The bounds of heavy-tailed return distributions in evolving complex networks

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**Abstract**

We consider the evolution of scale-free networks according to preferential attachment schemes and show the conditions for which the exponent characterizing the degree distribution is bounded by upper and lower values. Our framework is an agent model, presented in the context of economic networks of trades, which shows the emergence of critical behavior. Starting from a brief discussion about the main features of the evolving network of trades, we show that the logarithmic return distributions have bounded heavy tails, and the corresponding bounding exponent values can be derived. Finally, we discuss these findings in the context of model risk.

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1. Introduction: a note on agent models for social systems

Similarly to other fields in social sciences, most of the research made in finance and economics has been dominated by an epistemological approach, in which the behavior of the economic system is explained by a few key characteristics of the behavior itself, like the amplitude of price fluctuations or the analytical form of the heavy-tailed return distributions [1,2]. These key characteristics motivated researchers to assume such distributions as \(\alpha\)-stable Lévy distributions or truncated \(\alpha\)-stable Lévy distributions [3].

The reason for this assumption is given by the more general version of the central limit theorem – sometimes not so well known – which states that the aggregation of a growing number of random variables converges to an \(\alpha\)-stable Lévy distribution, i.e. a Gaussian distribution. If the variances are infinite – or of the order of the system size – then \(\alpha < 2\) and the so-called heavy-tailed shape emerges as a result of the aggregation.

Further, non-Gaussian (heavy-tailed) distributions are associated with correlated variables and therefore it is reasonable to assume that measurements on aggregates of human activities will result in an \(\alpha\)-stable Lévy distribution, since humans are strongly correlated with each other. Henceforth, we refer to \(\alpha\)-stable Lévy distributions with \(\alpha < 2\) as Lévy distributions and with \(\alpha = 2\) as Gaussian distributions.

Without leaving an epistemological approach, we could address the study of the resulting distributions by ignoring the previous arguments and construct a function that fits any set of empirical data just by building up fitting parameters until the plotted function fit the empirical data. Such approach would be the best one, if economic processes were stationary. Unfortunately they are not [5–7] and this means that we cannot disregard the underlying mechanisms generating the data we are analyzing.

Since heavy tails are observed in the returns of economic variables, one would expect that practitioners use Lévy distributions. The particular case of Gaussian distribution was the first to be considered for modeling price of European options, through the well-known Black–Scholes model [8] proposed in 1973. This model ended a story started already in 1900 with Bachelier and his Theory of Speculation [9] where Brownian motion was used to model stock price evolution.

The Black–Scholes model for option-pricing is however inconsistent with options data, since stock-price behavior is essentially not Gaussian. To overcome the imperfections of the Black–Scholes model, more sophisticated models were proposed since 1980s and 1990s, which basically assume processes more general than Brownian processes. These processes are called Lévy processes [10] and the probability distributions of their increments are infinitely divisible, i.e. one random variable following that probability distribution can be decomposed into one sum of an arbitrary integer number of independent identically distributed random variables.

Still, despite considerable progresses on modeling financial data with Lévy processes, practitioners continue to show a strong preference for the particular class of finite moment’s distributions...
and there are good reasons for that. Assuming that Lévy distributions are good representations of economic variables fluctuations, a model based on them is closed when one fits the distribution to empirical data choosing properly the parameter values, which represent the valuable information for financial insight and decision making. However, as said above, fitting is no good when the series are not stationary: there is no guarantee that today’s fitting will be the same as tomorrows. Since working with a Gaussian curve is more straightforward than working with a Lévy distribution and needs less parameters for curve fitting, there is no practical gain in abandoning Gaussian distribution to model the distribution of fluctuations according to a prescribed mathematical model, even though it is not entirely correct. In other words, if a Lévy distribution is fitted to empirical data of a non-stationary process one will carry basically the same model risk, as if a Gaussian distribution is used.

On a more ontological approach, when modeling financial and economic networks, random variables are translated into agents. Agent-based models for describing and addressing the evolution of markets has become an issue of increasing interest [11] and appeals for further developments [12–15]. They enable one to access thoroughly investigated [16,12] financial indices. Several of such bottom-up approaches were thoroughly investigated [16,12]. The Solomon–Levy model [17] defines each agent as a wealth function \( \omega(t) \) that cannot go below a floor level, given by \( \omega_0(t) = \omega_0 + \alpha \omega(t) \) where \( \omega(t) \) is the agent average \( \omega \) at instant \( t \) and \( \omega_0 \) is a proper constant. The imposition of the floor based on the mean field \( \omega(t) \) means that on average \( \langle \omega(t) - \bar{\omega}(t) \rangle \sim N \) and, by basic statistics, \( \text{var}(\omega(t)) \sim N^2 \). Consequently, the result of the Solomon–Levy model, despite the interesting idea of the introduction of a floor similar to what was done by Merton [18] in the agent dynamics, will surely be an \( \alpha \)-stable distribution with a power-law heavy tail, i.e. \( \alpha < 2 \). Percolation based models like Cont and Bouchaud [19] or Solomon and Weisbuch [20], by the nature of the phenomena, also brings up variations of the order of the system size, leading also to Lévy-type distributions.

In our approach, we follow the above considerations, to address the following question: what are the fundamental assumptions, common e.g. to all economic systems, that naturally lead to the emergence of macroscopic distributions that are characterized by heavy tails? Taking an economic system as a prototypical example for the emergence of heavy-tailed distributions, we argue that there are three fundamental assumptions.

First, agents tend to trade, i.e. to interact. Human beings are more efficient in doing specialized labor than being self-sufficient and for that they need to exchange labor. The usage of the expression ‘labor’ can be regarded as excessive by economists, but we look at it as the fundamental quantity that is common to labor, money or wage. Something must be common to all these quantities; if not, we wouldn’t exchange them. The physicists can regard such fundamental quantity as an ‘economic energy’.

Second, we only consume and produce a finite amount of the overall product that exists within our environment. This assumption justifies the emergence for each agent of a maximum production and minimum consumption. If an agent transposes that finite amount he should not be able to consume anymore.

Third, human agents are different and attract differently other agents to trade. For choosing the way “how” agents attract each other for trading, we notice that this heterogeneity should reflect some imitation, where agents tend to prefer to consume (resp. produce) from (resp. to) the agents with the largest number of consumers (resp. producers). The number of producer and consumer neighbors reflects, respectively, supply and demand of its labor. With such observation its is reasonable to assume that combining both kinds of neighbors should suffice to quantify the price of the labor exchanged.

Heavy-tailed distributions have been subject to intensive research activity till very recently, e.g. when addressing the formation and construction of efficient reservoir networks [21], which shows self-organized criticality with critical exponents that can be explained by a self-organized-criticality-type model. In this Letter, we deal with heavy tails found in economic systems and show that heavy-tailed return distributions are due to the economic organization emerging in a complex economic network of trades among agents governed under the above three assumptions. Further, the model reproducing empirical data is also of the self-organized-criticality-type model, but its main ingredients result from economical reasoning and assumptions.

Our central result deals in particular with the return distribution found in both data and model: we show that the power-law tails are characterized by an exponent that can be measured and is constrained by upper and lower bounds, which can be analytically deduced. The knowledge of such boundaries is of great importance for risk estimates: by deriving upper and lower bounds, one avoids either underestimates, which enable the occurrence of crisis unexpectedly, as well as overestimates, which prevent profit maximization of the trading agents.

We start in Section 2 by describing the ubiquity of heavy tails in financial time series, namely in stock indices. We will argue that such heavy tails result from the combination of a dynamical critical state in real economic systems and an underlying scale-free topology. Applied to a real system such as the financial market, such bounded behavior leads naturally to a maximum and minimum value on risk evaluation, improving the knowledge about the uncertainty of the market future evolution. These bounding values will be derived in Section 3 based in the assumptions listed above and an application to risk model is discussed. Section 4 concludes this Letter.

2. Critical behavior underlying return distributions

Heavy tails are observed in return distributions of data in finance and economics. Fig. 1 presents data from several stock market indices. Fig. 1(a) shows the probability density functions (PDF) of the logarithmic returns of each index, symbolized as \( x \), where one can observe the heavy tails. The exponent characterizing the tails of these distributions are given in Fig. 1(b).

While the heavy-tailed shape of the return distributions was already known and several times reported [22], the explanation for their emergence, and in particular the values of the exponent characterizing them, was up to our knowledge not so frequently addressed.

The emergence of the heavy tails of the return distribution was recently reproduced with a simple model [7] which takes one economic connection as an exchange of labor between two agents, say \( i \) and \( j \), dissipating an amount of energy \( U_{ij} \), representing the deficit of \( i \) that results from the labor exchange between \( i \) and \( j \). Agent \( i \) delivers an amount of labor \( W_{ij} \) to agent \( j \) and gets a proportional amount of “reward” \( E_{ij} = \alpha_{ij} W_{ij} \) where \( \alpha_{ij} \) can be interpreted as an ‘exchange rate’ of labor. Fig. 2 illustrates the eco-
the coefficient \( \alpha \) establishes an incoming connection with (consumption from) agent \( j \). This coefficient takes into account how many incoming and outgoing connections the agent and its neighbors have, i.e. how much demand and supply they have respectively [7].

Since the energy consumption is necessary to establish economic connections, agents cannot leverage themselves to infinity. To take this fact into account, each agent in the model is not allowed to exceed its internal energy more than a maximum fraction of its total amount of trades. We can regard this maximum fraction as a limit for default, as in credit risk modeling [23]. For the particular case of financial systems, we recently showed how unexpected results may appear when varying such threshold [24].

Since trades are only regulated by supply and demand principles, the system may lead one agent to eventually exceed its maximum fraction of total amount of trades. This also occurs in real economic systems in what one calls typically a case of insolvency: the agent is no longer able to guarantee the "payment" \( E_{ij} \) of the corresponding labor units \( W_{ij} \) it consumes. Therefore it stops to consume such labor units, i.e. the agent loses its incoming connections (consumption links).

By losing its consumption links, the collapsing agent leads to the breaking of some production links of its neighbors, changing also their consumed fraction of total amount of trades, eventually also exceeding the maximum fraction, and thus also leading to their collapse. Consequently, each collapse is able to trigger a chain reaction originating a branching process as illustrated in Fig. 3. In the economic context, one chain reaction is called a "crisis" whereas in the physical context its is usually called "avalanche", borrowing the illustrative examples of avalanches in the field of granular materials and complexity [21].

The probability for an avalanche to involve exactly \( r \) agents is given by Otter's theorem [25–28], which yields \( P(r) \propto r^{-2} \). This probability is observed as long as the underlying topology enables a branching process in a critical state [26].

Still, the number of collapsed agents in a real network is difficult to recount for. What is measured when an avalanche occurs in such a real network is the number of links destroyed during the avalanche. This number of links accounts for a macroscopic property of the system, namely the overall product \( UT \) which sums up all outgoing product of all agents. Therefore, we want to express \( P(r) \) in terms of the total number of destroyed links.

To that end we recall the third fundamental assumption listed in the introduction above, which considers heterogeneity among agents, where agents tend to establish trades with those agents having already large number of trades, i.e. neighbors. Some authors in Economics call this phenomenon imitation [5]. Physicists call it preferential attachment and it was introduced by Simon [29] and developed later by Barabási and Albert [30] in several other contexts.

The important consequence of this assumption is that the distribution of the number \( k \) of connections one agent has follows a
The observable $U_T$ together with the averaged main topological properties, all of them as functions of the number of trades $k$ (neighbors, degree), namely: (b) the degree distribution $P(k)$, (c) the degree–degree correlations $D(k)$, (d) the average shortest path length $l(k)$ and (e) the clustering coefficient $C(k)$.

Implementing the above ingredients altogether yields a network of trades which evolves in time. Between two time-steps, new connections and agents are introduced following the preferential attachment scheme and old connections are partially removed, through the collapse of some agents, both in such a balance that the overall product fluctuates, as shown in Fig. 4(a). The increase of $U_T$ corresponds to the inflow of agents and connections – here, one at each time-step – while the decrease of $U_T$ corresponds to a chain of collapses.

Simultaneously, at each time-step, the underlying network topology also “fluctuates” around a “mean” structure. In Figs. 4(b)–(e) we show four main properties for characterizing the structure of the network of trades, averaged over time: the degree distribution $P(k)$, the degree–degree correlation $D(k)$ giving the average degree of neighbors of agents with $k$ neighbors, the average shortest path length $l(k)$ and the clustering coefficient $C(k)$ [30].

It is interesting to observe that while the degree distribution follows a power-law decay at least in the middle range of its $k$-spectrum (Fig. 4(b)), there are almost no correlations (Fig. 4(c)), with $D(k) \equiv \sum_{k'} k P(k'|k)$, typically between 6 and 7. In this context, the model of Ref. [7] for economical trading systems seems to belong to a general class of uncorrelated networks previously modeled [31]. Finally, the clustering coefficient is also approximately constant in the full observed $k$-spectrum, similar to other models [31] and for the average shortest path length one observes a logarithmic decay, $l(k) \sim \log k$.

Figure 4. The network evolution of economical trades in the model of Ref. [7] (see text). (a) The observable $U_T$, together with the averaged main topological properties, all of them as functions of the number of trades $k$ (neighbors, degree), namely: (b) the degree distribution $P(k)$, (c) the degree–degree correlations $D(k)$, (d) the average shortest path length $l(k)$ and (e) the clustering coefficient $C(k)$.

Important for our derivation in the next paragraph are the correlations, that from Fig. 4(c) can be neglected. Since the full structure shows no significant correlations, the correlations between the degree of collapsing agents in one single chain can also be neglected.

As explained above, at the macroeconomic scale the size of an avalanche is observed through the number of destroyed connections which exactly corresponds to the $r$ agents involved in the avalanche. Since the probability for this to occur is $P(r) \sim r^{-\gamma/2}$ the next question to answer is: taken the topological results plotted in Fig. 4, what is the amount of destroyed connections measured? We first take $K_T$ as the average number of destroyed connections corresponding to $r$ agents and, since $D(k) \sim 0$ (Fig. 4(c)), one takes $K_T = r \sum_{m} k_m^{\gamma+1}$ with $m$ running over the different degrees. If all affected agents have the same degree, that degree is itself proportional to $K_T$ and thus $r \sim K_T^{\frac{\gamma}{2}}$. If the affected nodes have different degrees, one may still take this relation as an approximation by redistributing connections among the $r$ agents while keeping the total number $K_T$. Therefore, one estimates the probability for an avalanche to occur to follow $p(r) \sim r^{-\gamma/2} \propto K_T^{-\gamma/2}$. To stress that the variable that is observed is the “number of agents” we, for convenience, write henceforth $P(K_T)$ instead of $P(r)$.

So, the fraction of avalanches of size $K_T$, i.e. involving a number $K_T$ of lost connections, larger than $s$ is given by

$$P(K_T \geq s) \propto \int_{s}^{+\infty} x^{-\frac{3}{2}\gamma} dx \alpha s^{-\frac{3}{2}\gamma+1} \equiv s^{-m}.$$  

Eq. (2) should hold for all types of trades and macroscopic observables of the economic product in one economic network, having a scale-free topology, which results from the third fundamental assumption presented above in the Introduction.

Eq. (2) establishes the relation between the structure of microscopic interactions (connections or trades) between agents and the distribution of the returns of one macroscopic quantity. The former is characterized by exponent $\gamma$ of the degree distribution, while the latter is characterized by exponent $m$, which according to Eq. (2) satisfies

$$m = \frac{3}{2} \gamma - 1.$$  

Fig. 1(b) shows explicitly this relation for each stock market index, comparing it with the agent model that yields $m \approx 5/2$ and also the bounding values $m_{\min}$ and $m_{\max}$ corresponding to the bounding values $\gamma \in [2, 3]$.

The bridge between a network of trades and macroscopic observables is subtle. The value of a stock index is the result of an aggregation of successive trades between single agents (buys and sells). Similarly, the macroscopic variable $U_T$ accounts for the aggregated summing up of trade connections weighted by the exchange rate coefficient. Thus, one can take a stock index as a particular case of $U_T$. Taken as a stock index, the dropping and growth periods of $U_T$, are result of the underlying respective addition and removal of connections between economical agents, taken as buys and sells. In this context, one can draw conclusions for the evolution of stock indices by looking the behavior of avalanches on such networks of trades. Next, we will derive the $\gamma$ bounding values.

3. Bounding values for the avalanche size distribution

All indices in Fig. 1(b) take values around the model prediction $m = \frac{3}{2}$, see Ref. [7], and lay within the range $m_{\min} \equiv 2 < m < \frac{3}{2} \equiv m_{\max}$. From Eq. (3), one concludes that the above range of $m$-values corresponds to the range $2 < \gamma < 3$, which is a typical range of exponents observed in empirical scale-free networks specially in the economic ones like airports [32], Internet [33] and international trade of products and goods [34]. With such observations we ask: what are then the topological causes underlying the emergence of those bounding values? In this section, we derive $m_{\min}$ and $m_{\max}$ applying renormalization methods [35] to the case of undirected networks.
Fig. 5. Illustration of renormalization in complex networks. Starting at connection $AB$ between two clusters of agents, one scales down finding each cluster composed by two sets of agents, $A_1$ and $A_2$ on the left and $B_1$ and $B_2$ on the right connected again by $A_1A_2$ and $B_1B_2$ respectively. Each set of agents of this new scale can also be decomposed in two connected sets and so on downscale. For undirected networks, the number of probable states grows with $N_p^2$, with $N_p$ being the renormalized number of agents.

The bounding values of $m$ result directly from bounded values of $\gamma$ (see Eq. (3)), and this latter values can be derived under the assumption that the degree distribution if scale invariant.

As mentioned above, links are either outgoing or incoming and the probability for an agent to have $k$ outgoing links – or correspondingly $k$ incoming links – depends on the scale one is considering: at each scale $p$ there is a fraction $P(p, k)$ of agents with $k$ connections. Fig. 5 illustrates three successive scales $p = 1, 2$ and 3 for directed networks. When the connections are directed, from one scale to the next there are $N$ admissible connections $[35, 36]$. Undirected networks can be regarded as compositions of two directed networks, since the degree law $P(p, k)$ is the probability for an agent to have $k$ start links or $k$ end links indistinctly. Consequently, when going from one scale to the next, the renormalization generates $N_p^2$ admissible states leading to $\sum P_p(k_p) = 0$.

Therefore, the self-similar transformation of the agent degree, i.e. the number of links in an agent will be ruled by

$$N_p^2 P(k) \, dk = N_p^2 P(k_p) \, dk_p$$

where $k$ and $k_p$ symbolize, respectively, the total and renormalized number of links and $N$ and $N_p$ are the correspondent number of agents.

The power law in Eq. (1) is invariant under renormalization, i.e. $P(k) \sim k^{-\gamma}$ and $P(k_p) \sim k_p^{-\gamma}$. Defining $l_p$ as the distance between agents at a given scale $p$, as the average number of links separating a randomly chosen pair of agents at a given scale $p$, the fractal dimension $d_f$ of the network can then be calculated using the box-counting technique $[37, 35]$:

$$N_p = N l_p^{d_f}.$$  \hspace{.5cm} (5)

Similarly, the number of links scale as

$$k_p = k l_p^{d_f}.$$  \hspace{.5cm} (6)

And finally, substituting Eqs. (1), (5) and (6) in Eq. (4) yields

$$\gamma = 1 + \frac{d_f}{d_k}.$$  \hspace{.5cm} (7)

This result retrieves a topological constraint for the value of $\gamma$ and, consequently, for the “weight” of the heavy tail in the degree distribution. It is known that whenever the above results holds the corresponding degree distribution is invariant under renormalization (see Supplementary Material of Ref. [36]). At each scale the number of connections of each agent varies between two limit cases, one where each agent connects to only one neighbor, and another where everybody is connected with everybody else, within the same scale. In the first limit case, each agent links to a single neighbor at each scale and consequently the connections will scale like the agents, $d_k = d_f$, yielding $\gamma = 3$. In the other limit case, agents should connect to all neighbors at each scale, i.e. for each set of $N_p$ agents we find $N_p^2 - N_p \sim N_p^2$ links and thus $d_k = 2d_f$, i.e. $\gamma = 2$. Since both limit cases yield a relation between $d_k$ and $d_f$, the same conclusion should hold even in non-fractal networks similar to what is reported in Ref. [36]. Not all power-law degree distributions are invariant under renormalization. Still, it is reasonable to expect that even in the case they are not strictly invariant, the exponent characterizing their power-law degree distribution should lie between these two limit cases of degree distributions. It is therefore a general result as shown next for observed financial indices.

In a real network, at each scale each agent should have a typical number of connections between these two extremes, namely one and $N$, resulting in an exponent $\gamma$ between 2 and 3 and in the corresponding two bounding values for $m$ in Eq. (3), $m_{min} = 2$ and $m_{max} = 7/2$. Fig. 6 plots the cumulative distributions for all indices together with the boundaries $P_{min}(dx/x) \sim (dx/x)^{-m_{min}}$ and $P_{max}(dx/x) \sim (dx/x)^{-m_{max}}$. This is an important result since, independently of the network complexity, the return distributions are characterized by heavy tails in a limited range of frequencies. Consequently, the amplitude of the associated risk measure is also limited.

To finish this section we discuss possible applications from these findings. Having such bounding values an important application deals with risk evaluation. The ability to measure risk is fundamental when we talk about any economic activity. When for instance banks lend people money to buy houses, they must have a way of estimating the risk of those activities. In short, what is the most one can lose on a particular investment? The financial property Value at Risk, or simply VaR, provides an answer. Value at Risk evaluates the percentile of the predictive probability distribution for the size of a future financial loss. Mathematically, for a prescribe $\alpha$ degree of confidence and within a
time horizon $\Delta t$ the value at risk is defined as the value $x^*$ such that

$$\text{VaR}_\Delta (x^*, \Delta t) = \int_{x^*}^{\infty} p(x) dx = 1 - \alpha$$

where $p(x)$ is the PDF for the loss or the negative return of an economic variable relevant for the intended investment. If one is dealing with shares portfolio, the relevant variable would be one such as the ones in Fig. 1, symbolized here as $x$. Value-at-Risk framework was created by J.P. Morgan[38] based on Gaussian returns but the framework is valid for other more general continuous distributions of returns.

The confidence of the estimate given for $\text{VaR}_\Delta (x^*, \Delta t)$ depends therefore on the choice of the PDF $p(x)$ for the losses or returns. Since under the assumptions above we can take the PDF $p(x)$ as a Pareto distribution and since we can bound the exponent value defining such a Pareto distribution, we get a straightforward way for bounding any estimate of VaR. While VaR is a measure of risk, i.e. a risk model for estimating how much one can lose in a specific event, it’s value through the two bounding exponent values deduced above we are able to evaluate how “risky” are such risk models and risk measures. By “risky” we refer more specifically to the choice of $p(x)$ when evaluating the risk measure, in this case $\text{VaR}_\Delta$. In other words, our bounding exponent values can provide us with a way to evaluate the “model risk” of a particular model for risk evaluation.

4. Conclusion: towards a risk model

In this Letter we derive a relation that bridges between basic economic principles and features of the empirical return distributions, namely the values of the exponent describing their heavy tails. First, we show that three fundamental assumptions in economics [39] suffice to explain the emergence of economic links according to a power law and relate the exponent of the heavy tails observed in the macroscopic variable with the exponent of the degree distribution describing the underlying topology of the network. Second, we show that this latter exponent for the agents degree distribution assumes values in the range between two and three, which combined with the first results delimits the heavy tails of return distribution between $2$ and $\frac{5}{2}$.

These findings help to solve the controversy about Mandelbrot hypothesis [22] that the distribution of financial returns are explained by Lévy distributions, and therefore would yield an exponent smaller than $3$. Some authors have argued against Mandelbrot hypothesis, basing their positions [2] in empirical measures of the return distributions which yield exponents larger than $3$. In this Letter we presented evidence that both statements are in fact correct. Each one is considering a different effect of the same phenomenon: though what we measure in the time series of returns are links between agents, corresponding to exponents larger than $3$, the random variables behind Lévy distributions are the agents, which corresponding to the exponent $\gamma$ which is limited by $2 < \gamma < 3$.

Finally, since the exponent is bounded, the total risk associated with the process being observed is also bounded between one lower and one upper boundary values, enabling one to actually measure the “risk” of a particular model for risk evaluation. We described the particular case of risk measure, namely the Value at Risk, but other approaches could be also taken, for example the expected shortfall [40,41], which considers the average Value at Risk with respect to its confidence level $\alpha$.

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References