On Financial Markets Trading

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Abstract.
Starting from the observation of the real trading activity, we propose a model of a stockmarket simulating all the typical phases taking place in a stock exchange. We show that there is no need of several classes of agents once one has introduced realistic constraints in order to confine money, time, gain and loss within an appropriate range. The main ingredients are local and global coupling, randomness, Zipf distribution of resources and price formation when inserting an order. The simulation starts with the initial public offer and comprises the broadcasting of news/advertisements and the building of the book, where all the selling and buying orders are stored. The model is able to reproduce fat tails and clustered volatility, the two most significant characteristics of a real stockmarket, being driven by very intuitive parameters.

Keywords: Econophysics; Herding Behavior; Artificial Financial Market; Coupling

PACS: 89.90.+n; 05.45.Tp; 64.60.-i

INTRODUCTION

The dynamics of the stock market oscillations is still object of a great debate. Variation of stock prices is usually considered a random process and there are many alternatives about the proper model of the distribution of return. In any case, some universal features have been found: They resemble the scaling laws characterizing physical systems dominated by the interaction of a large number of units. It is therefore of a great interest the introduction of a model that is able to reproduce these aspects through a proper tuning of its parameters. Also interesting is the understanding of the direct influence of them, provided they have a physical meaning.

Previous models are all essentially based on the assumption that two different kinds of economic agents are interacting in the market: Some authors [1] call them dealers and savers, others [2] use the names fundamentalists and noise traders (further distinguishing between optimistic and pessimistic), others more [3] say
rational and chartists. If one goes into the details of these models, one sees that fundamentalists follow the premise of the efficient market hypothesis in that they expect the price to follow the fundamental value of the asset. A fundamentalist trading strategy consists of buying when the actual market price is believed to be below the fundamental value and selling in the opposite case. Noise traders, on the other hand, do not believe in an immediate tendency of the price to revert to its underlying fundamental value: They try to identify price trends and consider the behavior of other traders as a source of information, giving rise to the tendency towards herding.

Looking at the scaling law characterizing physical systems where large numbers of units interact [4–7], anyway, one observes that there is no need to introduce different classes of agents. Since the details of the circumstances governing the expectations and decisions of all the individuals are unknown to the modeler, the behavior of a large number of heterogeneous agents may best be formalized using a probabilistic setting. Such a statistical modeling concept has a certain tradition in the so-called synergetics literature [4] which has adopted techniques from elementary particle physics to study various problems of social interactions among humans [8]. In a statistical approach the properties of macro variables are not necessarily identical to those of the corresponding micro variables nor does the mere aggregation of micro components always yield sensible macroeconomics relationships.

The most important aspect to be taken into account, therefore, is the behavior of the single particle and the coupling between units. A realistic model, in our opinion, should be able to avoid the distinctions among classes of traders, because they introduce some collateral problems to be solved. In [2], for instance, it is necessary to let people move from one group to another and to introduce an exogenous change of the fundamental value, but these two requirements sound somehow artificial. It is in fact clear that without the fundamentalists the price would follow just one trend at infinitum and without the noise traders the price would never escape the range of its fundamental value. In [3] this fact becomes clear, since already a 20% of fundamentalists is enough to confine the market price within the range of the rational traders. Just very short deviations occur before common sense was restored. Some authors even assume that the relative changes of the fundamental value are Gaussian variables, leading to the completely unrealistic situation where rational traders do invest according to some source of randomness.

In [2] the authors want to show that although the news arrival process lacks both power-law scaling and any temporal dependence in volatility [9], their model generates such a behavior as the result of the interactions between agents. But then one realizes that the market price follows very closely the fundamental value, i.e. it is itself almost random. In [10], furthermore, it has been shown that behavioral models can produce a shape of the return distribution remarkably similar to that derived from empirical data; therefore any unobservable news arrival process is not necessary in order to explain the salient characteristics of empirical distributions of returns. On the contrary, the high peaks and fat tails property can be derived from the working of the market process itself.
In our model there is only one type of investor, whose goal is maximizing the profit while minimizing the risk. Every trader has a limited amount of money and a given disposition towards investment. Furthermore the time comes into account, since a given gain has a different meaning whether realized within few weeks or after several years. At the beginning of the simulation, one agent is supposed to be the central bank responsible of the Initial Public Offer (IPO): All the shares belong to one agent. We provide a mechanism to generate news and advertisements as a way to introduce a global coupling into our model. During the IPO, traders feel a strong pressure to buy and in fact almost all of them want to order some quotas. Since the bank responsible of the IPO cannot buy back any shares at the moment, this transient has a limited length and the simulation enters the permanent regime after few iterations. The main building blocks of the model are the price formation and the book, where all the pending orders are stored. Every trader, when willing to buy a share, has to identify a fair price according to past values of the price, opinion of the media and suggestions coming from acquaintances. This is the price with which he/she would like to enter the market; starting from it every agent keeps in mind a target price and a stop-loss price (respectively according to the desired gain and the maximum loss). They are of fundamental importance to decide whether and when to sell some shares, together with a threshold in time. We neither introduce any fundamental price nor make use of any exogenous input. In the following sections we describe the model in more details, present some simulation runs and study the influence of the parameters.

**THE MODEL**

We consider $N$ traders who want to trade a stock with $M$ shares on a common market. For simplicity only one stock is involved in the model. The information related to every trader are the following:

- **Initial amount of money**: According to [11–14], it is likely that the Zipf’s law is quite universal. On the light of this observation, we have decided to distribute the money to traders following such a distribution. A lot of money to a small amount of agents, few resources to the majority of people.

- **Inclination towards investment**: Usually traders tend to keep cash a part of their resources, in order to be able to have money to exploit the market at special time.

- **Number of shares owned**.

- **List of friends with which sharing information**: Through this local coupling we are able to model the herding behavior. In [12] it has been shown that interactions of order higher than pairwise are not relevant in the dynamics that lead to Zipf’s law.

- **Invested money**, to keep trace of the average buying price for further purchase.
• Cash: Amount of resources immediately available, sometimes called liquid.

• Expected gain, randomly chosen between $g_{\text{min}}$ and $g_{\text{max}}$. Once such a profit has been realised the trader wants to sell the shares in order to convert this invested money into cash.

• Maximum loss, randomly chosen between $l_{\text{min}}$ and $l_{\text{max}}$. It is sometimes better to sell the shares losing some money than keeping them during a crash (and therefore losing more money after that).

• Personal target price, decided when inserting the buying order.

• Personal stop loss, decided when inserting the buying order.

• Threshold: Amount of time after which the trader may start to change idea about the investment: In real situation the gain alone is not enough to say whether an investment has been a good one or not. Everything has to be related with time (10% gain in one year is of course a worst investment than 5% gain in one month if we do not consider speculation taxes).

When an agent wants to trade, a new record in the book is created. All the orders are stored according to the type (buy or sell), to the price and to the submission time. A transaction occur whenever the cheapest price among the sell list matches with the most expensive offer in the other list: That price defines the market price of the stock at that particular instant of time (tick). In the following table we can see the first five levels of the book. Every line contains information about time, trader, number of involved shares and desired price. Entries are ordered according to the price (and eventually to the time for equal prices), in a decreasing way for the buying list and in an increasing manner for the selling list.

| BUY ORDERS | SELL ORDERS |
|------------|-------------|
| time  | trader | shares | price | price | shares | trader | time |
| 89102 | 128 | 11 | 10902 | 10907 | 8 | 321 | 89802 |
| 87015 | 807 | 5 | 10896 | 10910 | 5 | 902 | 86501 |
| 88897 | 341 | 13 | 10894 | 10911 | 3 | 563 | 90001 |
| 88902 | 561 | 4 | 10894 | 10913 | 59 | 121 | 87875 |
| 90010 | 3 | 75 | 10893 | 10914 | 6 | 492 | 85103 |

**TABLE 1.** Example of the first five levels of the book. No transaction can take place because the highest buying price is smaller than the cheapest selling order. Entries are ordered according to price and occurrence time.

Once terminated the IPO phase, a typical simulation iteration involves the following steps:
• Selection of trader: This is done in a completely random way, without taking into account the different weight of agents, nor any other characteristic. This part represents material for a future work, where we can introduce some feedback between the type of trader and how often he/she trades.

• Control of the presence of some pending order: The trader has NO pending order.
  
  – Check whether the trader owns shares. If the trader owns NO share, then:
    
    * Evaluate the probability of a buying order for the trader. Formulate the fair price according to Eq.1 and target (stop loss) price according to expected gain (maximum loss).

  – Else (the trader has one pending order):
    
    * Check the market price and since when the trader owns the shares. If the actual price is below the stop loss then evaluate the probability that the trader performs a caution sell and the probability related to an averaging purchase. This decision is taken according to the news suggestions (buy, keep or sell) and to the available amount of money. If the market price is over the target then the trader will sell all the shares, inserting a limit order with a price in the range (target price, market price).
    
    If the price is in the range (stop-loss price, target price) and the trader has bought the shares a long time ago (longer than the threshold), evaluate the probability to sell, inserting a limit order at the previously computed target price.

  • Else (for simplicity we suppose that every trader cannot afford more than one pending order simultaneously):

    – Check the kind of the order. If it is a request to SELL, then:
      
      * If the order is sufficiently old (older than the threshold), then evaluate the probability that the trader decides to remove it.
      
      * If the market price is below the stop loss price, then evaluate the probability that the trader performs a market sell or an averaging buy.

    – Else (request to BUY):

      * Evaluate the probability that the trader decides to convert the limit order in a market order. This is done according to the media and the acquaintances.
      
      * Compare the time with the threshold: If the order is too old, then evaluate the probability that the trader removes the order. It is also possible to change just some parameters of the order.
• Check the book. If there is a price-matching (the cheapest selling order equals the highest buying price), then:
  
  – Define this price as the market price at the actual time (tick).
  
  – If the buyer has got all the desired shares then this buying order is removed from the list and the trader can immediately place a selling order (through an evaluation of the probability).
  
  – If the seller has been able to sell all the desired shares, then this selling order is removed from the corresponding list.

When formulating the fair price, every trader makes the decision according to the opinion of some acquaintance (contained in the price $p_1$), to the media (they suggest the price $p_2$) and to some past values of the stock price itself (through the forecasted price $p_3$, inspired by [15]).

• $p_1$ represents the opinion of the friends of the selected trader. Every agents who owns shares, has his/her own target price. We average all the target price of the friends which are making profit (who would believe to people which are losing money?) and then establish an enter price rescaling it by the expected gain ($eg$) of the selected trader: 

$$p_1 = \frac{1}{n} \sum_{i=1}^{n} tp_i (1 - eg)$$

• $p_2$ represents the target price broadcasted by the media, in our model an internal global information of the system$^1$. It is generated starting from the last price $p_u$, comparing the current ratio between the number of buyers and the number of sellers in the book ($b_u$ stands for book unbalance) with the parameter $B$ (unbalance of the book), in the following way: 

$$p_2 = p_u (1 + r_{max}) \text{ if } b_u > B, \quad p_2 = p_2 \text{ if } \frac{1}{B} < b_u < B \text{ or } p_2 = p_u (1 - r_{max}) \text{ if } b_u < \frac{1}{B}.$$ 

• $p_3$ represents the expected price due to the actual trend. It is formulated taking into account the trend over the past MEM prices and comparing it with the last price, $p_3 = p_u + (p_u - p_{trend})$.

Finally, the price $p$ is obtained as a weighted average of $p_1$, $p_2$, and $p_3$ in the following way:

$$p = \frac{p_1}{\alpha_1} + \frac{p_2}{\alpha_2} + \frac{p_3}{\alpha_3}$$  \hspace{1cm}(1)$$

with $\alpha_1$, $\alpha_2$ and $\alpha_3$ such that $\sum_{i=1}^{3} \frac{1}{\alpha_i} = 1.$

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1) This behavior is realistic because in real life these infos are still internal, since also media and the big institutions invest in the stock market and often broadcast biased news in order to make easy money.
SIMULATION RUNS

In every model there is the effort to avoid a parameter explosion: It is in fact clear that, with a sufficiently large number of degrees of freedom, one can approximate and reproduce every behavior and any feature of a given system. When modeling, nevertheless, one has to keep in mind that a model is meaningful as long as the parameters have a clear meaning and a directly observable influence.

The result of a typical simulation run is shown in Fig.1: The upper panel is related to the market price, whereas the lower panel reports about the corresponding amount of exchanged shares. We can clearly see the IPO phase lasting few hundreds of ticks, where the price remains constant because the bank offers the shares to the traders at a suggested value. After this transient, the pressure made from people without shares becomes visible: The volumes are high and the price tends to raise. Letting the time evolve, one runs into a tranquil period, with a slowly oscillating price and very low volumes: Owners do not want to sell because they hope to get more money if they wait a little bit, agents without shares want to buy at a lower price. This dynamical equilibrium is unstable: After a significant increase in the volumes a small burst occurs and the price increases to a more suitable value for owners. A rally is usually followed by a crash (a kind of settlement), as reported in [16] under the name of on-off intermittency, an aperiodic switching between static, or laminar, behavior and chaotic bursts of oscillations.

We explain in the following the origin, the tuning and the effect of the parameters
involved in the model.

- **Number of traders** $N$: The number of active agents trading on the market.

- **Threshold** $T$: The number of ticks after which the trader may start to have some doubts about the performed investment. This value ranges among a decade in order to model the different temporal horizons of the investments (differences between short-time speculators and long-time traders).

- **Number of shares** $S$ and **IPO’s price** $I$: Their product defines how the company is initially worth. The value of these two parameters is chosen after an analysis of the typical IPOs taking place in the European stockmarket.

- **Amount of money** $M$ initially distributed among the traders. As in the case of the threshold, this is not equal for all the players. Differently from the threshold, the initial wealth of the traders follows a Zipf’s distribution. Inspired by [11–14] we have decided to distribute the richness according to a Zipf’s law in the following way: the 20% of the traders possesses around the 80% of $M$ and among the two groups this rule is applied again in a recursive way. In this way we are able to model the difference between a normal agent and an institutional investor and the different effect they produce when they decide to enter the market. Anyway a minimal value of money $m$ is provided to all the traders and added to the amount coming from the previous distribution.

- **Length of the past values’ list** $MEM$: Chartists look for trends and patterns in the historical time series of the market price. Given the very short correlation in time, it is not so meaningful to look to much in the past, but some differences arise according to the tuning of this value. $MEM$ is not constant for all the traders, since some of them have access to more information than others.

- **Unbalance of the book** $B$: This value takes into account how balanced are the sell and the buy list with respect to each other. In case of a strong asymmetry an automatic mechanism generates news and advertisements. Through this parameter we introduce a global coupling in the model.

As already mentioned, universal characteristics exhibited by financial prices comprise a distribution with fat tails (events with a distance bigger than $3\sigma$ from the average return are not so uncommon as a Gaussian distribution would forecast) and a correlation in the volatility (alternation between tranquil and turbulent periods). In Fig.2 we show the presence of a strong persistence in the volatility. This is done estimating the self-similarity parameter $H$ [17] for raw and absolute returns (being the latters a measure of volatility). The lower panel of Fig.2 is related to raw returns: A random time series with the same variance of our simulated evolution of

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2) As already mentioned in the text, the Zipf’s law is quite universal. Just to provide some examples, the directory size in a hard drive, the CPU time used by processes in a workstation, the number of hits per homepages, the income distribution in companies, the debts of bankrupt companies, the city distributions, they all follow a Zipf’s law.
FIGURE 2. Typical snapshot from a simulation run. Estimation of the self-similarity parameter $H$. Upper panel: Absolute returns. Lower panel: Raw returns. It is interesting to note the emergence of correlations when passing from raw to absolute returns. This happens to empirical data, a stock belonging to the S&P500 index, and to our model, but not to the white-noise process. The strong persistence characterizing the absolute returns of our simulation and of a real stock is an indication of the so-called correlated volatility. This is also visible looking to Fig.3, where a clear alternation between tranquil and turbulent periods is present.

the price gets a value $H=0.50$, corresponding to brownian motion. A time series of a stock belonging to the S&P500 index gets a slightly smaller value ($H=0.41$), with our simulation we have got $H=0.55$. The proof of the presence of correlations in the volatility comes from the upper panel, when considering absolute returns. The random time series is still uncorrelated ($H=0.53$), while a time series coming from a real or a simulated stockmarket shows a kind of memory ($H=0.84$ and $H=0.85$ respectively).

Fat tails are detectable through the probability density function (PDF) of the returns. In Fig.3 we show the PDF of our simulated time series together with a gaussian distribution of returns having the same standard deviation. Extreme events happen with a higher frequency in the simulation, giving raise to the typically observed alternation between tranquil period, rally days and crashes.
PARAMETERS’ ANALYSIS

Let us consider now the following quantity $P$, what we call *buying factor*:

$$P = \frac{M + mN}{S_1}. \quad (2)$$

We have obtained significant results only if $P$ belongs to the interval $[4, 8]^3$ and we have the following explanation. The numerator of Eq.2 indicates the total amount of money that the traders could invest in the stock. The denominator, on the other hand, is an indication of the value of the company at the initial public offer. If people do not have enough money (small value of $P$), they are not encouraged to trade and the market price decays. If the agents have a too big amount of resources compared to the company’s value (i.e. $P$ is big), then the market price starts to increase until the resource limit is reached.

This represents, on our opinion, a realistic upper limit for the market price, since nobody would buy anything if they cannot afford it (maybe the reality is a little bit different; traders stop buying shares when the price is too high not because they do not have money, but because they believe that the price is too far away from a fair

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3) Just to give some colors to these numbers, we can imagine the following situation, not too far away from the reality in a big european country. Suppose that 10 million of traders are interested in trading a given new stock and they would like to invest, on average, 3000 EUROs. They have an investing power of 30 billions of EUROs. Suppose now that the new stock comes out with 100 million of shares at an IPO’s price of 50 EUROs. The initial value of the company is 5 billions of EUROs and the value of $P$ is 6.
price for the given stock, a concept that could be modeled with the introduction of a fundamental value, something that we strongly want to avoid).

In Fig. 4 we present the dependence on the buying factor $P$. Values of $P$ in the range $[4, 8]$ present the already discussed features. When $P = 10$ the price increases very fast, namely it twices after a few thousand of iterations. With $P = 2$, the model is not able to end the simulation of the IPO phase: Although traders had enough money to buy all the shares available at the bank, they do not want to invest too much at the beginning, according to their inclination towards investment.

One comment about demand and supply. It had been a common sense in economics for a long time that demand and supply balances automatically, however, it becomes evident that in reality such balances are hardly be realized for most of popular commodities in our daily life [18,19]. The important point is that demand is essentially a stochastic variable because human action can never be predicted perfectly, hence the balance of demand and supply should also be viewed in a probabilistic way. If demand and supply are balanced on average the probability of finding an arbitrarily chosen commodity on the shelves of a store should be $1/2$, namely about half of the shelves should be empty. Contrary to this theoretical estimation shelves in any department store or supermarket is nearly always full of commodities. This clearly demonstrates that supply is much in excess in such stores.

In general the stochastic properties of demand and supply can be well characterized by a phase transition view which is consisted of two phases: The excess-demand
FIGURE 5. Upper panel: Market price evolution on time. Middle panel: Volumes of exchanged shares on time. Lower panel: Evolution of the book. For this simulation we have used N=1000. Almost all the traders have placed an order and are waiting. Note the symmetry of the two number of orders with respect to the half the number of agents. At the beginning the two lists are empty, then almost all the traders want to own some shares and nobody wants to sell, either because he/she does not own any, or because the price is not convenient. After few thousand of iterations a dynamical equilibrium is reached.

and excess-supply phases. It is a general property of a phase transition system that fluctuations are largest at the phase transition point, and this property also holds in this demand-supply system. In the case of markets of ordinary commodities, consumers and providers are independent and the averaged supply and demand are generally not equal. The resulting price fluctuations are generally slow and small in such market because the system is out of the critical point.

On the contrary in an open market of stocks or foreign exchanges, market is governed by speculative dealers who frequently change their positions between buyers and sellers. It is shown that such speculative actions make demand and supply balance automatically on average by changing the market price, resembling a kind of self organized criticality. Fig.5 is in total agreement with that: Contrary to [3] we do not need to impose that the number of the shares has to be half of the number of traders in order to get a balance between demand and supply. The three circles in the upper panel indicate the most extreme events taking place in the price evolution: There is a corresponding movement in the book and a peak in the volumes. As the system is always at the critical point the resulting price fluctuations are generally quick and large [19]. This result is in agreement with [20], where the authors present an analogy between large stock market crashes and critical points.
In Fig. 6 we report on the influence of the media on the market price. In particular we note that a small value of B (B=2, lower panel) forces with more strength the underlying price than a bigger value of the unbalance parameter (B=3, upper panel). The power of the advertisement!

The effect of the parameter MEM is shown in Fig. 7. Large fluctuations are present as a consequence of the herding behavior: Traders can ask each other about values and look at the history of the market. But, as shown in Fig. 2, correlations among prices are very short. As a consequence, if the parameter MEM becomes too big, then the agents tend to take into account events that are uncorrelated and thus they perform a kind of averaging on the price: No trend has the change to fully develop itself because it is only a small part of the window into which every trader is looking to.

In Fig. 8 we show the performance of each trader. Agents are ordered according to the amount of money they have received at the beginning of the simulation: The leftmost trader was the richest one, the rightmost was the poorest one. The gain is given in percent. We note a very interesting feature, namely traders with more power (money) are systematically more lucky than the others. This is because they produce a bigger echo when they trade: If one wants to buy a significant fraction of a stock, then the price will rise up and maybe someone else will try to do the same, having identified a trend in the price and wanting to use this chance to
make money. As a consequence, the price may really increase of such an amount sufficient for the big trader to get the desired profit and to decide to sell. After this operation, there is no immediate chance for the small agents to get money, since the price is decreasing now as a consequence of the action of the powerful trader. Small agents perform with a delay such that they are not able to get advantage from every speculative event. They are always waiting for the events, not being able to induce them.

Presenting this result, anyway, we assume the following, not so realistic, thing: The richness of a trader is given by the sum of his/her cash and the money he/she has invested in shares. We should note that these two numbers are different: One can use the latter provided he/she has sold the shares. Considering the invested money as real money we suppose (without any reason) that the trader is able to sell the shares exactly at the buying price. This is obviously not true. Fig.9 shows a consequence of this assumption: the virtual richness increases (decreases) when the market price increases (decreases), with a small delay. We define virtual this richness because one is sure to own a certain amount of share but not to have a certain amount of money, unless he/she is able to perform the conversion from shares to money just selling them.

The market we are simulating is a closed one, i.e. the total amount of involved money must remain constant. But Fig.9 shows the opposite: The virtual richness is positively correlated with the market price (delayed of a small amount of time).

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4) This would not be the case in presence of commissions, a percentage of money to be paid to the bank for every transaction.
FIGURE 8. Distribution of the gain obtained by each trader. Agents are ordered according to the initial richness, with the richest one in the leftmost position. Traders with less initial resources get systematically a worse performance, because their actions are not able to affect significantly the market.

FIGURE 9. On the dependance of the (virtual) richness on market price. This behavior is a consequence of the assumption that the richness of a trader is given by the cash plus the invested money. In this way it seems that the closed market is able to produce money.
Although not shown in Fig.9, if the price comes back to the IPO value\(^5\), then the total richness comes back to the original value. So, one way of getting rid of the problem is to replace the invested money with the number of owned shares times the IPO price. Doing so, the total richness remains constant, assuming the initially distributed value all the simulation long.

In Fig.10 we report the richness of every agent after the conversion from shares to cash, with the IPO as buy-back price. The systematicity of Fig.8 is no longer present. The reason is the following: Big traders loose all their advantages because just during a speculative period they cannot proceed and convert the shares into cash because we have decided to stop the simulation (and to convert their shares into cash at the IPO price instead of the current \textit{virtual} market price).

Maybe this is not a proper manner to act, but it is the only way to maintain isolated the system and to avoid any artificial production of money. As a consequence of this abrupt end, many traders realize to have done a mistake in performing a transaction because we impose from outside a price for the shares which is different compared to the self organized one. This explains why according to the distribution of Fig.10 all the traders get similar performance independently from their initial

\(^{5}\) It should not only come back to the IPO value, but also remain constant for a sufficiently long time, in order to let all the traders sell and buy the shares exactly at this price. In other words, it should happen that all the shares have been traded at the IPO price.
We are interested now in the association of a real temporal scale to our tick time. To this end, we have performed a correlation analysis on our simulations and compared it to the results presented in [7,21]. Since the autocorrelation function vanishes after approximately 20 ticks and the typical correlation length in financial time series is supposed to be around 20 minutes, we can reach the conclusion that one of our tick corresponds to one real-life minute. This is the reason according to which we have decided to use the following value of the time related parameters during the simulation runs:

- Total number of iterations, namely total number of ticks = $10^6$ (10 years).
- Threshold = 10000 (1 month).
- Threshold variability [0.1, 1]. Combined with the threshold, this gives a time variable from a minimum of 1 month to a maximum of 1 year. After this time, traders start to ask themselves what to do with the shares if the price remains too stable.

**CONCLUSIONS**

In this paper we have introduced a model for the stockmarket whose parameters have a physical meaning. They have been tuned as a direct consequence of observations of a typical trading activity. The main issue we wanted to address is that our model is able to reproduce the two main characteristics of empirical data, namely correlated volatility and fat tails of the PDF of returns, with only one class of agents sharing the same goal: They all want to become as rich as possible. In particular we do not need any external input nor a fundamental price, whose evolution would require some artificial assumptions. What we need is just a proper set of constraints: Traders have a limited amount of money, they can wait only for a limited time, they have some desired gain in mind and they do not want to lose too much money. Furthermore they do not invest all the money they have at disposal, since they want to use it in the most appropriate and less risky way. We have proved the cruciality of the parameters, showing the dependance of a typical simulation run from their realistic tuning. Interpretations of the meaning of these values are also given, as they are mainly in agreement with every-day situations. In our opinion a model is really useful only as far as its parameter are completely understandable and influence directly the evolution of the market price.

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