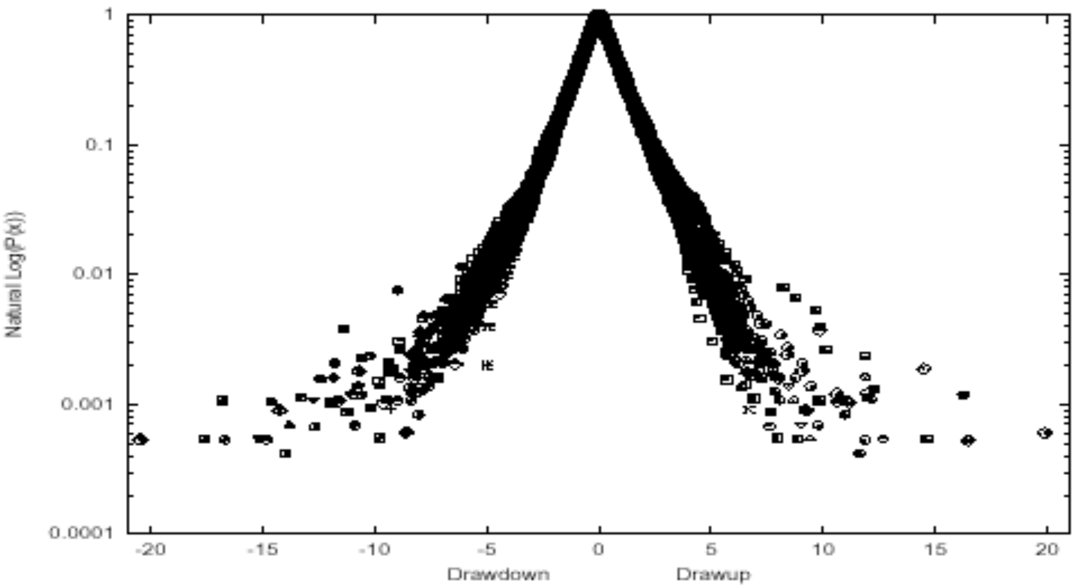


Outliers, Kings, "Black swans"

(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%



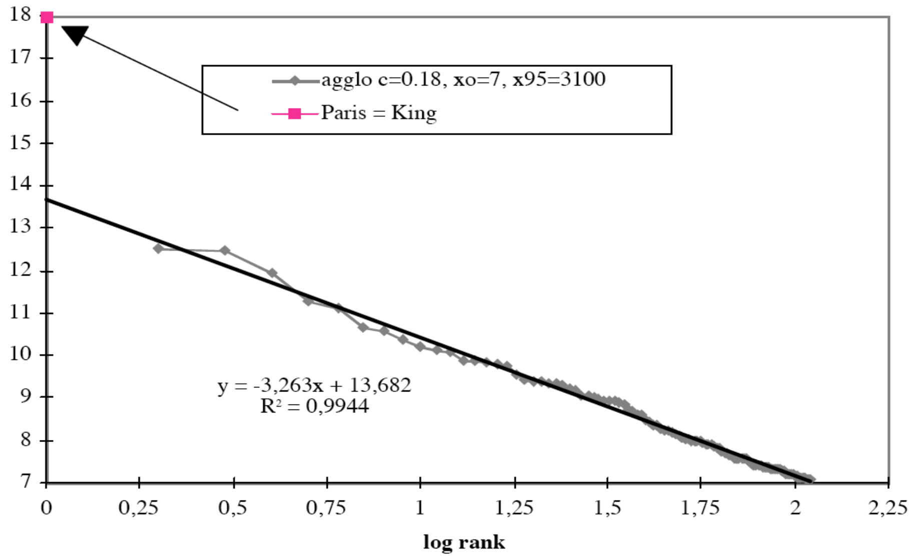


Fig. 7. French agglomerations: stretched exponential and "King effect".

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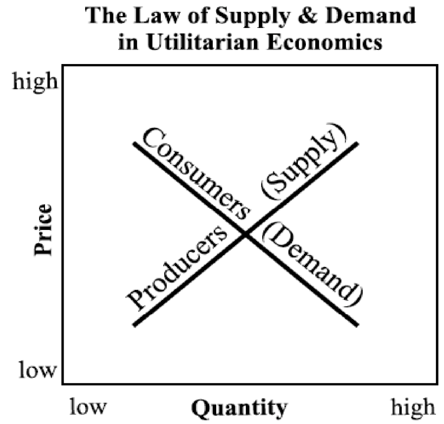
Feedbacks: negative but also POSITIVE

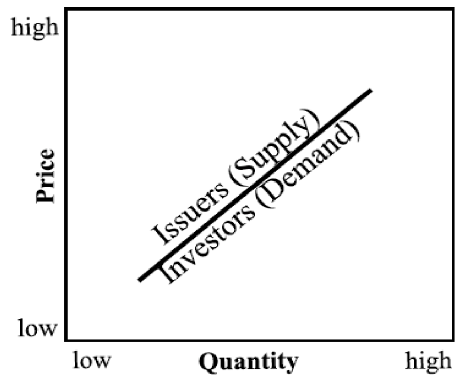
•**Systemic risks: "In handling systemic issues, it will be necessary to address, on the one hand, risks to confidence in the financial system and contagion to otherwise sound institutions, and, on the other hand, the need to minimize the distortion of market signals and discipline." (Basle Committee on Banking Supervision)**

Mechanisms for positive feedbacks in the stock markets

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

- Behavioral mechanisms for positive feedbacks
  1. It is rational to imitate
  2. It is the highest cognitive task to imitate
  3. We mostly learn by imitation
  4. The concept of "CONVENTION" (Orléan)





The problem of predictability

•Algorithmic complexity theory: most complex systems have been proved to be computationally irreducible, i.e. the only way to decide about their evolution is to actually let them evolve in time.

•The future time evolution of most complex systems appears inherently unpredictable… BUT…

… lesson from PHYSICS (RG)

Lesson from bottom-up hierarchical grouping

Computational Irreducibility and the Predictability of Complex Physical Systems

256 nearest neighbor 1D cellular automata (Wolfram)

Class 3 → Class 1

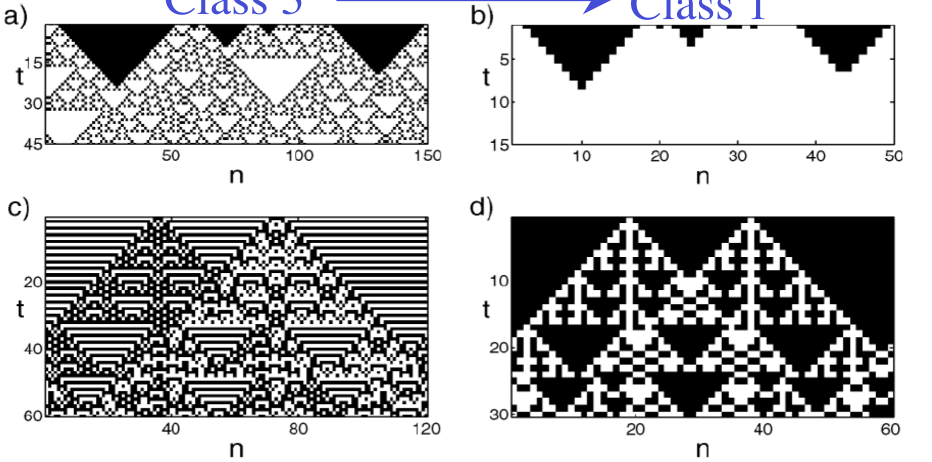


FIG. 1. Examples of coarse-graining transitions. (a) and (b) show coarse-graining rule 146 by rule 128. (a) shows results of running rule 146. The top line is the initial condition and time progress from top to bottom. (b) shows the results of running rule 128 with the coarse-grained initial condition from (a). (c) and (d) show coarse-graining rule 105 by rule 150. (c) shows rule 105 and (d) shows rule 150.

$$C(f_A^{T\cdot t}a(0)) = f_B^t C(a(0)).$$

Namely, running the original CA for Tt time steps and then coarse graining is equivalent to coarse graining the initial condition and then running the modified CA t time steps. The constant T is a time scale associated with the coarse graining.

240 coarse-grainable

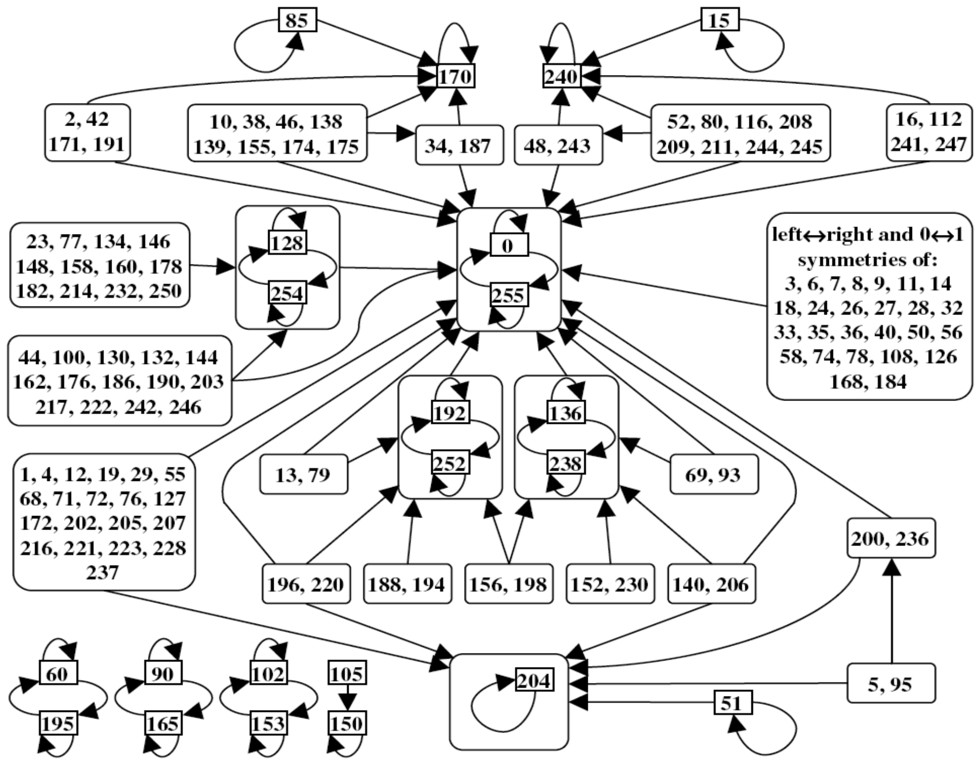
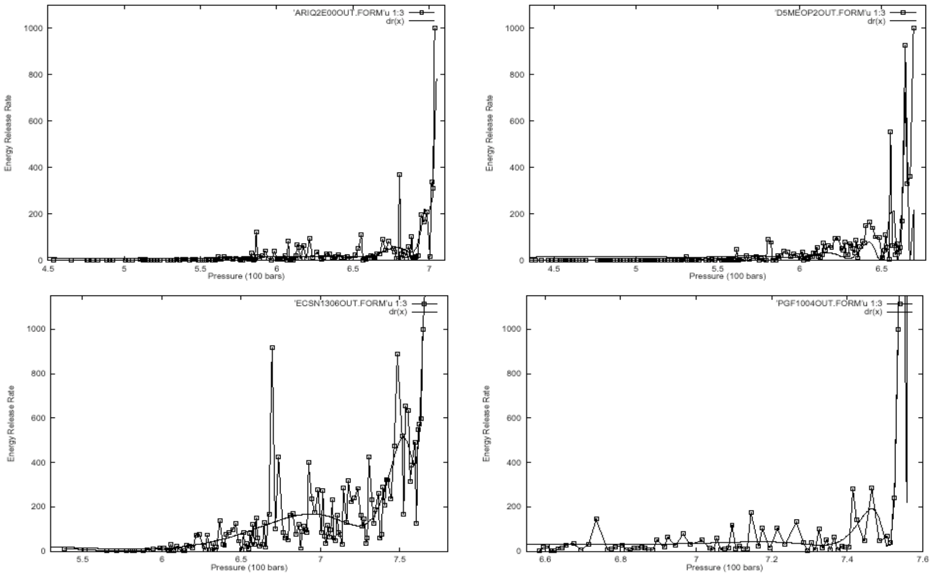


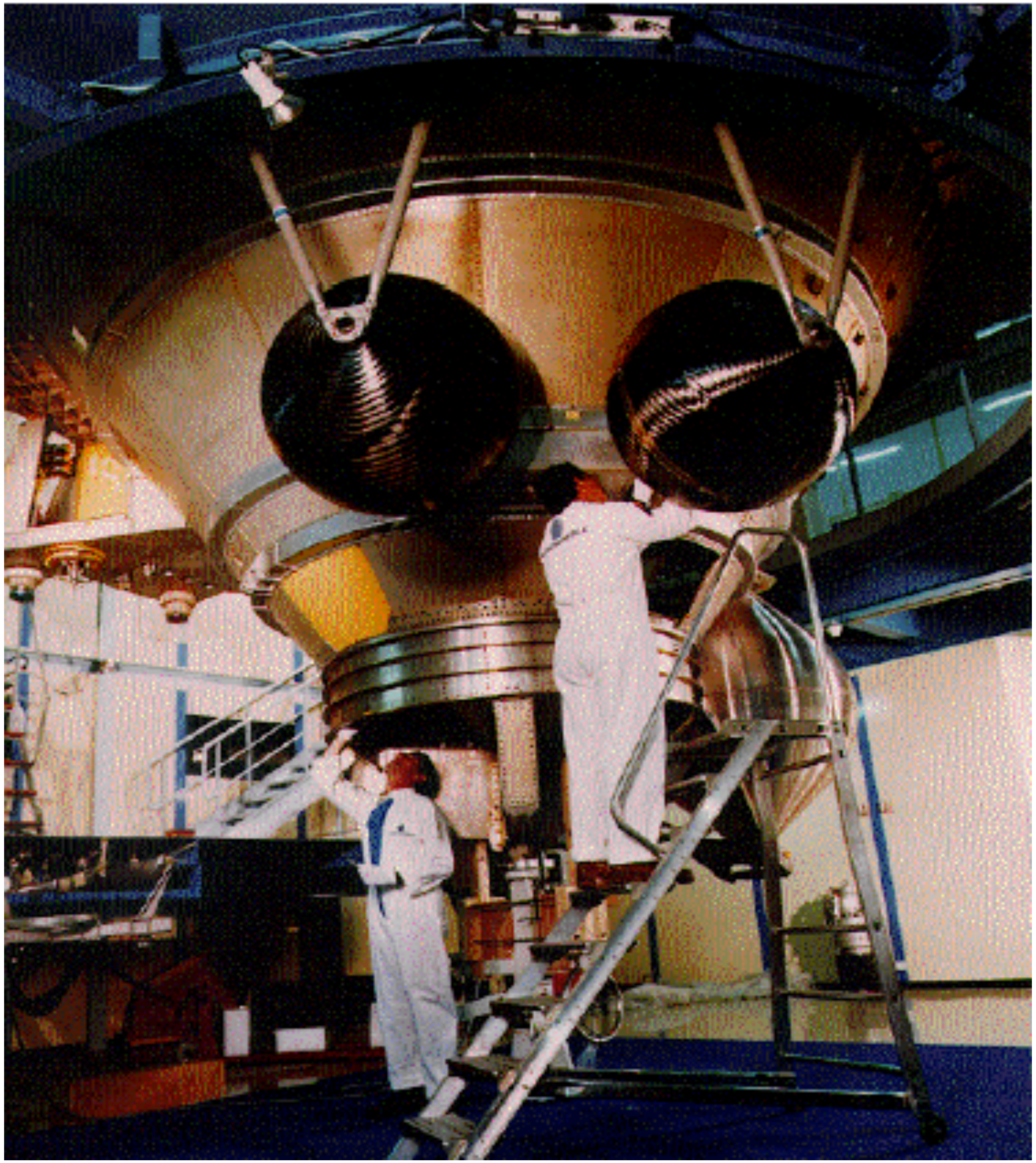
FIG. 2. Coarse-graining transitions within the family of 256 elementary CA. Only transitions with a cell block size $N = 2$, 3, and 4 are shown. An arrow indicates that the origin rules can be coarse grained by the target rules and may correspond to several choices of N and P.

Coarse-graining rule 110: CIR => C1

Navot Israeli and Nigel Goldenfeld PhysRevLett.92.074105

Strategy: look at the forest rather than at the tree



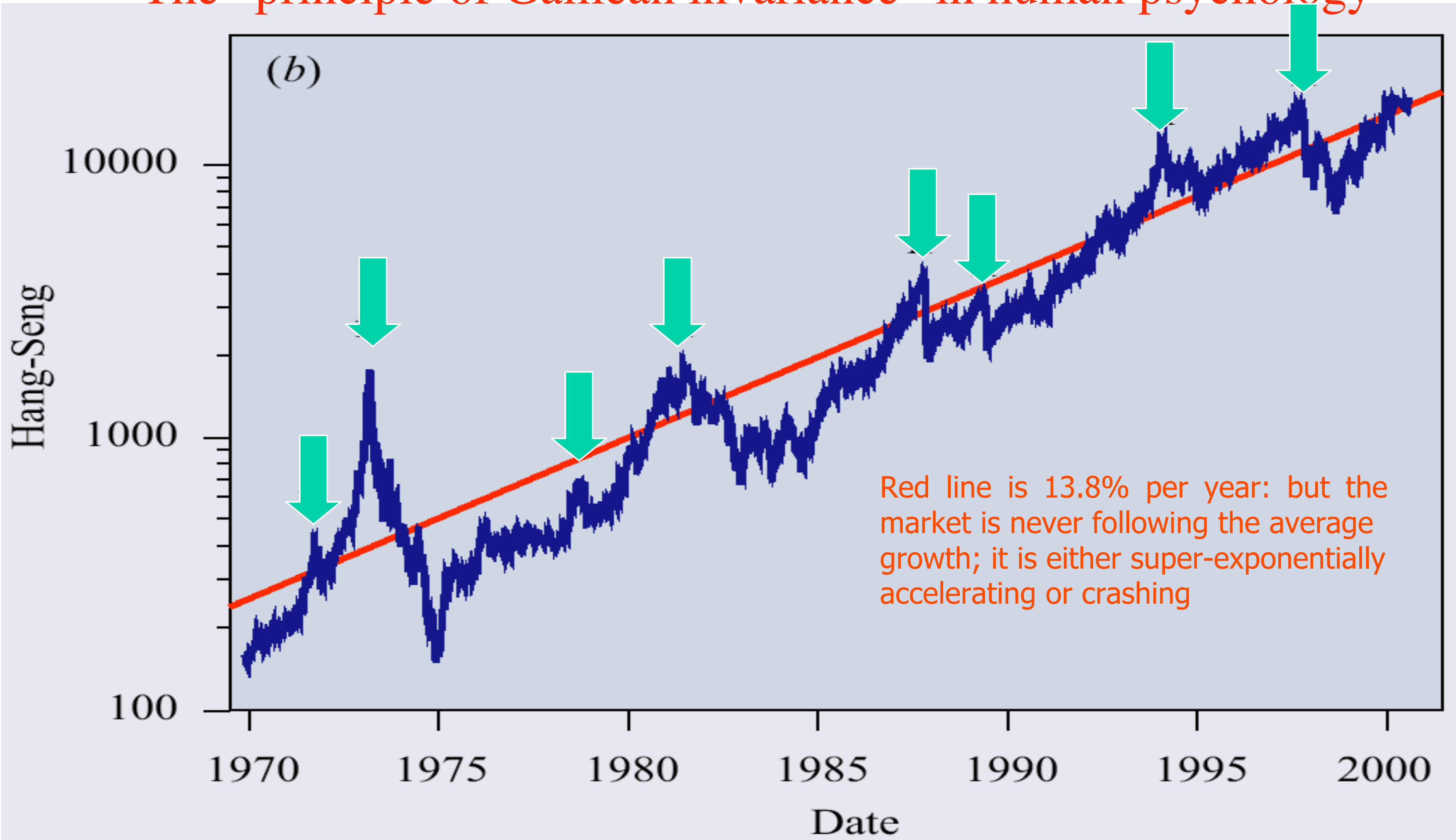


Our prediction system is now used in the industrial phase as the standard testing procedure.

EADS LAUNCH VEHICLES

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

Psychology of Investors and Entrepreneurs
The "principle of Galilean invariance" in human psychology



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

Figure 12. Hong Kong crash of 1971. The parameter values of the fit with equation (3) are $A \approx 569$, $B \approx -340$, $C \approx 17$, $\beta \approx 0.20$, $t_c \approx 1971.73$, $\phi \approx -0.5$ and $\omega \approx 4.3$.

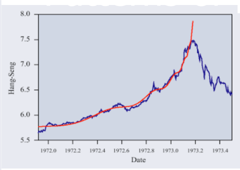


Figure 11. Hong Kong crash of 1973. The parameter values of the fit with equation (3) are $A \approx 10.8$, $B \approx -5.0$, $C \approx -0.05$, $\beta \approx 0.11$, $t_c \approx 1973.19$, $\phi \approx -0.05$ and $\omega \approx 8.7$. Note that for this bubble, it is the logarithm of the index which is used in the fit.

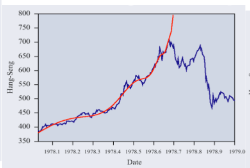


Figure 10. Hong Kong crash of 1978. The parameter values of the fit with equation (3) are $A \approx 824$, $B \approx -538$, $C \approx -28.0$, $\beta \approx 0.40$, $t_c \approx 1978.69$, $\phi \approx -0.17$ and $\omega \approx 5.9$.

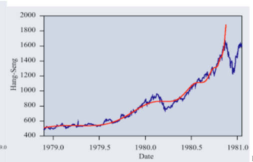


Figure 9. Hong Kong crash of 1980. The parameter values of the fit with equation (3) are $A \approx 2006$, $B \approx -1286$, $C \approx -55.5$, $\beta \approx 0.29$, $t_c \approx 1980.88$, $\phi \approx 1.8$ and $\omega \approx 7.2$.

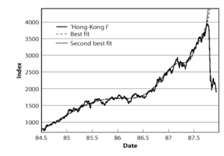
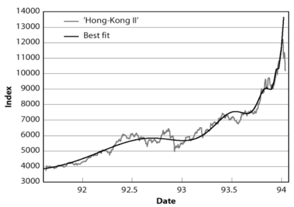


FIG. 7.9. Hong Kong stock market bubble ending with the crash of October 1987. On October 19, 1987, the Hang Seng index closed at 3362.4. On October 26, it closed at 2241.7, corresponding to a loss of 33.3%. See Table 7.1 for the parameter values of the fit with equation (15). Note that the two fits are almost indistinguishable except at the very end of the bubble. Reproduced from [218].

Figure 8. Hong Kong crash of 1989. The parameter values of the fit with equation (3) are $A \approx 3515$, $B \approx -1072$, $C \approx 225$, $\beta \approx 0.57$, $t_c \approx 1989.46$, $\phi \approx 0.5$ and $\omega \approx 4.9$.



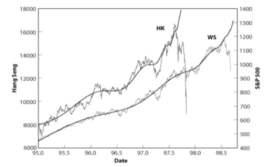


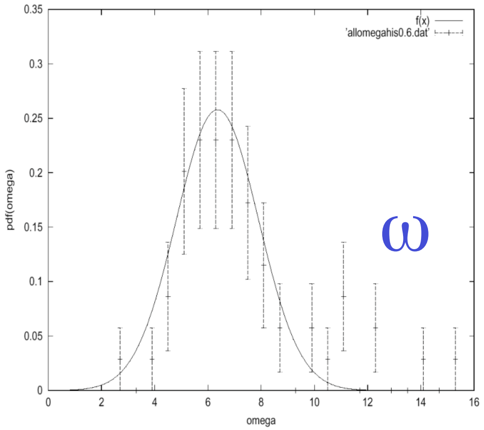
FIG. 7.17. The Hang Seng index prior to the October 1997 crash on the Hong Kong Stock Exchange already shown in Figure 7.11 and the S&P 500 stock market index prior to the crash on Wall Street in August 1998. The fit to the S&P 500 index is equation (15) with $A_2 \approx 1321$, $B_2 \approx -402$, $B_2C \approx 19.7$, $m_2 \approx 0.60$, $t_c \approx 98.72$, $\phi \approx 0.75$, and $\omega \approx 6.4$. Reproduced from [221].

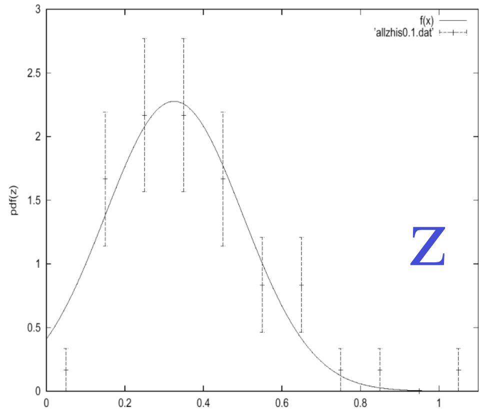
Endogenous vs exogenous crashes

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**

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





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

Results: In worldwide stock markets + currencies + bonds

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

A. Johansen and D. Sornette, Shocks, Crash and Bubbles in Financial Markets, in press in Brussels Economic Review on Non-linear Financial Analysis 149-2/Summer 2007 (http://arXiv.org/abs/cond-mat/0210509)

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.

- What tail risks? Power law vs Stretched exponentials
- Heavy-tail of PDF of firm sizes and new risk factors
- Power laws? No: Better measures of risks = “kings”
- Imitation, herding, conventions: bubbles and crashes
- Illusion of control

The illusion of control

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

✓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 (Don Guyon, 1909)

✓Many academic works suggest that most managers underperform "buy-and-hold" strategy; persistence of winners is very rare, etc.

✓Rats beat humans in simple games: 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! (T. Grandin and C. Johnson, Animals in translation (Scribner, New York, 2005)

The illusion of control: Minority game

(J. Satinover and D. Sornette, 2006)

Total action of agents $A^{\mu}(t) \equiv \sum_i a_i^{\mu}(t)$

Parameters: m, s, τ, N

Price equation

$$\log(P(t+1)) = \log(P(t)) + A^{\mu}(t+1/2)/N$$

Example of strategy

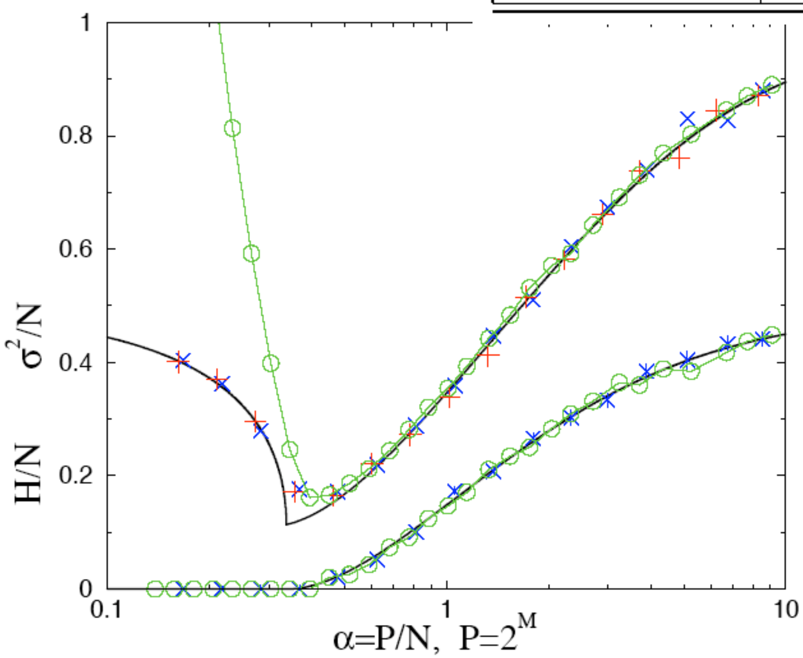
signal (μ)	*prediction*
000	0
001	0
010	1
011	0
100	1
101	0
110	1
111	0

MG payoff of strategy i :

$$g_i(t) = -a_i(t)A(t)$$

✓Inductive reasoning

✓Minority mechanism



The illusion of control: Minority game example

(J. Satinover and D. Sornette, 2006)

Parameters: m, s, τ, N

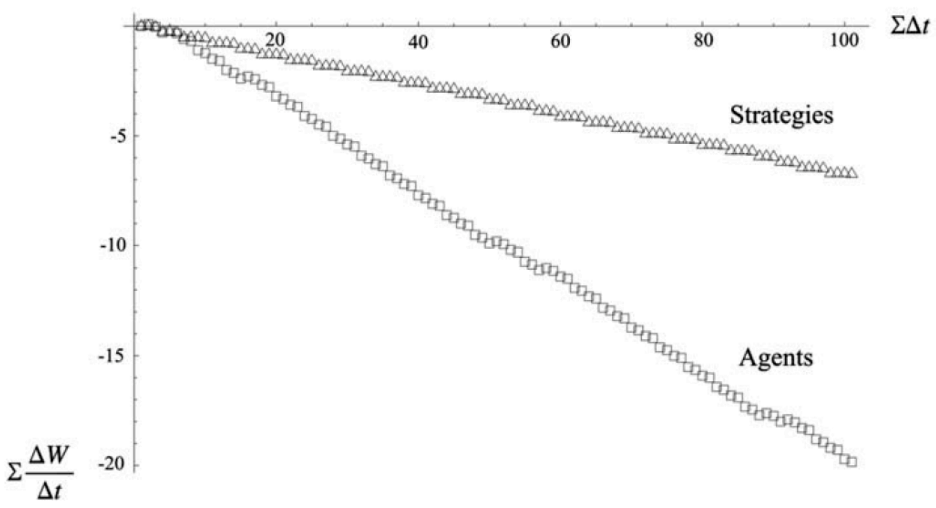
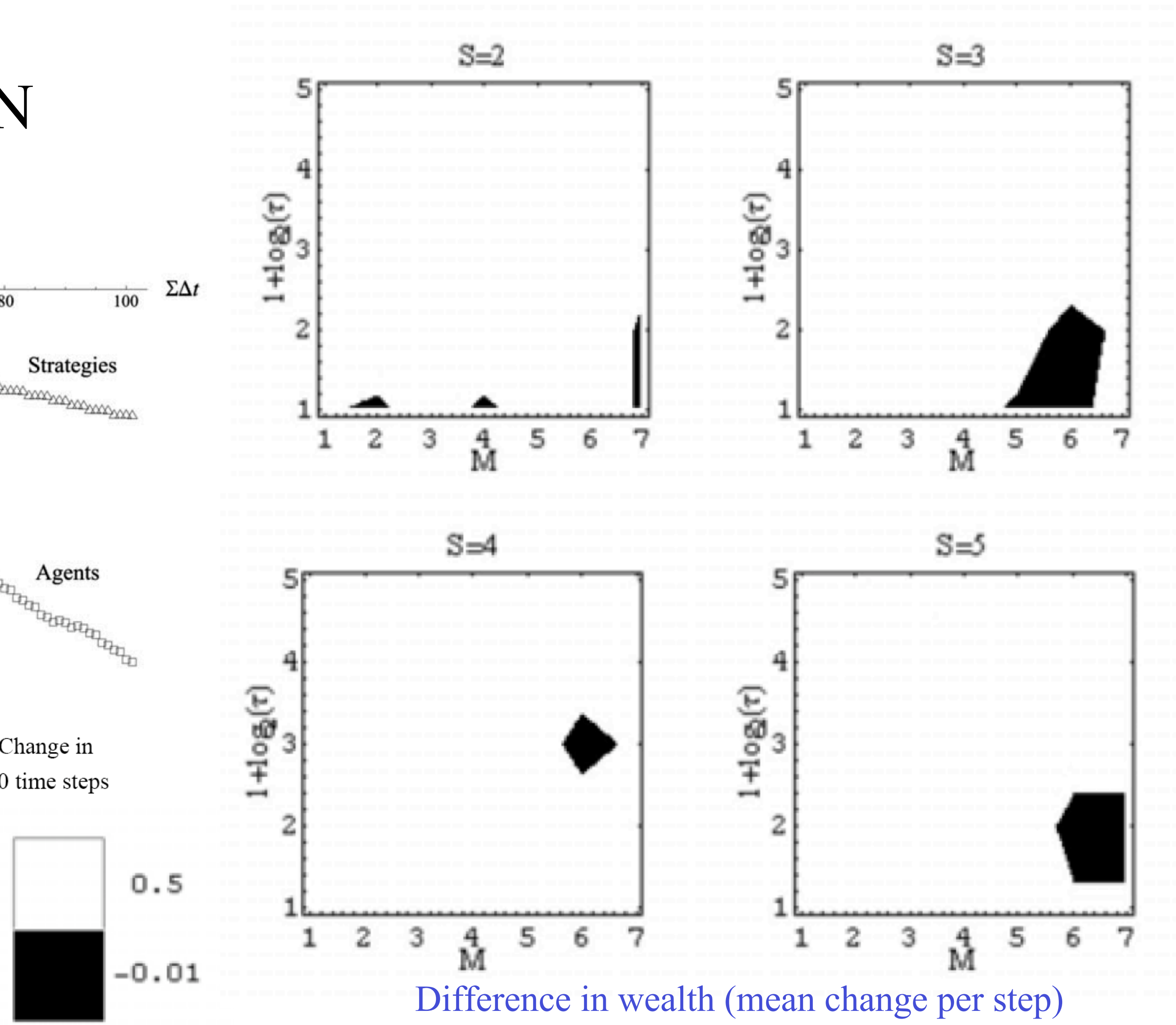


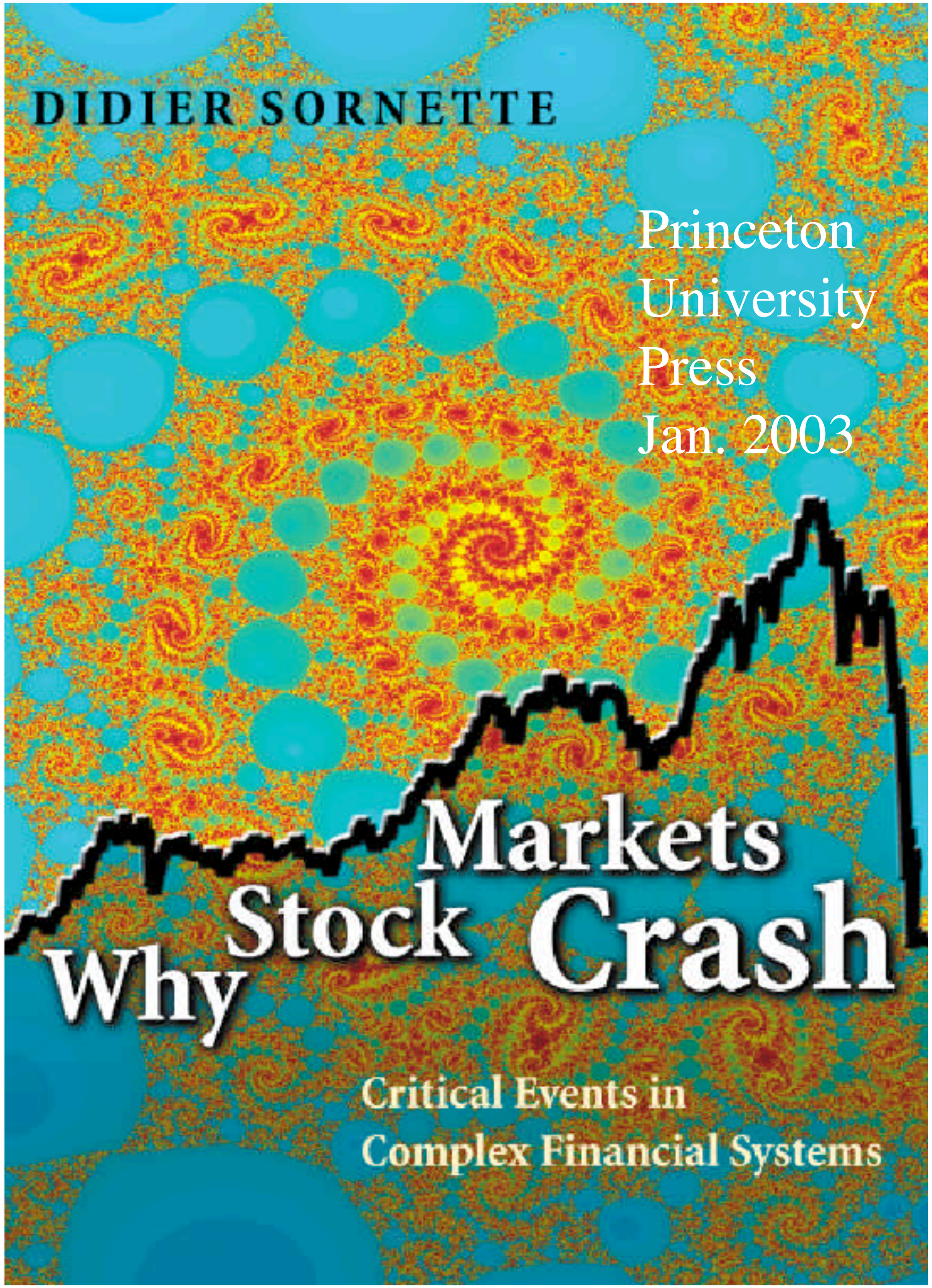
Figure 2: Mean Strategy versus Agent Cumulative Change in Wealth in the THMG. $\{m,S,N\}=\{2,2,31\}$; 100 time steps

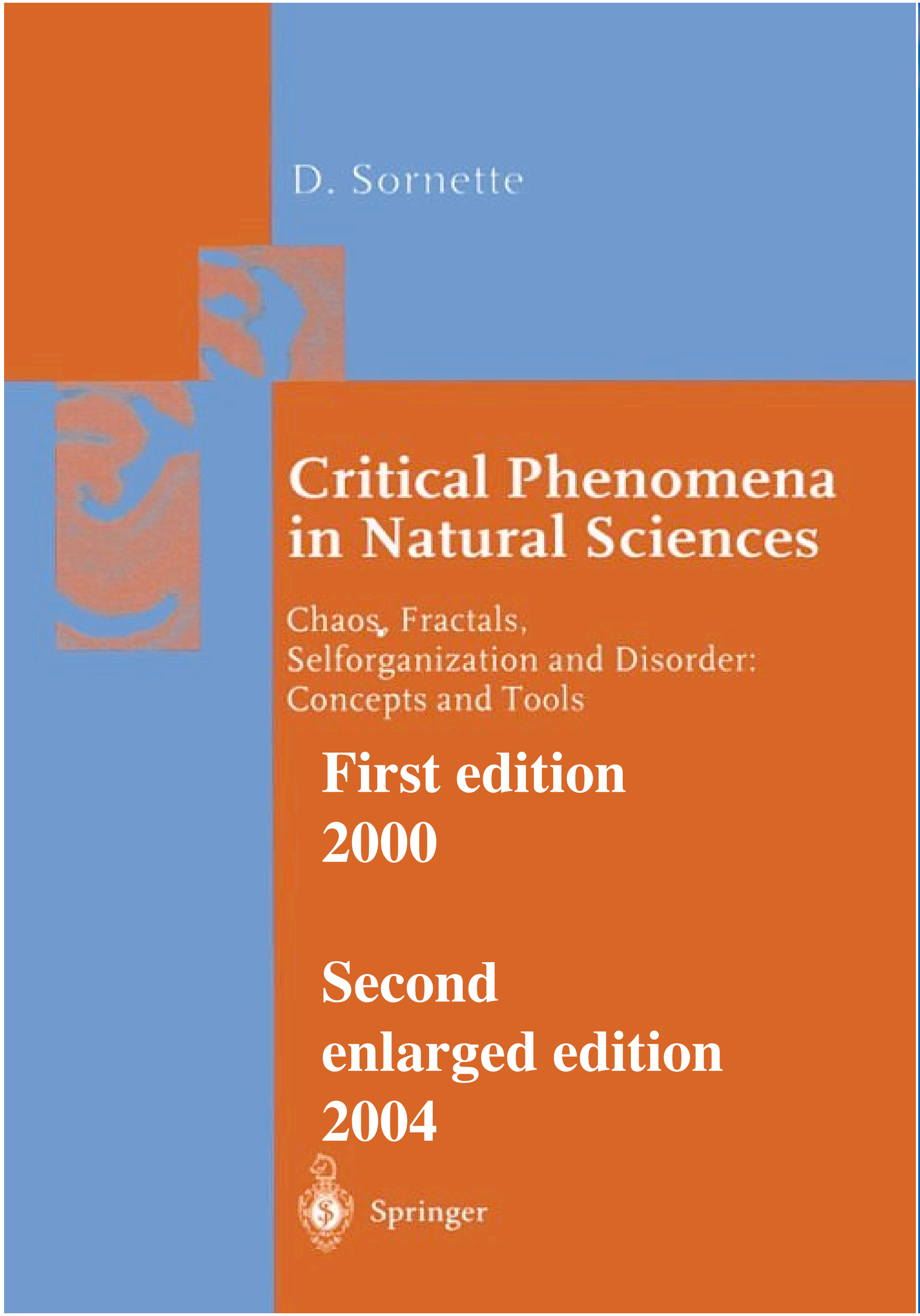


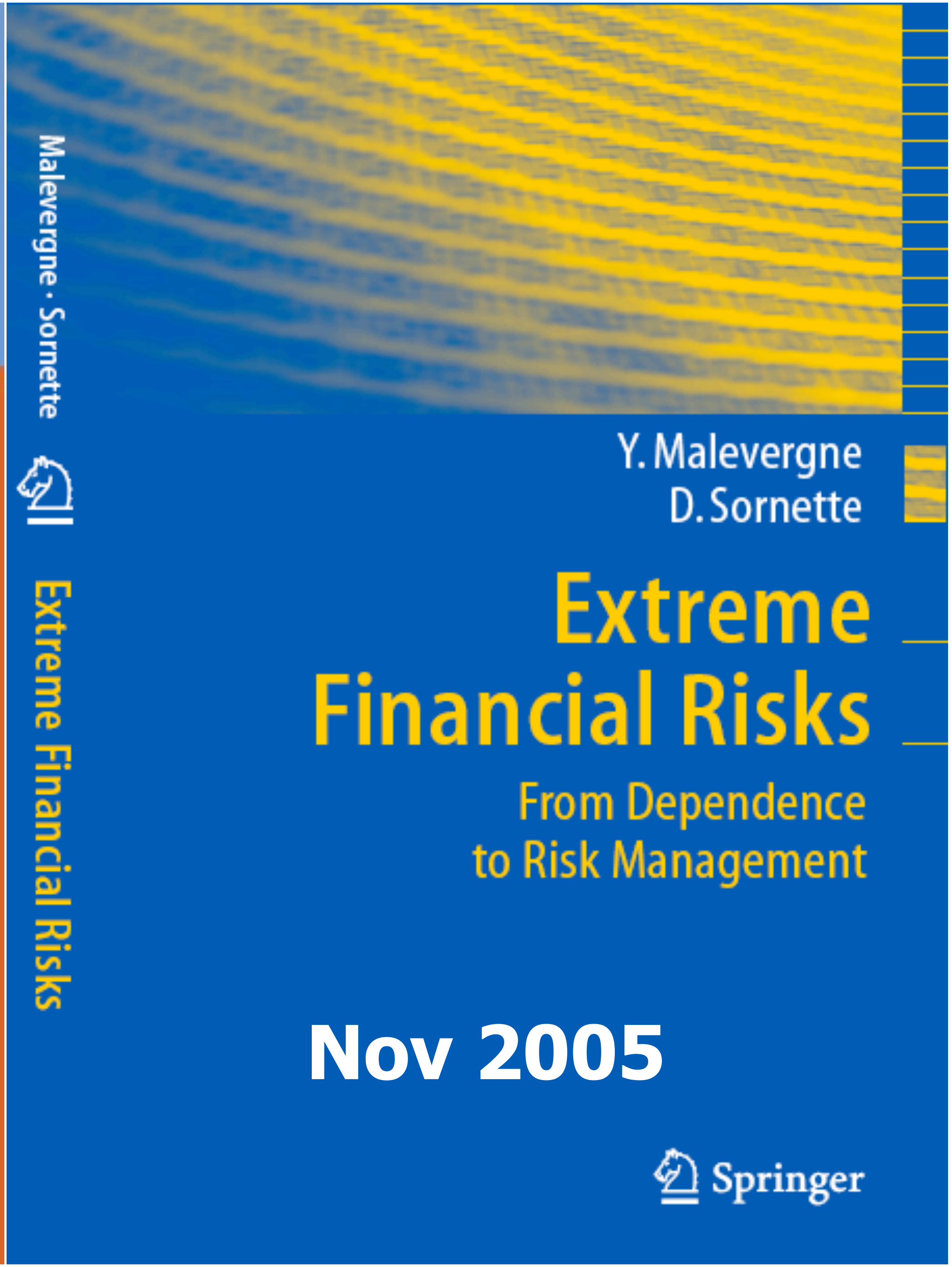
Difference in wealth (mean change per step) between strategies and agents

My Research Agenda to Address Risks in Financial Management

- Added-value strategies / expected returns
  1. Asymmetric information between managers and investors
  2. Reverse engineering of hedge-funds and derivative strategies
  3. Combining portfolio and investment strategies
- Risk measure and control
  1. Scenario and crises analyses
  2. Robust statistical methods to address model error
- Bubbles, crashes and extreme risks of unsustainable regimes
  1. The "Crisis Observatory" and crash alarm index
  2. Robust multivariate scanning of world assets
  3. NL models with positive and negative feedbacks
- Macro and micro economic analyses
  1. Separating information from "noise" and false consensus
  2. Endogenous vs exogenous extreme risks


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