Financial markets and Self-Organized Criticality

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Financial markets often experience extremes, called “bubbles” and “crashes”. The underlying dynamics is related to avalanches, the size of which is distributed according to power laws – see Mandelbrot (1997), Mantegna-Stanley (1996), Ghashghaie et al. (1996), Farmer (2002), Bouchaud-Potters (2000), Sornette (2003), Helbing (2013), and many others.

Power laws imply that crashes may reach any size and threaten the entire financial system. Many scientists see “herding behavior” as the origin of such dangerous avalanches, as Akerlof-Shiller (2009), Camerer et al. (2011), Hommes et al. (2008), Shapira et al. (2009), Preis et al. (2012), Krawiecki et al. (2002), Parisi et al. (2013), among others.

We explore whether it is possible to stop or reduce them. In particular, our study explores how huge herding avalanches in financial trading might be reduced by introducing a certain percentage of traders who adopt a random investment strategy.
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In a previous paper, Biondo et al. (2013), we explored the role of random strategies in financial systems from a micro-economic point of view. In particular, we simulated the performance of five trading strategies, including a completely random one, applied to four very popular financial markets indexes, in order to compare their predictive capacity. Our main result, which is independent of the market considered, is that standard trading strategies and their algorithms, based on the past history of the time series, although have occasionally the chance to be successful inside small temporal windows, on a large temporal scale perform on average not better than the purely random strategy, which, on the other hand, is also much less volatile.
We use an agent-based model that produces the phenomenon of self-organized criticality (Bak, et al. 1987). Specifically, we adapt the Olami-Feder-Chrstensen (OFC) model (see Olami et al. 1992 and Caruso et al. 2007) that has been proposed to describe the dynamics of earthquakes.
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In this context, we assume information cascades between agents as the underlying mechanism of financial avalanches. We assume that agents interact within a small-world (SW) network of financial trading (Caruso et al. 2006) and that there is social influence among them (Grund et al. 2013). Such an approach is used in recent contributions, among which, Tedeschi et al. (2012) and Biondo et al. (2017).
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In successive studies (Biondo 2018a, 2018b, 2018c) a specific analysis of the role of information on stability of markets is performed, by discussing individual and systemic features that the policy maker can tune in order to reduce fat tails of financial returns.
The Financial Quakes Model (FQM) is built on a small-world (SW) network of $N$ traders $A_i$. The total number of agents is $N = 1600$. The SW network is obtained from a square 2-dimensional $40 \times 40$ lattice, by randomly rewiring the nearest neighbors links with a probability of $p = 0.02$ (depicted in Fig.1 with $N = 22 \times 22 = 484$ for graphic convenience). The resulting network topology allows the information to spread over the lattice through long-range links and preserves the clustering properties of the network and its average degree ($< k > = 4$).

![SW 2D network of traders. White agents are RSI traders (Relative Strength Index trading strategy); red agents (10% of the total) are random traders, uniformly distributed at random among the population.](image)
The information spreading is simulated by associating to each trader a real variable $I_i(t)$ ($i = 1, 2, \ldots, N$), representing the information possessed at time $t$, which initially (at $t = 0$) is set to a random value in the interval $(0, I_{th})$. $I_{th} = 1.0$ is a threshold value that is assumed to be the same for all agents. At each discrete time step $t > 0$, due to public external information sources, all these variables are simultaneously increased by a quantity $\delta I_i$, which is different for each agent and randomly extracted within the interval $[0, (I_{th} - I_{max}(t))]$, where $I_{max}(t) = \max\{I_i(t)\}$ is the maximum value of the agents’ information at time $t$. 

![Diagram showing information pressure coming from external sources]
If, at a given time step $t^*$, the information $I_k(t^*)$ of one or more agents $\{A_k\}_{k=1,\ldots,K}$ exceeds the threshold value $I_{th}$, these agents become "active" and take the decision of investing a given quantity of money by betting on the bullish (increasing) or bearish (decreasing) behavior of the market compared to the day before.
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In order to make their prediction $P_j$ (positive or negative) about the sign of the index difference $(E_j - E_{j-1})$ at time $t^*$, active agents are assumed to follow the standard Relative Strength Index (RSI) trading strategy. Its definition is: $RSI(t) = 100 - 100/(1 + RS(t, \tau_{RSI}))$, where $RS(t, \tau_{RSI})$ is the ratio between the sum of the positive returns and the sum of the negative returns occurred during the last $\tau_{RSI}$ days before $t$ (we set $\tau_{RSI} = 14$). Once calculated the RSI index for data in the last 14-days window preceding the time $t$, the trader makes his/her prediction on the basis of a possible 'divergence' between the original time series and the new RSI one (by comparing the slopes of their trend lines).
Once activated, agents transfer part of their information to their neighbors:

\[
I_k > I_{th} \Rightarrow \begin{cases} 
I_k \rightarrow 0, \\
I_{nn} \rightarrow I_{nn} + \frac{\alpha}{N_{nn}} I_k.
\end{cases}
\]

(1)

where “nn” is the set of nearest-neighbors of the active agent \(A_k\), \(N_{nn}\) is the number of direct neighbors, and \(\alpha\) controls the level of dissipation of the information during the dynamics. In analogy with the OFC model, we set a non conservative dynamics, i.e., part of information is lost during the herding process, and set \(\alpha = 0.84\).

The herding rule can activate, in turn, other agents, thus producing a chain reaction. The resulting information avalanche may be called a “financial quake”: all the agents involved bets with the same prediction \(P_j\) as the agent from which they have received the information. The financial quake is over when there are no more active agents in the system (i.e. when \(I_i < I_{th} \forall i\)). Then, the prediction \(P_j\) is finally compared with the true sign of the difference \((E_j - E_{j-1})\), thus deciding whether investors have won or lost.
the model: individual information spreading

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Random traders are designed to receive exclusively the global informative pressure: they do not receive, nor transfer, any signal from/to neighbors. Once activated they make their prediction, by tossing a fair coin.

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results: 1) financial quakes series

The time sequence $s(t)$ of “financial quake” sizes during a single simulation run. A positive sign means that all the involved agents win and a negative sign that they loose. Each avalanche corresponds to each entry of the S&P 500 index series, since each initial investment (“bet”) on the market coincides with the occurrence of a financial quake (this means that the series in Fig. 2 and Fig. 3 have the same length $T$). As in the OFC model, we observe a sequence of quakes that increases in size over time. In other words, the financial system is progressively driven into a critical-like state, where herding-related avalanches of any size can occur: most of them will be quite small, but sometimes a very big financial quake appears, which can be either positive (bubbles) or negative (crashes).
The SOC-like nature of this dynamics is shown by reporting the probability distribution $P_N(s)$ of financial quakes size, measured by its absolute value and cumulated over 10 simulations (open circles). The resulting distribution can be very well fitted by a power-law $P_N(s) \propto s^{-1.87}$, a slope consistent with the one obtained for earthquakes in the OFC model on a SW topology (see Caruso et al. 2006).
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One can also investigate how the size of the avalanche changes with the increase of the amount of random traders considered, if they are uniformly distributed over the network: the maximum size of the avalanches observed drops by a factor of 5 in the presence of only 5% of random traders, reaching almost its final saturation level of 3% when $P_{RND} = 10\%$. These results indicate that even a relatively small number of random investors distributed at random within the market is able to suppress dangerous herding-related avalanches.
results: 3) topological diffusion of random traders

Two examples of small-world networks with 10% random traders (red agents) grouped in one or four communities, respectively. New simulations for our network of $N = 1600$ agents with an increasing percentage of random traders, clustered in either one community or four communities, respectively, show that the beneficial effect shown above (still present) is smaller. More precisely, the original power law distribution of avalanches is less affected by random investments for any percentage $P_{RND}$. 

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This, in turn, implies a slower decrease of the maximum avalanche sizes as $P_{RND}$ increases: the uniform random distribution of random investors over the whole network is quite crucial in order to significantly dampen avalanches. A percentage between 1% and 2% of uniformly distributed random traders is enough to reduce the financial quakes size as much as 10% grouped random investors.
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, each trader is endowed with an initial capital $C_i$ according to a normal distribution with an average of $< C > = 1000$ credits and a standard deviation equal to $0.1 < C >$. After a financial quake, the capital of each agent involved in the herding-related avalanche will increase or decrease by the quantity $\delta C_i$, computed as:
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- if an agent wins, $\delta C_i = 0.5 C_i$;
- if an agent loses, $\delta C_i = 0.1 C_i$. 

Results (cumulated over 10 runs for each scenario) show that, interestingly, a Pareto power law (with an exponent equal to $-2.4$) spontaneously emerges from the dynamics of the model, independently of the number of random traders. Such a finding is quite robust, even adopting different investment criteria.
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It is also interesting to underline the wealth distribution within the community of random traders, apart from the rest of the population, in case of a network with 10% random traders (results are cumulated over 10 realizations): random traders have a final wealth distribution very different from a power law, which can be fitted with an exponential curve, represented by a dashed line, with an exponent equal to $-0.00134$ (the fact that the random traders component is not changing the global power law distribution is evidently due to its small size, i.e., 160 agents on 1600). In addition, average final wealth of all traders is 767, sensibly lower than the average wealth within the random investors community, which is 923.

![Wealth distribution graph](image)
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Results show that 14% of RSI traders have more wealth in the end than in the beginning, whereas the analogous percentage for random traders is 26%. In particular, 40% of RSI traders have a final capital smaller than the worst random trader, whereas only 3% of RSI traders perform better than the best random trader.

Similar results have been obtained by adopting other historical time series, such as, for example, FTSE UK or FTSE Mib.
This paper builds on the previous one: after having characterized the financial application of the OFC herding engine, the successive step was to model a naive financial market with endogenous trading activity, based on the concepts of bounded rationality and behavioral heterogeneity.
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Limited access to information and bounded rationality (Simon 1957, Kahneman-Tversky 1974 and 1979) are the core of the mechanism of contagion spreading and characterize individual choices within the social context (Simon 1957). Thus, decisions reflects human interactions and individual psychology, driven more by rules of thumb than by perfect knowledge and optimal computational ability (Akerlof-Shiller 2010).
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In contrast with the mainstream rational-expectations paradigm, whose limits and problems are discussed in a number of papers (as in Camerer 2003, Barberis-Thaler 2003, Colander et al. 2009, among many others) a new approach must be adopted for macroeconomic analysis (Delli Gatti et al. 2011, Gallegati et al. 2017 and Gallegati 2018).
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A very wide literature deals with the agent-based approach for financial markets simulations, as in Brock-Hommes (1997) and (1998), Chiarella (1992), Chiarella-He (2001), Day-Huang (1990), Franke-Sethi (1998), Hommes (2001), Lux (1995) and (1998), Lux and Marchesi (1999), among many others. In particular, the Heterogenous Agent Models (HAM) represent a fruitful approach able to study the complex interactions of different individuals with different behaviors.
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Differently from other attempts to describe herding in financial markets (Alfarano et al. 2008 and Kononovicious-Gontis (2013), our model considers the pressure coming from the accumulation of information, by recalling some features of the OFC model of earthquakes and presents a number of key-features: (i) an endogenous price setting mechanism that can reproduce all relevant stylized facts of true financial markets, (ii) heterogenous agents organized in different groups, with a realistic imitative behavior, (iii) an emergent aggregate dynamics that suitably describes extreme events involving market participants as in true financial bubbles/crashes.
In the greatest part of the HAM-related literature, surveyed in LeBaron (2006) and Lux-Westerhoff (2009), agents are divided in two typical categories: **fundamentalists** and **chartists**. Fundamentalists are traders with an eye on the fundamental value of assets; chartists are technical analysts. Part of the existing literature usually describes the imitation on financial markets by assuming that a trader can switch group, from fundamentalists to chartists or vice versa, (see Cristelli 2014). We propose, instead, to refer to the trading decision of the trader, i.e. to the price: the agent who decides to imitate a trader, simply follows the price prevision assumed by that trader, no matter which group the latter belongs to.
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In previous studies, links between extreme events in financial markets and the dynamics of informative cascades have been investigated, Biondo et al. (2013) and (2015). However, the present model considers a realistic feedback mechanism that let the heterogenous traders determine prices under the influence of prices dynamics itself. For these reasons, we call it Contagion Financial Pricing.
The network topology is identical to the one adopted in the Financial-Quakes Model: a small world network with $N = 1600$ traders, obtained from a square 2-D regular lattice, by randomly rewiring its short-range links with a probability $p = 0.02$, therefore creating a given number of long-range links. The final average degree of the network is equal to $< k > = 4$.

Our main goal is to study the role of composition of the population of traders and that of the spreading of information in influencing the market dynamics, its stability and the probability of bubbles and crashes. Because of this reason, the price time series that our model generates, $p_t$ where $t$ is the time, has to be considered as the result of the transactions occurring among the traders, even if we do not describe either the order-book or the portfolio dynamics of investors.
The model

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The population is characterized by the existence of three groups of traders: (i) fundamentalists, (ii) chartists, and (iii) random traders.
the model: traders

A fundamentalist bears in mind a *fundamental value* that she believes is the “correct” value of the asset being traded: she believes that the market dynamics will tend to let this correct value prevail. Thus, she participates to transactions by stating her price $p_{t+1}^f$ on the basis of the discrepancy between the last observed price, $p_t$, and this fundamental value, $p_f$:

$$p_{t+1}^f = p_t + \phi(p_t - p_t) + \epsilon$$

(2)

The sensitivity parameter $\phi$, normally distributed with given mean and std-dev, regulates how much of the discrepancy will be embedded in the new price. Finally, $\epsilon$ is a stochastic noise term, randomly chosen (with uniform probability) in the interval $(-\sigma, \sigma)$, with $\sigma$ fixed at the beginning of simulations.
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A chartist, instead, is a technical analyst and decides her behavior according to her inspection of charts of past prices, by considering the average of the last \( M \) prices, as:

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p_{t+1}^c = p_t + \kappa \left( p_t - p_M \right) + \epsilon
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Both \( M \) and \( \kappa \) (respectively the *length* of trader’s retrospective sight and the sensitivity of forecasts to past prices) are extracted from a normal distribution with previously fixed mean and standard deviation values and, again, \( \epsilon \) is a stochastic noise term defined as before.
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$$p_{t+1}^c = p_t + \kappa \left( \frac{1}{M} \sum_{i=1}^{M} p_i - p_M \right) + \epsilon$$

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Both $M$ and $\kappa$ (respectively the *length* of trader’s retrospective sight and the sensitivity of forecasts to past prices) are extracted from a normal distribution with previously fixed mean and standard deviation values and, again, $\epsilon$ is a stochastic noise term defined as before.

A random trader is defined as an investor who decides her price, $p_{t+1}^r$, by choosing it randomly from a uniform distribution of values, ranging from 0 and the last market price value, i.e.:

$$p_{t+1}^r \in [0, p_t]$$

(4)
The global market price, $p_{t+1}$, will be obtained as the weighted average of individual prices, the weight being the proportion of each group ($F$, $C$, $R$) relative to the total population $N = F + C + R$:

$$p_{t+1} = \frac{F}{N} \sum p_{i+1}^f + \frac{C}{N} \sum p_{i+1}^c + \frac{R}{N} \sum p_{i+1}^r + \omega$$

(5)

where $\omega$ is a global noise term that is related to the information accumulated by traders, as defined below.
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where \( \omega \) is a global noise term that is related to the information accumulated by traders, as defined below.

Consistently with previous studies, we depict a situation where each agent is a sort of informative recipient, exposed to two streams of pressures: a *global* one (\( a \)) and an *individual* one (\( b \)). Once activated, each trader sets her new price following equations (1), (2) or (3) and, if non-random, she transfers the signal to her neighbors, according to the OFC herding mechanism described before.
The global market price, $p_{t+1}$, will be obtained as the weighted average of individual prices, the weight being the proportion of each group ($F$, $C$, $R$) relative to the total population $N = F + C + R$:

$$p_{t+1} = \frac{F}{N} \sum p_{t+1}^f + \frac{C}{N} \sum p_{t+1}^c + \frac{R}{N} \sum p_{t+1}^r + \omega$$  \hspace{1cm} (5)$$

where $\omega$ is a global noise term that is related to the information accumulated by traders, as defined below.

Consistently with previous studies, we depict a situation where each agent is a sort of informative recipient, exposed to two streams of pressures: a global one ($a$) and an individual one ($b$). Once activated, each trader sets her new price following equations (1), (2) or (3) and, if non-random, she transfers the signal to her neighbors, according to the OFC herding mechanism described before.

As a consequence of the received amount of information, someone of the involved neighbors may become active too and pass the threshold level as well, thus transmitting, in turn, her signal to her neighbors and so on. All traders involved in the financial avalanche will imitate the price $p_{t+1}^k$ set by the agent who originated the avalanche, regardless of their own group (fundamentalist or chartist). Random traders, instead, are affected only by the general climate ($a$) of the market: they do not influence, nor are influenced by, other traders.

Finally, the global market price $p_{t+1}$ is determined according to equation (4), where the global noise is assumed to be $\omega = \epsilon e^{\beta l_{av}(t)}$, where $\epsilon$ is the same noise term as in Eqs.(1) and (2), $\beta$ is a constant chosen in a suitable interval and $l_{av}(t)$ is the average value of the information accumulated by all the traders at time $t$. 

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### Null-model Settings

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>POPULATION $N$</td>
<td>$1600$</td>
</tr>
<tr>
<td>FUNDAMENTAL PRICE</td>
<td>$p_f = 5000$</td>
</tr>
<tr>
<td>FUNDAMENTALISTS’ SENSITIVITY PARAMETER</td>
<td>$\phi = 2.0$</td>
</tr>
<tr>
<td>AMPLITUDE OF STOCHASTIC NOISE</td>
<td>$\sigma = 200$</td>
</tr>
<tr>
<td>LENGTH OF RETROSPECTIVE SIGHT</td>
<td>$M \in [0, 90]$</td>
</tr>
<tr>
<td>CHARTISTS’ SENSITIVITY PARAMETER</td>
<td>$\kappa = 2.0$</td>
</tr>
<tr>
<td>EXPONENT OF THE GLOBAL NOISE TERM</td>
<td>$\beta = 16$</td>
</tr>
<tr>
<td>DISSIPATION PARAMETER</td>
<td>$\alpha = 0.92$</td>
</tr>
</tbody>
</table>

In the following, we compare the stylized facts obtained for a CFP global price time series and relative log-returns $r_t = \log(p_{t+1}) - \log(p_t)$ of 10000 iterations (red), with the corresponding series of the General Electric (GE) stock (black), collected day by day from 01/01/1962 to 14/03/2014.
As expected, the present model generated financial quakes. Their pdf can be fitted by a power-law with slope $-1.6$, thus confirming the SOC-like character of the herding dynamics. Such an internal feature, combined with the global informative pressure, strongly affects the emerging global price series.

![Graph showing avalanche size distribution and number of avalanches over time](image)
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The stylized facts that are usually reported and verified in true price series (see for example Chakraborti et al. 2009) and that we successfully tested in our model, are:

1. Fat Tails of Distribution of Returns
2. Absence of Auto-Correlations of Returns
3. Volatility Clustering
On the left, the comparison between the pdf of simulated returns generated by our model (open circles) and the one of the GE stock (open squares). For both we considered normalized returns, \((r_t - r_{av}) / r_{std}\). Simulation and real data are also compared with a Gaussian \(N(0, 1)\) (dashed blue curve): fat tails and asymmetry are well visible in both the returns distributions, which can be fitted by a \(q\)-Gaussian, defined as \(G_q = A[1 - (1 - q)Bx^2]^{1/(1-q)}\) (see Tsallis (2009), Tsallis et al. (2003), Ludescher et al. (2011), Mirritello et al. (2009), Pluchino et al. (2013) for further reference). The entropic index \(q\) measures deviations from Gaussian behavior with exponential tails (obtained for \(q = 1\)): in our case, \(q = 1.55\) (the other fitting parameters are \(A = 0.7, B = 3\)).

On the right, the QQ-plot of the returns obtained from both the GE and CFP price series. The curves clearly deviate from the \(x = y\) test line, thus confirming the presence of fat tails for both returns distributions.
On the left, the Auto Correlation Function (ACF) for both the GE and the CFP Returns Series, showing no evidence of autocorrelations. On the right, the Auto Correlation Function (ACF) for absolute returns exhibit a long-range slowly decaying autocorrelation function in CFP and GE data, showing that in both cases a persistent autocorrelation exists and that it decays quite slowly, staying above zero for any lag’s size, even if with different positive values (GE values oscillate around a greater average value than CFP ones).
Above, results are shown to be quite robust: features remain essentially unchanged independently of parameters values. Vertical bars measure the correspondent standard deviations, over 50 events. In all cases, variability of values observed lays within the standard deviation.
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Below, it is shown that neither population composition, nor population size affect features of simulated returns.
Consistently with previous studies, the presence of a group of random traders reduces fat tails and let the pdf of simulated returns approach a Gaussian-like behavior.
Presented models belong to the econophysics stream of literature, whose “facts-centric” models are addressed to study more the statistical features of the market as a dynamic process than the individual characterization of markets and their participants.

Examples are: Bak et al. (1997), Maslov (2000), Daniels et al. (2003), Smith et al. (2003), Farmer et al. (2005), Mike and Farmer (2008), Bouchaud et al. (2009), Farmer and Foley (2009), Cont et al. (2010), Cont and de Larrard (2011).
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An intermediate and promising standpoint comes from agent-based models, which can simulate true economic interactions among individually-designed heterogeneous traders, giving rise to emergent phenomena at the aggregate level.

Examples are: Raberto et al. (2001), Chiarella and Iori (2002), Consiglio et al. (2005), Gil-Bazo et al. (2009), Chiarella et al. (2009), Anufriev and Panchenko (2009), Tedeschi et al. (2009), (2012). Two detailed surveys of the wide literature of existing ABM models of financial order books, can be found in Parlour and Seppi (2008) and Chakraborti et al. (2011).
In 2018, a series of articles have been published, containing a complete financial market, with a truly operative order book, able to ensure the empirical compliance with true data and to provide reliability and robustness in order to test policy interventions against market instability.

- Order book modeling and financial stability, JEIC *forthcoming*


- Fat Tails and Similarity in Order Book Stories of Imitation and Reputation (work in progress)
steps ahead: the policy challenge
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Such papers, based on an orders-driven order-book model, with different orders types (of variable quantity), heterogeneous population, variable (and bounded) fundamental value, independent (and variable) chartists myopia, true portfolio constraints, true physical time (including pre-opening and pre-closing auctions), true transactions and liquidity constraints, provide tests to reduce fat tails, showing that the policy maker can intervene on some specific factors.
Previous results contained in Biondo (2018a), (2018b) and (2018c), showed some causes of the departure from Gaussianity of density functions of financial returns:

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Previous results contained in Biondo (2018a), (2018b) and (2018c), showed some causes of the departure from Gaussianity of density functions of financial returns:

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   1.b) in technical analysis
2) the role of subjectivity
   2.a) individual perceptions
   2.b) impact of random choices
3) qualification of orders
   3.a) quantity constraints
   3.b) order book length
   3.c) time validity
4) consequences of indolence and taxes
5) the role of individual risk aversion in a dual-horizon forecasting (SR vs LR)
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Finally, the last paper (still in preparation) will show that other causes are linked to: i) the topology of the social network in which the imitation propagates; ii) the way in which traders define reputation when deciding whom to imitate; iii) the clustering properties of small communities.
Thank you for your attention.
Financial markets and Self-Organized Criticality

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