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Wealth dynamics in a sentiment-driven market

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HIGHLIGHTS

- I proposed a framework in which the stock price environment is in one-to-one correspondence with a given driving processes.
- These driving processes, which I call sentiments, influence the short-term price trends, the volatility surges, and the trading intensity.
- The dynamics of the agents' wealth is studied for the initial identical, uniform, normal, and Pareto wealth allocations. Regardless of the initial wealth allocation, the trading activity of the agents results in the Pareto wealth distribution for the tail of the wealthiest agents (this is in an agreement with the literature). I study the time-dependence of the exponent of the Pareto tail.
- I proposed to study the configuration in which various groups of agents follow different sentiment processes. I described how the wealth of the groups of agents evolves as a result of such a setting.
- I discuss the possible future work, in which it would be interesting to infer the underlying sentiment processes for the given stock price time series.

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ABSTRACT

We study dynamics of a simulated world with stock and money, driven by the externally given processes which we refer to as sentiments. The considered sentiments influence the buy/sell stock trading attitude, the perceived price uncertainty, and the trading intensity of all or a part of the market participants. We study how the wealth of market participants evolves in time in such an environment. We discuss the opposite perspective in which the parameters of the sentiment processes can be inferred a posteriori from the observed market behavior.

1. Introduction

Simulation is a possible way to approach the problem of modeling the properties of a system with many degrees of freedom and a complicated interaction pattern. In the cases when an analytical description of a system is impossible one can try to come up with a simulation based on a few built-in assumptions in an attempt to model some of the prominent experimentally observed phenomena. In this spirit a simulated stock market models have been extensively studied in the literature, with the goal to describe the real stock price behavior and investigate strategies of market participants. Some of the original models have been proposed in [1–8], for a review see [9], and references therein.

A typical simulated market environment includes a large number of agents possessing units of cash and shares of stock (the simplest models consider the world with just one kind of stock, although multi-asset models exist, in particular among the references above), who manifest their trading activity by submitting stock buy or sell orders to the stock exchange. One possibility is to have a stock exchange which puts orders into the order book, and fills orders by searching for an intersection of the stock supply and demand curves, determining the equilibrium stock price, and clearing the possible buy and sell orders. This is re-iterated over a large number of steps and the resulting emergent stock price time series is observed.

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Generally the artificial stock market models consider agents which perform their trades in accord with certain strategies, such as trend-following, contrarian, fundamental trader, etc. That is, the agents might be basing their strategy on analyzing and drawing conclusion from the past stock price behavior. Various groups of agents might be set up to compete against each other, and the winning trading strategy is optimized in real time by the agents, as the new information becomes available to them (see e.g. [4] for the model of agents using genetic algorithms to shape the most optimal trading strategy). Such models are known to have successfully reproduced some of the well-recognized facts about the stock prices time series, such as fat tails of the logarithmic stock returns [10] and volatility clustering.

In contrast to the models reviewed above, the simulated market environment which we set up and implement in this paper does not endow its agents with any ability to analyze information from the past stock time series, or any mechanism to make predictions of a possible future directions of the stock price. The agents therefore will not attempt to readjust their portfolios for any particular optimization purpose. Instead, behavior of agents in our model will be influenced by the market environment driven exclusively by an externally given processes, which we call sentiments. (A different kind of a sentiment incorporation into the agents' behavior can be found in [11].) Agents do not influence each other's sentiment, but all (or large groups) of agents receive the sentiment from the same source.

In other words, we will be using the framework in which the state of the market, considered in the given time period, is uniquely defined by the sentiment processes driving the market evolution during that period. In this framework we assume that the strategies of market participants converge collectively to what can be effectively modeled by a driving sentiment process. The choice of a specific sentiment process will constitute our prior belief about the stock market. For instance, all of the agents might settle into a belief that arrival of a breaking news about the stock means the volatility surge by e.g. factor of two. Or a subgroup of agents might decide that the stock is overvalued, and be more willing to sell it than buy it. The task is then to determine how the stock price is going to behave in the market where the participants follow these attitudes. This paper is concerned with such a task.[1]

At each time step t the first question which faces the agent is whether to stay out of the market during the step or submit some order. We will model the market activity by our agents as the Poisson process, with the agent's orders being separated by exponentially distributed waiting times. (In [12–14] it was pointed out that in reality inter-trade separation times follow a Weibull distribution.) The mean waiting time between the trades, $\rho(t)$, is itself a random process. It is defined as an external trading intensity sentiment, which is used by all or a part of the agents to gauge intensity of their own market activity. Each agent A_n picks its own $\rho_n(t)$ as a gaussian draw around the commonly given $\rho(t)$.

If the agent decides to participate in the market during the given trading session it needs to decide whether it wants to buy or sell the stock. We specify that this decision is also influenced by an external sentiment $\psi(t)$, common for all (or large groups of) agents. The $\psi_n(t)$ for the agent A_n is a gaussian random variable, centered around $\psi(t)$, and prescribing the buy vs sell dis-balance sentiment. When $\psi_n = 0$ the agent is equally likely to buy or sell, it leans towards buying when $\psi_n > 0$, and towards selling when $\psi_n < 0$, as we describe in Section 2.1.

Once the agent decides to buy or sell it needs to determine the limit price for its order. We prescribe that regardless of the buy or sell side of the order the agent will draw the limit price as a gaussian random variable with the mean equal to the most recent stock price, and the standard deviation $\sigma_n(t)$ defined by the external volatility sentiment $\sigma(t)$.

The $\sigma(t)$ is an external time-series process, which we specify as the Poisson process of the jump volatility kind [15,16]. For simplicity we assume that the volatility $\sigma(t)$ takes the calm value $\mathcal{N}(\sigma_c, \delta\sigma_c)$ most of the time, and the breaking news value $\mathcal{N}(\sigma_b, \delta\sigma_b)$, arriving once in a while according to the exponential distribution with the mean λ. The σ_b is significantly larger than σ_c, and the non-vanishing small $\delta\sigma_{c,b}$ are introduced for gaussian randomization purposes.

The last needed ingredient is given by the size of the order. We can augment our model by giving the agents some ability to plan the strategies, deciding on what specific size of the order to submit. However we leave this for the future work, and refrain to a uniform draw [5] for the order size for the rest of this paper.

We use our market environment described above to explore dynamics of wealth in the simulated society of agents. We will consider various starting allocation distributions for the wealth of the agents: identical, uniform, gaussian, and Pareto. We discover that regardless of the initial wealth distribution the resulting distribution quickly converges (in the tail of 25% of the wealthiest participants) to the Pareto law, consistent with the analogous studies in the literature [17–19].

For recent empirical studies of the wealth power-law distribution see [20]. See also [21,22], which applied the statistical equilibrium ideas of [23] and the maximum entropy distribution principle of [24] to argue in favor of the power law distribution of wealth, see [25] for a review.

The rest of this paper is organized as follows. In Section 2 we set up the market environment in the most general form, preparing the background for the simulation models which we will be studying in the subsequent sections. In Section 3 we review some of the relevant properties of the Pareto distribution, which will be useful for our analysis of the wealth distribution in the society of agents. In Section 4 we study dynamics of the wealth distribution in a simple simulation over a large number of steps. In Section 5 we study the jump volatility model with a non-trivial buy/sell sentiment process, and investigate the resulting stock price behavior. In Section 6 we separate the system into four subgroups of agents, each receiving its own sentiment, and study the resulting wealth dynamics. We discuss our results in Section 7. Appendix is an appendix where we describe design of our stock exchange.

[1] We can attempt to go further and determine posterior probabilities for various possible sentiment processes considered to be driving the market. It would be interesting to develop a full Bayesian framework to fulfill this task. We discuss this in Section 7.