Life in the Stockmarket - a Realistic Model for Trading

Fabio Franci, and Lorenzo Matassini
Max-Planck-Institut für Physik komplexer Systeme, Nöthnitzer Str. 38, D 01187 Dresden, Germany

We propose a frustrated and disordered many-body model of a stockmarket in which independent adaptive traders can trade a stock subject to the economic law of supply and demand. We show that the typical scaling properties and the correlated volatility arise as a consequence of the collective behavior of agents: With their interaction they determine a price which in turn affects their future way of investing. We introduce only one type of investors, since they all share the same hope: They simply want to maximize the profit minimizing the risk. The best utilization of resources occurs at a critical point characterized by the transition between the excess-demand and the excess-supply phases.

PACS numbers: 05.45.Tp, 05.65.+b, 64.60.-i, 87.23.Ge

Financial prices have been found to exhibit some universal features that resemble the scaling laws characterizing physical systems in which large numbers of units interact. Given that, one challenge is to build up a model which is able to reproduce this behavior and whose parameters have a physical meaning. We propose such a model, belonging to the frustrated and disordered many-body systems. Frustration enters in that not all the individual inclinations can be satisfied simultaneously, whereas the model is disordered because traders have randomly chosen expectations and resources but they share the same strategy. In contrast with previous works we do introduce only one kind of investor: On our opinion the usual distinction between fundamentalists and noise traders is not necessary. Looking at both strategies, in fact, we note 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. This gives rise to the tendency towards herding behavior.

In a model is introduced where the main building blocks are movements of individuals from one group to another together with the exogenous changes of the fundamental value. We believe that such a requirement is somehow artificial. It is in fact clear that without the fundamentalists the price would follow a trend at infinitum and without the noise traders the price would never escape the range of its fundamental value, as clearly stated in , where a 20% of fundamentalists is enough to confine the price within the range of the rational traders. We want to raise serious doubts on the blind use of the fundamental price, especially when assumed that the relative changes are Gaussian random variables: Why should agents risk money just believing in a random walk behavior?

A more realistic assumption is based on the following wish: Gaining the maximum, taking the smallest possible risk. Agents make decisions to buy or to sell, adjust prices, and so on according to the information available at the time, as well as individual preferences such as tolerance for risk and time deadlines. We therefore simulate the book for the ask and for the bid. Every trader, when buying a share, has to identify a fair price and then put an order keeping in mind a target price and a stop-loss price. These quantities are the result of the interaction with other agents, the study of past values of the price and the influence of incoming news. The decision to sell some shares is made on the basis of the current price (to be compared with the personal target and stop-loss price) and of the age of the shares: After a sufficiently long period of time agents start to ask themselves whether it is worth keeping the money invested in that way. The model leads to a self-organized criticality which is responsible of the alternation between laminar and turbulent trading.

| BUY ORDERS | SELL ORDERS |
|-------------|-------------|
| time | trader | shares | price | price | shares | trader | time |
| 21005 | 240 | 4 | 11122 | 11123 | 4 | 576 | 19802 |
| 25008 | 207 | 70 | 11121 | 11124 | 4 | 876 | 14706 |
| 24506 | 647 | 3 | 11118 | 11125 | 2 | 806 | 12150 |
| 19002 | 820 | 2 | 11108 | 11130 | 49 | 301 | 17203 |
| 20148 | 100 | 12 | 11106 | 11130 | 4 | 792 | 20101 |

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 in case of equal prices.

We consider $N$ traders and one stock with $M$ shares on the market. Each trader is characterised through the following information: (i) Initial amount of money. (ii) 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. (iii)
Number of shares owned. (iv) List of friends with which
he is sharing information, to model the herding effect.
(v) Invested money, to keep trace of the average buy-
ing price. (vi) Desired gain. (vii) Maximum loss. (viii)
Threshold: Amount of time after which the trader may
start to change idea about his/her investment.

Every order is stored in the corresponding list, accord-
ing to the type of it (buy or sell), to the requested price
and to the time at which it was submitted. A transac-
tion occur whenever the cheapest price among the sell list
matches with the most expensive offer in the buyers’ list:
This value defines the market price of the stock at that
particular instant and it will of course affect the future
behavior of the traders.

We provide a mechanism to produce news, whose pur-
pose is to let all the agents know some information about
the overall behavior of the market, i.e. the unbalance of
the two books and the actual volatility. It is very impor-
tant to note that these signals are endogenous: The infor-
mation they provide was already present in the system.
In this way our model takes into account both a local and
global coupling, via shared information with neighbours
and generation of news and advertisements, respectively.

The simulation consists of two parts. At the beginning
we assign all the shares to one trader and we broadcast
advertisements to induce people to put a buy order. The
purpose of this first step is to simulate the Initial Pub-
lic Offer (IPO) and the selected trader can be thought
as the bank responsible of the initial selling of the stock.
This part ends when the number of shares owned by the
IPO trader vanishes. We then reset his amount of money
and enter the second phase.

At each update step the algorithm performs the follow-
ing operations: (i) Select randomly a trader. (ii) If the
trader has no pending order and no share then he/she
is eventually willing to buy, formulating a limit price, a
target price and a stop-loss price and inserting a buying
order. (iii) In case of owning some shares, the trader
may decide to sell, according to the market price and the
threshold. (iv) If the trader has a pending order, he/she
may change some parameter because the conditions that
led to that decision may have changed. We suppose that
every trader can afford only one pending order. Every
time a buyer has got all the desired shares, he/she is im-
mEDIATELY asked whether he/she wants to place a selling
order.

When formulating the prices, every trader makes the
decision in a deterministic way, computing a weighted av-
erage among the opinion of some acquaintance, the in-
dication of the news and some past values of the stock price.
Every time that two complementary orders match, we de-
fine the market price for that particular instant: Usually
only one of the two orders disappears, namely the one
with the smallest amount of shares involved. The other
cannot be removed from the corresponding list, since only
a part of the desired transaction has taken place.

So the main ingredients of the model are: (i) Disorder,
since the initial money is distributed according to a
Zipf’s law and some parameters characterizing the agents
are randomly chosen, but the overall behavior is deter-
ministic, (ii) frustration, because not all the individual
wishes can be satisfied at the same time, (iii) delayed
feedback, involving the use of past values of the market
price and volatility during the decision formation, (iv)
phase transition between the excess-demand and the
excess-supply phases [8].

![FIG. 1. Typical snapshot from a simulation run. Upper panel: Development with time of the market price. Lower panel: Development with time of the corresponding volumes of exchange.](image1)

The comparison with a best-fitted normal distribution reveals the presence of fat tails.

![FIG. 2. Upper panel: Price returns, random series shifted for eye guide. Lower panel: Returns distribution. The comparison with a best-fitted normal distribution reveals the presence of fat tails.](image2)
shares. The model is able to reproduce all the typical features observed in empirical data. At the beginning the price remains constant due to the IPO’s phase, namely the bank offers the shares to the traders at the fixed price, the IPO price. After that, one can see the typical pressure made by agents who did not get enough shares during the initial public offer: The volumes are high and the price tends to raise. Then, after a normal settlement, the price starts to oscillate with very low volumes: Traders with shares do not want to sell because they hope to get more money if they wait a little bit more, agents without shares do not buy because the price is too high and there is no evidence of a trend on it. Then oscillations become bigger and bigger and when the volumes are big as well, then a small crash occurs and the price comes back to a more interesting value for potential buyers. As a consequence, volumes remain high and the price follows a so-called rally period, followed again by a crash, maybe due to the fact that the bubble phase has been too optimistic.

The model makes use of the following parameters: (i) Number of traders N: The number of agents involved in the process of buying and selling shares. (ii) Threshold T: The critical age of the shares. After this time the trader may rise some doubts whether it is worth waiting for the events. This value is not constant for all the traders, but ranges among a decade in order to take into account the differences between intraday speculators and long-time agents. (iii) Number of shares S and IPO’s price I: Their product defines the initial value of the company. (iv) Amount of money M initially distributed among the traders. Inspired by [7,8] we have decided to distribute the richness according to a Zipf’s law: the 20% of the traders possess around the 80% of M and among the two groups this rule is applied again, recursively. 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 (responsible for the disorder). A minimal value of money m is provided to all the traders and added to the previous distribution. (v) Length of the past values’ list MEM: chartists look for trends and patterns in the historical time series of the market price. (vi) Unbalance of the book B: This value takes into account how balanced are the sell and the buy list. In case they are out of balance, then news and advertisements are generated.

As shown in Fig. 3, the probability density function of the returns of our simulated stock shows a strong leptokurtic nature. For comparison, the Gaussian with the same measured standard deviation is also reported. The time series of returns exhibits a higher frequency of extreme events and clustering of volatility. This aspect becomes clear thanks to Fig. 3. When considering absolute returns as a measure of volatility, we see that the transformed price data behave differently from their counterpart derived from the Gaussian distribution. The estimation of the self-similarity parameter H (using the approach presented in [10]) reveals a strong persistence in volatility.

One comment about demand and supply. It had been a common sense in economics for a long time that demand and supply balance automatically, however, it becomes evident that in reality such balances are hardly realized for most of popular commodities in our daily life [12]. 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 consists of two phases: The excess-demand 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 buy-
ers and sellers. It is shown that such speculative actions make demand and supply balance automatically on average by changing the market price, as Fig. 4 clearly shows. Contrary to [4] 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 are corresponding movements in the book and in the volumes, since they are the reason for such a sudden variation. As the system is always at the critical point the resulting price fluctuations are generally quick and large [12]. This result is in agreement with [13], where the authors present an analogy between large stock market crashes and critical points with log-periodic correction to scaling: Complex systems often reveal more of their structure and organization in highly stressed situations than in equilibrium.

Performing a correlation analysis on our simulations and comparing it to the results presented in [8], we can associate a temporal scale to our tick by tick time: 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 speculate that one of our tick corresponds to one real-life minute.

Therefore the involved time scales are the following: (i) Total number of iterations, namely total number of ticks $= 10^6$ (10 years), (ii) threshold $= 10000$ (1 month), (iii) threshold variability in the range [0.1, 1]. This gives a time variable from a minimum of 1 month to a maximum of 1 year to have second thoughts.

To summarize, we have proposed a model for the stock-market which is able to reproduce the two main characteristics of empirical data, namely the correlated volatility and fat tails of the PDF of returns. We have performed this task avoiding the use of different classes of agents and the artificial introduction of a fundamental price. We just make use of realistic assumptions about the behavior of traders (limited amount of money, limited time to liquidity, desired gain, maximum loss, inclination towards investment) and we tune the parameters through a real-life analysis of the trading activity. Disorder, frustration and the behavior at the critical point do the rest. The model is intrinsically a minority game in that agents in the minority are rewarded, i.e. they can carry out their investment plan, and those in the majority punished, i.e. they have to wait with a pending order or sell at an unfair price.

![Simulation run with N = 1000. Upper panel: Market price evolution on time. Middle panel: Volumes of exchanged shares on time. Lower panel: Evolution of the book. Almost all the traders have placed an order and are waiting. Note the symmetry of the two paths with respect to the half of the number of agents (N/2 = 500).](image)

FIG. 4. Simulation run with N = 1000. Upper panel: Market price evolution on time. Middle panel: Volumes of exchanged shares on time. Lower panel: Evolution of the book. Almost all the traders have placed an order and are waiting. Note the symmetry of the two paths with respect to the half of the number of agents (N/2 = 500).

1. Haken, H. Synergetics: An introduction. Springer, Berlin (1983).
2. Mantegna, R.N. & Stanley, H.E. Scaling behavior in the dynamics of an economix index. Nature 376, 46-49 (1995).
3. Lux, T. & Marchesi, M. Scaling and criticality in a stochastic multi-agent model of a financial market. Nature 397, 498-500 (1999).
4. Lux, T. The socio-economic dynamics of speculative markets: Interacting agents, chaos, and the fat tails of return distributions. Journal of Economic Behavior & Organization 33, 143-165 (1998).
5. Mantegna, R.N. & Stanley, H.E. An introduction to econophysics. Correlations and complexity in finance. Cambridge University Press (2000).
6. Bak, P., Paczuski, M. & Shubik, M. Price variations in a stock market with many agents. Physica A 246, 430-453 (1997).
7. Paczuski, M., Bassler, K.E. & Corral, A. Self-organized networks of competing boolean agents. Physical Review Letters 84, 3185-3188 (2000).
8. Savit, R., Mameca, R. & Riolo, R. Adaptive competition, market efficiency, and phase transitions. Physical Review Letters 82, 2203-2206 (1999).
9. Marsili, M. & Zhang, Y.C. Interacting individuals leading to Zipf’s law. Physical Review Letters 80, 2741-2744 (1998).
10. Okuyama, K., Takayasu, M. & Takayasu, H. Zipf’s law in income distribution of companies. Physica A 269, 125-131 (1999).
11. Peng, C.K., Buldyrev, S., Havlin, S., Simons, M., Stanley, H.E. & Goldberger, A.L. Mosaic organization of DNA nucleotides. Physical Review E 49, 1685-1689 (1994).
12. Takayasu, H. & Takayasu, M. Critical fluctuations of demand and supply. Physica A 269, 24-29 (1999).
13. Sornette, D. & Johansen, A. Large financial crashes. Physica A 245, 411-422 (1997).