Econophysics and sociophysics: their milestones & challenges

Part 2*

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Abstract. We continue to discuss the milestones of econophysics and sociophysics. We chose them in the context of the challenges posed by contemporary socio-economic reality. We indicate their role in building research areas in econophysics and sociophysics. This part is devoted primarily to complexity, incredibly complex networks, and phase transitions, particularly critical phenomena and processes, agent-based modeling, risk issues in the context of financial markets, and elements of modern sociophysics.
Keywords: science of complexity, complex networks, scaling-laws/power-laws and critical phenomena; financial, currency & cryptocurrency and company markets, agent modeling. market and systemic risks

Abstrakt. Kontynuujemy omawianie kamieni milowych ekonofizyki i socjofizyki. Wybraliśmy je w kontekście wyzwań jakie niesie ze sobą współczesna rzeczywistość społeczno-ekonomiczna. Wskazujemy na ich rolę w budowaniu obszarów badawczych ekonofizyki i socjofizyki. Ta część poświęcona jest przede wszystkim złożoności, a w tym sieciom złożonym, przemianom fazowym a szczególnie zjawiskom i procesom krytycznym, modelowaniu agentowemu, zagadnieniom ryzyka w kontekście rynków finansowych oraz elementom współczesnej socjofizyki.
Słowa kluczowe: nauka o złożoności, sieci złożone, prawa skalowania/prawa potęgowe i zjawiska krytyczne; rynki finansowe, walutowe oraz rynki firm, modelowanie agentowe. ryzko rynkowe i systemowe

Preamble: The last three years can characterized by the particularly intensive work of the econophysicists community on describing and understanding the new reality in which the world has found itself. What is being sought is a multidimensional response to the emerging extreme, multiple unique challenges on an unprecedented scale. The summary of this intensive work can be, for example, conferences:

- 11th Polish Symposium in Economy and Social Sciences (FENS 2021), Kraków 1-3 July 2021
- Conference on Complex Systems 2021 - Satellite on Econophysics, Lyon 27-28 October 2021
- Econophysics Colloquium, Thessaloniki 24-26 August 2022

In this context, advanced data analysis, particularly research of shocks, crashes, crises, and recessions, and besides reality modeling, and especially computer simulation of complex systems, recognition and analysis of various types of risks and threats, and forecasting of socio-economic reality, have to take into account extreme ("black swans") and super-extreme ("dragon kings") events. From a factual point of view, this work concerns the period before 2020. However, the last three years require in-depth reflection, for which the proper basis is provided by, among other things, this paper and the Special Issues [2, 3].

1. The complexity of econophysics and sociophysics

We characterize the relationship between econophysics/sociophysics and areas related to complexity using the diagram shown in Fig. 3 in Part 1 [4]. These areas also show the wealth of topics in econophysics and sociophysics. Only some of them are presented in this first part of the article. This part is mainly devoted to discussing the complexity of econophysics and sociophysics in the context of complex networks, agent-based modeling as well as phase transitions and critical phenomena, which are widely practiced research directions of econophysics and sociophysics.

2. Complex networks

Important tools to describe and understand the collective behavior of financial time series (based on correlated

*This second part of the article is partially a reprint of the article [1] with some modifications. For example, we have introduced the Preamble, the short section 1, and a paragraph in section 7, while one paragraph we removed; we also extended the Abstract. Besides, the bibliography has been limited and the numbering of sections has changed. Moreover, it was stripped of the last paragraph compared to the original article. Elsevier License Terms and Conditions No. 5380360858688

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graphs) include the minimal spanning tree (MST) [5]. This was applied to finance for the first time by Rosario Mantegna [6], opening a new, extremely prolific chapter in econophysics and recently to sociophysics.

The MST (is a connected graph) that allows only such unique paths connecting nodes of a complete graph, which minimizes the sum of edge distances [7]. In this way, MST extracts the most important relevant informations in financial time series [8] and numerous applications [9] (e.g., in seismic, meteorological, cardiological, and neurological time series).

The analysis of cluster hierarchy deserves special attention within MST. It well reproduces the sectorial nature of stock exchange. It must be said, however, that the MST is not robust in a sense that by removing one data one gets another (topologically non-equivalent) tree. Only the proper family of MST trees enables to give a sufficiently robust result [10, 11].

The MST based work [12] details numerical and empirical evidence for dynamical, structural and topological phase transitions on the Frankfurt Stock Exchange (FSE) in the temporal vicinity of the worldwide financial crash 2007/8. Indeed, using the MST technique, two typical transitions of the topology of a complex network representing the FSE were found. The first transition is from a hierarchical Abergel scale-free MST representing the stock market before the recent worldwide financial crash, to a superstar-like MST decorated by a scale-free hierarchy of trees. The latter one represents the market's state for the period containing the crash. Subsequently, a transition is observed from this transient, (meta)stable state of the crash to a hierarchical scale-free MST decorated by several star-like trees after the worldwide financial crash.

Another method, called Planar Maximally Filtered Graphs (PMFG), is a powerful tool to study complex datasets [13, 14, 15]. It has been shown that by making use of the 3-clique structure of the PMFG a clustering can be extracted allowing dimensionality reduction. This keeps both local information and global hierarchy in a deterministic manner without the use of any prior information [16]. Filtered graphs can also be used to diversify financial risk by building a well-diversified portfolio that effectively reduces investment risk. This is done by investing in stocks that occupy peripheral, poorly connected regions in the financial filtered networks [17, 18, 19].

However, the algorithm so far proposed to construct the PMFG is numerically costly with $O(N^3)$ computational complexity and cannot be applied to large-scale data. There is a challenge therefore to search for novel algorithms that can provide, in a numerically efficient way, such a reduction to planar filtered graphs.

A new algorithm, called the TMFG (Triangulated Maximally Filtered Graph), was introduced to efficiently extracts a planar subgraph, which optimizes an objective function. The method is scalable to very large data sets and it can take advantage of parallel and GPUs computing. The method is adaptable allowing online updating and learning with continuous insertion and deletion of new data as well changes in the strength of the similarity measure [20].

Network filtering procedures are also allowing to construct probabilistic sparse modeling for financial systems that can be used for forecasting, stress testing and risk allocation [21, 22, 23].

The problem of studying the economic growth patterns across countries is actually a subject of great attention to economists and econophysicists [24, 25]. Cluster analysis methods allow for a comparative study of countries through basic macroeconomic indicator fluctuations. Statistical (or correlation) distances between 15 EU countries are first calculated for various moving time windows. The decrease in time of the mean correlation distance is observed as an empirical evidence of globalization. Besides, the most strongly correlated countries can be partitioned into stable clusters. The Moving Average Minimal Length Path algorithm indicates the existence of cluster-like structures both in the hierarchical organization of countries and their relative movements inside the hierarchy.

All the above mentioned methods enabled effective exploration of any complex networks, opening new, extremely interesting research fields and triggering a real flood of not only econophysical and sociophysical works but also far beyond these research areas (e.g., in biology, ecology, climatology, medicine, telecommunications).

3. Systemic risk and network dynamics

This type of risk has spread widely culminating in the subprime crisis of 2007/08. The analysis and control of systemic risk has therefore become an extremely important social and economic challenge. This challenge was taken up by economics, finance, and also by econophysics. It was found that the role of the financial institutions' network was crucial in the dissemination of the financial crisis of 2007/08. The greater the degree of cross-linking, the greater the risk of system crash. This was thoroughly considered in review entitled: *Econophysics of Systemic Risk and Network Dynamics* edited in 2013 by the Abergel, Chakrabarti, Chakraborti, and Ghosh [26].

3.1. Financial market risk and the first-passage time problem

The uncertainty and risk are inextricably linked to the activity of financial markets [27, 28]. One has approached the very promising issue of risk evaluation and control as a first-passage time (FPT) problem. The mean first-passage time (MFPT) was used as a basis for the assumption of stochastic volatility (exploited within the Heston model) [29]. One significant result is the evidence of extreme deviations – which implies a high risk of default – when the strength of the volatility fluctuations increases. This approach may provide an effective tool for risk control, which can be readily applicable to real financial markets both for portfolio management and trading strategies. Analysis of extreme times considered in [30] (also as a significant quantity of FPT) is closely related to at least two challenging problems which are of great practical interest: the American option pricing and the issue of default times and credit risk. Both problems require the knowledge of first-passage times to certain thresholds. It was found that the MFPT versus the threshold level can be represented as a power law. Thus the usefulness of FPT approach to financial times series analysis has been proven.

3.2. Agent-based modelling

Agent-based modelling (ABM) opens the possibility for describing the phenomena and processes occurring on financial markets (and not only) at ab initio level. In general, the market modelling is one of the challenges of modern econophysics [31, 32, 33, 34, 35, 36]. The main purpose of market modelling is to reveal the laws and underlying processes of market behavior supplying (as one of the results) some signatures or warnings of upcoming extreme events or crashes.

Agent-based models, also called computational economic models, are widely exploited, for instance, in economics (Ausloos et al., 2015 [37]; Farmer and Foley, 2009 [38]), sociology (Macy and Willer, 2002 [39]) and in the environmental sciences (Billari et al., 2006 [40]). A thorough review was made from the econophysics point of view in 2014 year in the collective review publication entitled: *Econophysics of Agent-Based Models* edited by Abergel, Aoyama, Chakrabarti, Chakraborti, and Ghosh [41].

The hallmark of ABMs is the coupling of individual and collective degrees of freedom of the analyzed system that is, its micro- and macroscales. The former is represented by individual agents, while the latter one by the system as a whole (or its macroparts). Frequently, agents are divided into two completely different groups: stabilizing (e.g., fundamentalists or rebalancers) and destabilizing market activity (e.g., chartists, noise traders or portfolio insurers). The competition between them can be a source of long-range and long-term nonlinear correlations, critical phenomena and fat-tailed distributions.

Firstly, a few inspiring canonical models belonging to the field of portfolio analysis are presented. The pioneering Kim-Markowitz (KM) agent-based model [42, 43] was inspired by the stock market crash of 19th October 1987, when DJIA decreased by more than 20% per day. This model confirmed by numerical simulation a common observation that strategies of portfolio insurers (and not that of rebalancers) destabilize financial markets. This model has raised hopes for the promising agent-based modelling capabilities.

Besides, the Levy-Levy-Solomon (LLS) model [44] was developed to consider the risk-averse investors having arbitrary long memory. The LLS model describes the spontaneous periodicity of the market, its booms and crashes. Although the results obtained depend significantly on the initial conditions assumed, the model has demonstrated (by numerical simulation) that the wealth available on the market (in the form of shares and bonds) will, after sufficiently long time, be taken over by a group of investors equipped with a long memory (one hundred steps back in simulation). This outcome is in line with expectations.

An extremely popular model describing the evolution of the market, going beyond the aforementioned portfolio analysis category is the Lux-Marchesi (LM) model [45]. It is able to correctly describe many stylized facts, for example: volatility clustering, power-law distribution of returns, and long-term autocorrelation of absolute returns. This model is based on the concept of mutual exchange and interaction between different groups of investors (i.e. chartists and fundamentalists) and on the process of price adjustments with a demand-supply imbalance. Additionally, chartists are divided into optimists and pessimists - the competition between them as well as with fundamentalists create an effective opinion of agents leading to strong interconnection of chartists amount with the price amplitude. This interconnection is responsible for the observed large market fluctuations. A similar influence of portfolio insurers is observed within the Kim-Markowitz model. The technical disadvantage of the LM model is the large number of free parameters in the model involved.

A very important category of models describing the behavior of financial markets, and inspired by models drawn from physics, are primarily Ising-like on complex networks, whose prominent example is the Iori numeric model [46]. The agent is represented here by three-state spin vector, where state +1 means buying a stock, −1 selling, while 0 means inactive state. Obviously, the agent activity is limited by amount of his capital however, his activity has still a probabilistic character with threshold. Besides, the market maker is present guarding the liquidity of the market. The price in this model depends not only on the ratio of the supply of securities to their demand but also on the available securities volume. This multiparameter model managed to describe all the stylized facts (i.e. volatility clustering of returns, the positive correlation between volatility and trading volume, the power-law decay of autocorrelation).

The above models inspired the econophysicists in a significant way. The first model that grew out of this society and was characterized by a small number of parameters was the Cont-Bouchaud (CB) model [47] based on a discrete percolation phenomenon – a phenomenon previously analyzed in the field of chemistry and statistical physics, condensed matter physics and mathematics. A year later, Dietrich Stauffer also used percolations to model the behavior of financial markets [48].

As a part of the CB model, neighboring network nodes form a cluster making collectively investment decisions in a probabilistic manner. Therefore, it can be said that this model is based on the so-called lattice-gas model isomorphic with canonic Ising model. The market price is (as usual) a function (here exponential) of the difference between demand and supply. This type of approach is very flexible, generating (depending on the input probability) either Gaussian distributions or various types of power-laws distributions – both observed on financial markets.

The next interesting ABM is the Bornholdt spin model [49, 50] primarily designed to recreate the price dynamics in short time horizons. Similarly to the KM and LM models, it assumes that there are two types of investors on the market: fundamentalists and noisy traders. The fundamentalists only respond to price changes, making the market price as close as possible to the fundamental value of stock. The mutually interacting noisy traders take the probabilistic decisions to buy or sell the stocks depending on the market situation. This situation is described by the local, time-dependent threshold function of influence having a threshold character. The size of this threshold is connected linearly with the volume. In this model, the interacting traders are responsible for non-Gaussian behavior of the market. The Bornholdt model describes a lot of stylized facts: power-law return distributions, volatility clustering, positive correlation between volatility and volume, and self-similarity between volatilities on various time scales. Unfortunately, the shape of the absolute-returns autocorrelation function is not a power law herein.

Although the ABMs circumscribed above are valuable and useful, none of them were used to model the interevent-time statistics so much significant in a study of correlations on financial markets. In 2014 the model of so-called cunning agents was developed [51], which reproduces not only stylized facts but also empirical statistics of interevent times. One can say that we are dealing with a cunning agent if he accepts a position, for example, a long one indicating the willingness to buy additional items and informs his neighbors about it, but in fact, simultaneously sells the possessed assets. The situation is similar in the short and neutral position. Recently, a model appeared [52], which starting from the level of stochastic dynamic equations, was able to reproduce mentioned above the empirical statistics of interevent times.

The interesting extension of the Geometrical Brownian Motion was made by Dhesi and Ausloos [53] who introduced so-called the Irrational Fractional Brownian Motion model. They re-examined agent behaviour reacting to time dependent news on the log-returns thereby modifying a financial market evolution. Authors specifically discuss the role of financial news or economic information as a positive or negative feedback of such irrational (or contrarian) agents upon the price evolution. A kink-like effect reminiscent of soliton behaviour was observed, suggesting how forecasts uncertainty induces stock prices. This way they proposed a measure of irrational force in a market, which seems to be a very significant for understanding the dynamics of stock market.

It should be emphasized that agent-based models, along with network models, have gained immense popularity not only in the society of econophysicists but also sociophysicists.

4. Phase transitions, catastrophic and critical phenomena

Phase transitions, catastrophic and critical phenomena have long been studied both in the framework of econo- and sociophysics (see, for instance, [54, 55]). However, phase transition of the global financial system observed at the end of 2008 deserves the special attention. This is because it was just after the bankruptcy of Lehman Brother [56]. The signature of this transition is a sharp increase in the susceptibility/sensitivity of the system to the negative global shock with an initially well-defined epicenter focused on mortgage backed securities. This shock was the source of the observed cascade of defaults or a succession of problems associated with the most prominent global institutions (belonging to the banking, insurance and mortgage sectors). This cascade caused crash on the stock market and the subsequent panic among economical institutions from the global ('too-big-too-fall') to the local ones – leading many of the latter to bankruptcy.

The model developed in paper [56] is, in essence, a simplified discrete correlated random walk of walkers (or firms) on the ladder consisting of the effective credit rating grades (ECRGs), where the firm either remains at a given ECRG or change its value by one (with blocking boundary condition at top and the bottom of the ladder). By using the statistical-mechanic partition function based on the Ising-like sociological influence function, the conditional single-step probability for each firm is constructing in the exponential form. This partition function contains the field of panic taking into account the firm's bankruptcy. For simplicity, the direct coupling between firms is a random variable drawn from the Gaussian distribution. This model exhibits a critical behaviour that is, the second-order phase transition at well-defined critical point. Besides, the phenomenon of spontaneous symmetry breaking is observed (by the increasing the number of bankruptcies) due to the nonvanishing of the panic field. The model offers the phase diagrams and enables the system time evolution. This is the first so complete model in the field although earlier more sociophysical oriented models by Schweitzer et al. were published [57].

One should also mention works that still raise controversy regarding the presence of bifurcation on the stock exchange or, more generally, phase transformations of the first order. The related issue of the critical and catastrophic slowing down phenomenon are the most refined indicators of whether a system is approaching a critical point or a tipping point – the latter being a synonym for the catastrophic threshold located at a catastrophic bifurcation transition. The still open problem raised by Scheffer et al. [58] is whether early-warning signals in the form of a critical or catastrophic slowing down phenomena (such as those observed in multiple physical systems) are present on financial market. The possibility of existence of the above-mentioned early-warning signals was highlighted in publication of Kozłowska et al. [59] and refs. therein.

A microscopic approach to macroeconomic features has always been a challenge [60] and refs therein. A birth-death lattice gas model for macroeconomic behavior under heterogeneous spatial economic conditions takes into account the influence of an economic environment on the fitness and concentration evolution of the economic entities. The reaction-diffusion model can be also mapped onto a high order logistic map. The role of the selection pressure along various dynamics (with entity diffusion on a square symmetry lattice) has been studied by Monte-Carlo simulation. The model leads to a sort of phase transition for the fitness gap as a function of the selection pressure and to cycles. The scalar control parameter is a sort of a "business plan". The business plan(s) allows for spin-offs or merging and enterprise survival evolution law(s), once bifurcations, cycles and chaotic behavior are taken into account.

The problem whether a power-law or an exponential law describes better the distribution of occurrences of economic recession periods is significant not only for econo- and sociophysics but primarily for socio-economical science and life. In order to clarify the controversy a different set of GDP data were examined in [61] for example. The conclusion about a power law distribution of recession periods seems to be more reliable though the matter is not entirely settled. The case of prosperity duration is also studied and it is found to follow also a power law. Considering that the economy is basically a bistable system (recession/prosperity) a characteristic (de)stabilisation time is posssible to quantitatively derive.

5. Significant elements of global economy

The global economy has its source in important connections (dependences, interactions, influences, etc) between countries and regions [62]. An international trade is a glaring example of this. Obviously, the globalization is one of the central processes of our age. The common perception of such process is that, due to declining communication and transport costs, distance becomes less and less important. However, the distance coefficient in the economical gravity model of trade [63] (which grows in time) indicates paradoxically that the role of distance becomes a more important. In the paper [62] it was shown that the fractality of the international trade system (ITS) provides a simple solution for this globalization puzzle. It was argued that the distance coefficient corresponds to the fractal dimension of ITS and not to the Cartesian distance.

The world economic conditions evolve and are quite varied on different time and space scales. This evolution forces developing of macroeconomic entities within a geographical type of framework [64, 65]. For the firm fitness evolution a constraint is taken into account such that the disappearance of a firm modifies the fitness of nearest neighboring ones (as in Bak-Sneppen population fitness evolution model [66]). The concentration of firms, the averaged fitness, the regional distribution of firms, and fitness for different time moments, the number of collapsed, merged and new firms as a function of time have been recorded and are discussed. A power law dependence, signature of self-critical organization, is seen in the firms' birth and collapse asymptotic values for a high selection pressure (control parameter) only. A lack of self-organization is also seen at region borders. The research and market modeling of companies is still one of the main goals of econophysics.

6. Contemporary sociophysics

The systematic research on society that gives rise to the modern sociology is mainly due to the work of Quetelet [67] (see also [68]). Today it is clear that only a comprehensive approach to economic phenomena and processes, including both psychology, social psychology and sociology, enables the description and understanding of the mechanisms governing socio-economic life (including also financial markets). This was shown convincingly in 2006 in the collective work [69]. We are increasingly attempting to understand the emotional nature of human activity and activity of human communities. This emotional component can be seen particularly clearly in cyberspace – this has been well presented in the collective work entitled: *Cyberemotions. Collective Emotions in Cyberspace*, edited by Janusz A. Hołyst [70]. This type of interdisciplinary approach to the complex socio-economic reality is extremely inspiring, stimulating and promising. In this context, we should say about the role of the Sznajd model ('united we stand, divided we fall' – USDF model) [71, 72]. It has become credible thanks to its success in predicting the result of elections in Brazil, opening the way for contemporary sociophysics. The Sznajd model easily introduces the possibility of obtaining a consensus by exchanging opinions between members of a given community. It is based on the Ising model with characteristic social interaction – it is by far the most exploited by sociophysicists toy model with the cluster-like ever-growing number of different variants. A complementary, important model that should also be mentioned here is the Bonabeau model [73] showing how hierarchies are created in a given community. Let us add that currently the study of various hierarchical structures, cascades, and networks is fashionable and very advanced [74, 75].

The social impact is one of the most important and the most common social phenomena. The dynamical theory of this impact proposed in 1990 [76] gave rise to a huge stream of works. The sociophysicists have made a significant contribution to the development of this trend. Today, this type of modeling is a canonical component of the sociophysics without which one cannot imagine an advanced analysis of the societies' behavior.

The attempts made by physicists to understand so-called social "forces" have lasted at least since the mid-1970s [77]. Quite interestingly, the source of social force is attributed to technological innovation made by competing goods and new population. Another view about quantifying social forces (found in [78]) pretends that they result as coupling to some external fields.

The role of emotions in opinion dynamics mentioned above was used in a variant of the ABM complementary to the Sznajd model. The combination of information and emotions interplay was used successfully to predict the results of Polish election in 2015 [79, 80]. This is the prominent evidence of the practical use of sociophysical modeling.

Let us add that the collective work entitled: *Why Society is a Complex Matter* edited by Philip Ball in 2012 [81] also played a prominent role in the development of contemporary sociophysics. This collective work pointed to sociophysics as a new kind of science. There the Helbing's work [82] (see also [83]) has shown a crucial role of information and communication technology for society.

It should be noted that in the last decade issues related to the evolution of cultures (including linguistics) have been continuing to represent an attractive, intriguing course of research [84, 85, 86, 87, 88]. A key tool for modeling this evolution is the Axelrod model and its various variants [84].

The Axelrod model [89] is defined by stochastic process which, similarly to the voter model, contains a social interaction between nodes of a network, but unlike the voter model also accounts for homophily. The aim of the model is to describe and explain macroscopic observations in real-world social networks, based on simple microscopic rules. These microscopic rules are also inspired by empirical observations or concluded from sociology or psychology. Every node of the network is described, in the frame of the model, by a vector of traits representing internal degrees of freedom. The idea behind the model was simple – to explain cultural diversity observed in societies, despite the fact that people become more alike within a face to face interaction. Therefore, Axelrod asked why eventually all differences do not disappear? In his model the vector of traits describes culture of an individual (regional society or nation) in a sense of habits, beliefs, religion, language, hobbies, views, etc. During the evolution two individuals become more similar to each other, unless they stay different. This is a crucial observation leading to an interesting result, because only that one can obtain frozen (or equilibrium) states. Depending on the initial conditions, simulations can end in one of the states: in a homogeneous state with a monoculture or heterogeneous with many small subcultures, called 'domains'. The coexistence of these many different subcultures is a main result, confirming the possibility of existence of heterogeneous societies, despite people become more and more similar.

The model gained interest among physicists a few years later [90] along with the discovery of the phase transitions between homogeneous and heterogeneous states (continuous or discontinuous types). To make the model more realistic, it was extended to complex networks with very different topologies [91] as well as to dynamic complex networks. Moreover, this latter issue was addressed in [92], where different rewiring mechanisms were analyzed. It was then possible to obtain real-world features, like power-law degree distribution or high values of clustering coefficient. Besides, it was shown that a key to the proper scaling of the number of languages is triadic closure – type of rewiring proved to be very important in social networks [93].

A "degree of freedom" in a population is also the religion adhesion. The pioneering work on such adhesion aspect, in fact similar to market/company growth and market share influence, was published almost a decade ago [94]. The observed features and some intuitive interpretations point to opinion based models with vector like agent rather than scalar ones (many degrees of freedom instead of one). This supports the assumption of the Axelrod approach.

It is worth to mention also the works from the borderline of econo- and sociophysics regarding household incomes (especially in the European Union and the United States). The approach based on the stationary solution of the reinterpreted Fokker-Planck equation turned out to be particularly useful [95, 96]. This approach allowed to describe the distribution of income of all three social classes: low income, medium and high income well reproducing the Pareto laws (with different Pareto exponents) for the last two classes.

Concerning the wealth distribution, one of the most interesting outputs is the generic existence of a phase transition, separating a phase where the total wealth of a very large population is concentrated in the hands of a finite number of individuals (condensation phenomenon) from a phase where it is shared by a finite fraction of the population [97]. The rich phase diagram was examined in [98], in which both open and closed Pareto macroeconomics were studied. The wealth condensation takes place in the social phases both for closed (with the fixed total wealth) and open (with the fixed mean wealth) macroeconomy. The wealth condensation takes place also in the liberal phase for super-open macroeconomy (it was proved, indeed, in [97]). It was found that in the first two cases of macroeconomy, the condensation is related to the mechanism known from the balls-in-boxes model, while in the last case, to the fat tails of the Pareto distribution. Besides, for a closed macroeconomy in the social phase, the emergence of a "corruption" phenomenon was pointed out. A sizeable fraction of the total wealth is always amassed by a single individual. In publications cited above the dependence of Pareto exponents on microscopic parameters of the model was found. This is an achievement useful both for theoreticians and practitioners in social sciences.

Recently, several studies were published [99] (and refs. therein) which have given better insight into how birth is affected by exogenous factors. Especially, the adverse conditions (e.g. famines, epidemics, earthquakes, droughts, floods, etc.) temporarily affect the conception capacity of populations, thus producing birth rate troughs nine months after mortality waves. The challenge here is the discovery of the birth rate patterns and their interpretation. A promising step in this direction was made in paper [99], where several important patterns were found and discussed.

7. Challenges and warnings

It is already known that the analysis should take into account the feedback between econonophysics and sociophysics (including socio-psychology and even psychology of leaders and the policy of the state). Even roughly approximated modelling of reality should take into account the rivalry of the rational multicomponent with irrational one. The interdependence and networking of elements of socio-economical complex systems constitute (within econo- and sociophysics) the basis for the research even if the available empirical data is dirty and uncertain. The researchers realize that they are affecting the problems generated by complex systems. This complexity is the source of emergent phenomena and processes, including catastrophic and critical ones (on a macroscale). This may result in a dichotomy of descriptions within the micro- and macroscales. It is understand that, for example, breaking the principle of ergodicity may lead to the impassable barrier creating a dichotomy in the statistical description of socio-economical reality. That is, phenomena and processes in the macro scale mainly result from the properties of the system as a whole (especially when the system stays in a critical state) and not only from the behavior and properties of individual objects forming the system in the microscale. The understanding the role of dependency or correlation, causality, and coevolution or adaptation in markets or the complexity of markets and emerging phenomena and processes, become one of the greatest challenges for modern research of a socio-economical reality [100, 101, 102]. However, the econophysicists discoveries has miserable impact on the main stream works of financial economy (see Jovanovic and Schinckus [103]).

Finally, we must say about an event that puts a shadow on mathematics and financial physics as a great warning and a lesson for all of us. The portfolio analysis in the nineties of the previous century was based, in fact, on the canonical option pricing formula of Black-Scholes-Merton (BSM) derived in the canonical paper [104]. The BSM formula was derived mainly assuming that the prices of basic financial instruments, on which options were issued, are subject to the geometrical Brownian motion, while considered options are risk-neutral. As for the trend, its constant growth would be driven by investors constantly seeking arbitrage opportunities.

Based on this theoretical approach, the hedge fund Long-Term Capital Management (LTCM) was created in year 1994; the key people behind LTCM were Myron S. Scholes and Robert C. Merton – the Nobel Prize winners.

Although initially successful (for three consecutive years) with annualized return of over 20% netto, from August to September 1998 (short after the Asian financial crisis in 1997 and 1998 Russian financial crisis) LTCM lost, however, about 4.5 miliard (US billion) dollars severely disrupting global markets for several months. This was the consequence of violating the key assumptions of the theory in new market circumstances and neglecting the constant verification of these assumptions. Besides, used by LTCM leverage of portfolio composition has reached an unbearable ratio of debt-to-equity as 25:1. An in-depth systematic econophysical analysis of this subject, and especially issues related to market risks, was provided in year 2001 by Jean-Philippe Bouchaud and Marc Potters in the book *Theory of Financial Risks. From Statistical Physics to Risk Management* [105].

As a warning, we should also mention that the giant financial pyramid was discovered in 2008 by financial supervision. It was created by Bernard Madoff (co-founder and former chairman of the NASDAQ stock exchange operating today) as part of his elite *Madoff Investment Securities* hedge fund. The fraudulent fund led approximately 13,500 shareholders (including reputable banks and financial institutions) to roughly 35 billion USD in losses. As a result, Madoff spent the rest of his life in prison.

It must be clearly stated that we live in an increasingly risky society which is particularly vulnerable to extreme types of risk – both market and systemic [106]. Concerning the financial sector, among all possible extreme phenomena, indeed crashes are presumably the most striking events with an impact and frequency that has been increasing in the last two decades increasing the risk of market activity extremely. Understanding what is happening as well as risk control and management is an urgent challenge for investors and researchers alike.

Literatura

[1] Ryszard Kutner, Marcel Ausloos, Dariusz Grech, Tiziana Di Matteo, Christophe Schinckus, and H. Eugene Staanley: 'Econophysics and sociophysics: Their milestones & challenges', Physica A: Statistical Mechanics and its Applications 516, 240-253 (2019)

[2] Physica A, VSI: "Econophysics and sociophysics in turbulent world", Marcel Ausloos, Dariusz Grech, Tiziana Di Matteo, Ryszard Kutner, Christophe Schinckus, and H. Eugene Staanley (Eds.)

[3] Entropy, SI open access: "Three Risky Decades: A Time for Econophysics?", Ryszard Kutner, Christophe Schinckys, and H. Eugene Stanley (Eds.)

[4] R. Kutner: *Kamienie milowe & wyzwania ekonofizyki a także socjofizyki cz. 1*, Postępy Fizyki 73 (1), 11 (2022).

[5] A.L. Bárabási, *Network Science*, (Cambridge Univ. Press, Cambridge, 2017).

[6] R.N. Mantegna and H.E. Stanley, *An Introduction to Econophysics. Correlations and Complexity in Finance*, (Cambridge Univ. Press, Cambridge, 2002).

[7] F. Chin, D. Houck, *Algorithms for updating minimal spanning trees*, J. Comp. System Sciences 16(3), 333 (1978).

[8] R.N. Mantegna, *Hierarchical structure in financial markets*, Eur. Phys. J. B 11(1), 193 (1999).

[9] P.L. Graham, P. Hell, *On the history of the minimum spanning tree problem*, Annals Hist. Comp., 7(1), 43 (1985).

[10] H. Yaman, O.E. Karşan, M.Ç. Pinar, *The robust spanning tree problem with interval data*, Oper. esearch Lett. 29, 31 (2001).

[11] Th. Kirschstein, S. Liebscher, C. Becker, *Robust estimation of location and scatter by pruning the minimum spanning tree*, J. Multivariete Anal. 120, 173 (2013).

[12] A. Sienkiewicz, T. Gubiec, R. Kutner, and Z.R. Struzik, *Structural and topological phase transition on the German Stock Exchange*, Physica A 392, 5963 (2013).

[13] M. Tumminello, T. Aste, T. Di Matteo and R. N. Mantegna, *A tool for filtering information in complex systems*, Edited by H. Eugene Stanley, PNAS 102, 10421 (2005).

[14] T. Aste, T. Di Matteo, and S. T. Hyde, *Complex networks on hyperbolic surfaces*, Physica A 346, 20 (2005).

[15] T. Aste, R. Gramatica, and T. Di Matteo, *Exploring complex networks via topological embedding on surfaces*, Phys. Rev. E 86, 036109 (2012).

[16] Won-Min Song, T. Di Matteo, and T. Aste, *Hierarchical information clustering by means of topologically embedded graphs*, PLoS One 7(3), e31929 (2012).

[17] F. Pozzi, T. Di Matteo and T. Aste, *Spread of risk across financial markets: better to invest in the peripheries*, Scientific Reports 3, 1665 (2013).

[18] N. Musmeci, T. Aste, and T. Di Matteo, *Relation between financial market structure and the real economy: comparison between clustering methods*, PLoS ONE 10(3), e0116201 (2015).

[19] N. Musmeci, T. Aste, and T. Di Matteo, *Risk diversification: a study of persistence with a filtered*

correlation-network approach, J. Network Theory in Finance 1(1), 1 (2015).

[20] R. Morales, T. Di Matteo, and T. Aste, *Dependency structure and scaling properties of financial time series are related*, Scientific Reports 4 (2014) 4589. DOI: 10.1038/srep04589.

[21] R. J. Buonocore, T. Di Matteo, and R. N. Mantegna, *On the interplay between multiscaling and cross-correlation*, (2017) arXiv:1802.01113 [q-fin.ST].

[22] N. Musmeci, T. Aste, and T. Di Matteo, *Interplay between past market correlation structure changes and future volatility outbursts*, Scientific Reports 6, 36320 (2016).

[23] T. Aste and T. Di Matteo, *Sparse causality network retrieval from short time series*, Complexity 2017, Article ID 4518429, 13 pages(2017).

[24] M. Gligor and M. Ausloos, *Convergence and cluster structures in EU area according to fluctuations in macroeconomic indices*, Journal of Economic Integration 23(2), 297-330 (2008).

[25] M. Gligor and M. Ausloos *Cluster structure of EU-15 countries derived from the correlation matrix analysis of macroeconomic index fluctuations*, Eur. Phys. J. B 57 (2), 139-146 (2007)

[26] *Econophysics of Systemic Risk and Network Dynamics* edited by F. Abergel, B.K. Chakrabarti, A. Chakraborti, and A. Ghosh, (Springer-Verlag, London 2013)

[27] Y. Malevergne and D. Sornette, *Extreme Financial Risks. From Dependence to Risk Management*, (Springer-Verlag, Heidelberg 2006).

[28] *Uncertainty and Risk. Mental, Formal, Experimental Representations*, M. Abdellaoui, R.D. Luce, M.J. Machina, and B. Munier (Eds) (Springer-Verlag, Heidelberg 2007).

[29] J. Masoliver and J. Perelló, *First-passage and risk evaluation under stochastic volatility*, Phys. Rev. E 80, 016108 (2009).

[30] J. Masoliver and J. Perelló, *Extreme times for volatility processes*, Phys. Rev. E 75, 046110 (2007).

[31] R. Cont, *Empirical Properties of Asset Returns: Stylized Facts and Statistical Issues*, Quant. Finance 1, 223 (2001).

[32] J.-P. Bouchaud, *The Endogenous Dynamics of Markets: Price Impact, Feedback Loops and Instabilities* in *Lessons from the 2008 Crisis*, edited by A. Berd (Risk Books, Incisive. Media, London, 2011).

[33] A. Abergel, J.-P. Bouchaud, Th. Foucault, Ch. Lehalle, and M. Rosenbaum *Market microstructure. Confronting many viewpoints*, (J. Wiley and Sons, 2012).

[34] F. Slanina, *Essentials of Econophysics Modelling*, (Oxford University Press, Oxford 2014).

[35] D. Sornette, *Physics and financial economics (1776-2014): Puzzles, Ising and agent-based models*, Reports on Progress in Physics 77 (6): 062001 (2014).

[36] Ch. Schinckus, *1996-2016: Two decades of econophysics: Between methodological diversification and conceptual coherence*, Eur. Phys. J. Special Topics 225, 3299 (2016).

[37] M. Ausloos, H. Dawid, and U. Merlone, *Spatial Interactions in Agent-Based Modeling* in *Complexity and Geographical Economics: Topics and Tools*, P. Commendatore, S. Kayam, I. Kubin (Eds.), (Springer-Verlag, Heidelberg 2015), p. 353.

[38] J.D. Farmer and D. Foley, *The economy needs agent-based modelling*, Nature 457, 957 (2009).

[39] M.W. Macy and R. Willer, *From Factoras to Actors: Computational Sociology and Agent-Based Modeling*, Annu. Rev. Sociol. 28 (2002) 143.

[40] F.C. Billari, Th. Fent, A. Prskawetz, J. Scheffran, (Eds.) *Agent-Based Computational Modelling. Applications in Demography, Social, Economic and Environmental Sciences*, (Springer-Verlag, Heidelberg 2006).

[41] F. Abergel, H. Aoyama, B.K. Chakrabarti, A. Chakraborti, A. Ghosh (Eds.)*Econophysics of Agent-Based Models*, (Springer-Verlag, 2013).

[42] G. Kim, H. Markowitz, *Investment Rules, Margin, And Market Volatility*, Journal of Portfolio Management 16, 45-52 (1989).

[43] E. Samonidou, E. Zschischang, D. Stauffer, T. Lux, *Microscopic models of financial markets*, Rep. Prog. Phys. 70, 409 (2007).

[44] M. Levy, H. Levy, and S. Solomon, *A microscopic model of stock market: cycles, booms and crashes*, Econ. Lett. 45, 103 (1994).

[45] T. Lux and M. Marchesi, *Scaling and criticality in a stochastic multi-agent model of financial markets,*Nature 397, 498 (1999).

[46] G. Iori, *Avalanche dynamics and trading friction effect on stock market returns*, Int. J. Mod. Phys. C 10, 1149 (1999).

[47] R. Cont, J.-P. Bouchaud, *Herd behaviour and aggregate fluctuations in financial markets*, Macroecon. Dyn. 4, 170 (2000).

[48] D. Stauffer, *Percolation models of financial market dynamics*, Adv. Complex Syst. 4 19 (2001).

[49] S. Bornholdt, *Expectation bubbles in a spin model of markets: intermittency from frustation across scales*, Int. J. Mod. Phys. C 12 667 (2001).

[50] T. Kaizoji, *Speculative bubbles and crashes in stock markets: an interacting-agent model of speculative activity*, Physica A 287 493 (2000)

[51] M. Denys, T. Gubiec, and R. Kutner, *Reinterpretation of Sieczka-Hołyst financial market model*, Acta Phys. Pol. A 123(3) 513 (2013).

[52] V. Gontis, *Interplay between Endogenous and Exogenous Fluctuations in Financial Markets*. Acta Phys. Pol. A 129, 1023 (2016).

[53] G. Dhesi and M. Ausloos, *Modelling and Measuring the Irrational behaviour of Agents in Financial Markets: Discovering the Psychological Soliton*, Chaos Solitons & Fractals 88, 119 (2016).

[54] N. Vandewalle, M. Ausloos, Ph. Boveroux, A. Minguet, *How the financial crash of 1987 could have been predicted,* Eur. Phys. J. B 4 (1998) 139.

[55] N. Vandewalle, Ph. Boveroux, A. Minguet, and M. Ausloos,*The crash of October 1987 seen as a phase transition: amplitude and universality*, Physica A 225(1), 201 (1998).

[56] P. Sieczka, D. Sornette, and J. Hołyst, *The Lehman Brothers effect and bankruptcy cascades*, Eur. Phys. J. B 82: 257 (2011).

[57] F. Schweitzer, G. Fagiolo, D. Sornette, F. Vega-Redondo, A. Vespignani, and D.R. White, *Economic Networks: The New Challenges*, Science 325, 422 (2009).

[58] M. Scheffer, J. Bascompte, W.A. Brock, V. Brovkin, S.R. Carpenter, V. Dakos, H. Held, E.H. van Nes, M. Rietkerk, and G. Sugihara, *Early-warning signals for critical transitions*, Nature 461, 53 (2009).

[59] M. Kozłowska, M. Denys, M. Wiliński, G. Link, T. Gubiec, T.R. Werner, R. Kutner, and Z.R. Struzik, *Dynamic bifurcations on financial markets*, Chaos, Solitons and Fractals 88, 126 (2016).

[60] M. Ausloos, P. Clippe, J. Miśkiewicz, and A. Pękalski, *A (reactive) lattice-gas approach to economic cycles*, Physica A 344, 1 (2004).

[61] M. Ausloos, J. Miśkiewicz, and M. Sanglier, *The durations of recession and prosperity: does their distribution follow a power or an exponential law?*, Physica A 339, 548 (2004).

[62] M. Karpiarz, P. Fronczak, and A. Fronczak, *International Trade Network: Fractal Properties and Globalization Puzzle*, Phys. Rev. Lett. 113, 248701 (2014).

[63] J.M.C. Santos Silva and T. Silvana, *The Log of Gravity*, Rev. of Economics and Statistics 88 (4), 641 (2006).

[64] M. Ausloos, P. Clippe, and A. Pękalski, *Model of macroeconomic evolution in stable regionally dependent economic fields*, Physica A 337, 269 (2004).

[65] M. Ausloos, P. Clippe, and A. Pękalski, *Evolution of economic entities under heterogeneous political/environmental conditions within a Bak-Sneppen-like dynamics*, Physica A 332, 394 (2004).

[66] P. Bak and K. Sneppen, *Punctuated equilibrium and criticality in a simple model of evolution*, Phys. Rev. Lett. 71(24), 4083 (1993).

[67] A. Quetelet, *Mémoire sur les lois des naissances et de la mortalité à Bruxelles*, Nouveaux mémoires de l'Académie royale des sciences et belles-lettres de Bruxelles 1826, 3: 495 (in French).

[68] A. Quetelet, *Sur l'hommeetle développment de ses facultés, ou Essai de physique sociele*, Guillaumin et Cie, Paris, 1835.

[69] B.K. Chakrabarti, A. Chakraborti, and A. Chatterjee, *Econophysics and Sociophysics. Trends and Persepctives*, (Viley-VCH Verlag GmbH & Co KGaA, Veinheim 2006).

[70] *Cyberemotions. Collective Emotions in Cyberspace*, J.A. Hołyst (Ed.), Springer Complexity (Springer International Publishing Switzerland 2017).

[71] K. Sznajd-Weron and J. Sznajd, *Opinion evolution in closed community*, Int. J. Mod. Phys. C 11, 1157 (2000).

[72] D. Stauffer, *Sociophysics: the Sznajd model and its applications*, Comp. Phys. Comm. 146(1), 93 (2002).

[73] E. Bonabeau, G. G. Theraulaz, J. L. Deneubourg, *Phase diagram of a model of self-organizinghierarchies,* Physica A 217, 373 (1995).

[74] D. Pumain, *Hierarchy in Natural and Social Sciences*, (Springer-Verlag, 2006).

[75] R. Paluch, K. Suchecki, and J.A. Hołyst, *Models of random graph hierarchies*, Eur. Phys. J. B 88: 216 (2015).

[76] A. Nowak, J. Szamrej, B. Latané, *From Private Attitude to Public Opinion: A Dynamic Theory of Social Impact*, Psychological Review 97(3), 362 (1990).

[77] E.W. Montroll, *Social dynamics and the quantifying of social forces*, Proc. Nat. Acad. Sci. USA 75, 4633 (1978).

[78] M. Ausloos, *Another Analytic View about Quantifying Social Forces*, Advances in Complex Systems 16, 1250088 (2013).

[79] P. Sobkowicz and A. Sobkowicz, *Two-Year Study of Emotion and Communication Patterns in a Highly Polarized Political Discussion Forum*, Social Science Computer Review May 6 (2012).

[80] P. Sobkowicz, *Quantitative Agent Based Model of Opinion Dynamics: Polish Elections of 2015*, Plos One May 12 (2016).

[81] *Why Society is a Complex Matter. Meeting Twenty-first Century Challenges with a New Kind of Science. With a contribution of Dirk Helbing*, P. Ball (Ed.) (Springer-Verlag, Berlin 2012).

[82] D. Helbing, *New Ways to Promote Sustainability and Social Well-Beingin a Complex, Strongly Interdependent World: The FuturICT Approach* in *Why Society*

is a Complex Matter. Meeting Twenty-first Century Challenges with a New Kind of Science, (Springer-Verlag, Berlin 2012) p. 55.

[83] D. Helbing, I. Farkas, and T. Vicsek, *Simulating dynamical features of escape panic*, Naturew 407, 487 (2000).

[84] C. Castellano, S. Fortunato, and V. Loreto, *Statistical Physics of Social dynamics*, Rev. Mod. Phys. 81, 591 (2009)

[85] Th. Gross and B. Blasius, *Adaptive coevolutionary networks: a review*, J. Royal Soc. Interface 5, 259 (2008).

[86] M. Perc, J.J. Jordan, D. Rand, Zhen Wang, S. Boccaletti, and A. Szolnoki, *Statistical physics of human cooperation*, Phys. Rep. 687, 1 (2017).

[87] V. Loreto, A. Baronchelli, A. Mukherjee, A. Puglisi, and F. Tria, *Statistical physics of language dynamics*, J. Stat. Mech.: Theory and Experiment 2011, P04006 (2011).

[88] Sch. Christian and D. Stauffer, *Recent developments in computer simulations of language competition*, Computing in Science & Engineering 8, 60 (2006).

[89] R. Axelrod, *The dissemination of culture: A model with local convergence and global polarization*, J. Conflict Res. 41, 203 (1997).

[90] C. Castellano, M. Marsili, and A. Vespignani, *Nonequilibrium phase transition in a model for social influence*, Phys. Rev. Lett. 85, 3536 (2000).

[91] K. Klemm, V.M. Eguiluz, R.Toral, and M. San Miguel, *Nonequilibrium transitions in complex networks: A model of social interaction*, Phys. Rev. E 67, 026120 (2003).

[92] T. Raducha and T. Gubiec, *Coevolving complex networks in the model of social interactions*, Physica A 471, 427 (2017).

[93] M.A.L. Chavira and R. Marcelin-Jiménez, *Distributed rewiring model for complex networking: The effect of local rewiring rules on final structural properties*, Plos One 12(11), e0187538 (2017).

[94] M. Ausloos and F. Petroni, *Statistical dynamics of religions and adherents*, Europhys. Lett. 77(3), 38002 (2007).

[95] V.M. Yakovenko and J.B. Rosser, *Colloquium: Statistical mechanics of money, wealth, and income*, Rev. Mod. Phys. 81, 1707 (2009).

[96] M. Jagielski and R. Kutner, *Modelling of income distribution in the European Union with the Fokker-Planck equation*, Physica A 392(9), 2130 (2013).

[97] J.-P. Bouchaud and M. Mezard, *Wealth Condensation in a simple model of economy*, Physica A 282, 536 (2000).

[98] Z. Burda, D. Johnston, J. Jurkiewicz, M. Kaminski, M.A. Nowak, G. Papp, and I. Zahed, *Wealth condensation in Pareto macroeconomies*, Phys. Rev. E 65, 026102 (2002).

[99] C. Hertellu, P. Richmond, and B.M. Roehner, *Deciphering the fluctuations of high frequency birth rates*, Physica A 509, 1046 (2018).

[100] T. Aste and T. Di Matteo, *Introduction to Complex and Econophysics Systems: A Navigation map, in Complex Physical, Biophysical and Econophysical Systems* in World Scientific Lecture Notes in Complex Systems, edited by Robert L. Dewar & Frank Detering (World Scientific, Singapore 2010), Vol. 9, Chap. 1, pp. 1-35.

[101] R. J. Buonocore, N. Musmeci, T. Aste, and T. Di Matteo, *Two different flavours of complexity in financial data*, Eur. Phys. J. Special Topics 225, 3105 (2016).

[102] N. Musmeci, V. Nicosia, T. Aste, T. Di Matteo, and V. Latora, *The Multiplex Dependency Structure of Financial Markets*, Complexity, vol. 2017, Article ID 9586064, 13 pages, 2017, doi:10.1155/2017/9586064 (arXiv:1606.04872).

[103] F. Jovanovic, Ch. Schinckus, *Econophysics and Financial Economics. An Emerging Dialogue*, (Oxford Univ. Press, Oxford, 2017).

[104] F. Black, M.S. Scholes, and R.C. Merton, *The Pricing of Options and Corporate Liabilities*, Journal of Political Economy 81, 637 (1973).

[105] J.-Ph. Bouchaud and M. Potters, *Theory of Financial Risks. From Statistical Physics to Risk Management*, (Cambridge Univ. Press, Cambridge, 2001).

[106] Y. Malevergne and D. Sornette, *Extreme Financial Risks. From Dependence to Risk Management*, (Springer-Verlag, Heidelberg, 2006).