Mechanisms of self-organization and finite size effects in a minimal agent based model

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Abstract. We present a detailed analysis of the self-organization phenomenon in which the stylized facts originate from finite size effects with respect to the number of agents considered and disappear in the limit of an infinite population. By introducing the possibility that agents can enter or leave the market depending on the behavior of the price, it is possible to show that the system self-organizes in a regime with a finite number of agents which corresponds to the stylized facts. The mechanism for entering or leaving the market is based on the idea that a too stable market is unappealing for traders, while the presence of price movements attracts agents to enter and speculate on the market. We show that this mechanism is also compatible with the idea that agents are scared by a noisy and risky market at shorter timescales. We also show that the mechanism for self-organization is robust with respect to variations of the exit/entry rules and that the attempt to trigger the system to self-organize in a region without stylized facts leads to an unrealistic dynamics. We study the self-organization in a specific agent based model but we believe that the basic ideas should be of general validity.

Keywords: critical phenomena of socio-economic systems, interacting agent models, models of financial markets, scaling in socio-economic systems
1. Introduction

In this paper we discuss in detail the self-organization phenomenon which emerges in the minimal agent based model (ABM) that we have introduced in [1]–[3]. This model has the great advantage of being simple, mathematically well posed and able to reproduce the stylized facts (SF), i.e. the empirical evidences of real markets [4]–[6]. In this respect it can be considered a ‘workable model’ for which analytical approaches are possible in some cases and it can be easily modified to introduce variants and elements of realism.

We consider a population of heterogeneous interacting agents whose strategies are divided into two main classes: fundamentalist and chartist. Fundamentalist agents believe that the market is stable and fluctuates around a fair value, the fundamental price $p_f$, that they estimate by standard economic arguments. The fundamentalist strategy acts in a way to drive the price towards the fundamental value. Chartist agents instead try to detect local trends in the market by evaluating the price history. They try to speculate betting on these trends and so they contribute to the formation of bubbles and crashes. Agents can change their strategy during the dynamics by following some personal considerations or by imitating other agents’ behavior (herding). It is possible to see that, by considering a given finite number of agents, the dynamics shows an intermittent behavior. This means that the market is assumed to be dominated by fundamentalists at large times but bursts of chartists can appear spontaneously leading to high volatility. In principle the basic assumption of large time stability can be removed if one wanted to consider particularly turbulent situations but in the present study we will only refer to the simple case mentioned before.

The intermittent behavior is present only for a particular value of the number of agents and it disappears in the limit of infinite agents. This phenomenon has already been observed in other similar models but it has been interpreted as a negative element. Here we present a completely different perspective by showing that the finite number of agents necessary to produce the SF is not an artificial feature of the model to be
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eliminated. On the contrary, this finite size effect results as the natural outcome of a process of self-organization.

The basic concept is that the self-organization can be triggered by leaving the agents the possibility of entering or exiting the market following a mechanism based on a feedback on the price behavior. This mechanism encourages agents to enter the market if they perceive an interesting movement in the price. On the other hand a very stable market where nothing happens is not appealing for speculators who are likely to abandon such a market. From an economic point of view a very stable market can be attractive for some particular agents who only look for the conservation of their wealth, but these will not contribute to the SF and are irrelevant with respect to our discussion.

This dynamics for the agents is implemented by introducing two suitable thresholds which agents consider for deciding whether to enter or leave the market by comparing them with the price movement. By considering various initial situations with different starting number of agents we can observe that the resulting dynamics stabilizes around a finite number of agents which is the one corresponding to the SF. This phenomenon corresponds to the self-organization of the system in a state dominated by an intermittency due to finite size effects. In this respect it is not a case of self-organized criticality [7, 8] but rather one of self-organized intermittency.

The fact that real agents can be scared by a market that is too volatile may appear at first sight problematic with respect to our criteria for entering or exiting the market. This point requires a clarification of the timescales involved. For a market to be attractive, there has to be some price movement at a relatively long timescale corresponding to the operation performed. On the other hand volatility at shorter timescales may indeed appear as a disturbance for an agent. We have checked this point by analyzing the volatility also at a short timescale and considering this as a discouraging element for the agents. The general result is that the introduction of this additional and realistic element does not modify appreciably the phenomenon of self-organization discussed before. We have also checked the robustness of the self-organization mechanism along various directions. For example it is possible to see that if one tries to force the system to self-organize in a state without the SF one meets unrealistic scenarios for the evolution of the agent number.

In summary we propose a simple mechanism for the agents’ dynamics which is able to explain why real markets self-organize in a state corresponding to the SF. This mechanism is based on the idea that speculative agents dislike a too stable market and prefer to bet on price movements which they interpret as opportunities to exploit following their strategies. This mechanism is stable and does not contradict the natural fear of real traders of entering risky, highly fluctuating markets with respect to shorter timescales.

The paper is organized in the following way.

In section 2 we give a schematic description of the ABM introduced in [1]–[3]. In section 3 we discuss the basic mechanisms which lead to the self-organization towards the region with intermittent dynamics and SF. We also consider some variants and check the stability of the mechanism.

In section 4 we propose a more realistic generalization of the model with two temporal horizons to define the entry/exit strategies of the agents. In this way we can include the tendency of real traders to be scared by a noisy market and show that this does not interfere with the self-organization.
In section 5 the conclusions are drawn and we also outline some possible perspectives of the present study.

2. The minimal agent based model in a nutshell

The mathematical framework which we consider to study the self-organization mechanism is the minimal ABM that we have introduced in [1]–[3]. This ABM is composed of $N$ agents that can be chartists ($N_c$) or fundamentalists ($N_f$) and clearly $N = N_c + N_f$. The novelty of this model, which makes it a workable tool for considering a variety of questions, is a simplification of the elements to those which are strictly essential. In addition the equations for the dynamical evolution are mathematically well posed and general without any ad hoc assumption [9]–[11].

The chartists are recognized as destabilizing agents and an efficient way to describe them is represented by the potential method introduced in [12]–[15]. The action of these investors can be described, in the simplest case, in terms of a repulsive force proportional to the distance between the current price $p(t)$ and a suitable moving average $p_M(t) = M^{-1} \sum_{j=0}^{M-1} p(t-j)$.

On the other hand the fundamentalists believe in a fundamental price $p_f$ and bet on a reverting trend towards this value. A simple way to mimic their action is to define an AR(1) process where $p_f$ plays the role of an attractor.

We now assume that the price formation can be described in term of a linearized Walras mechanism (i.e. $dp/dt = ED$ where $ED = \text{excess demand}$) and the complete equation of price dynamics is consequently,

$$p(t+1) = p(t) + \sigma \xi(t) + \frac{1}{N} \left[ \sum_{i=1}^{N_c} \frac{b_i}{M_i-1} (p(t) - p_{M_i}(t)) + \sum_{j=1}^{N_f} \gamma_j (p_f - p(t)) \right].$$

For the sake of simplicity we set $\gamma_j = \gamma \forall j$, $b_i = b$ and $M_i = M \forall i$ which are respectively the strength of fundamentalist action, that of the chartist action and the memory of the moving average. The term $\sigma \xi$ is the white noise whose amplitude is fixed by $\sigma$.

The key element of the model is the dynamics of the evolution of the strategies. Here we use the simplified version of the probability of switching a strategy that models only an asymmetric herding effect. This asymmetry guarantees that fundamentalists will prevail at very long times (for a more detailed discussion see [1, 2]),

$$P_{cf} = B(1 + \delta) \left( K + \frac{N_f}{N} \right),$$

$$P_{fc} = B(1 - \delta) \left( K + \frac{N_c}{N} \right),$$

where $P_{cf}$ and $P_{fc}$ are respectively the probability of becoming fundamentalist being chartist and the probability of becoming chartist being fundamentalist. The parameter $\delta$ is the degree of asymmetry of the population dynamics and $B$ is a constant of proportionality to be fixed. The parameter $K$ prevents the dynamics from being captured indefinitely by the absorbing states $N_c = 0$ and $N_f = 0$. We set $K = r/N$ with $r < 1$ in order to be able to vary the number of agents $N$ without quitting the region of parameters in which the probability density function of the population is bimodal [1, 2, 16, 17].
Further and more exhaustive discussions about the intermittent behavior of the population dynamics, the origin of the volatility clustering and in general about the statistical properties of the model can be found in [1]–[3].

3. Basic mechanism for the self-organization

3.1. Self-organized intermittency

Equations (2) and (3) define the dynamics of $N_c$ and $N_f = N - N_c$. If we consider the variable $x = N_c/N$ it is possible to see that the distribution of $x$ depends explicitly on the value of the total number of agents $N$ active in the market [1, 2]. In particular when $N$ is very large the transition probability from fundamentalist to chartist becomes asymptotically small and essentially the system becomes frozen in the fundamentalist state. The resulting price dynamics is then extremely stable due to the stabilizing effect of fundamentalists. Clearly such a state does not show the anomalous fluctuations corresponding to the SF. This means that in the limit of an infinite size system $N$ the resulting dynamics loses the interesting properties which lead to the formation of the SF. This is different from what happens in the majority of physical models where the interesting (critical) phenomena appear in the thermodynamic limit. The opposite happens in the limit of very small $N$ where the population of agents undergoes very fast changes of strategy and the resulting dynamics is too schizophrenic. Only for an intermediate number of agents (the specific value depending on the other model parameters) one can recover the intermittent dynamics of the changes of strategy which leads to the SF. Of course this situation leads to the basic requirement of understanding the driving mechanism which makes real markets self-organize in the intermittent state with a finite number of agents.

The first consideration in this respect is that the number of agents $N$ should be itself a fluctuating variable and not a fixed parameter of the model. This implies the identification of a mechanism which rules the decision of agents to enter or leave the market depending on the price behavior.

The idea is that traders are usually attracted to enter the market if they detect an interesting signal in the price behavior which usually is an appreciable movement of the price. Otherwise, if the market is too stable, no gain opportunities appear and traders leave the market. We would like to stress that both chartist and fundamentalist agents described in our model are speculative traders of a kind in the sense that they try to profit by betting on future movements of the price. The behavior of extremely conservative investors who appreciate a completely stable situation is not part of this scheme because they do not contribute to the fluctuations leading to the SF.

The price movements which are attractive to agents are estimated in our model by considering a long-term ($T \approx 1000$) estimation of the standard deviation of the price,

$$
\sigma(t, T) = \sqrt{\frac{1}{T-1} \sum_{i=0}^{T-1} (p(t-i) - \bar{p})^2}.
$$

This quantity $\sigma$ is the one agents consider for deciding whether to enter or leave the market. If $\sigma$ is small, agents leave the too stable market where no profit opportunities appear. Otherwise if $\sigma$ is sufficiently large then significant movements in the price behavior
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Figure 1. Self-organization to the quasi-critical state. Three populations with different starting numbers of agents ($N = 50$, green line; $N = 500$, red line; $N = 1000$, blue line) evolve in time, following the threshold rule, towards the quasi-critical intermittent state which corresponds to the SF. Starting from a large population ($N = 1000$), agents exit the market because it is too stable. The opposite happens when the starting number of agents is small ($N = 50$). In this case agents enter the market to exploit the profit opportunities that they detect. When the populations starts from $N = 500$ the number of agents fluctuates around an almost stable value which is the one of the intermittent dynamics leading to the SF. In the inset the time fluctuations of the estimator $\sigma(t, T)$ are shown together with the thresholds ($\Theta_{\text{in}}$ and $\Theta_{\text{out}}$) used in the simulations. We can see the intermittent dynamics of the volatility $\sigma(t, T)$.

are expected and agents enter the market. This situation can be described in terms of the two threshold values $\Theta_{\text{in}}$ and $\Theta_{\text{out}}$. In particular agents will (in a probabilistic way) enter the market if $\sigma(t, T) > \Theta_{\text{in}}$ and leave the market if $\sigma(t, T) < \Theta_{\text{out}}$:

enter if $\sigma(t, T) > \Theta_{\text{in}}$,
exit if $\sigma(t, T) < \Theta_{\text{out}}$.

(5)

Chartists and fundamentalists have the same entry/exit rules and the same thresholds. In figure 1 we can observe the phenomenon of self-organization. Starting from a small value of $N$ ($N = 50$) the large price movements will attract more agents and $N$ increases. Starting instead from a large population of agents ($N = 5000$) the opposite happens and $N$ decreases. For $N = 500$ we have a relatively stable situation. The self-organization to the intermittent state which leads to the SF corresponds therefore to the fact that this is the attractive fixed point for the dynamics of the agents related to their threshold strategies. The fact that this occurs in our model for $N = 500$ depends on the specific parameters that we have adopted but clearly the phenomenon of self-organization is completely general and robust. In principle, by changing the parameters, one could have the intermittent state at different values of $N$. In the inset of figure 1 we have plotted the intermittent

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behavior of the estimator $\sigma$ as a function of the time compared with the two thresholds $\Theta_{\text{in}}$ and $\Theta_{\text{out}}$. We can call this attractive intermittent state ‘quasi-critical’ to distinguish it from the usual critical state of a statistical physics model.

Along this line of reasoning we can make two comments with respect to a real market:

(i) Different markets may correspond to very different parameters in our model. For each set of these parameters there would be a self-organization to a quasi-critical value $N^*$ leading to the SF. This permits us to explain why the number of agents can be different in different markets but still they all lead to SF with similar properties. However, this intermittent properties are due to finite size effects and for this reason a strict universality should not be expected.

(ii) In our model the total number of agents $N$ has a very precise mathematical meaning. It corresponds to the number of independent interacting variables in the model. The interpretation of an effective $N$ in a real market is therefore a subtle problem which requires a careful analysis. The herding mechanism induces a tendency of agents to behave similarly but this is not strictly compulsory. In reality if a group of agents, for whatever reason, act coherently in the market, they cannot be considered as mathematically different agents but are essentially a single agent. For this reason the estimation of the effective number of independent agents in a real market represents a very interesting and important problem.

3.2. Other possible rules

In section 3.1 we have seen that, by fixing the thresholds $\Theta_{\text{in}}$ and $\Theta_{\text{out}}$ in a region of values of the volatility $\sigma$ which is intermediate with respect to the two limit cases $\sigma_{N=5000}$ and $\sigma_{N=50}$, the system self-organizes in the intermittent state corresponding to an intermediate number of agents $N^* \simeq 500$.

In doing this we have chosen the threshold values to correspond approximately to the region of the fluctuations leading to the SF. This may induce the idea that by choosing different values of $\Theta_{\text{in}}$ and $\Theta_{\text{out}}$ one may force the system to self-organize to any preselected state, not necessarily the one corresponding to the SF. We are going to see that this is not the case because, choosing the region of unreasonable thresholds, the system does not reach an interesting or unique self-organized state. In figure 2 we have plotted the histograms of the volatility $\sigma$ corresponding to three different populations with a fixed number of agents $N$ with values $50, 500, 5000$. We can see that the volatility of the $N=5000$ population is very sharp and it is peaked around a small value of $\sigma$. In the case of $N=50$ the histogram is broader and has a maximum at a very high level of volatility. The situation is different in the intermediate case of $N=500$ where the distribution is very broad and asymmetric. It is peaked at small values of volatility but the tails reach very high values, much more than the $N=50$ population. The reason for the high values of price fluctuations of the intermediate case ($N=500$) with respect to the extreme case ($N=50$) is the following. A very large price fluctuation corresponds to a situation in which the chartists’ action can develop for a certain time. In the highly fluctuating regime ($N=50$) the lifetime of chartist action is too small for this to happen. In contrast, for the intermediate case chartist fluctuations are rarer but when they happen they may last for a longer time.

We now consider three different possibilities for the threshold values of $\Theta_{\text{in}}$ and $\Theta_{\text{out}}$. These regions are evidenced in figure 2 with different colors. The first region is centered
Figure 2. Histograms of the volatility $\sigma$ for different populations with fixed number of agents $N$. The picture refers to three populations with $N$ equal to 50 (green line), 500 (red line) and 5000 (blue line). The histograms referring to $N = 50$ and 5000 are almost symmetric with the difference that the first is broad and the second very sharp. The histogram for $N = 500$ is asymmetric and has tails which extend to very large values of the volatility $\sigma$, even larger than the ones of the $N = 50$ histogram. By considering this plot, we have identified three different regions (indicated in the picture with different colors), delimited by different values of $\Theta_{\text{in}}$ and $\Theta_{\text{out}}$, to trigger the self-organization towards different values of $N$. We will see that only by choosing a suitable region centered on the maximum of the histogram which refers to $N = 500$ can one obtain a market dynamics which self-organizes towards a stable value.

On low values of volatility, the second on high values and the third on intermediate values. On choosing this last region, that is the one used in section 3.1, the system self-organizes in the intermittent state which corresponds to a fluctuating intermediate number of agents ($N \simeq 500$). We are going to see that unrealistic anomalies occur if one chooses the other two regions. When the region defined by $\Theta_{\text{in}}$ and $\Theta_{\text{out}}$ is centered on low volatility values, and the starting number of agents is small, the system size grows until it reaches a number of agents which leads to an average value of the volatility $\sigma$ which is inside the region considered. Then the fluctuations from this average value are so small that the system is actually locked into a certain (high) value of the number of agents. The dynamics corresponding to this situation does not display the SF any longer. Of course when the starting number of agents is very large its average volatility level is always inside the region considered and the system size is constant in time. The dynamics corresponding to a low volatility centered region is shown in figure 3 (left) and it does not lead to the phenomenon of self-organization.

In contrast, as shown in figure 3 (right), when the region defined by the thresholds is centered on very high values of volatility the system size rapidly drops down because the system has an average volatility which is always smaller than the threshold considered.
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Figure 3. Self-organization using other rules. In this plot we have analyzed the self-organization phenomenon using values of $\Theta_{\text{in}}$ and $\Theta_{\text{out}}$ which define regions which are centered on low (left plot) and high (right plot) values of volatility. We can see that on choosing these regions the self-organization phenomenon is no longer observed. In the left panel we can see that the number of agents $N(t)$ is an always increasing function which becomes a constant when $N(t)$ exceeds a certain value. The opposite happens in the right panel where $N(t)$ decreases step by step, going towards the unrealistic situations with $N = 0$.

for entering the market. In this way the system collapses to the unrealistic situation of zero-agent population where the price fluctuations are only due to the random noise term. Therefore this study shows that the phenomenon of self-organization and the presence of SF are intrinsically linked and one cannot force the system to self-organize to a reasonable dynamics which does not lead to the SF. For example this forbids the possibility of self-organization associated with a random walk dynamics (associated with the SF).

3.3. Further simplification of the mechanism for the self-organization

In this section we consider a simple modification of the mechanism described in section 3.1 to obtain a self-organized market. The idea is that agents enter the market if the volatility is larger than a certain threshold $\Theta_{\text{in}}$ while they leave the market if this volatility is smaller than the threshold $\Theta_{\text{out}}$. Of course the interval $\Theta_{\text{in}} - \Theta_{\text{out}}$ is arbitrary and needs to be fixed. Actually we are going to see that this is not a crucial point for obtaining the self-organization of the market. In fact we have considered a situation in which agents enter or exit the market by looking only at one suitable threshold $\Theta_{\text{SOI}}$. Also in this case the system self-organizes in the intermittent case characterized by an intermediate number of agents. The only difference from the two-threshold dynamics, as one can see in figure 4, is that the number of agents continues to have relatively large fluctuations, which resemble periodic oscillations, even in the self-organized state.

4. Self-organization with risk-scared agents

The threshold mechanism could be apparently problematic because it may be argued that investors could be scared by a too fluctuating market [18]. However, this problem
Figure 4. Self-organization with only one threshold. This plot shows that the amplitude of the region defined by $\Theta_{\text{in}}$ and $\Theta_{\text{out}}$ is not a crucial point in the dynamics. Here we have considered a simulation where agents only compare the market volatility $\sigma$ to a unique threshold $\Theta_{\text{SOI}}$ which is chosen inside the region $\Theta_{\text{out}} - \Theta_{\text{in}}$. We have plotted the self-organizations phenomenon for three different starting numbers of agents such as in figure 1 ($N = 50$, green line; $N = 500$, red line; $N = 1000$, blue line). We can see that the results are almost the same as the ones obtained with the two-threshold dynamics.

can easily be clarified by the analysis of fluctuations at different timescales. The price movement which we interpret as a positive signal for the agents’ strategy corresponds to the volatility at relatively long timescale. On the other hand a large volatility at a shorter timescale would induce a high risk on such a strategy. In this section we consider how this problem may affect the self-organization mechanism. We are going to see that the introduction of this more complex and realistic scenario in the model does not change the essential elements of the self-organization phenomenon.

4.1. Small scale volatility threshold

We use the same estimator $\sigma(t, T)$ as was introduced in section 3.1 (equation (4)). Since we want agents to look at fluctuations on two time horizons, at each time step $t$ they now have to evaluate fluctuations $\sigma(t, T)$ for two different values of $T$ that we call $T_1$ and $T_2$ corresponding respectively to the small timescale and to the large timescale. We set $T_2 = 1000$ as in section 3.1 and we choose $T_1 = T_2/100$.

The fear of a too volatile market at a short timescale can be represented by the new threshold $\Theta_s$. If $\sigma(t, T_1) > \Theta_s$ the agent will consider the situation as dangerous and she will exit the market with a certain probability. If the agent is inactive and the previous condition is fulfilled she will not enter the market. Instead if the opposite condition is true (i.e. $\sigma(t, T_1) < \Theta_s$) the agents compare the long timescale fluctuations $\sigma(t, T_2)$ with the thresholds $\Theta_{\text{in}}, \Theta_{\text{out}}$ and enter/exit according to the same scheme of equation (5). In
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**Figure 5.** Self-organization with risk-scared agents. The introduction of a small scale threshold $\Theta_s$ does not change the results of figure 1; as in that case, the system self-organizes into the quasi-critical state $N^*$ independently of the starting number of agents. The unique effect introduced by $\Theta_s$ is a slight asymmetry between the rise and the decrease of the number of agents $N$.

**Figure 6.** Analysis of the volatility on different timescales. Large fluctuations of $\sigma(t, T_1)$ do not necessarily imply large fluctuations of $\sigma(t, T_2)$ and vice versa, as can be seen in the highlighted region. In fact while $\sigma(t, T_2) < \Theta_{in}$ we have at the same time that $\sigma(t, T_1) > \Theta_s$.

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Figure 7. Analysis of the short scale volatility threshold. We see that the condition $\sigma(t, T_1) > \Theta_s$ is fulfilled when the price makes very large fluctuations and grows (or drops) very quickly on the scale of $T_1$.

Figure 5 we show the same analysis as in figure 1 and we can see that, independently on the starting number of agents, the system tends to the quasi-critical state (i.e. $N^*$) with the SF as in section 3 for a suitable choice of the thresholds $\Theta_{in}, \Theta_{out}, \Theta_s$. The unique effect introduced by $\Theta_s$ is a slight asymmetry between the rise and the decrease of the number of agents $N$. The value of $\Theta_s$ that we adopt (figure 6) is quantitatively of the same order as $\Theta_{in}$ and $\Theta_{out}$, but it corresponds to shorter timescales.

It is also interesting to note that the presence of large fluctuations on the scale of $T_1$ does not imply large fluctuations on the scale of $T_2$ or vice versa, as figure 6 shows. In fact we can see in the highlighted region that, while $\sigma(t, T_2)$ is smaller than $\Theta_{in}$, $\sigma(t, T_1)$ is instead usually larger than $\Theta_s$. To conclude this section we report in figure 7 the price behavior and the fluctuations $\sigma(t, T_1)$; the small scale mechanism is active only when the price has large fluctuations on the small scale.

5. Conclusions

In this paper we have presented a critical discussion of the self-organization phenomenon in a market model dynamics. We have considered a minimal ABM able to reproduce market SF as a playground in which to analyze the self-organization phenomenon. In this model the dynamics strongly depends on the number of agents that one considers. For a finite intermediate number of agents one obtains an intermittent dynamics which leads to the SF. In the thermodynamic limit of many agents the price fluctuations decrease and no intermittency is observed in the dynamics. The result is a superstable market where the SF are not recovered. Also in the limit of very few agents the SF disappear, the price fluctuations being too high. The basic question is why real markets self-organize in the quasi-critical region with the intermittent dynamics and the SF. We propose a simple mechanism which triggers this self-organization in a population of agents who can enter or

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exit the market. The rule followed by the agents for deciding whether to enter or leave the market is based on the idea that the price must undergo some appreciable movements to appear appealing for speculative traders. In contrast, a superstable market with the price slowly fluctuating around a fundamental value does not display much profit opportunity and agents are not interested. We have studied the robustness of the self-organization with respect to variations of the threshold parameters. The result is that it is not possible to force the system to self-organize in a state without the SF.

We also consider the fact that agents may be discouraged from entering a risky, noisy market. This requires the analysis of fluctuations at long timescale (price movements) and short timescale (risky volatility). The result is that the introduction of these additional realistic effects does not appreciably modify the self-organization phenomenon. We believe that we have characterized in a reasonably, realistic and general scheme the self-organization leading to the SF in terms of the agents’ strategies for entering or exiting the market. This is a new concept, usually neglected in ABM, which, in our opinion, should instead be considered in the attempts to understand the origin of the SF in economic time series.

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