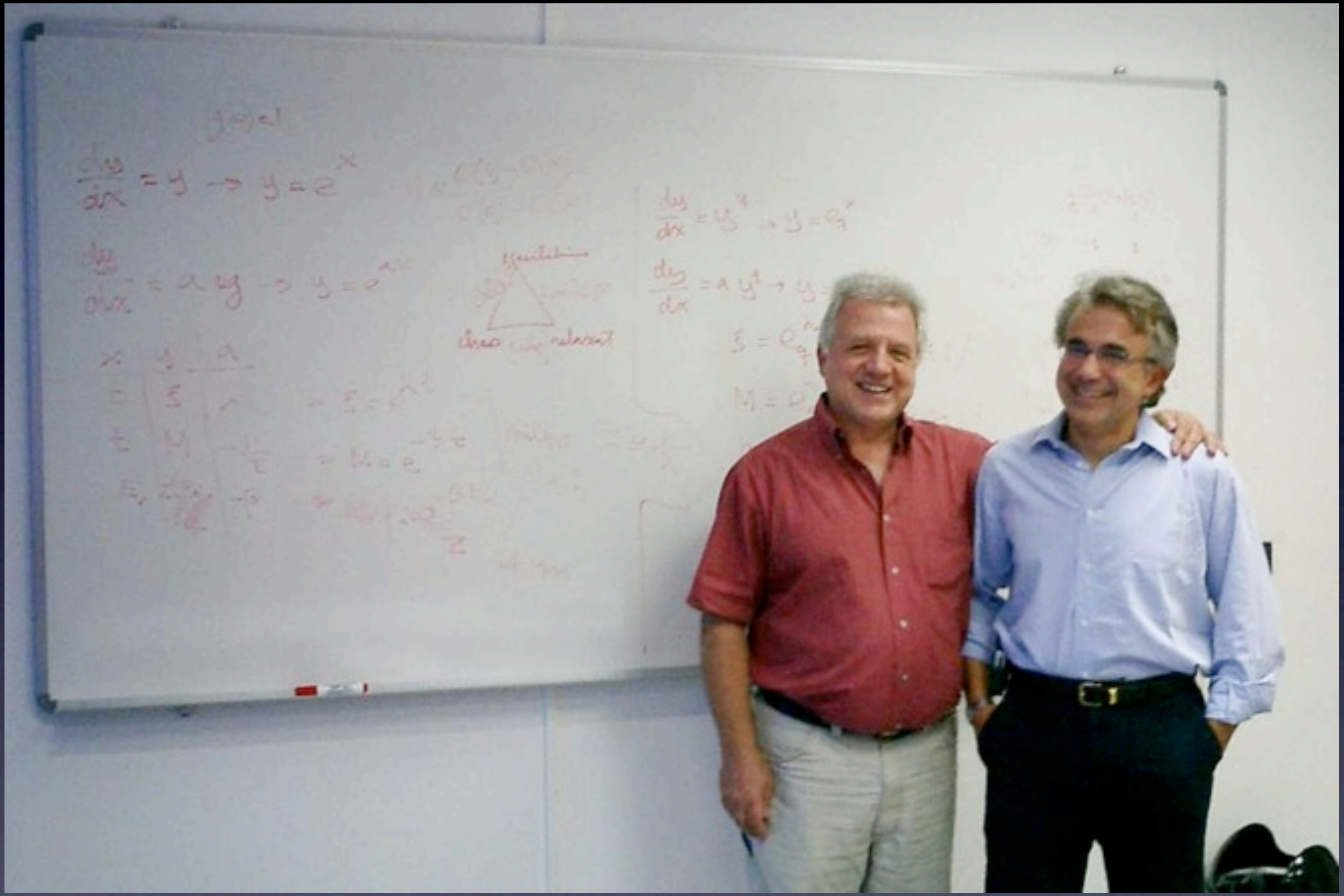
The beneficial role of random strategies in social and financial complex systems

A.E. Biondo[1], A. Pluchino[2], A. Rapisarda[2], D. Helbing[3]

[1] Dip. di Economia ed Impresa
[2] Dip. di Fisica e Astronomia
and INFN , Università di Catania
[3] ETH Zurich

A photo taken many years ago in Catania...



but it’s seems that time has not passed... at least for Constantino !!

Outline of the talk

- Introduction: The beneficial role of RaNdOMNEss.

  From Physics to Social Sciences

  - The case of the Peter Principle
  - The case of the Parliament

- RaNdOM strategies in financial markets

- Conclusions

Random noise is not always a disturbance to avoid and can also be very useful in physics: one example among many others is that one of stochastic resonance, introduced by Parisi et al. in 1981 to explain periodic climatic changes

Tellus (1982) *34*, 10–16

Stochastic resonance in climatic change

By ROBERTO BENZI, *Istituto di Fisica dell'Atmosfera, C.N.R., Piazza Luigi Sturzo 31, 00144, Roma, Italy,*
GIORGIO PARISI, *I.N.F.N., Laboratori Nazionali di Frascati, Frascati, Roma, Italy,*
ALFONSO SUTERA, *The Center for the Environment and Man, Hartford, Connecticut 06120, U.S.A.*
and ANGELO VULPIANI, *Istituto di Fisica "G. Marconi", Università di Roma, Italy*

(Manuscript received November 12, 1980; in final form March 13, 1981)

ABSTRACT

An amplification of random perturbations by the interaction of non-linearities internal to the climatic system with external, orbital forcing is found. This stochastic resonance is investigated in a highly simplified, zero-dimensional climate model. It is conceivable that this new type of resonance might play a role in explaining the 10^5 year peak in the power spectra of paleoclimatic records.

for a review see   Gammaitoni et al. Reviews of Modern Physics, Vol. 70, No. 1, 1998

RaNdoMnESs

can be useful also in social sciences

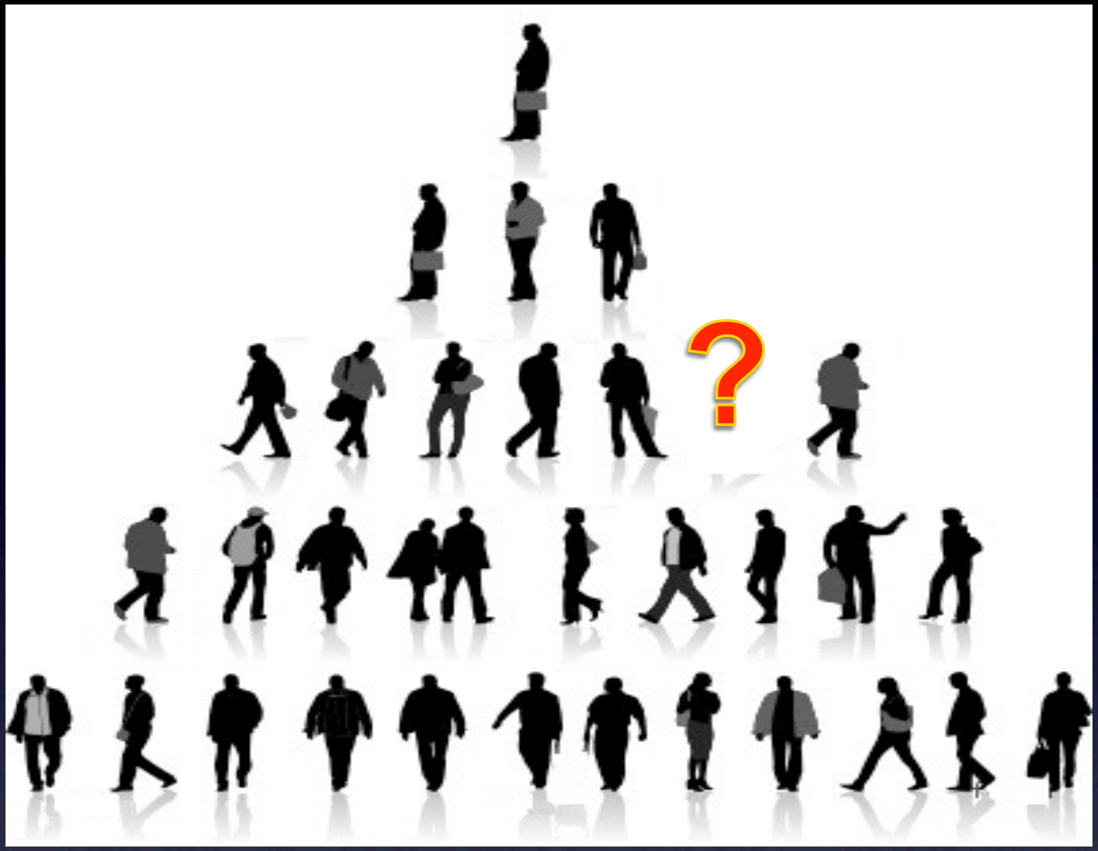
For example in order to face the problems of the Peter Principle

See:

Pluchino, Rapisarda, Garofalo, Physica A 389 (2010) 467

Pluchino, Rapisarda, Garofalo, Physica A 390 (2011) 3496

“Who should you promote to increase the efficiency of your organization?”



Common sense answer: within the reasonable **assumption** that a member who is competent at a given level will be competent also at an higher level of the hierarchy, it seems a good deal to **promote the best member** from the lower level!

But is such an assumption always valid?

Would you ever "promote" the best goalkeeper of your team...

to the vacant role of your missing forward player???

No, of course !!!

The Peter Principle

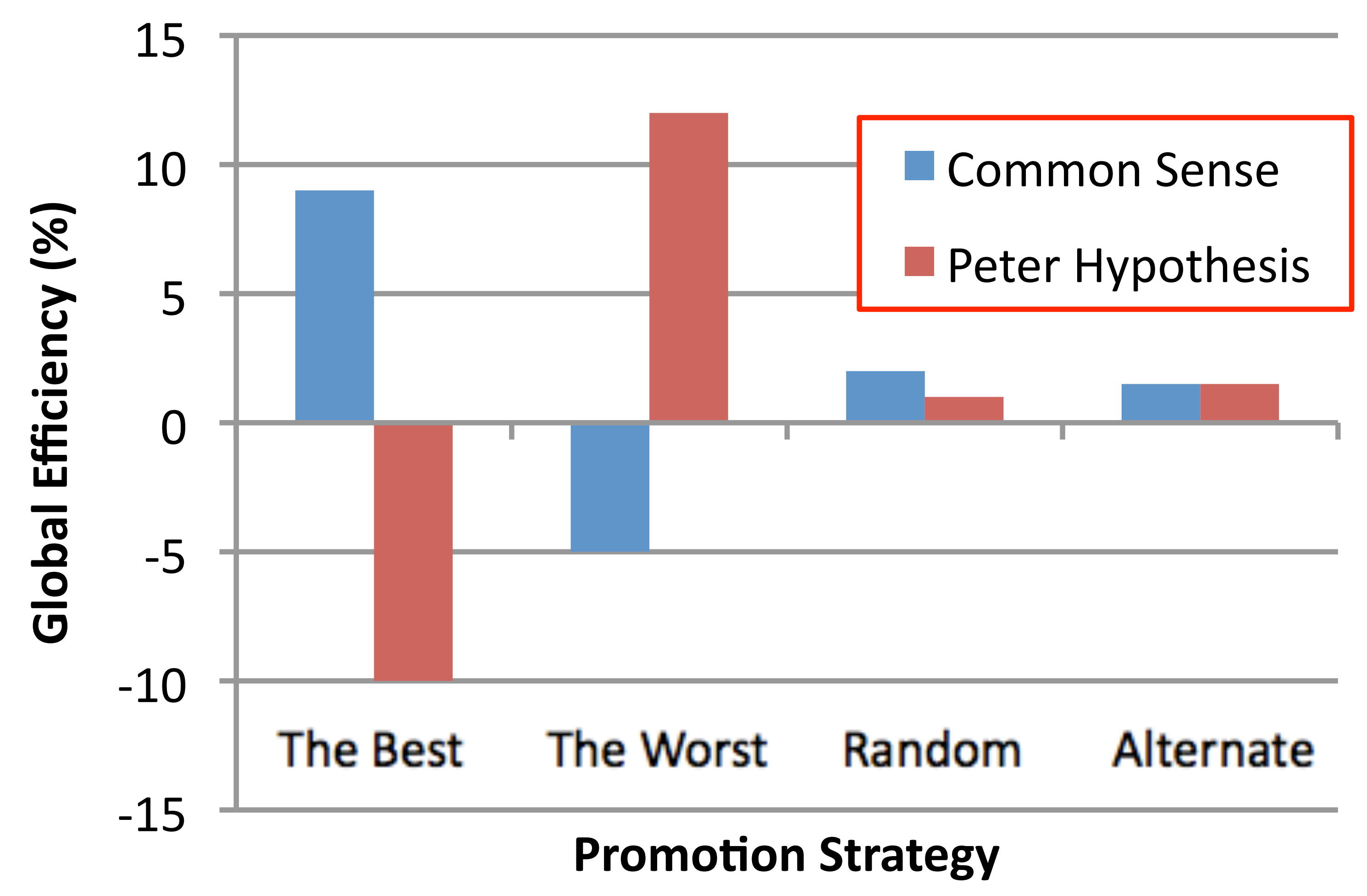
In the late sixties Laurence J. Peter advanced an apparently paradoxical principle, named since then after him, which can be summarized as follows:

‘Every new member in a hierarchical organization climbs the hierarchy until he/she reaches his/her level of incompetence’.

In a hierarchy, members are promoted as long as they work competently. Sooner or later they are promoted to a position at which they are no longer competent (their "level of incompetence"), and there they remain, being unable to earn further promotions.

Peter's Corollary states that "in time, every post tends to be occupied by an employee who is incompetent to carry out his duties" and adds that "work is accomplished by those employees who have not yet reached their level of incompetence".

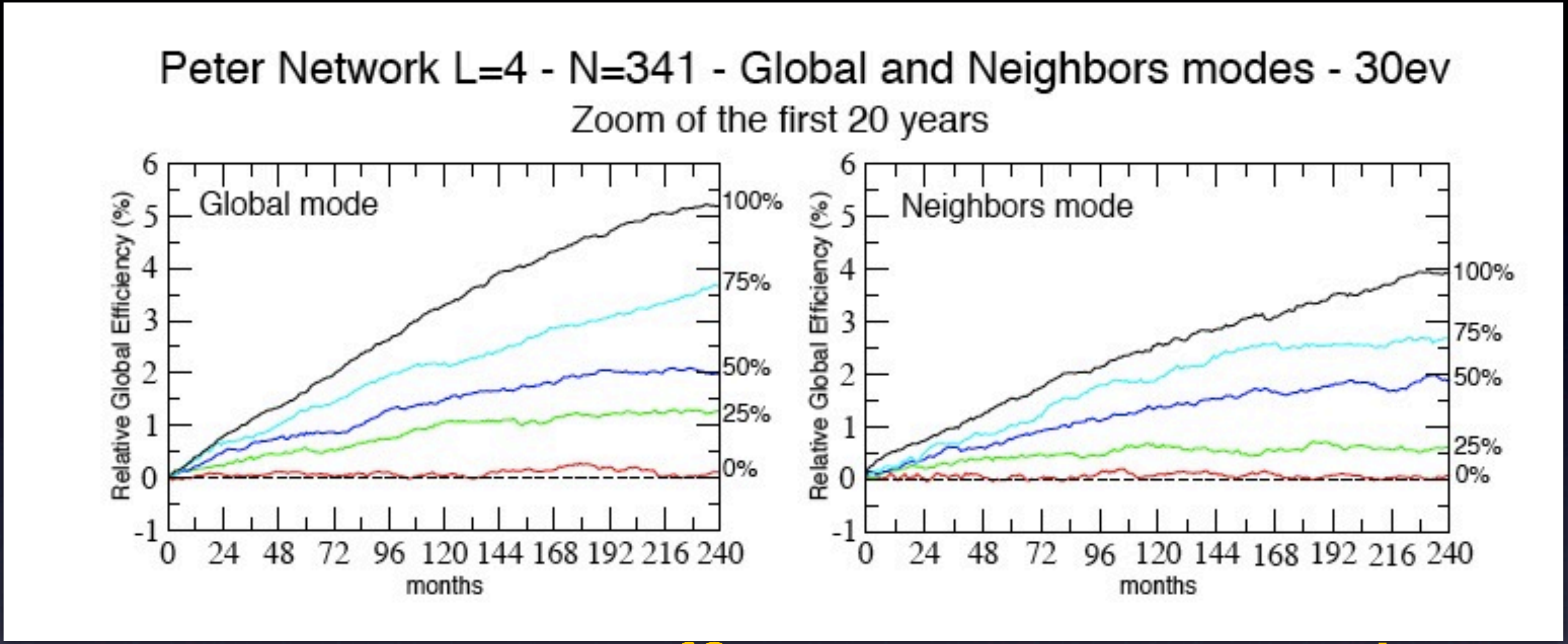
Summary of the results for different promotion strategies



These results are quite robust with respect to the numbers of the agents and the number of levels of the hierarchy

New results obtained with a more realistic model by using modular networks

Focusing on the initial period of 20 years



The increase in efficiency is immediate and persistent, reaching after only 20 years almost 80% of the asymptotic total gain

See: Pluchino, Rapisarda, Garofalo, Physica A 390 (2011) 3496

There are also some recent papers where Sornette and collaborators found analytically, by using Markov chains, that random choices are the best solution with respect to optimized ones in time-horizon minority games and Parrondo games, when there are many competing strategies and a high uncertainty about the results.

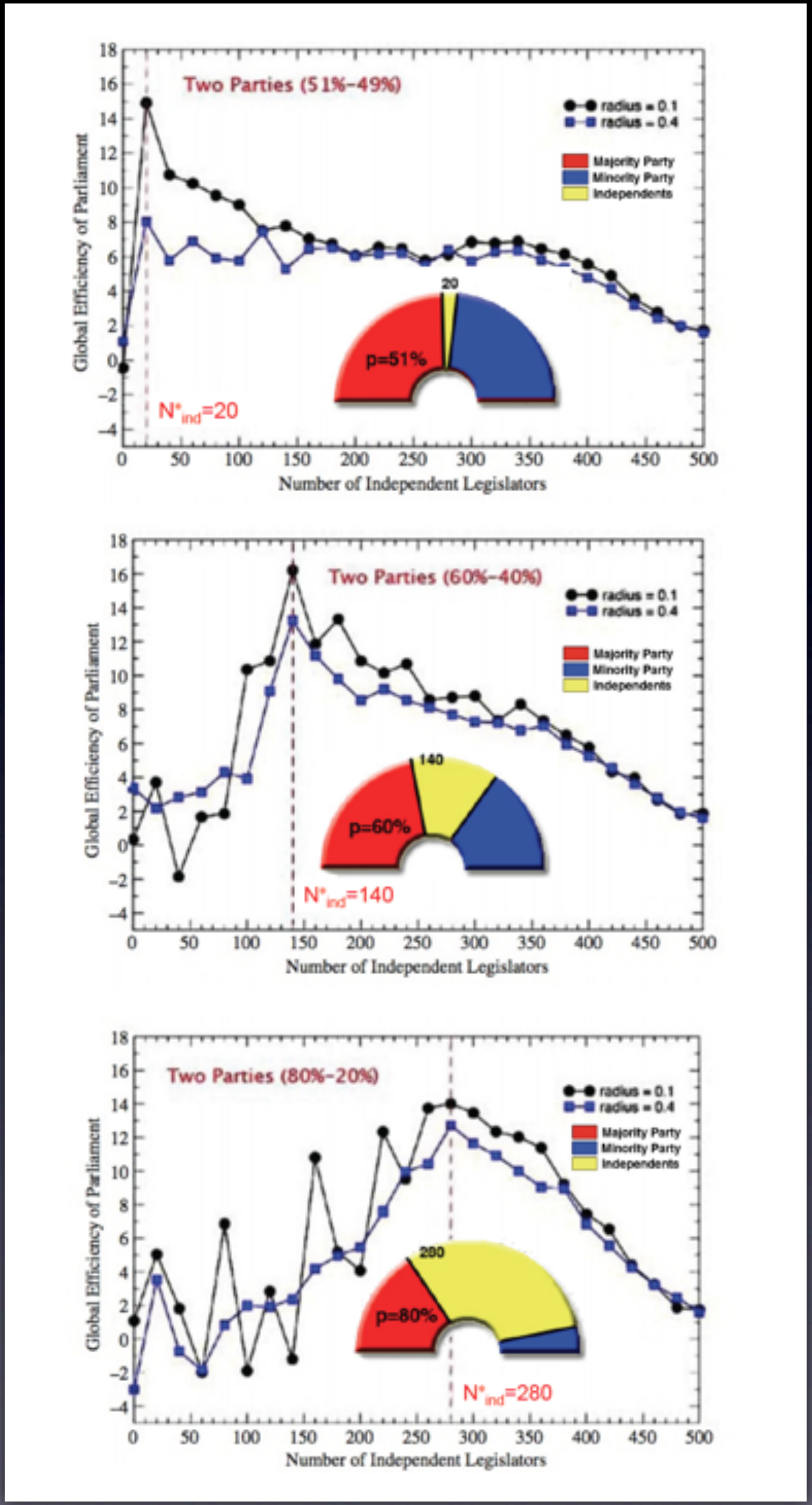
See for example

J.B. Satinover and D. Sornette, Eur. Phys. J. B **67**, 357–367 (2009)

RaNdOMNEss applied to elections:

How randomly selected politicians can improve the efficiency of the Parliament

A. Pluchino, C. Garofalo, A. Rapisarda, S. Spagano, M. Caserta,
Physica A 390 (2011) 3944.



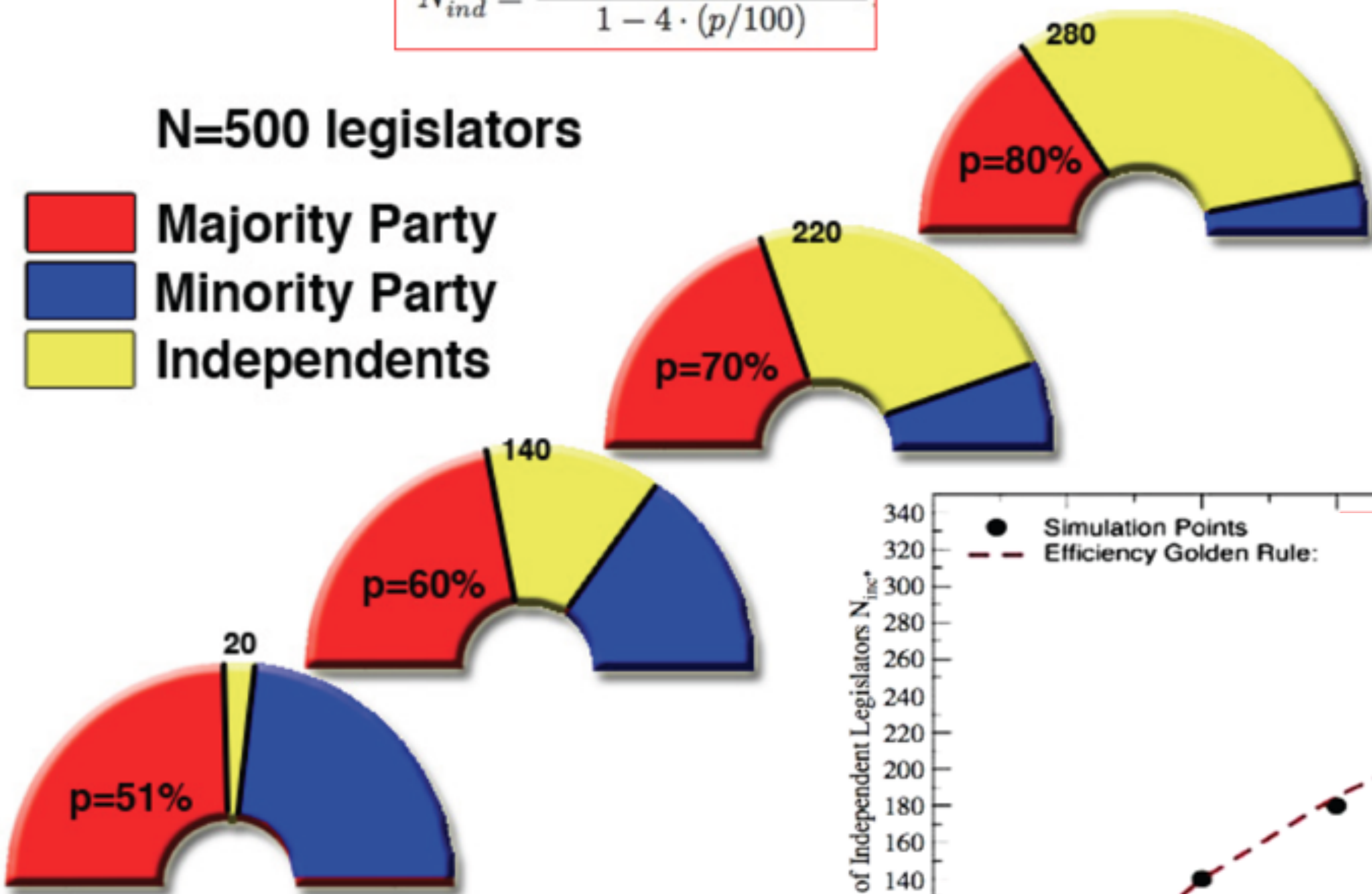
RESULTS

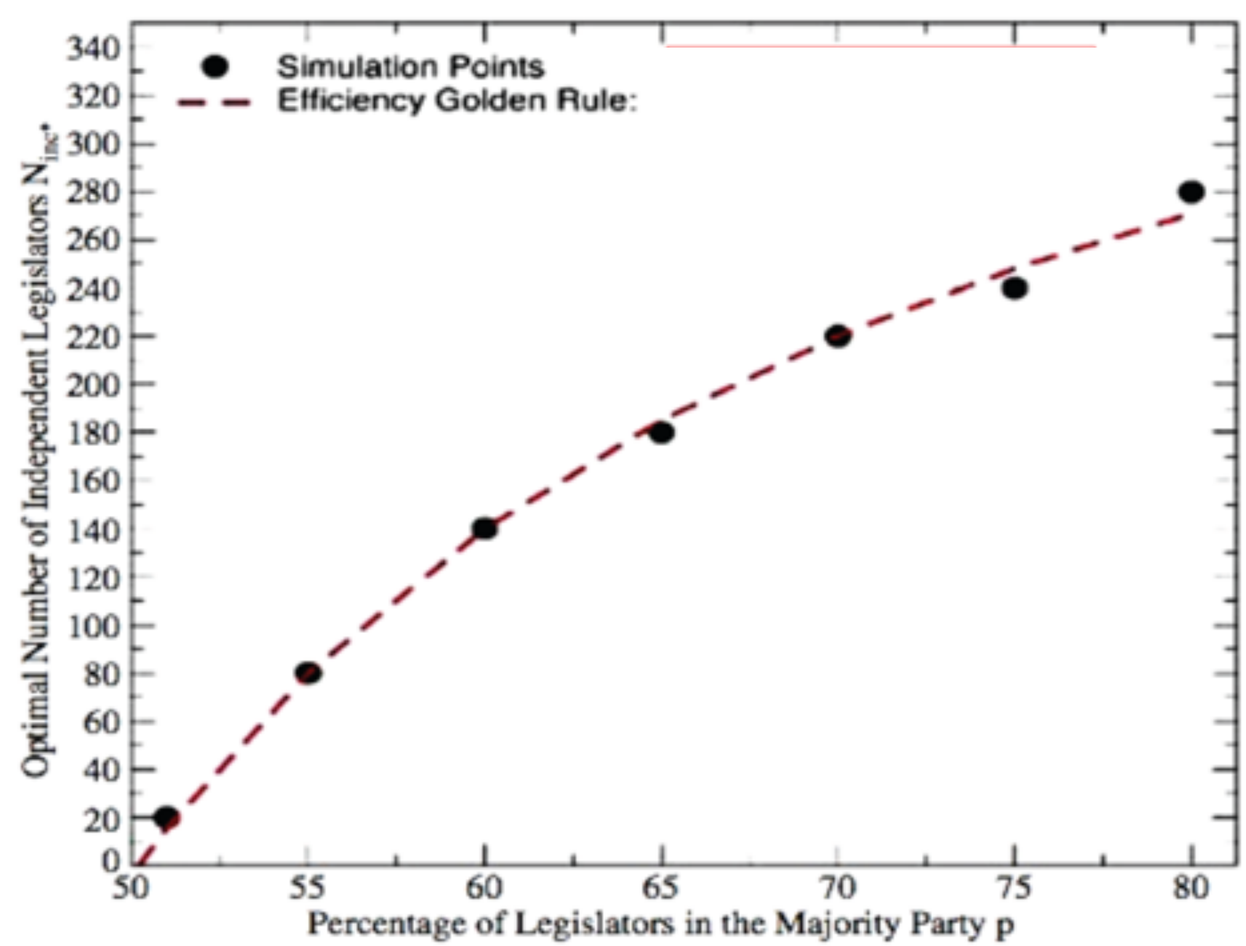
Considering the global efficiency of the Parliament as function of the number of independent legislators, one observes a pronounced peak in correspondence of a well defined value of N^*_{ind}

This value increases with the percentage of the majority party

Efficiency Golden Rule

$$N^*_{ind} = \frac{2N - 4N \cdot (p/100) + 4}{1 - 4 \cdot (p/100)}$$





November 2012

The case of financial markets

An interesting experiment made by the English psychologist Richard Wisemann in 2001

Given 5000 £

To a child

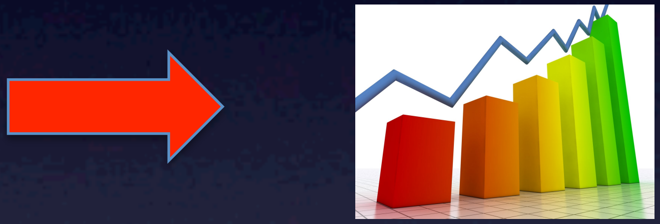
a finance expert

an astrologist

Results after one week !

child (random):	**- 4,6 %**
finance expert (optimization):	**- 7,1 %**
astrologist (stars):	**- 10,1 %**

Who will have more success in investing the money in a turbulent financial market ?



Results after one year !!

child (random):	**+ 5,8 %**
finance expert (optimization):	**- 46,2 %**
astrologist (stars):	**- 6,2 %**

Similar experiments have been done with chimpanzees or darts with analog results

see for example the paper

The Long-Term Value of Analysts' Advice in the *Wall Street Journal*'s Investment Dartboard Contest

Gary E. Porter

For nearly thirteen years, the Investment Dartboard column featured the stock recommendations of prominent equity analysts in a contest with the stocks selected by Journal *staffers throwing darts. Over the life of the column, investors who rebalanced their portfolios according to the analysts' recommendations achieved higher terminal wealth, but a lower risk-adjusted return, than an investment in an S&P 500 index fund, but investors who bought and held the securities selected by darts achieved the greatest terminal wealth and risk-adjusted return. The darts out-performed the analysts on a nominal and risk-adjusted basis during the recent market decline, with darts and analysts generating higher nominal and risk-adjusted returns than the market index fund. [G11, G14]*

JOURNAL OF APPLIED FINANCE — FALL/WINTER 2004

or this recent research study

FINANCIAL TIMES

March 31, 2013 4:32 am

Monkey beats man on stock market picks

By Chris Flood

Researchers used computers to choose a thousand stocks at random

Even a chimpanzee picking stocks at random could easily beat the US stock market, according to academics at the Cass Business School in London. They calculated 10m "monkey" portfolios to analyse how well smart beta indices and a conventional market capitalisation weighted index compared with an approach based solely on luck.

"The results were quite shocking," says Andrew Clare, professor of asset management at Cass.

An investment of $100 in the US stock market at the start of 1968 would have grown to just under $5,000 by the end of 2011. But half the monkeys generated more than $8,700, a quarter returned more than $9,100 and 10 per cent made more than $9,500.

Cass Business School
CITY UNIVERSITY LONDON

AON Hewitt

Cass Consulting
www.cassknowledge.com

An evaluation of alternative equity indices
Part 1: Heuristic and optimised weighting schemes

Andrew Clare, Nick Motson and Steve Thomas

March 2013

Thus we performed some numerical simulations to check the previous experiments

A.E. Biondo, A. Pluchino, A. Rapisarda, *Journal of Statistical Physics 151 (2013) 607.*

A.E. Biondo, A. Pluchino, A. Rapisarda, D. Helbing, (2013) PLoS ONE 8(7): e68344

A.E. Biondo, A. Pluchino, A. Rapisarda, D. Helbing, arXiv:1309.3639

We considered four historical time series

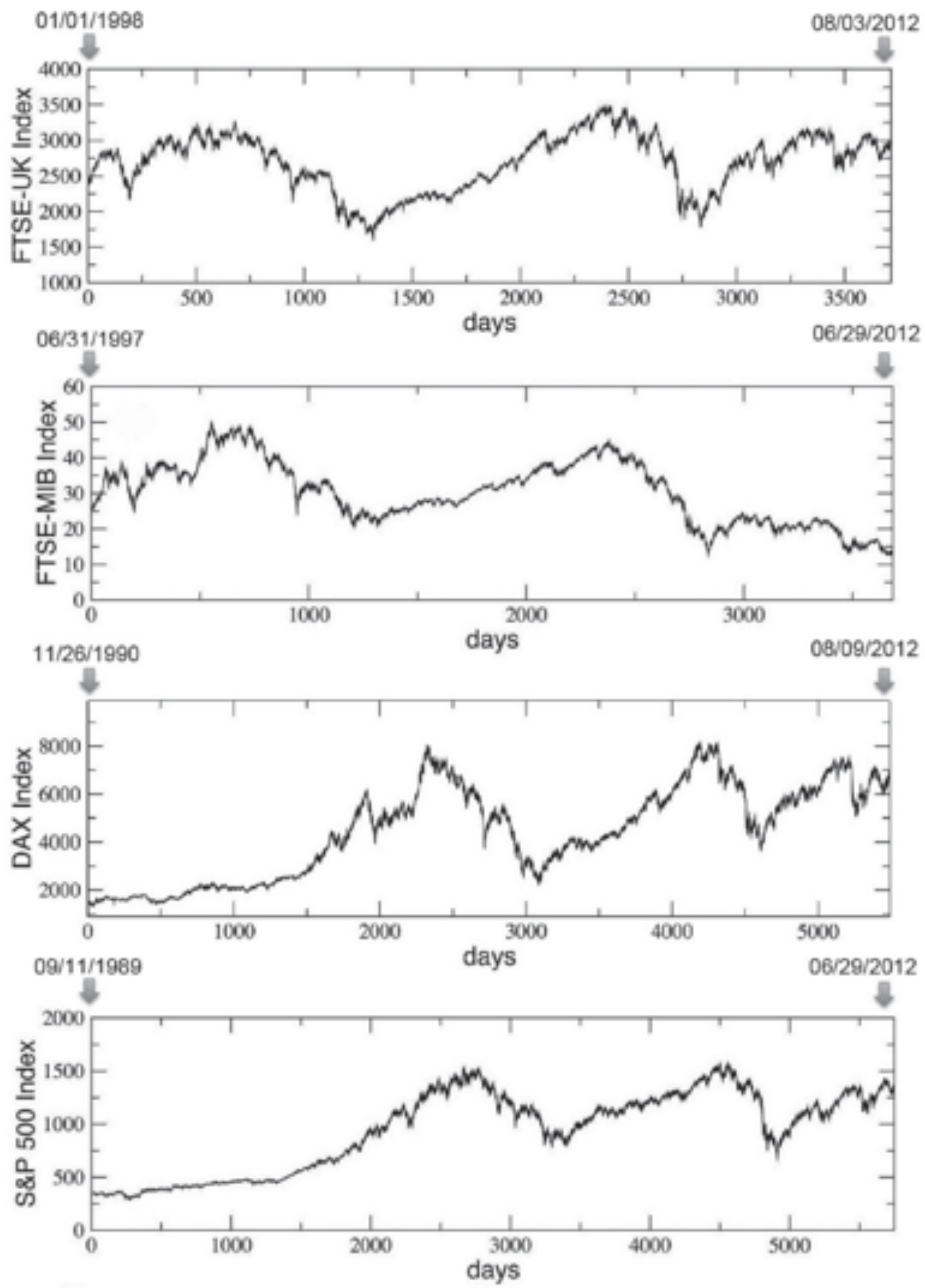


Figure 1. Temporal evolution of four important financial market indexes (over time intervals going from 3714 to 5750 days). From the top to the bottom, we show the FTSE UK All-Share index, the FTSE MIB All-Share index, the DAX All-Share index and the S & P 500 index. See text for further details.
doi:10.1371/journal.pone.0068344.g001

FTSE-UK

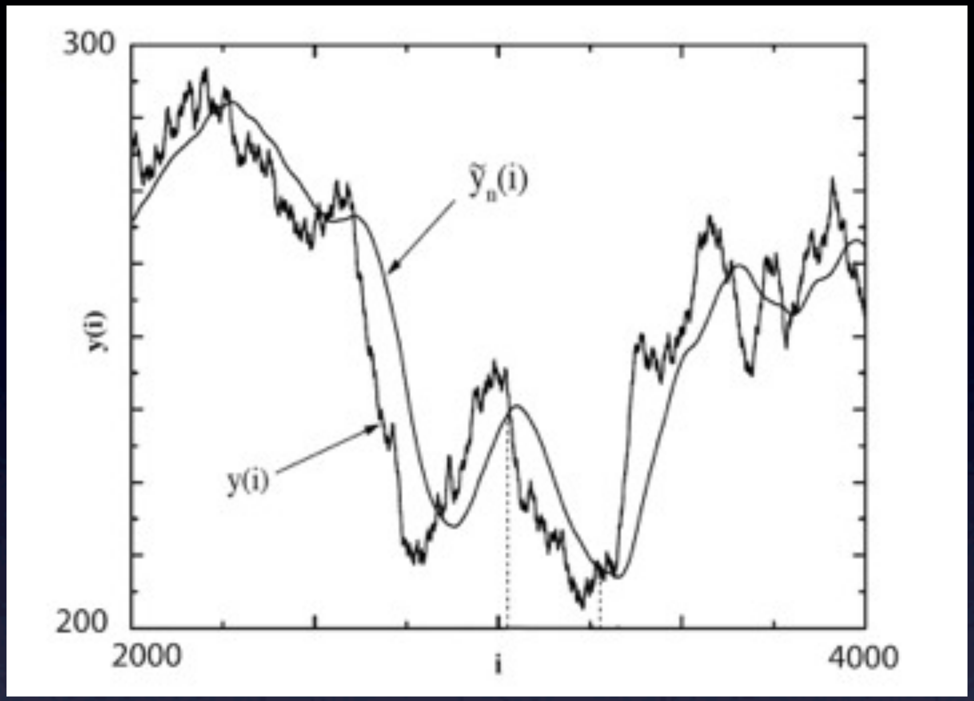
FTSE-MIB

DAX

S&P500

Are there correlations in our time series ?

Detrended Moving Average to calculate the Hurst exponent



$$\sigma_{DMA}(n) = \sqrt{\frac{1}{N_{max}-n} \sum_{t=n}^{N_{max}} [y(t) - \tilde{y}_n(t)]^2},$$

$$\tilde{y}_n(t) = \frac{1}{n} \sum_{k=0}^{n-1} y(t-k)$$

average calculated in each time window of size n

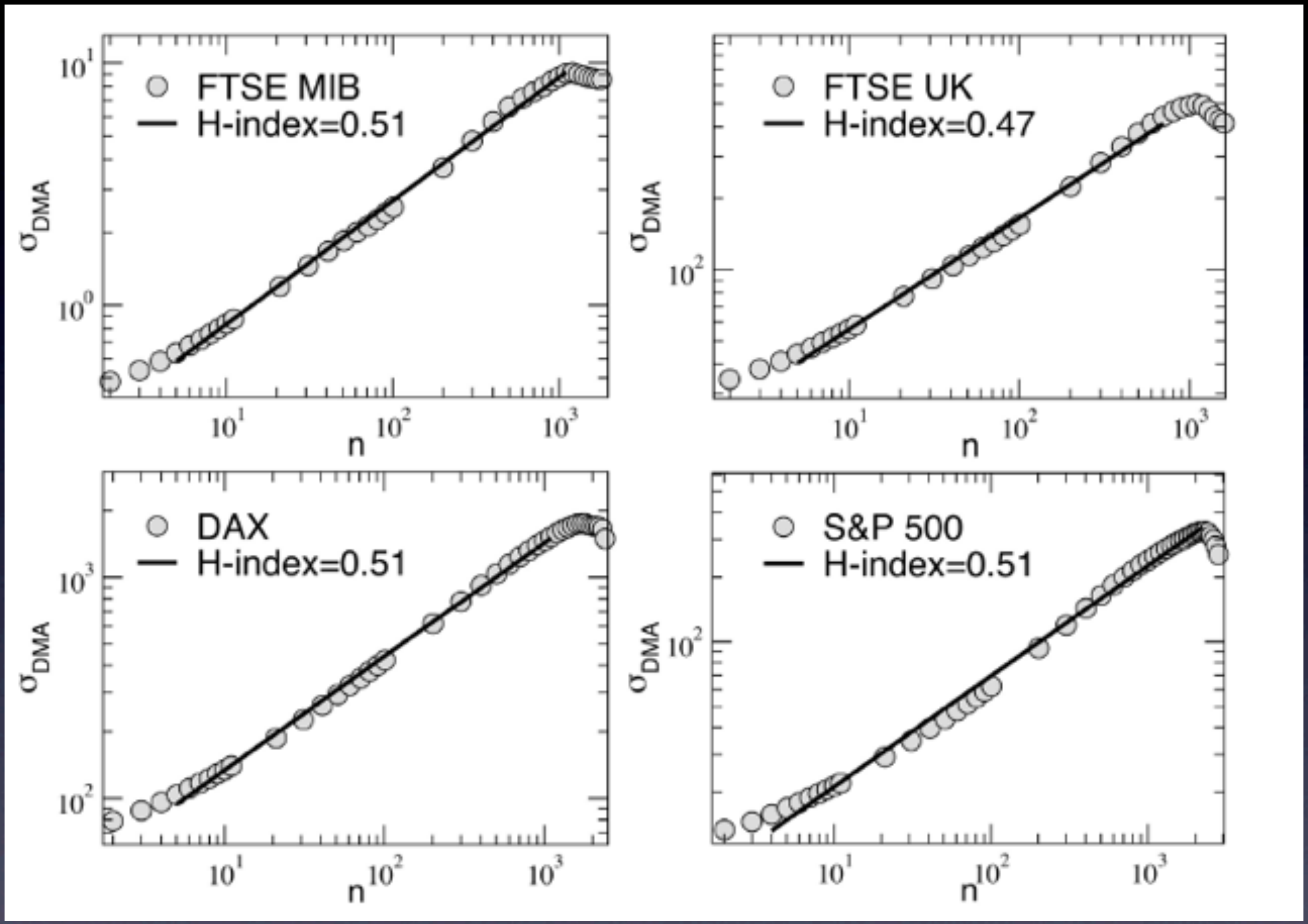
$$\sigma_{DMA} \propto n^H$$

IF $0 \leq H \leq 0.5$ Negative correlations or antipersistent behavior

IF $0.5 \leq H \leq 1$ Positive correlations or persistent behavior

IF $H = 0.5$ No correlations or Brownian motion behavior

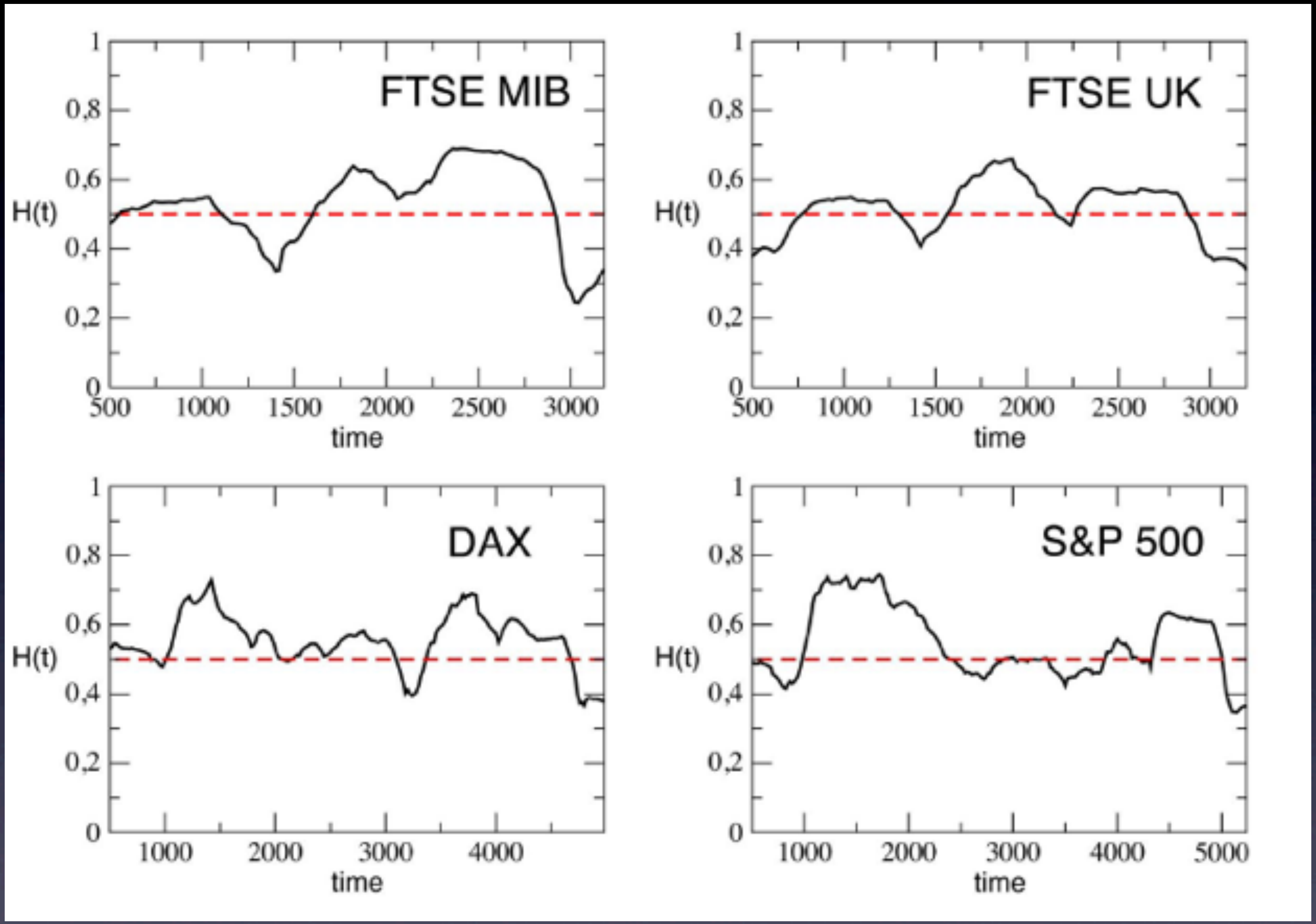
Results of Detrended Moving Average for the Hurst exponent along the complete four time series



The value of the H exponent is compatible with 0.5 for all time series, indicating the absence of correlations along the entire time interval

Hurst exponent as a function of time

It is interesting to calculate the Hurst exponent locally in time.



We consider subsets of the complete series by means of sliding windows W_s of size N_s, which move along the series with time step s.

Thus a sequence of Hurst exponent values H(t) is obtained as function of time.

In the figure we show the results obtained for the parameters N_s=1000, s=20.

Local correlations in time do exist

We assume the lack of complete information for our traders and we try to answer to the following question

would a random trading strategy perform, on average, as good as standard "trading deterministic strategies"?

Our simple simulation will perform a comparative analysis of the performance of different *"trading strategies"*, i.e. our traders have to predict, day by day, if the market will go up ('bullish' trend) or down ('bearish' trend).

Tested strategies are: the Momentum, the RSI, the UPD, the MACD, and a completely Random one.

Rational expectations theoreticians would immediately bet that the random strategy will loose the competition as it is not making use of any information but, as we will show, our results are quite surprising.

Comparison between random strategies and some of the most used deterministic techniques to predict market behavior*

Momentum strategy

This strategy is based on the so called 'momentum' $M(t)$ indicator, i.e. the difference between the index value $I(t)$ and the value $I(t - T_M)$, being T_M a given trading interval.
If $M(t) = I(t) - I(t - T_M) > 0$, the trader predicts an increment of the closing index for the next day (i.e. it predicts that $I(t + 1) - I(t) > 0$) and vice-versa.
We considered $T_M = 7$ days, since this is one of the most used time lag

RSI strategy

Based on the 'RSI', defined as $RSI(t) = 100 - 100/[1 + RS(t)]$, where $RS(t, T_{RSI})$ is the ratio between the sum of the positive returns and the sum of the negative returns occurred during the last T_{RSI} days before t.

Once calculated the RSI index for all the days included in a given time-window of length T'_{RSI} immediately preceding the time t, the trader makes his prediction on the basis of a possible reversal of the market trend, revealed by the so called 'divergence' between the original series and the new RSI one. The presence of such a divergence translates into a change in the prediction of the $I(t + 1) - I(t)$ sign, depending on the *'bullish* or *'bearish'* trend of the previous T'_{RSI} days. We considered $T'_{RSI} = T_{RSI} = 14$ days,

*For more info see: Murphy JJ (1999) Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications. New York Institute of Finance.

We performed a comparison between random strategies and some of the most used deterministic ones*

Up and Down strategy

This deterministic strategy does not come from a technical analysis. However, we decided to consider it because it seems to follows the apparently simple alternate "up and down" behavior of market series that any observer can see at first sight.
The strategy is based on the following very simple rule: *the prediction for tomorrow market's behavior is just the opposite of what happened the day before.*

MACD strategy *

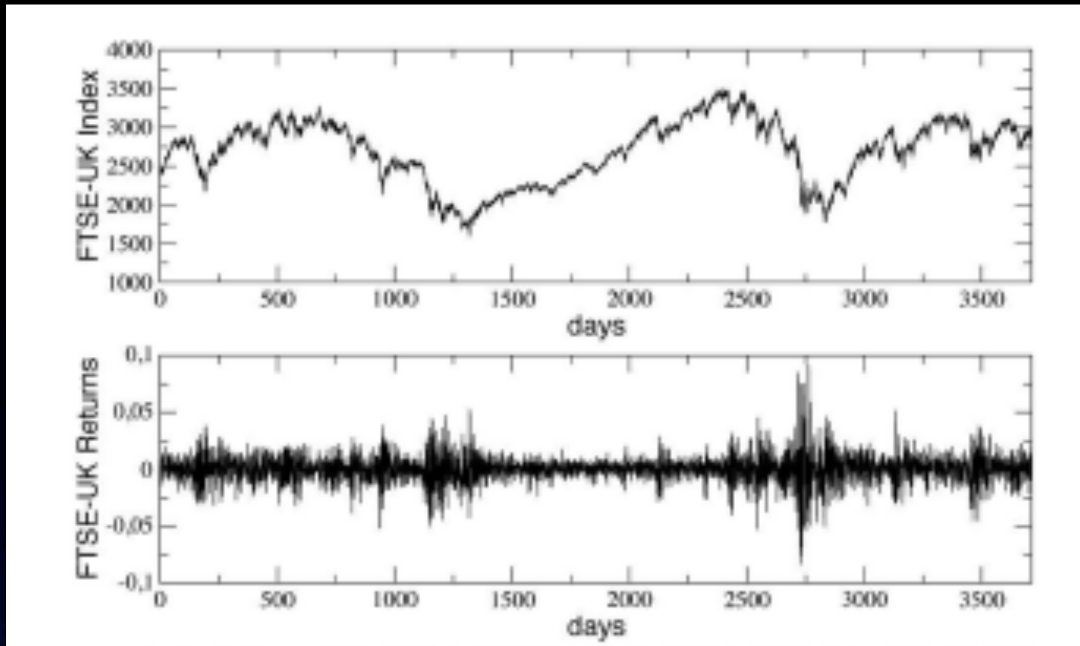
The 'MACD' is a series built by means of the difference between two Exponential Moving Averages (EMA) of the market index, referred to two different time windows, one smaller and one larger. At time t,

$$MACD(t) \sim EMA^{12d}(t) - EMA^{26d}(t) .$$

Once the MACD series has been calculated, its 9-days Exponential Moving Average is obtained and, finally, the trading strategy for the market dynamics prediction can be defined: the expectation
for the market is bullish (bearish) if $MACD - EMA^{9d}_{MACD} > 0$ ($MACD - EMA^{9d}_{MACD} < 0$)

*For more info see: Murphy JJ (1999) Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications. New York Institute of Finance.

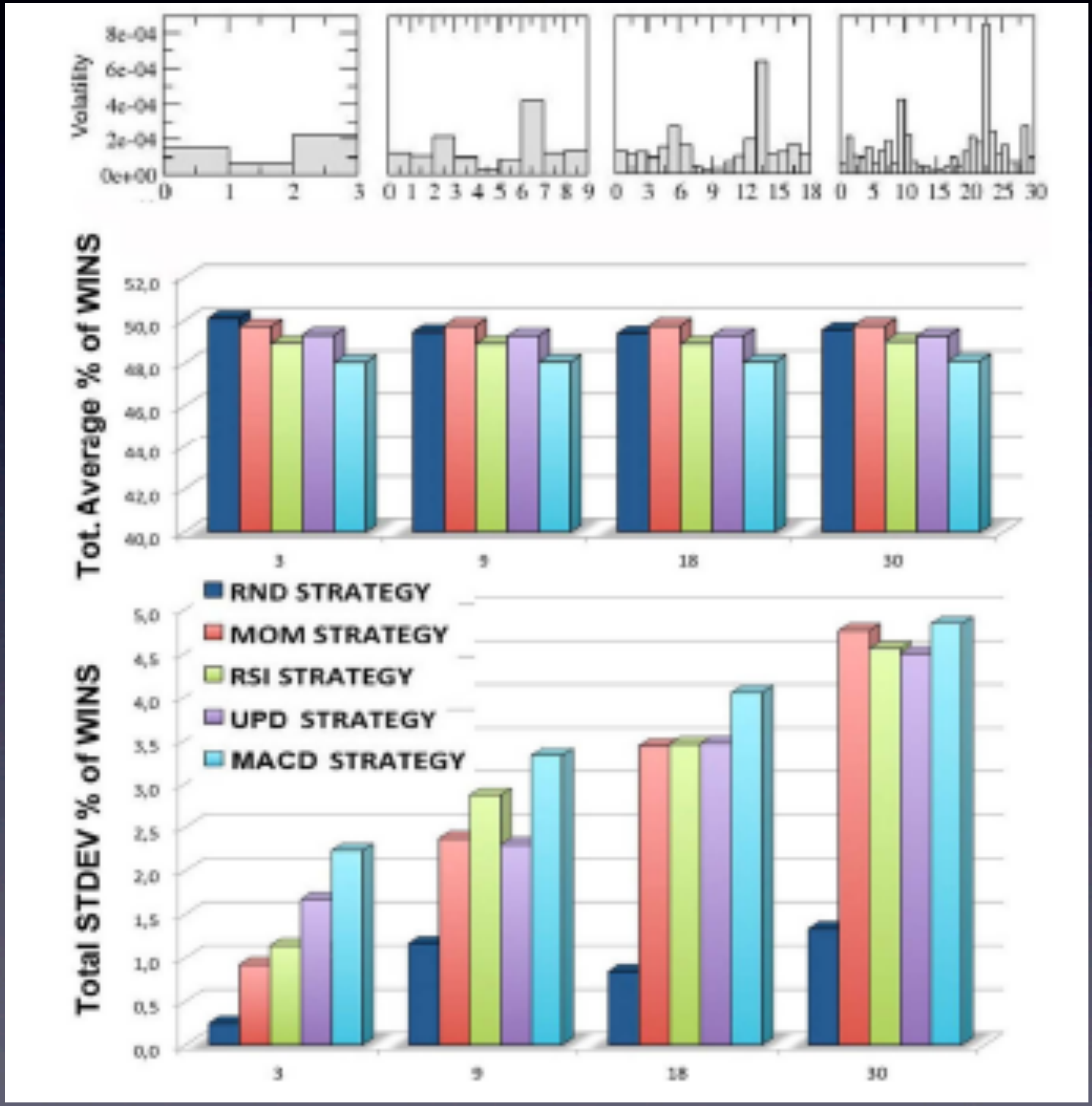
Results for FTSE-UK



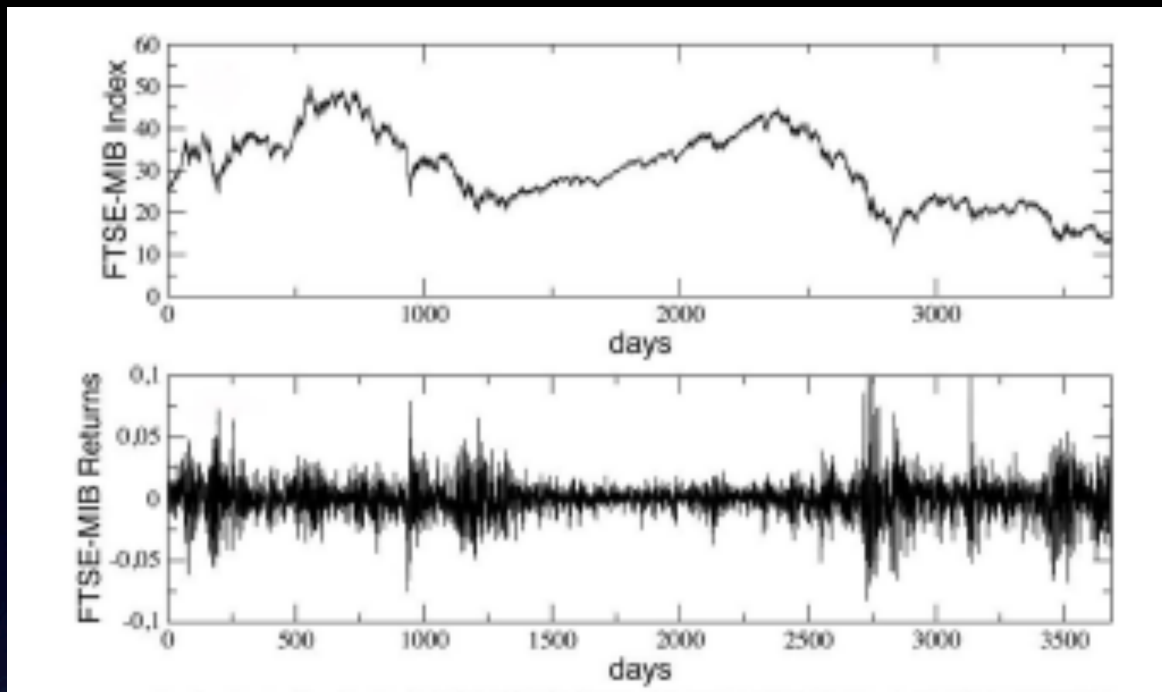
Volatility of the returns, i.e. the variance of the previous series, calculated inside each window for increasing values of the trading window size

The average percentage of wins for the five trading strategies considered, calculated for the same four kinds of windows (the average is performed over all the windows in each configuration, considering different simulation runs inside each window)

The corresponding standard deviations for the wins of the five strategies.



Results for FTSE-MIB



Volatility of the returns, i.e. the variance of the previous series, calculated inside each window for increasing values of the trading window size

The average percentage of wins for the five trading strategies considered, calculated for the same four kinds of windows (the average is performed over all the windows in each configuration, considering different simulation runs inside each window)

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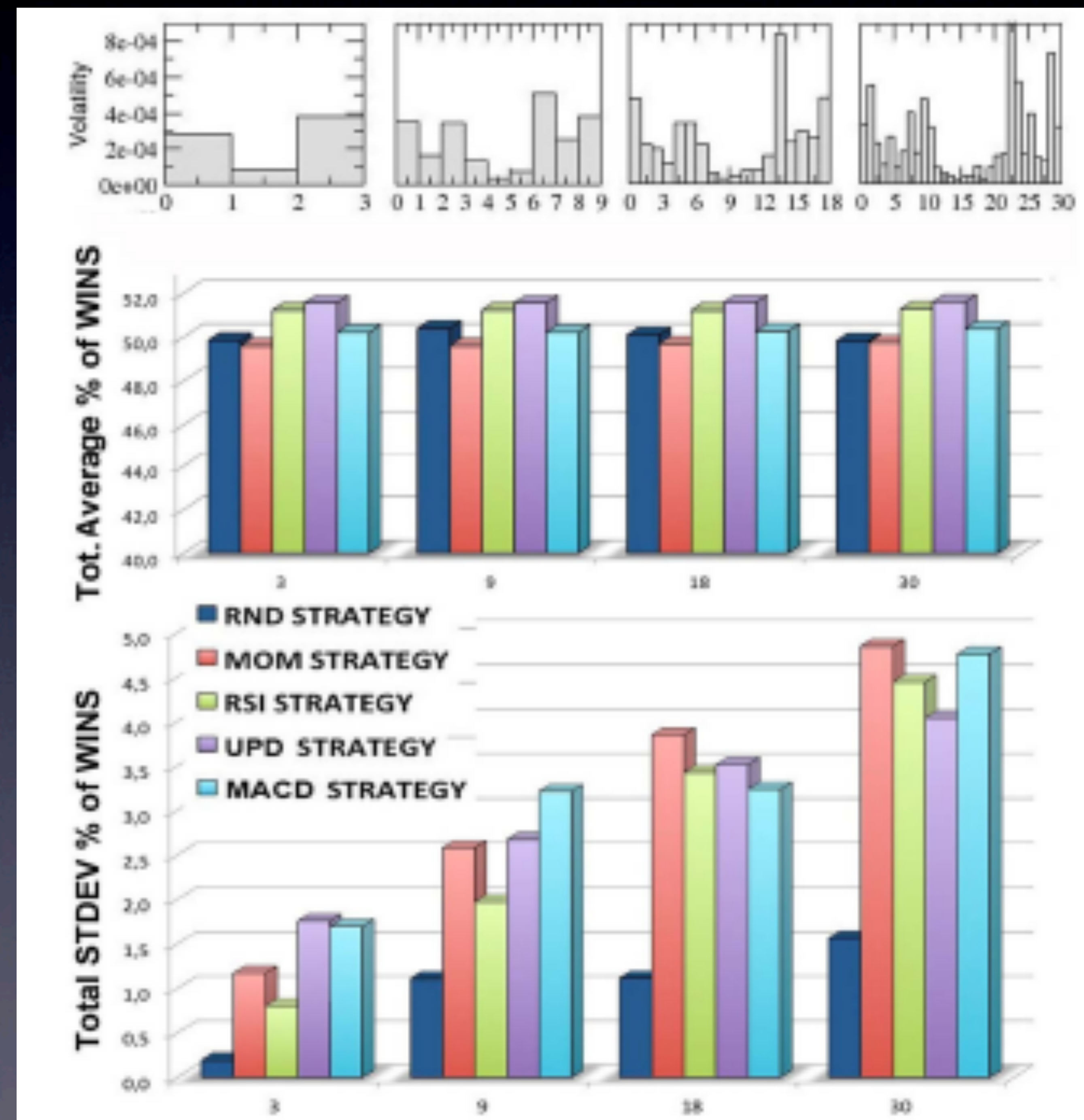
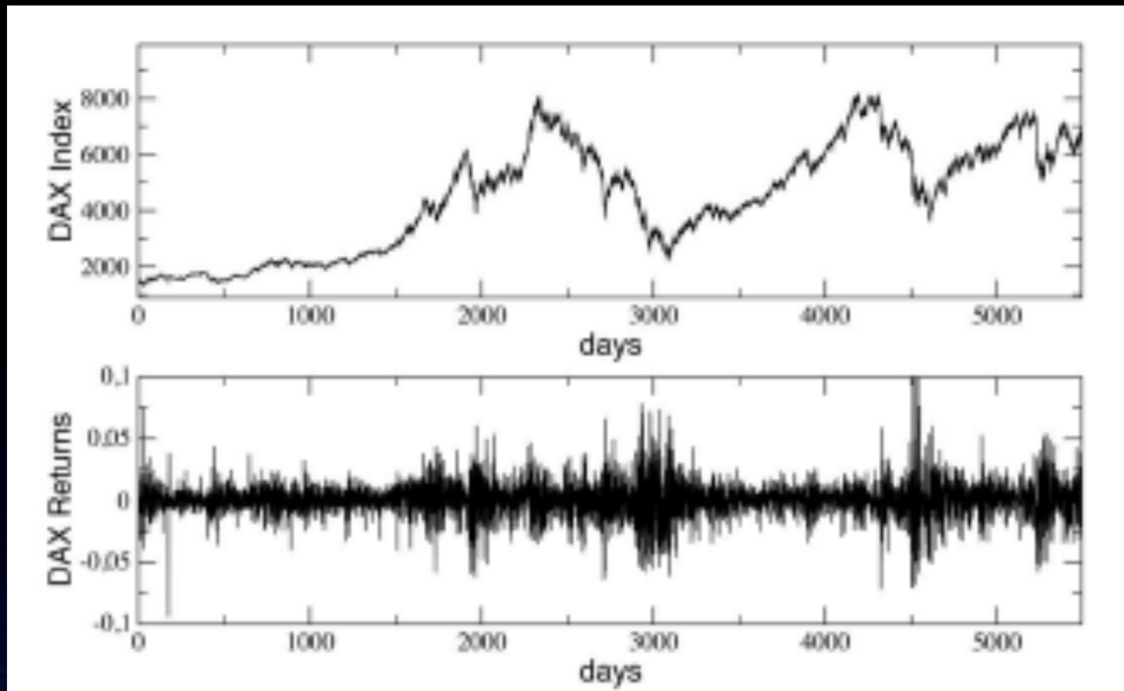
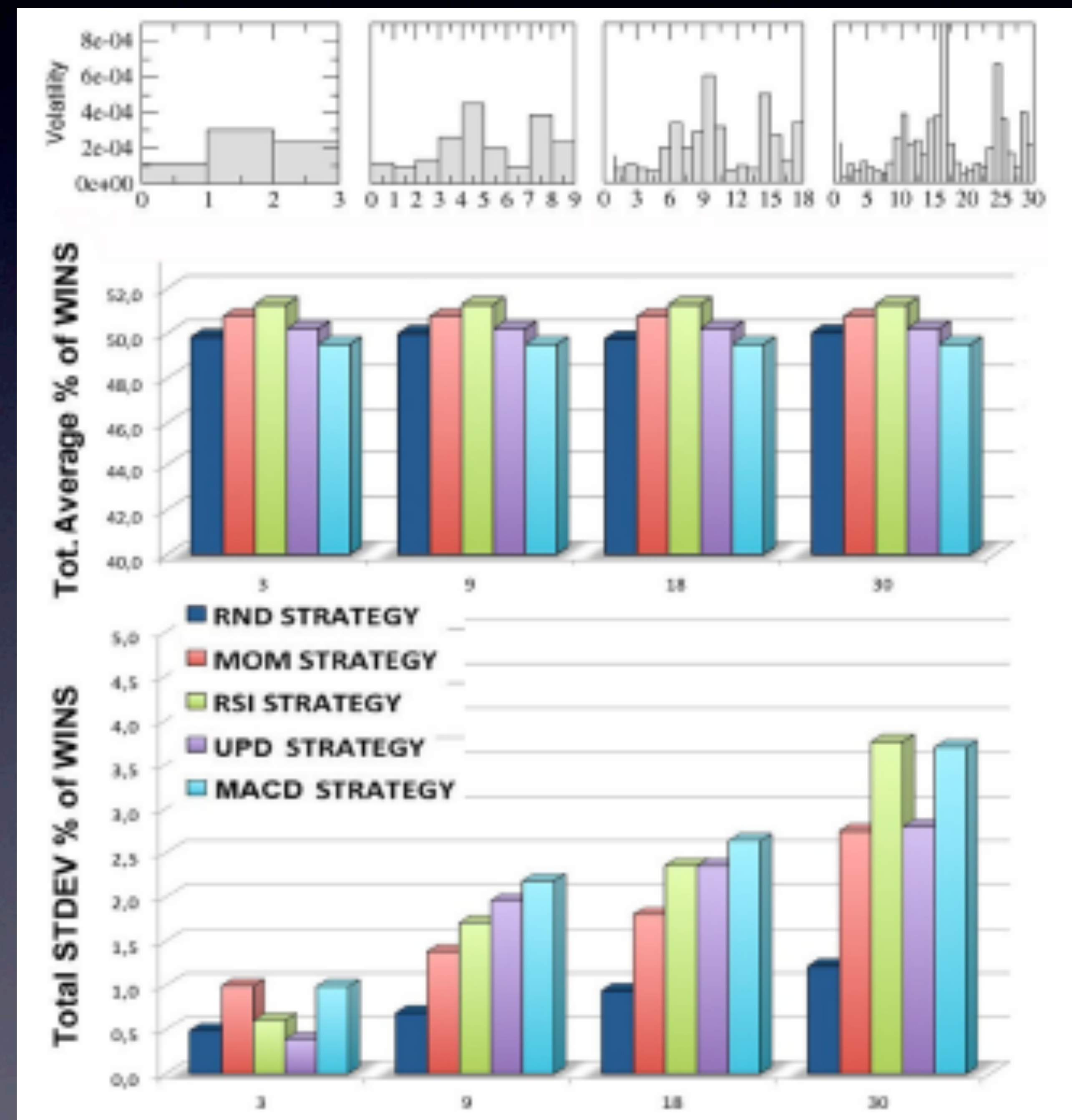


Results for DAX



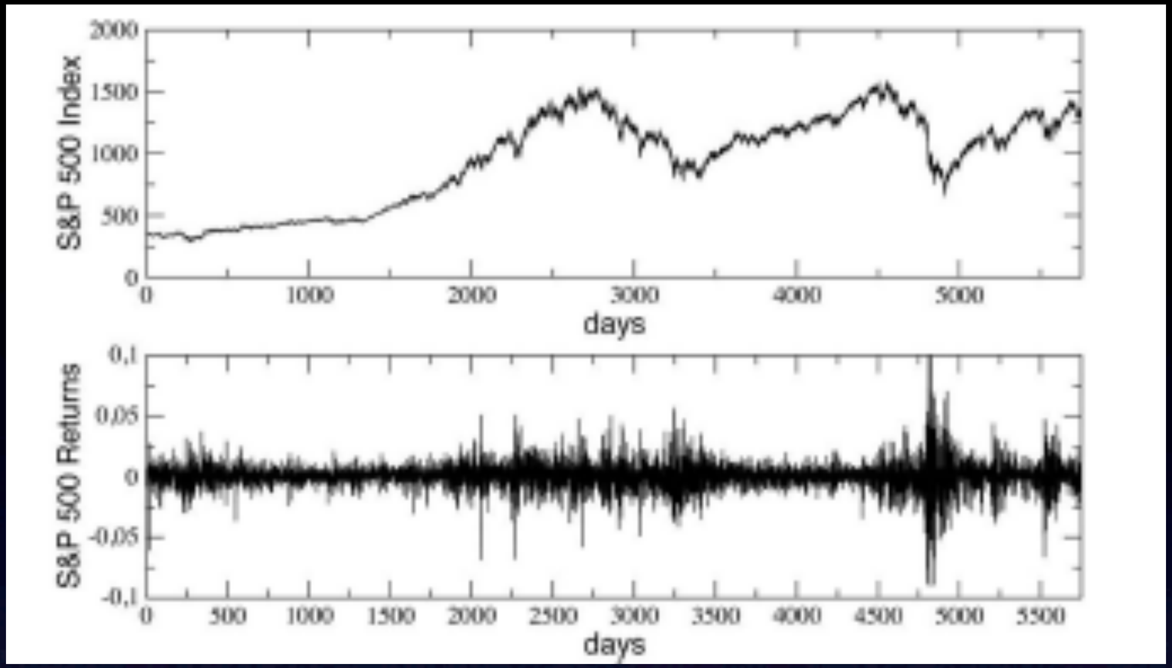


Volatility of the returns, i.e. the variance of the previous series, calculated inside each window for increasing values of the trading window size

The average percentage of wins for the five trading strategies considered, calculated for the same four kinds of windows (the average is performed over all the windows in each configuration, considering different simulation runs inside each window)

The corresponding standard deviations for the wins of the five strategies.

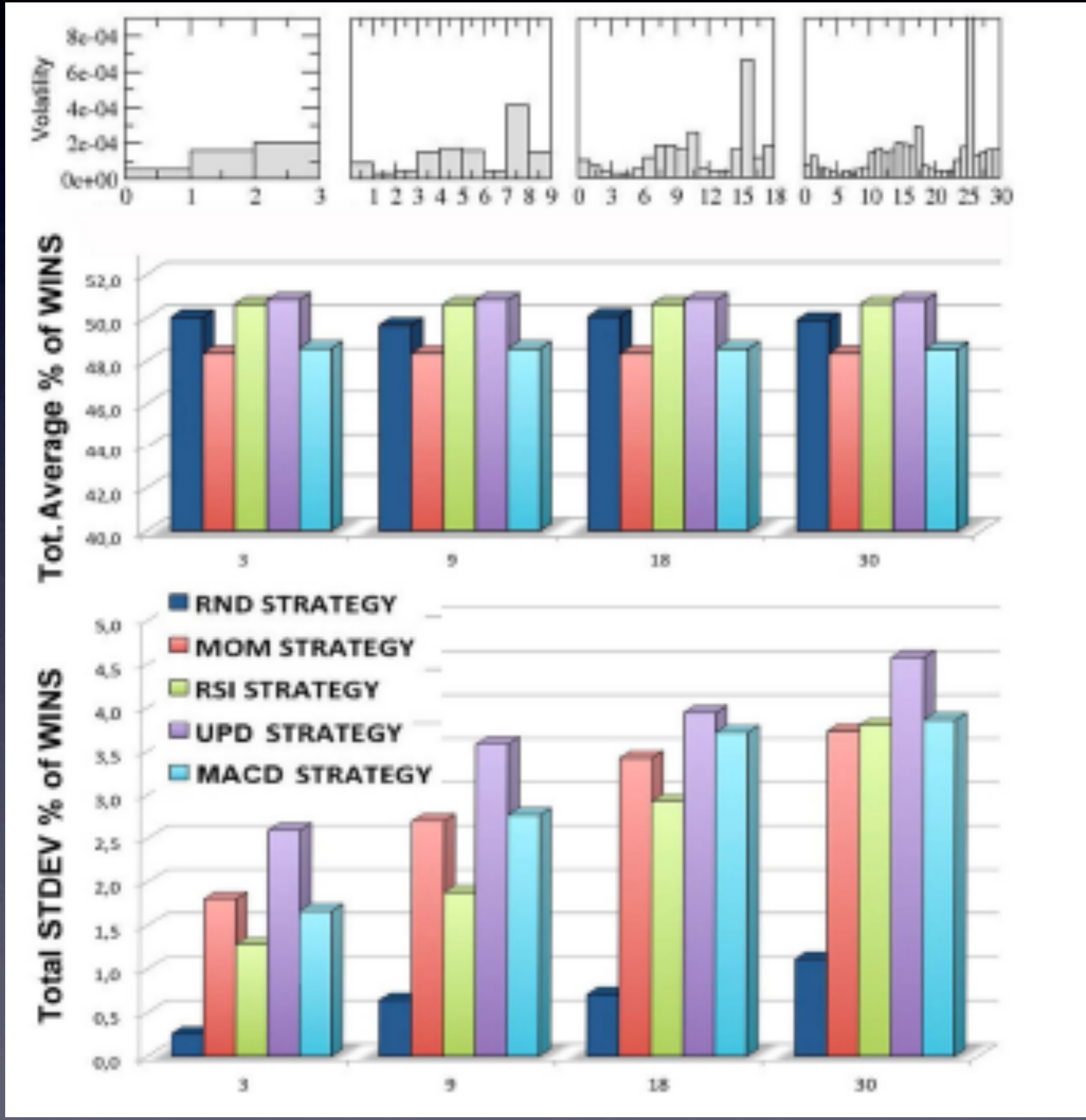
Results for S&P 500

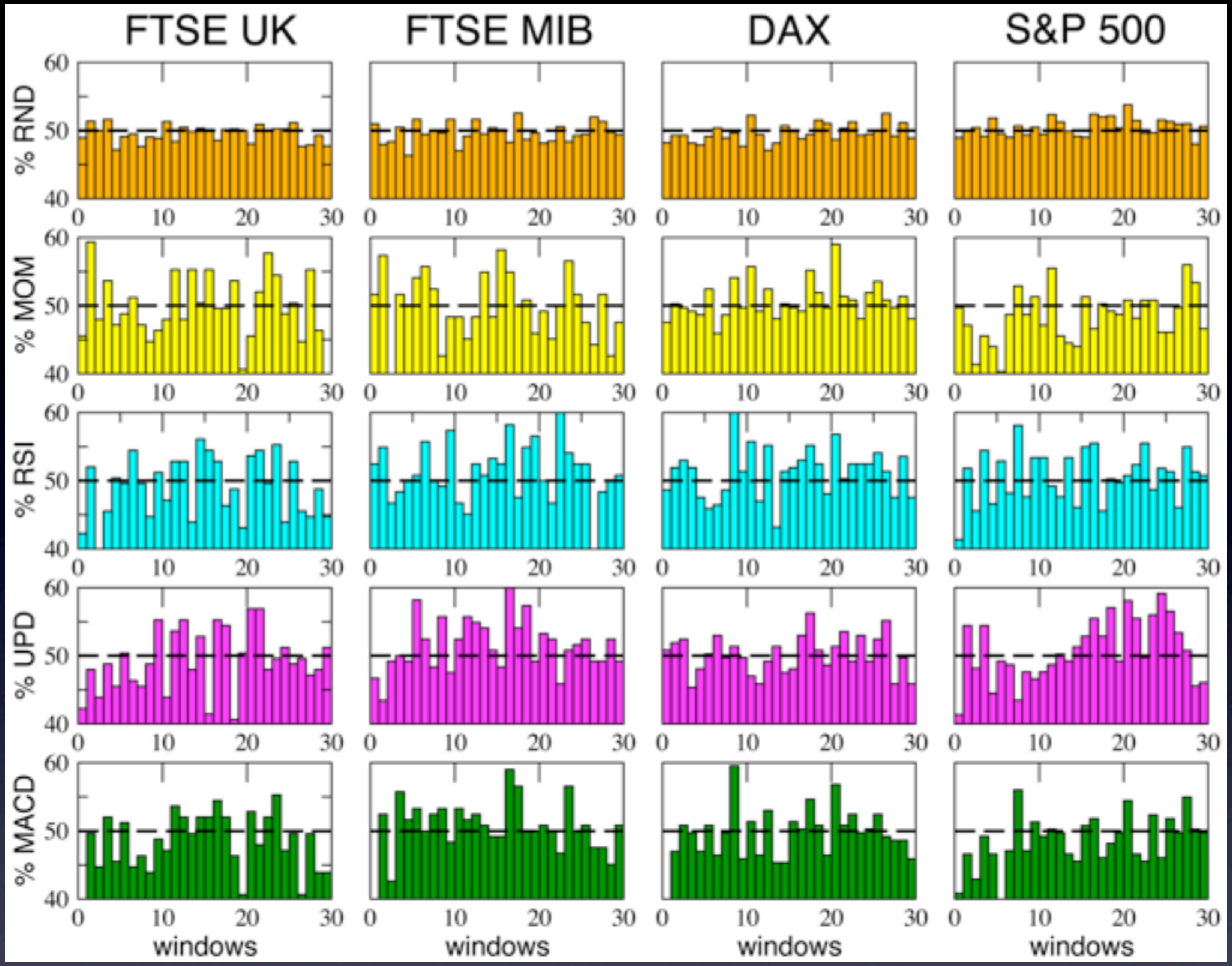


Volatility of the returns, i.e. the variance of the previous series, calculated inside each window for increasing values of the trading window size

The average percentage of wins for the five trading strategies considered, calculated for the same four kinds of windows (the average is performed over all the windows in each configuration, considering different simulation runs inside each window)

The corresponding standard deviations for the wins of the five strategies.





The percentage of wins of the different strategies inside each time window - averaged over 10 different events - is reported, in the case N_w = 30, for the four markets considered.

The performances of the strategies can be very different inside a single time window: large fluctuations are observed in general for deterministic strategies, while fluctuations are minimal in the case of random strategies

In the long run, the performance of random strategies is as good as the most used deterministic ones and quite often even better.

In addition, random strategies are costless and present smaller fluctuations

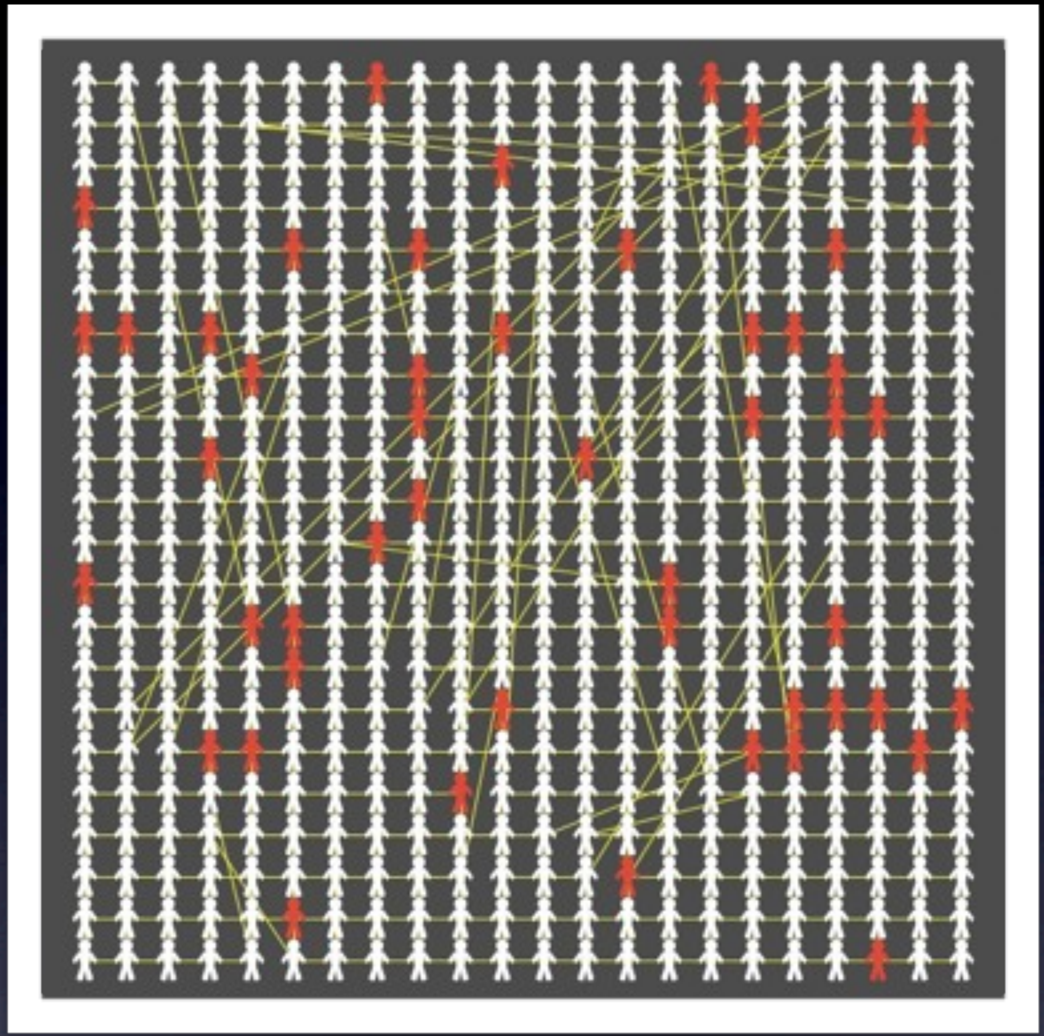
More recent results

Random strategies can be very successful not only at the microscopic level (single trader) ,but also at a macroscopic level (for a community of traders) because they can stop the occurrence of big dangerous herding-related avalanches

A.E. Biondo, A. Pluchino, A. Rapisarda, D. Helbing, arXiv:1309.3639

More recent results

Financial Quake Model



Let us consider a community of A_i traders (i=1,2,...N, N=1600) who bet on the bullish or bearish day-by-day behavior of the stock market (the S&P 500 for example).

Traders are connected according to a small-world topology. Each of them has an initial information I_k which is increased at each time step. They bet only if they overcome a certain threshold of informative pressure I_{th} and can activate their neighbors according to the rule

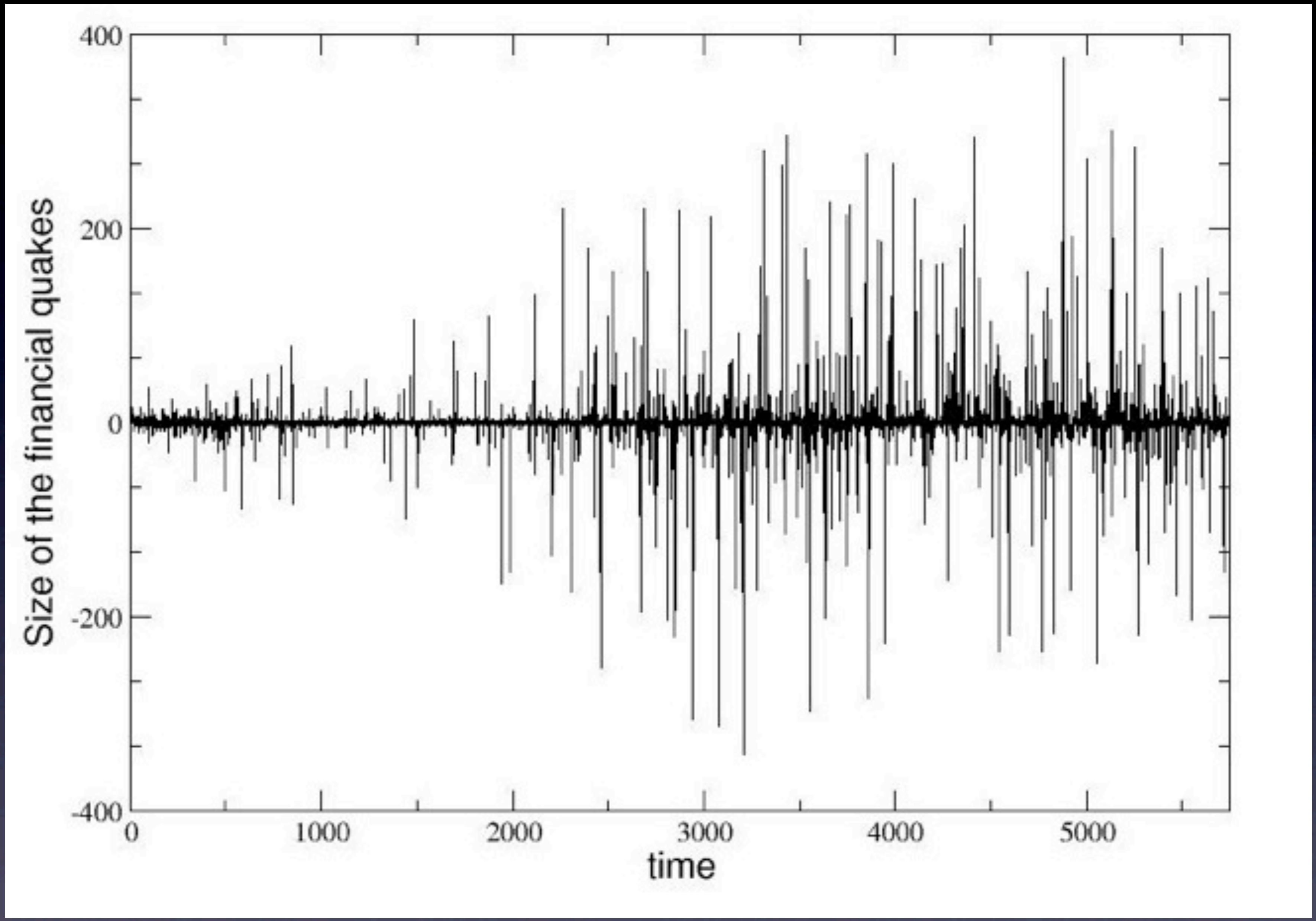
$$I_k > I_{th} \Rightarrow \begin{cases} I_k \to 0, \\ I_{nn} \to I_{nn} + \frac{\alpha}{N_{nn}} I_k, \end{cases}$$

$$\alpha = 0.84$$

Avalanches and SOC behavior is generated in this way in a very similar way of the Olami Feder Christensen model for earthquakes. Financial quakes can be positive (right guess) or negative (wrong guess)

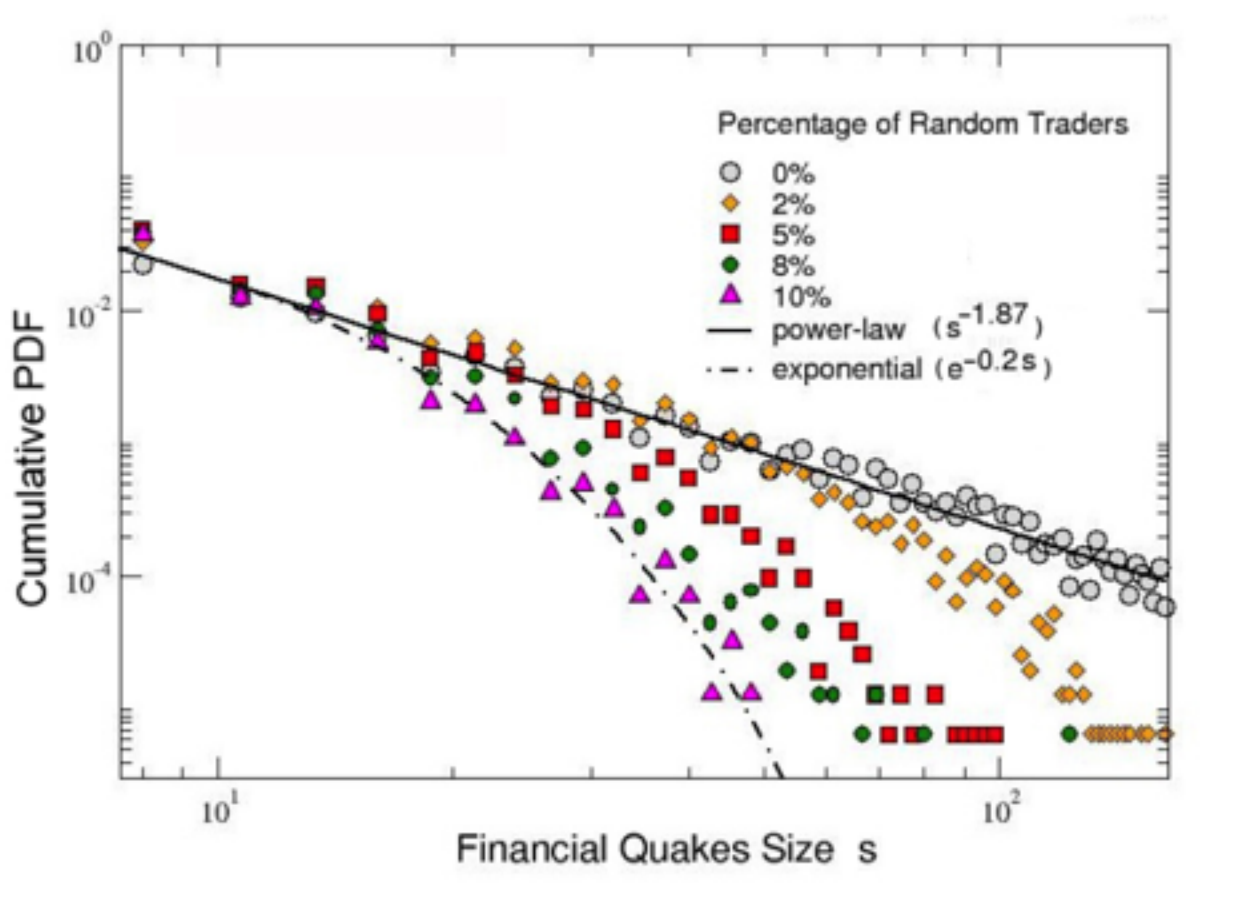
Agents follow a deterministic trading strategy (RSI for example), but a few of them, red ones, bet using a random strategy and are not activated by their neighbours nor do they activate neighbors: they can be also seen as random damaged sites of the network.

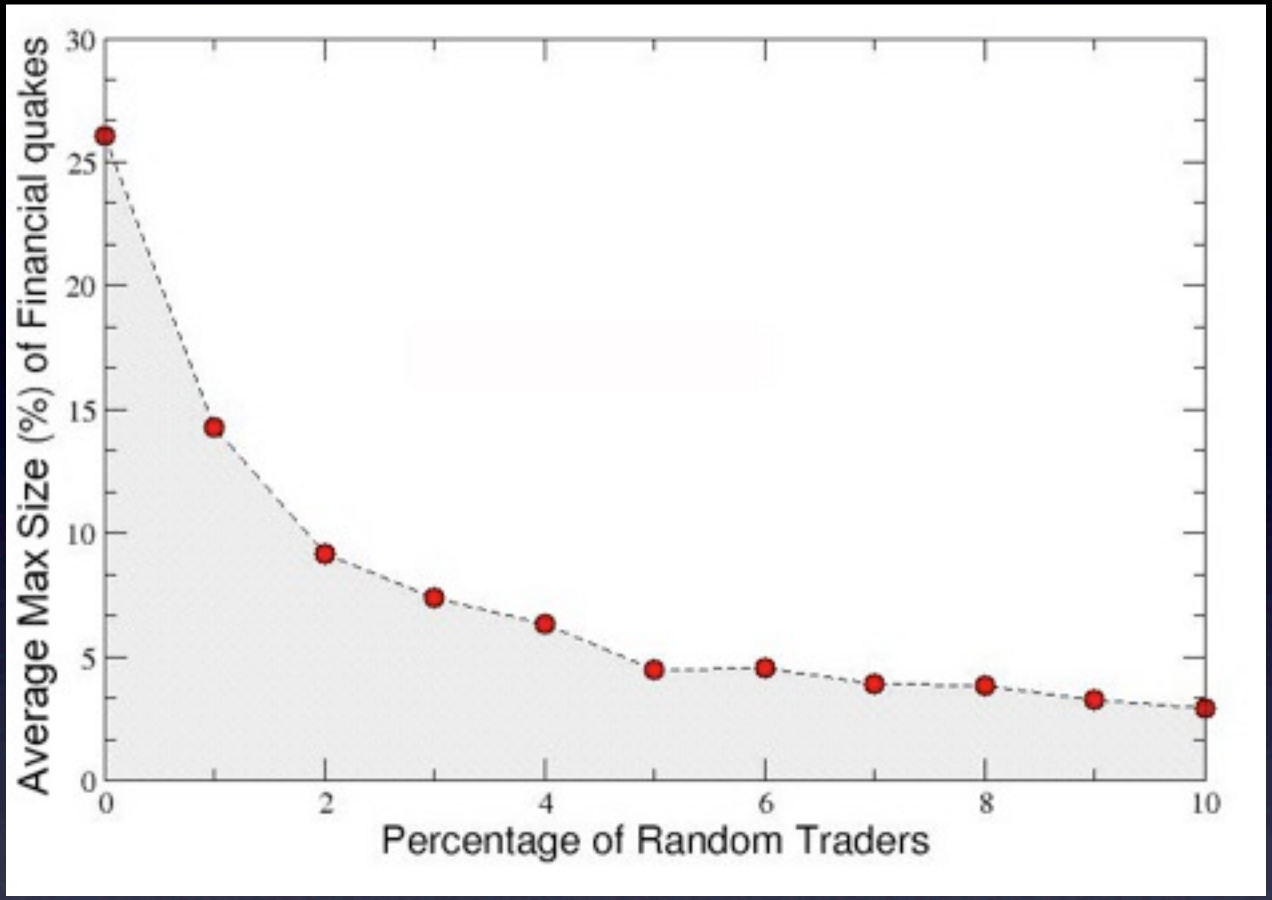
Results without random traders



Big avalanches and SOC behavior

Effect of a uniform random presence of random traders





A small percentage of random traders uniformly distributed at random in the small-world network is able to reduce in a very efficient way the number of avalanches and their size !

Results

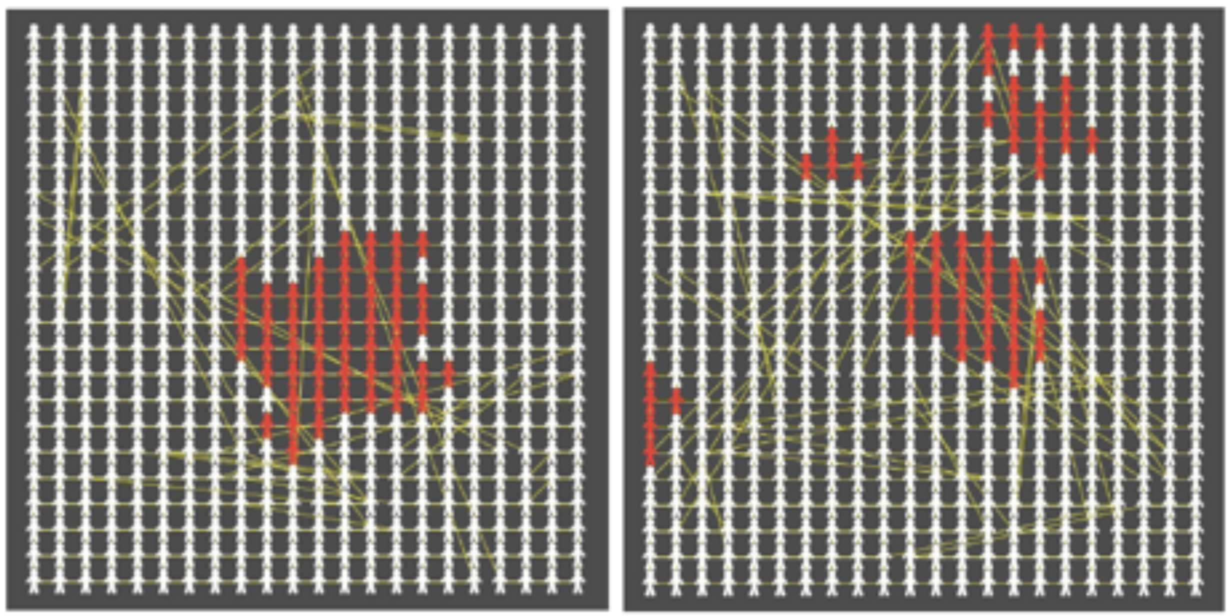
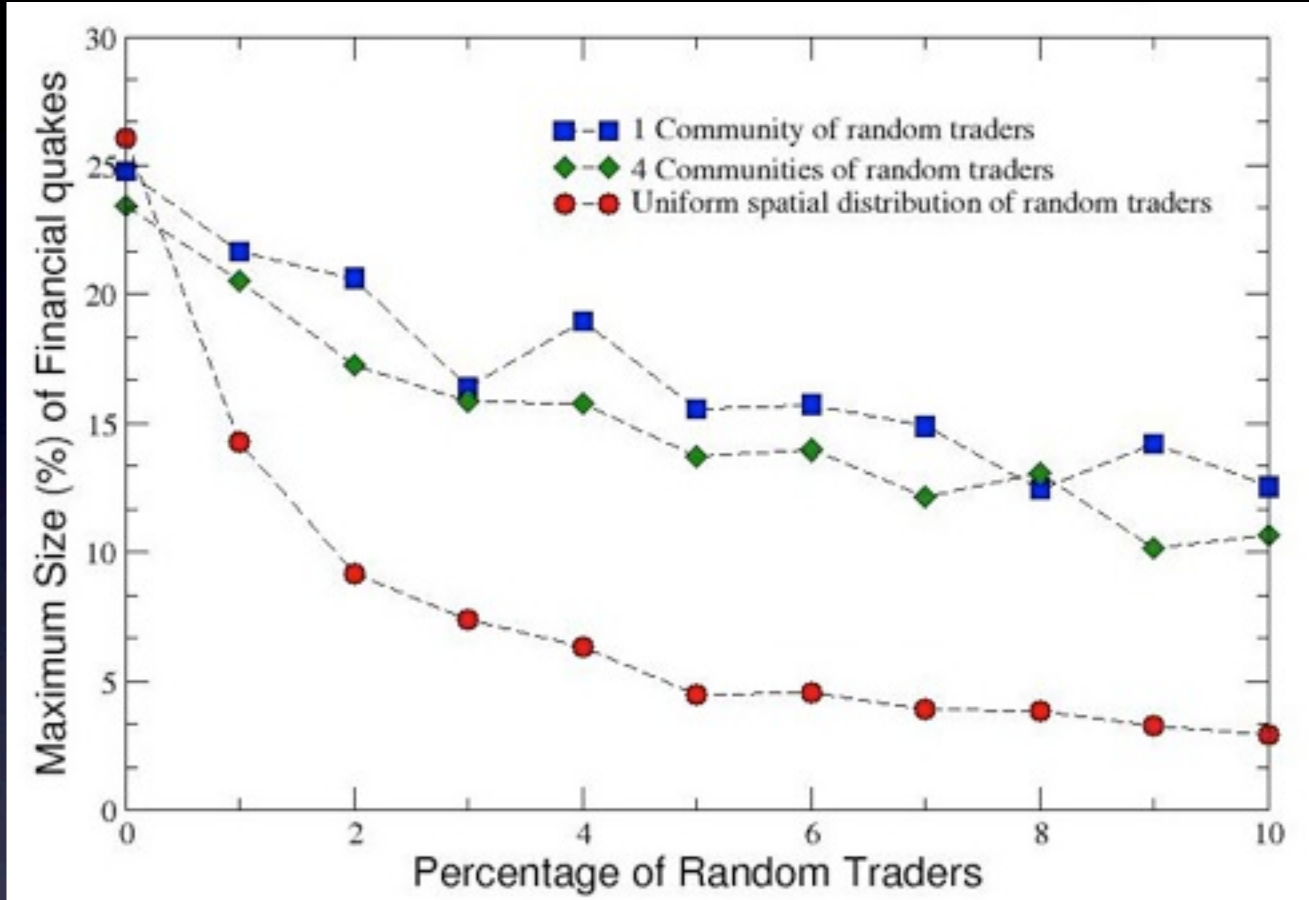


FIG. 6: Two different examples of small-world $2D$ network, with $N = 500$ agents, where random traders (colored agents, 10% of the total) are grouped in, respectively, one community (left panel) or four communities (right panel).



Random traders distributed at random are more efficient than clustered random traders in reducing herding-related avalanches

Capital/wealth distribution of traders

It is also interesting to study the capital gain or loss, i.e. the change in wealth, of the agents involved in the trading process during the whole period considered

At the beginning of each simulation, we assign to each trader (RSI or random) an initial capital Ci according to a normal distribution with an average value of < C >= 1000 credits and a standard deviation equal to 0.1 < C >.

Then we let them invest in the market according to the following rule:

- if an agent wins in the next investment she will bet a quantity

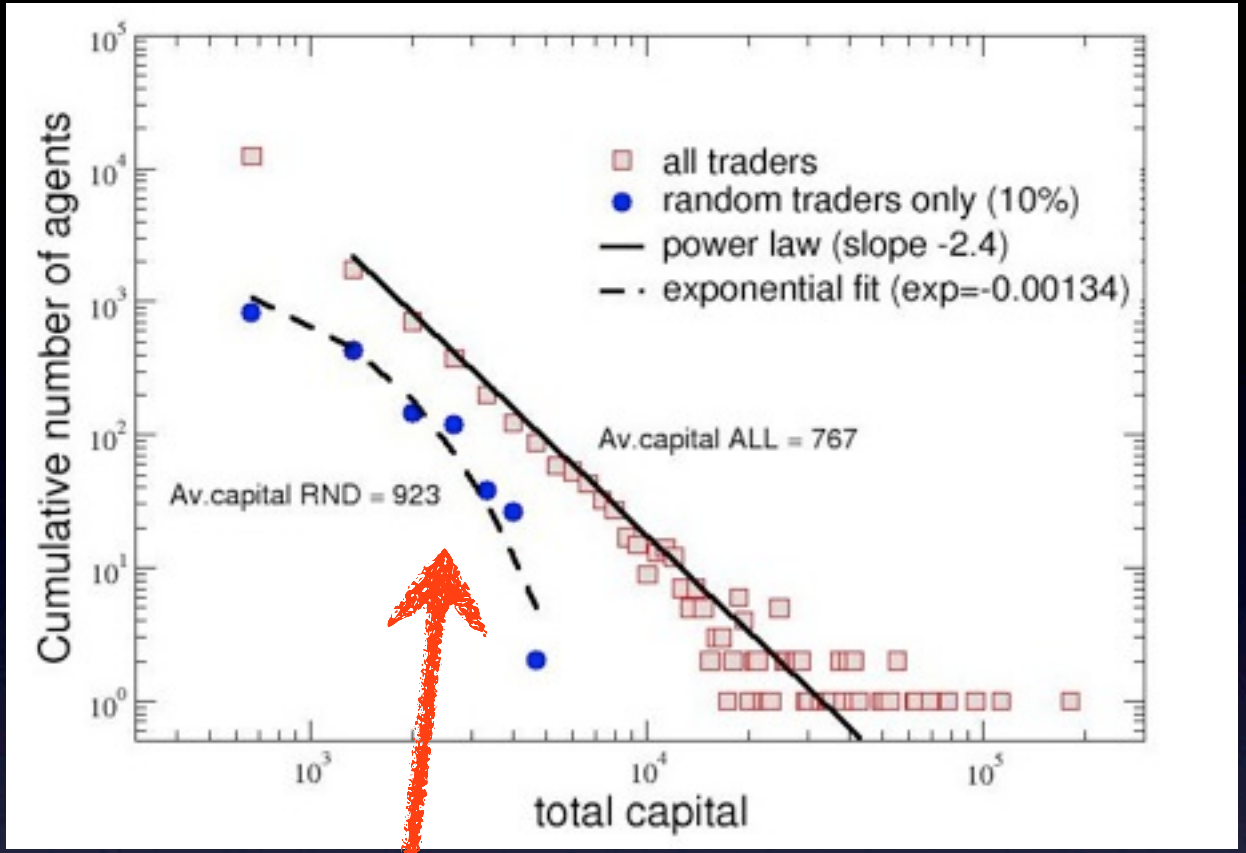
$$\delta C_i = 0.5 C_i$$

- if an agent loses, due to an unsuccessful investment, the next time she will invest only

$$\delta C_i = 0.1 C_i$$

In both cases, after a financial quake, each agent involved in the herding-related avalanche will increase or decrease her total capital by the quantity

$$\delta C_i$$



The wealth distribution of random traders can be fitted with an exponential curve.

The average capital of random traders is greater than that of all traders.

40% of RSI traders have a final capital smaller than that of the worst of random traders

only 3% of RSI traders *performed better than the best random trader.*

26% of random traders increased their initial capital against a 14 % of RSI traders

Conclusions for the case of financial markets

Random strategies can be beneficial for the single trader, since they have small fluctuations and are less risky

but they can be also very useful for the entire system, since they can be very efficient in stopping herding and financial bubbles / crashes

General conclusions

- The role of random noise can be very useful not only in Physics
- We have seen several socio-economic examples where random strategies are beneficial
- A bit of randomness can really help in finding new original and costless solutions, overcoming our prejudices

Happy Birthday Constantino !!!

...and really many thanks for your frequent and stimulating advices source of great inspiration