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Calibration of the agent-based continuous double auction stock market by scaling analysis

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ABSTRACT

This paper proposes one calibration method for the agent-based continuous double auction (CDA) stock market by scaling analysis based on the work by Pasquini and Serva (1999) [12]. We design and build an agent-based CDA stock market, which uses the same trading mechanism as the Chinese stock market. We also perform a scaling analysis of the absolute returns in both the artificial and real stock markets. The results show volatility correlations as power laws in all the markets. More importantly, the power-law exponent is not unique, and all such exponents follow a multi-scale behavior. All exponents $\beta(\gamma)$ trend to the theoretical value 0.5 with increasing scaling index γ. Scaling character is an important intrinsic quality of the stock market, and this method can be used in calibrating the agent-based stock market model.

1. Introduction

Agent-based modeling helps people learn the complexity of our world from a different perspective. This type of modeling replicates the world from microscopic behavior to macrodynamics by building heterogeneous bounded rational agents, interaction networks, and so on [6,22,31]. With the advancements in computer science, agent-based artificial stock market modeling has developed rapidly over the last 20 years. Beginning with the development of the Santa Fe Institute agent-based artificial stock market model [1,23], numerous agent-based models emerged in an endless stream from different views of social economic areas [5,7,9,10,16,24,26,34]. Agent-based modeling helps facilitate understanding of some areas that traditional homogeneous models cannot explain very well [6,22,25], such as financial crises and bubbles [5,14], market microstructure [9,10,19], various anomalies and stylized facts [20,25] and market dynamics [4,8,18], among others. However, some agent-based stock market models have their own ad hoc rules and methods for modeling, with different agents' design and price clearing patterns and market conditions, for instance, Chinese vs. US markets. Therefore, the model's explanation of the real world remains unclear, and calibration becomes a very important issue in agent-based modeling [21]. The complexity of the real world and the modeling technologies and tools used by different researchers make calibration more difficult to solve by employing both the theoretical and empirical methods [12,29].

Generally, there are three popular methods are employed to calibrate agent-based stock markets [22,3]. The first method involves verifying whether the model can replicate the stylized facts which exist in real markets [23], such as fat tails, excess volatility, and volatility clustering, among others. The second method involves determining whether the model can adapt to real market changes when real market data are imported prior to simulation [13]. The third one is an empirical method that estimates the parameters from real stock markets or compares such parameters with human experimental markets [11,32,33]. The empirical methods should employ the same price formation mechanism in both the agent-based stock

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market and the real world. Also, it is important that mining the data from different angles for capturing the intrinsic quality of the market so as not to rely solely on the primary statistical functions.

The data analytic methods in physics can also be used to calibrate agent-based models by comparing the intrinsic quality of the agent-based stock market with that in the real world. Power-law scaling analysis is one particular method that can be used. Mantegna and Stanley [27,28] first published their research results on *Nature* and showed the S&P 500 index as power-law with a component of 0.53, which is close to the theoretical value of 0.5 [15]. Furthermore, Pasquini and Serva [30] studied the index data of the New York Stock Exchange (NYSE), which contained 8120 pieces of data that were obtained from January 1966 to June 1998. They found that the volatilities of returns are power-laws ranging from a scale of 1 day to 1 year. They also found that the power-law components of absolute returns are not unique and exhibit the multi-scale behavior. Empirical results show that the power-law scaling character is a special intrinsic quality of the real stock market. Recent research shows that this power-law behavior also exists in the Chinese stock market [2,17]. Therefore, we use this characteristic to calibrate our agent-based continuous double auction (CDA) stock market, which uses the same trading mechanism as the Chinese stock market. As well as we are expected to show some real case observations in order to justify the utilization of this model, which is in particular for the Chinese stock market.

The paper is organized as follows. Section 2 discusses the details of our agent-based CDA stock market model. Section 3 analyzes the data from the agent-based computations and the real China stock market (Hu-Shen 300 Security Index, China Vanke Co., Ltd., and PetroChina Co., Ltd.). The multi-scale character will be also analyzed using the method of Pasquini and Serva [30]. Finally, we will discuss some of the conclusions about whether the scaling analysis is suited for calibrating the agent-based stock market in Section 4.

2. Agent-based CDA stock market modeling

CDA is the most popular trading mechanism used in numerous electronic stock markets worldwide. Traders can submit their market orders or limit orders at any time during the trading process. The orders are matched instantly when the best bid order overlaps the best ask order. Orders are stored in the order book and sorted by price priority at the time level and time priority at the price level until they are executed completely or canceled.

Chiarella and Iori [9] pioneered a study of agent-based CDA stock market modeling, which is similar to the real market. They use a mix-decision agent model for forecasting the expected return. The mix-decision agent model has three information components, namely, the fundamental information, the historical trading information, and the noise. Each component has a weight parameter obtained from uniform distribution. Each agent only can buy (sell) one unit asset when a price increase (decrease) is expected with a quote price based on the current price. Their model has been updated with a constant absolute risk aversion (CARA) utility function to determine the quantity that agents want to buy or sell [10].

In this paper, we use a mix-decision model for agent decision-making, which is similar to [9,10]. The agents will consider the fundamental information, historical trading price, and noise in their decisions. When they decide to buy (sell), they will send orders based on the current order book and adjust their quote price according to the trading rules, such as tick size and price limit, among others, similar to that shown in Fig. 1.

2.1. Decision-making behavior of agents

In this model, there are two types assets: risky (stock) and risk-free assets (bond) with a fixed interest rate r. Agents are affected by the three components, namely: the fundamental value of the risky asset, historical trading prices, and some noise from the market, as described in Fig. 1. Based on the information, agents will decide on their portfolio and trading in the market according to their wealth constraints and trading rules.

At each time t, agents will decide whether to enter the market based on their expectations of the risky asset's future price. At time t agent i will expect the risky asset's price at $t+\tau_{i,t}$. Thus,

$$\hat{p}_{t,t+\tau_{i,t}} = \frac{1}{n^F_{i,t} + n^C_{i,t} + n^N_{i,t}} \left[n^F_{i,t}\hat{p}^f_{i,t} + n^C_{i,t}\overline{ma}_{i,t} + n^N_{i,t}e^{\epsilon_{i,t}} \right]. \tag{1}$$

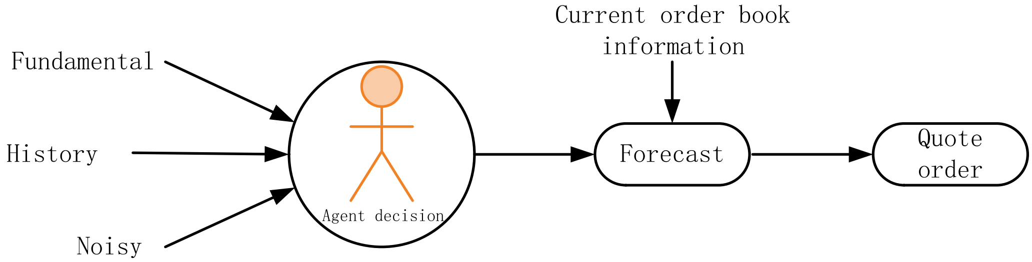

Fig. 1. Decision-making process of agents.