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Greed, fear and stock market dynamics

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Abstract

We present a behavioral stock market model in which traders are driven by greed and fear. In general, the agents optimistically believe in rising markets and thus buy stocks. But if stock prices change too abruptly, they panic and sell stocks. Our model mimics some stylized facts of stock market dynamics: (1) stock prices increase over time, (2) stock markets sometimes crash, (3) stock prices show little pair correlation between successive daily changes, and (4) periods of low volatility alternate with periods of high volatility. A strong feature of the model is that stock prices completely evolve according to a deterministic low-dimensional nonlinear law of motion.

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1. Introduction

Stock markets are driven by the fast and hectic trading of a large number of traders. Although the behavior of stock prices is quite complex, certain universal features may be identified [1–3]. For instance, we observe a positive price trend in the long run which is occasionally interrupted by crashes. Moreover, log price changes

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(i.e., returns) are uncorrelated while temporal independence of absolute returns is strongly rejected.

According to classical finance theory [4], the statistical properties of price fluctuations are wholly caused by those of the underlying fundamental process. For instance, volatility clustering arises since the intensity of news varies over time. A more convincing explanation is provided by behavioral models that take into account the trading decisions of heterogeneous agents (for surveys see [5–8]). Note that the trading behavior of agents is at least partially observable and thus may be approximated. For example, some traders base their trading decisions on technical analysis rules such as moving averages whereas others simply expect prices to return towards fundamental values. Complex (chaotic) price motion may occur due to nonlinear interactions between the agents. If one adds dynamic noise to these setups, they may even be able to replicate some of the aforementioned stylized facts [9–12].

This paper aims at developing a deterministic behavioral stock market model in which agents are influenced by their emotions. To be precise, the trading activity of the agents is characterized by greed and fear. They optimistically believe in booming markets, but panic if prices change too abruptly. In addition, the agents switch between two activity levels. If market historical volatility is low, they are rather calm and vice versa. Although the model is deterministic, it replicates several aspects of actual stock market fluctuations quite well. For instance, we observe the absence of autocorrelation in raw returns but significant autocorrelation in absolute returns.

We think that having a good understanding of what is going on in financial markets is quite important. On the one hand, it may allow us to develop better investment strategies. Some studies have recently made interesting progress in predicting the course of the stock market [13]. On the other hand, it may help regulators to control the markets. One may, for instance, use these models as computer laboratories and test whether mechanisms such as transaction taxes are able to reduce volatility [14–16].

The paper is organized as follows. In Section 2, we present our model and in Section 3, we discuss our results. The last section concludes the paper.

2. The model

In our model, prices adjust according to a log-linear price impact function. Such a function describes the relation between the number of assets bought or sold in a given time interval and the price change caused by these orders [17].[1] Accordingly, the log of the price in period $t+1$ is given as

$$P_{t+1} = P_t + D_t \,, \tag{1}$$

where D denotes the excess demand. Clearly, excess buying drives the prices up and excess selling drives them down.

[1] However, recent empirical evidence indicates that the price impact function displays a concave curvature with increasing order size, and flattening at larger values [18].

As is well known, agents are boundedly rational and their behavior is influenced by their emotions [19]. In our model, the actions of the traders are governed by greed and fear. The agents know that the stock market increases in the long run and thus they greedily take long positions. However, they also know that such behavior is risky. The larger the risk, the more the agents reduce their investments. If prices change too strongly, they even panic and go short. For simplicity, we assume that greed and fear-based behavior only occurs for two activity levels. As long as the market evolves stably, the agents are rather calm. However, in turbulent times both greed and fear increase.

The emotional regime switching process may be formalized as follows:

$$D_t = X_t - \frac{2}{X_t}(P_t - P_{t-1})^2 \tag{2}$$

and

$$X_t = \begin{cases} 0.025 & \text{for } \frac{1}{5}\sum_{t=1}^{5} \left|P_{t-i+1} - P_{t-i}\right| < 0.0225 \;\wedge\; |P_t - P_{t-1}| < 0.05, \\ 0.05 & \text{otherwise} \end{cases} \tag{3}$$

where X indicates the activity level. We assume that the agents are rather calm if the average volatility in the last 5 trading periods is below 2.25 percent and if the most recent absolute log price change is below 5 percent. Otherwise the activity level increases from $X = 0.025$ to $X = 0.05$. Now we can interpret the excess demand equation. The first term of (2) reflects the greedy autonomous buying behavior of the agents whereas the second term of (2) captures the fear of the agents. Note that in the turbulent regime, extreme log price changes can be as large as ±5 percent. In the calm regime, extreme returns are restricted to ±2.5 percent.[2]

3. Simulation results

In this section, we explore the dynamics of the model. Let us begin with illustrating some properties of actual stock markets. The first panel of Fig. 1 shows daily quotes of the Dow Jones Index between 1901 and 2000. Visual inspection reveals a long run upward trend. However, stock markets are risky since they regularly crash. The two panels in the second line of Fig. 1 contain two of the most prominent crashes. The left-hand (right-hand) panel shows the evolution of the Dow Jones Index for the years 1928 and 1929 (1986 and 1987). In both cases the price decline was dramatic. The last two panels show autocorrelation functions for raw returns and absolute returns for the first 100 lags. While price changes appear to be random, volatility is quite persistent.

[2] Of course, one can easily rescale (3) such that it produces even more extreme price changes.

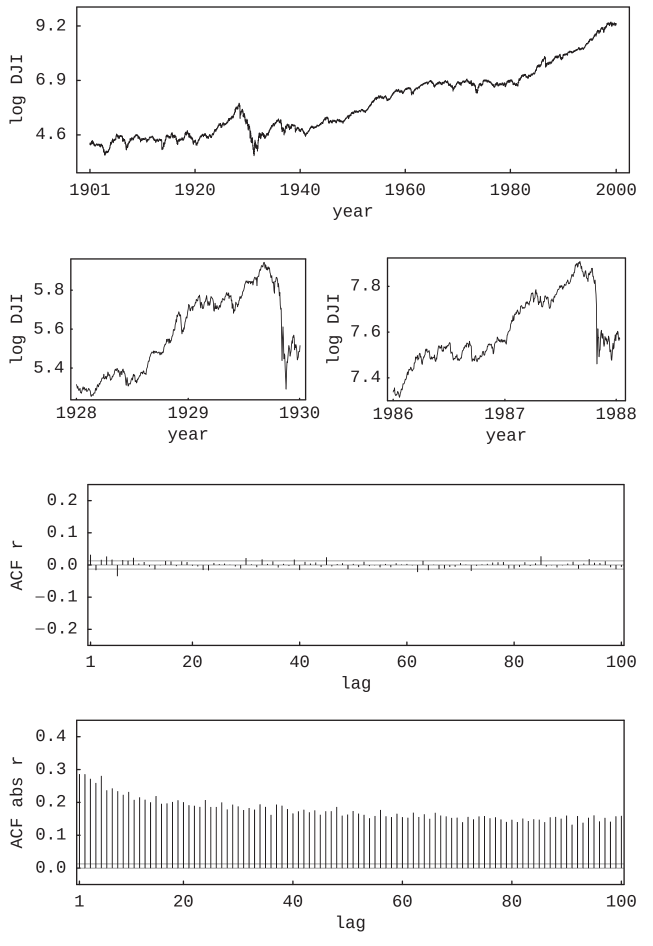

Fig. 1. The dynamics of the Dow Jones Index. The first panel shows daily log quotes for the Dow Jones Index from 1901–2000 (25,034 observations). The left-hand (right-hand) side of the second panel contains the same data for the years 1928 and 1929 (1986 and 1987). The last two panels display the autocorrelation function of raw returns and absolute returns for the first 100 lags, respectively (with 95 percent confidence bands).

Can our model mimic these facts? Fig. 2 presents the dynamics of simulated prices. The first panel depicts the development of log prices in the time domain for 5000 observations. Again, we observe a positive price trend. But a different picture emerges in the short run. The two panels in the second line of Fig. 2 show snapshots of the dynamics for 250 observations. The model has the power to produce crashes too. Note also how erratically the prices may change. This observation is further supported by the penultimate panel. For almost all lags, the autocorrelation coefficients of raw returns are not significant. Nevertheless, the bottom panel

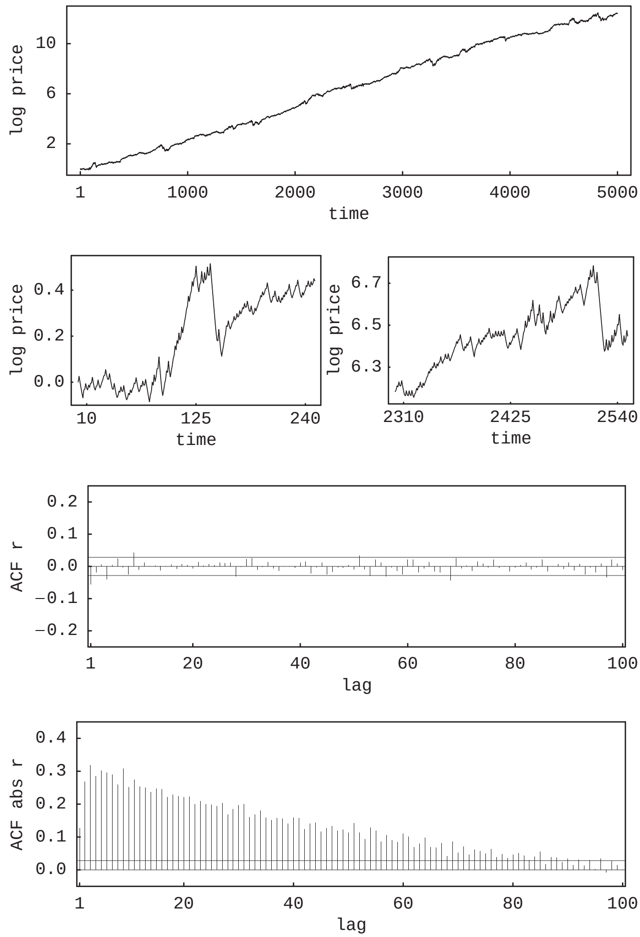

Fig. 2. The dynamics of our stock market model. The first panel shows simulated log prices in the time domain (5000 observations). The panels in the second line contain the same data for two sub-samples. The last two panels display the autocorrelation function of raw returns and absolute returns for the first 100 lags, respectively (with 95 percent confidence bands).

indicates strong temporal dependence in volatility. The autocorrelation coefficients of absolute returns are significant for more than 80 lags.[3]

To sum up, our simple stock market model has the power to generate a positive price trend in the long run, severe crashes, uncorrelated price changes and volatility

[3]If X is constant, say $X = 0.05$, we still observe intricate price dynamics. For instance, the autocorrelation coefficients of raw returns are not significant. However, the model loses its ability to produce volatility clustering. Clearly, temporal dependence in absolute returns requires regime shifts. Moreover, for a constant value of X, the model does no longer generate a positive long run price trend.

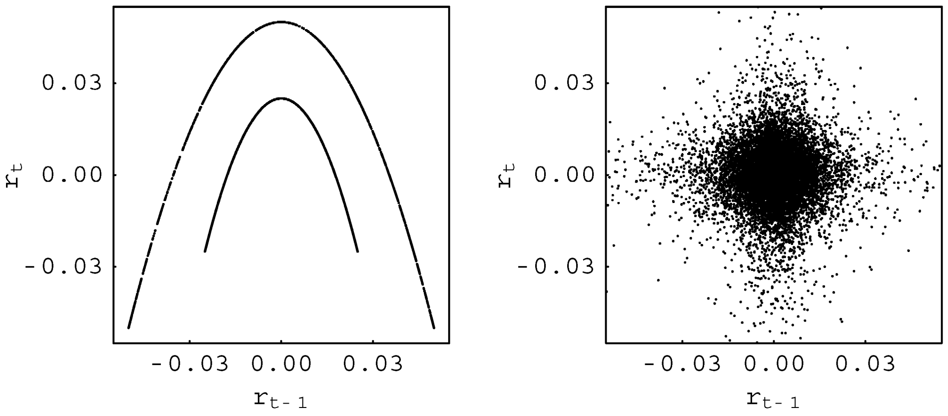

Fig. 3. Artificial and actual returns in phase space. The left-hand panel contains simulated returns while the right-hand panel contains Dow Jones Index returns.

clustering. This is remarkable since the dynamics is completely deterministic. However, our model "fools" one of the statistical estimators discussed here.[4] The autocorrelation function of raw returns suggests that prices are unpredictable. But this is not the case. Fig. 3 displays the dynamics in phase space. In the right-hand panel the returns of the Dow Jones Index of period t are plotted against the returns of period $t-1$. At least at first sight, no structure is discernible. The left-hand panel shows the same for simulated returns. Now a pattern is clearly visible, indicating a strong order in the return process.

A few final comments seem to be in order. Remember that agents switch only between two activity levels. The dynamics may become even more complex if one would allow for more regimes. In addition, the remaining structure in the return process may be further destroyed by adding noise to the system equations. However, one aim of this paper is to show that even simple deterministic behavior of agents may trigger intricate price motion. Finally, we only display one simulation run here. As revealed in further simulations, our results are quite robust (which may easily be checked).

One may further enrich our model by incorporating elements from related setups. Within our model, the agents are influenced by their emotions. Switching between greed and fear causes complex price motion. Sornette and Ide [20] derive interesting dynamics from the interactions between nonlinear trend-followers and nonlinear value investors. Their two-dimensional dynamical system reaches a singularity in finite time decorated by accelerating oscillations. In Brock and Hommes [21], the agents follow linear technical and fundamental trading rules. A nonlinearity—and thus chaotic price motion—arises since traders switch between forecast rules with respect to past realized profits. Such behavior may be regarded as quasi rational. By

[4]Note that our simple stock market model is, of course, not in harmony with all stylized facts of real stock markets. Most importantly, the distribution of the returns possesses no fat tails.

contrast, Corcos et al. [22] stress the importance of consensus formation. Their model has the power to produce hyperbolic bubbles, crashes and chaos. In [22], a crash is associated with a too-large consensus. In our model, strong price declines are triggered by too-abrupt price changes.

4. Conclusions

Models with heterogeneous interacting agents have proven to be quite successful in replicating the stylized facts of financial markets. One may thus view the asset price fluctuations as being the result of the interaction between deterministic elements, e.g. orders generated by simple trading rules, and stochastic elements, e.g. the arrival of new information. Offering a better understanding of financial market dynamics is clearly important for both solving practical investment problems and improving policy tools to regulate the markets.

One aim of this paper is to develop a complete deterministic model which nevertheless has the power to mimic some important features of stock markets. Most importantly, we find that our simple behavioral model is able to generate quite intricate price changes and temporal dependence in volatility. Many other contributions need to add substantial noise to the law of motion in order to generate such an outcome. Our model furthermore suggests that emotions such as greed and fear may play a role in the determination of stock prices. Of course, further analysis is needed in this area.

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