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Nonlinear dynamic modeling analysis of herd behavior in tradable green certificate markets

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Abstract In complex financial markets, investors' behavior is often influenced by those around them, which in turn generates a herd effect. This paper explores the emergence process of flocking behavior in the tradable green certificate market using an Agent-based nonlinear dynamics model. By constructing a simulation environment, the impact of investors' decision-making based on imitation behavior is analyzed, and the evolution mechanism of herd behavior in the market is revealed. The experimental results show that the intensity of flocking behavior is affected by the quality of information, the initial state of the market and individual imitation tendency. In the baseline scenario, when the imitation probability of low-quality information subjects is high, the flocking behavior shows a significant increase; the flocking behavior of high-quality information subjects fails to show up when the initial imitation probability is low. Specifically, when the initial imitation scale of high-quality information subjects is less than 0.439, the flocking behavior does not appear, while the imitation behavior of low-quality information subjects has a significant impact on the market price. The experiment verifies the validity of the model, and the deviation of the simulation data from the actual market data is less than 0.05, indicating the feasibility of the model in practical application. The study provides a theoretical basis for understanding the volatility of the green certificate market and predicting herd behavior.

Index Terms Flock Behavior, Nonlinear Dynamics, Green Certificates, Agent Model, Imitation Behavior, Market Volatility

I. Introduction

The realization of the “dual-carbon” goal is a broad and profound economic and social systemic change, and has become a medium- to long-term strategy for implementing the new development concept and building a new development pattern. Energy green low-carbon transition is a key task to support the realization of the “dual-carbon” goal, through the construction of clean low-carbon energy as the main energy supply system, the formation of non-fossil energy to basically meet the incremental demand for energy and the scale of the fossil energy stock to replace the energy production and consumption pattern [1]-[4]. In order to promote the energy green low-carbon transition, scientific top-level institutional design of the energy system has become a key scientific issue to realize the energy green low-carbon transition [5]. Renewable energy quota system and green certificate trading system is an important system innovation to promote the development of renewable energy industry. The quota system and the green certificate trading system take the tradable green certificate market as a carrier, internalize the positive externalities of renewable energy power through the market, realize the sharing and mutual aid and optimal allocation of renewable resources within the country by scientifically guiding renewable energy investment, and then effectively solve the problem of unbalanced distribution of resources and the reverse distribution of energy supply and demand [6]-[9]. However, the information asymmetry between supply and demand of new energy generation makes the green certificate market grow irrationally, while the price of green certificates is affected by the quota system and the fluctuation of the power market, which leads to the presentation of a nonlinear coupling in the tradable green certificate market [10], [11].

With the promotion of green certificates and the improvement of the willingness of the whole society to consume green electricity, the trading volume of green certificates will grow further [12]. However, due to the expansion of the scope of green certificate trading subjects, the significant differences in risk preferences of the subjects, the increasingly complex trading strategies of market participants, as well as the increased market liquidity and insufficient market regulation, leading to increased market risk and affecting market efficiency [13]-[15]. In the green certificate market, limited rational trading individuals will exchange information with each other and learn to imitate other subjects' strategies, thus contributing to the emergence of herd behavior at the macro level [16]. Flock behavior is a kind of group behavior that ignores private information and imitates the strategies of other subjects, and the reciprocal symbiotic relationship between interacting subjects drives the synergistic evolution of flock behavior. The formation of herd behavior is influenced by various factors, under the premise of limited rationality of the subject, the factors that cause the emergence of herd behavior mainly include rational factors for the purpose of profit maximization and irrational factors caused by group pressure, rational factors include information asymmetry, reputation and remuneration, and irrational factors include herd mentality and cognitive bias [17]-[20]. The limited rational behavior of trading subjects spreads under the effect of herd behavior, which will interfere with the stable operation of the market, increase the risk of renewable energy investment, and affect the market of tradable green certificates [21].

This study proposes a dynamic model considering flock behavior based on the Agent model, taking into account the characteristics of the tradable green certificate market. The Agents in the model are heterogeneous, i.e., each Agent makes decisions based on its own beliefs and expectations of the market. By simulating these Agents, it is possible to reveal the generation mechanism of herd behavior in the market and its impact on the market price. In addition, the study introduces the important factor of imitation behavior and explores how different types of information affect investors' decisions and further influence the overall performance of the market.

The study focuses on analyzing the effects of different information quality, individual initial imitation size, and the initial state of the market on herd behavior. Through the experimental simulation, it can be clearly observed that the flocking behavior will be more obvious when there is a higher proportion of low-quality information subjects in the market. In contrast, the herd behavior of high-quality information subjects presents more complex dynamic characteristics. Under different scenarios, investors' imitative behaviors not only exacerbate market price volatility, but also may trigger irrational market volatility.

Specifically, this study provides an in-depth discussion from three aspects: theory construction, model design to computational experiment. First, the importance and practical significance of the study of herd behavior is clarified through the analysis of the background and current situation of the green certificate market. Next, an Agent-based nonlinear dynamics model is constructed, and based on this, computational experiments of various scenarios are carried out to verify the validity of the model and its practical application value. Finally, combined with the simulation results, relevant policy suggestions to suppress herd behavior and control market volatility are proposed.

II. Modeling and computation of nonlinear dynamics based on emergence of flocking behavior

II. A. Basic elements of complex networks

II. A. 1) Degree and degree distribution

In network theory, degree can be understood as the number of neighbors of that node. The degree of a node is a fundamental topological feature that is important for understanding the structure and nature of a network.

For an undirected network, the degree of a node is the number of edges connected to it. For a directed network, a node has an in-degree and an out-degree, which indicate the number of edges pointing to that node and the number of edges pointing from that node to other nodes, respectively. The in-degree indicates the number of connections or degree of association of other nodes pointing to the node. The out-degree indicates the number of connections or degree of association of that node pointing to other nodes. The average degree is the average number of connections of all nodes in a network, denoted as $\langle k\rangle$, and the average degree is calculated as follows:

$$\langle k\rangle = \frac{\sum_{i=1}^{N} k_i}{N} \tag{1}$$

where N is the total number of nodes and k_i is the degree of the i th node. The average degree is an important indicator of the network structure, which helps us to understand the average level of connectivity of the nodes in the network, as well as the overall denseness of the network.

The degree distribution indicates how the degree of a node is distributed throughout the network. The degree distribution is usually represented using a probability mass function or a probability density function. For an undirected network, the probability mass function of the degree distribution can be expressed as:

$$P(k) = \frac{N_k}{N} \tag{2}$$

where $P(k)$ is the probability that a node has degree k, N_k is the number of nodes with degree k, and N is the total number of nodes. Some networks may have normally distributed degree distributions where most nodes have similar degrees. However, a common situation in complex networks is a power-law distribution, where there exist some nodes with very high degrees and most nodes with relatively low degrees. By studying the degree and degree distribution of a network, the topology, stability, vulnerability, and the laws of information propagation of the network can be better understood.

II. A. 2) Clustering coefficients

The clustering coefficient [22] is a measure of the degree of clustering of nodes in a network, which describes how dense the relationships between nodes in the network are. Specifically, the clustering coefficient measures the relationship between the proportion of actual connections between a node's neighbors and the maximum number of possible connections. It measures how closely the friends of nodes in the network are connected to each other, i.e., how many pairs of nodes in the neighborhood of a node of degree k are connected to each other.

The clustering coefficient can be expressed as:

$$C_i = \frac{2E_i}{k_i\left(k_i - 1\right)} \tag{3}$$

where E_i is the number of edges that actually exist between neighbors of node i and k_i is the degree of node i. The calculation of clustering coefficient helps us to understand the connectivity pattern of nodes in the network. A high clustering coefficient implies that the nodes in the network tend to form tight clusters, while a low clustering coefficient may indicate that the nodes in the network are relatively sparsely connected. The clustering coefficient is a commonly used metric in complex networks and is important in network analysis to help us understand the local structure and community organization characteristics of a network. By calculating the clustering coefficients of the nodes, it is possible to identify the community structure in the network, assess the stability and robustness of the network, and study the process of information propagation and dynamics.

II. A. 3) Average path length

The average path length is the average length of the shortest paths between nodes in a network, and is used to characterize the global connectivity and information dissemination efficiency of the network. Specifically, for a network, its average path length L is defined as the average of the shortest path lengths between all pairs of nodes. It can be expressed as:

$$L = \frac{2}{N(N-1)}\sum_{i \geq j} d_{ij} \tag{4}$$

where N represents the total number of nodes and d_{ij} is the shortest path length from node i to j. The average path length reflects the speed and efficiency of information or influence propagation in the network. Usually, the shorter the average path length is, the faster the information spreads in the network and the stronger the connectivity of the whole network. Therefore, the average path length is one of the important indexes for evaluating network connectivity and information propagation efficiency. It is also one of the important properties about network structure in complex network theory. By calculating the average path length of a network, the overall connectivity and information propagation efficiency of the network can be evaluated, providing an important reference for network design and analysis.

II. B.Agent-Based Approach to Modeling Artificial Financial Markets

II. B. 1) Heterogeneous actor model

The analytical modeling for individual behavior is built on the Heterogeneous Actor Model [23] (HAM) within a general equilibrium framework. In the model, Agents holding heterogeneous beliefs respectively adopt behavioral strategies consistent with their beliefs to form expectations, and will utilize the adaptive belief system (ABS) to achieve belief updating based on the market performance of different behavioral strategies, which is directly manifested in the change of the proportion of heterogeneous-belief Agents in the market.

The specific modeling process is as follows: in a publicly traded market of two assets, bonds and stocks, there exists both H classes of Agents with heterogeneous beliefs, which generate demand for stocks at moment t based on a short-sighted mean-variance demand function:

$$z_{h,t} = E_{h,t}[\tilde{R}_{t+1}] \big/ \lambda V_t[\tilde{R}_{t+1}] \tag{5}$$

where $E_{h,t}[\tilde{R}_{t+1}]$ is the conditional expectation of the Agent choosing strategy h on the excess return of the stock at the moment $t+1$, $h = 1, \cdots, H$; and for the convenience of parsing the computation, all Agents have the same risk aversion coefficient λ and conditional variance $V_t[\tilde{R}_{t+1}]$.

Under the assumption of zero supply of stocks, the market clears when aggregate demand equals aggregate supply, producing an equilibrium price of stocks:

$$\sum_{h=1}^{H} n_{h,t} \frac{E_{h,t}[p_{t+1}+d_{t+1}]-(1+r_f)p_t}{\lambda V_t[\tilde{R}_{t+1}]}=0 \tag{6}$$

where $n_{h,t}$ is the proportion of Agents in the market choosing strategy h at moment t, and d_{t+1} and r_f are the dividend and the risk-free interest rate, respectively; the solution to this pricing equation, p_t, is the current equilibrium price of the stock.

Based on the realized profit $\pi_{h,t}=R_t z_{h,t-1}$ under each behavioral strategy, the adaptive updating of Agents in the market between H classes of heterogeneous beliefs is represented by the proportion of the number of Agents choosing the strategy h at the moment $t+1$ according to the Discrete Choice Model Evolution:

$$n_{h,t+1}=\frac{\exp[\rho\pi_{h,t}]}{Z_t} \tag{7}$$

where $Z_t=\sum_{k=1}^{H}\exp[\rho\pi_{k,t}]$ is the regularization factor, and ρ is the strength of selection. When $\rho=0$, all strategies are equivalent and the Agents choose randomly; when $\rho=\infty$, all Agents choose the best strategy.

II. B. 2) SFI artificial stock market

The implementation of the individual behavioral calculus is the SantaFe Artificial Stock Market (ASM) built within a computer simulation framework represented by Arthuretal. The specific modeling process is as follows: N short-sighted Agents with the same Constant Absolute Risk Aversion (CARA) utility function: $U(W)=-\exp(-\lambda W)$ in a market with publicly traded two assets - bonds and stocks - determine their optimal share of stock holdings $x_{i,t}$ by maximizing single-period utility. Under the assumption that the share of stock supply is also N, the market clears:

$$\sum_{i=1}^{N} x_{i,t}=\sum_{i=1}^{N}\frac{\hat{E}_{i,t}[p_{t+1}+d_{t+1}]-(1+r_f)p_t}{\lambda\hat{\sigma}^2_{i,t,p+d}}=N \tag{8}$$

where p_t is the stock price at moment t, $\hat{E}_{i,t}[p_{t+1}+d_{t+1}]$ and $\hat{\sigma}^2_{i,t,p+d}$ are Agent i's expectations of the conditional mean and variance of stock price and dividend, respectively.

Regarding the Agent's expectation formation and learning evolution, it is realized by the Holland Genetic Classification System (GCS) which contains three basic elements: Agent i with M prediction rules, selects the best matching prediction rule $f_{i,t}\to[S_t(a_{i,t},b_{i,t}),e^2_{t-1,i,t}]$, i.e., the rule with the smallest prediction variance among the activated rules to form price expectations:

$$\hat{E}_{i,t}[p_{t+1}+d_{t+1}]=a_{i,t}(p_t+d_t)+b_{i,t} \tag{9}$$

and uses $e^2_{t-1,i,t}$ to predict the conditional variance $\hat{\sigma}^2_{i,t,p+d}$; when the optimal share of stockholding of all Agents is passed to the market at the same time, based on the generated stock price p_t, Agent i updates the accuracy $e^2_{i,t}$ of all the prediction rules it has been activated, and it is substituted into the adaptation function that judges the goodness of the prediction rules:

$$\begin{aligned} f_{i,t,j} &= -e^2_{i,t,j}-Cs \\ &= -\left\{(1-\theta)e^2_{t-1,i,t,j}+\theta\left[(p_t+d_t)-\hat{E}_{t-1,j}(p_t+d_t)\right]^2\right\}-Cs \end{aligned} \tag{10}$$

where θ is the memory strength of the prediction variance and C is the cost of the eigenvalue s of the rule; based on the adaptation value, Agent i evolves the prediction rule set using a genetic algorithm averaging over k periods to eliminate the bad rules by selection, crossover, and mutation, and retains and generates the new rules for personal learning based on the market quotations.

II. B. 3) Fixed Networks and Diffusion Propagation Models

The computation for the flocking behavior is built on the regular grid structure, and the cellular automata model (CAM), in which Agents simply interact with each other based on a fixed network, and the diffusion propagation model (PDM), in which Agents randomly interact with each other based on the penetration theory with a certain probability, are considered respectively.

The construction of both CAM model and PDM model is divided into two steps: the first step is to set the interpersonal network of Agent; the second step is to determine the contagion mechanism of herd behavior in the market, including the process of behavioral contagion as well as the formation of Agent's decision.

The clusters formed by the Agent in the PDM model based on the penetration process on the two-dimensional ring network, on the premise that each cluster is an investment group that owns the same information and makes the same investment behaviors, take the trading strategy of its cluster, and then evolve with the changes of its own cluster. There are two basic types of osmosis processes: point osmosis and edge osmosis.

Regarding the setup of the contagion mechanism of herd behavior: in the CAM model, assume that there are N Agents participating in a market where an asset is publicly traded. At t moment, Agent i is in one of the three states of buy, sell and wait-and-see, and its $t+1$ moment state will be determined by the transfer probability matrix. the Agent state transfer matrix in the CAM model is shown in Table 1, where $A_i(t)$ denotes the state that occurs most often in the Moore-type neighborhood of Agent i, $p \in [0,1]$ is the the follower probability, which portrays the likelihood that the Agent will listen to the decisions of the majority of the people around it, and measures the strength of the market to produce herd behavior.

Table 1: The agent state transfer matrix in CAM model

$A_i(t)$	$t+1$ time buying probability	$t+1$ time buying probability	$t+1$ time buying probability
Buy	p	$(1-p)/2$	$(1-p)/2$
Hold	$(1-p)/2$	p	$(1-p)/2$
Sell	$(1-p)/2$	$(1-p)/2$	p

In the PDM model, it is assumed that there are N Agents participating within a market that publicly trades an asset, and at moment t, Agent i has a demand for the asset of $\Phi_i(t)$. Disregarding the specific process of individual Agent decision-making, the total market demand at moment $t+1$ is determined by the nature of each cluster in the network, where the probability of both buying and selling is a, the probability of being in a wait-and-see state is $1-2a$, and the volume of each cluster's transaction is proportional to the size of the cluster s in terms of clusters. Assuming the existence of k clusters, prices are determined by the difference between supply and demand, with an adjustment relation:

$$\Delta p(t) = \frac{1}{\lambda}\sum_{i=1}^{k} s_i \Phi_i(t) = \frac{1}{\lambda}\left(\sum_s s n_s^+ - \sum_s s n_s^-\right) \tag{11}$$

where λ is the market depth, which is used to measure the market liquidity; n_s^+ and n_s^- are the number of clusters of size s that are in the buying or selling state, respectively.

II. C.Agent-based modeling of tradable green certificate market

II. C. 1) Agent-based stock market modeling framework

The Agent-based tradable green certificate market model constructed in this paper is based on the complex system theory, and the investors (Agents) in the ultimately constructed tradable green certificate market are not completely rational and have the behavior of mimicking the surrounding Agents to make investment decisions. In addition, the micro-behavior of the Agent-based tradable green certificate market constructed in this paper can be based on behavioral finance theory. The tradable green certificate market based on Agent's herd behavior constructed in this paper mainly includes the following four aspects:

(1) The traders in the market, i.e. Agent, the Agent has the behaviors including the rules of buying and selling stocks, the rules of stock price expectation, and the rules of imitation;

2) The change of stock price in the market, there is only one stock in this model, and the modeling of it includes the rule of stock price change as well as the modeling of stock return;

3) Herd behavior [24] modeling, this paper describes the herd behavior in the tradable green certificate market based on imitated investment decision behavior;

4) Modeling of the market environment, i.e., the parameter settings of the overall market, stock market historical

information, price clearing, market makers and other rules.

In the tradable green certificate market, Agent will adjust its own price prejudgement based on its own historical trading returns, and the investment decisions made by other Agents, thus generating Agent's adaptation so that it can benefit as much as possible.

II. C. 2) Investor Agent Modeling

The Agent in the model, i.e., the investor in the tradable green certificate market, is a dummy that participates in the buying and selling of stocks, which is the key part of the model in this paper.

(1) Interaction Structure

The Ising model was first used to describe the behavior of complex ferromagnets, and the two-dimensional Ising model is one of the simplest statistical models for the existence of phase transitions. The real stock market system and the particle system of ferromagnets are both composed of single individuals, and groups of single individuals interact into complex systems.

At the beginning of the simulation cycle, each Agent owns $M_i(0)$ and $N_i(0)$ units of cash and stock respectively, in each cycle, Agent invests $S_i(t)$ units of stock according to the investment decision, and $S_i(t)$ can take three values: 1, 0, and -1, which represent the three strategies of buy, sell, or wait-and-see, respectively.The Agent's final investment behavior is also limited by its own wealth structure. The Agent's final investment behavior is also limited by its own wealth structure. If the Agent has no cash, even if $S_i(t)$ is 1, it cannot buy stocks; similarly, if the Agent has no stocks, even if $S_i(t)$ is -1, it cannot sell stocks. It is assumed that there is a market maker in this interactive system that helps to clear the demand and adjust that price, while the market maker is also subject to the above restrictions.

(2) Agent investment signaling

In each cycle, Agents first make inquiries and exchange investment information with each other, and each Agent can get decision signals $S_j(\overline{t})$ from its "neighbors" as a temporary decision, and summarize these decisions as $Y_i(\overline{t})$:

$$Y_i(\overline{t}) = (1-A)\times \sum_{<i,j>} J_{ij} S_j(\overline{t}) + A\times u_i(t) \tag{12}$$

where $S_j(\overline{t})$ - investment strategy signals of neighbors around the Agent, $<i,j>$ - coordinates of the 12 nearest neighbors, J_{ij} - influence factors of other Agents, $u_i(t)$ - signals of own expectations about prices, A - average confidence coefficient of all Agents in the market, $Y_i(\overline{t})$ - the combined information of Agent's integrated neighbor investment decision and own expectations.

The overall performance of the model is affected by J_{ij}, when J_{ij} is 0, the investment decisions made by Agents in the market are uncorrelated with each other, when J_{ij} is 1 and the market is an Ising model, the similarity of Agents' decisions in the market is enhanced, and the volatility of the stock price is intensified, and the main results of this paper are for the case where J_{ij} is equal to 1. Some results Consider J_{ij} as a Gaussian random number obeying mean 0 and variance 1. In each cycle, $u_i(t)$ is assumed to be a Gaussian distributed random number obeying (μ_p, σ_p), and $u_i(t)$ is kept constant during the cycle. the Agent confidence level A can have an impact on how much the Agent is affected by its own signals and the signals of the other Agents, and the higher the confidence level is the less it imitates the neighbors, and the more confident the judgement of itself is. The higher the confidence, the smaller the degree of imitation of the neighbor, the more confident in its own judgment, and vice versa, the higher the degree of imitation of the neighbor's strategy.

(3) Trading strategy

In the case of a market with complete information, Agent is able to trade when it receives even a small buy or sell signal, buying if it receives even a small positive signal and selling if it receives a small negative signal. In order to portray the case of incomplete information, we assume that Agents have thresholds for making investment decisions, and only engage in buying or selling behavior when they exceed the thresholds. Each Agent will compare the signal it gets with its own threshold, starting with a Gaussian distribution obeying (μ_p, σ_p), such that the Agent's risk preference threshold is $\xi_i(t)$, and the starting value. $\xi_i(t)$ is invariant in a single cycle, and will be adjusted in different cycles according to the Agent's learning, and the adjustment function is:

$$\xi_i(t+1) = \frac{\xi_i(t+1) * P(t)}{P(t-1)} \tag{13}$$

It can be seen that Agent adjusts its threshold based on the previous stock price and the current stock price, after which it makes an investment decision by using the following formula:

$$\begin{cases} S_i(\overline{t}) = 1 & if \;\; Y_i(\overline{t}) \geq \xi_i(t) \\ S_i(\overline{t}) = 0 & if \;\; -\xi_i(t) < Y_i(\overline{t}) < \xi_i(t) \\ S_i(\overline{t}) = -1 & if \;\; Y_i(t) \leq -\xi_i(t) \end{cases} \tag{14}$$

where $S_i(\overline{t})$ - Agent interim investment decision, $\xi_i(t)$ - Agent decision threshold, $Y_i(\overline{t})$ - synthesized information accepted by the Agent.

When the synthesized information $Y_i(t)$ accepted by the Agent is greater than its own threshold $\xi_i(t)$, it buys 1 unit of the stock; when the synthesized information $Y_i(t)$ accepted by the Agent is less than its own threshold $-\xi_i(t)$, it sells 1 unit of the stock; and in other cases, it takes a wait-and-see attitude.

In each running cycle, the threshold value $\xi_i(t)$ and the expected signal of price $u_i(t)$ are kept constant, so that the comprehensive information $Y_i(t)$ and investment decision $S_i(t)$ obtained by the Agents converge and converge. Eventually, each Agent has the final set of information $Y_i(t)$ and investment decision $S_i(t)$.

II. C. 3) Modeling of flock behavior

Herd behavior is an important research area in behavioral finance, in the real stock market, investors do not always complete their investment decisions based on their own private information, but follow the investment behavior of the majority of people in the market, there is obviously herd behavior.

Bikhchandani and Sharma define herding behavior as the tendency of investors to ignore their own valuable private information and follow the decision making style of the majority in the market. From the above definition of flocking behavior, a measure of flocking behavior in an artificial market can be determined: the level of flocking behavior HM is the average level at which the Agent's combined decision-making information is the same as that of its surrounding neighbors, and the opposite of its own private information. Then the level of flocking behavior in the tradable green certificate market in a single simulation period is:

$$HM(t) = \frac{\sum_i M_i(t)}{L^2} \times h \tag{15}$$

where L^2 - is the number of Agents in the market, h - the adjustment parameter, $M(t)$ - the number of neighbors that are consistent with the integrated decision made by the Agent and contrary to the Agent's private information, i.e., $S_j \times Y_i(t) > 0$ and $u_i(t) \times Y_i(t) < 0$.

III. Analysis of the results of the emergence of herding in the market for tradable green certificates

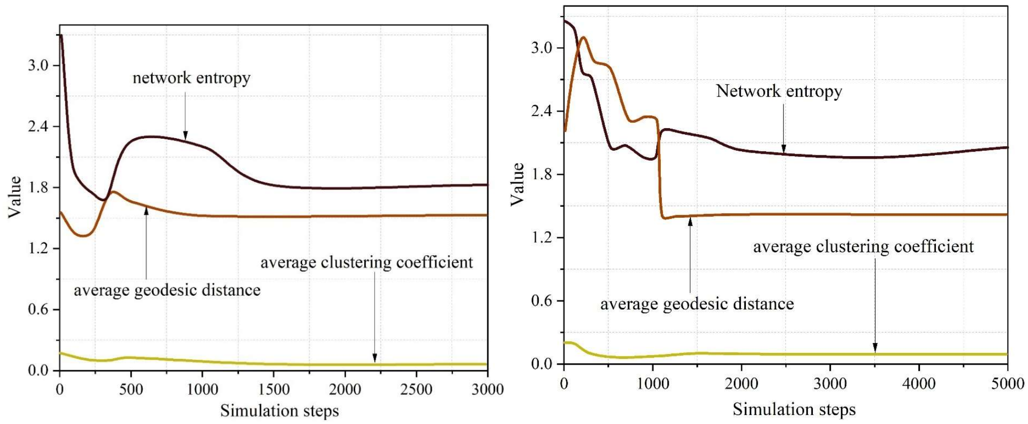
III. A. Network Characterization and Rationalization of Cluster Behavior

III. A. 1) Network characterization

In this section, we further analyze the communication topology interconnection model from the perspective of complex networks, because the topology interconnection relationship is more suitable to be analyzed by complex network theory. First, in the analysis process, we choose many network characteristic indicators to explore the intrinsic laws in the model, which include network entropy, average geodesic distance, average clustering coefficient, and network density.

The trends of multiple network characteristics are shown in Fig. 1, where (a) and (b) represent clustering and sub-clustering behaviors, respectively. Each parameter index eventually tends to a fixed value, which also means that the whole group gradually tends to a stable state during the interaction between individuals in the group. In the process of the movement of the whole group, a critical point of sub-cluster behavior can be found, after crossing this critical point, the whole group splits into two sub-clusters. At this time, the entropy value of the network increases significantly, and the average geodesic distance in each subgroup decreases, which also indicates the close connection between individuals in each subgroup. The average geodesic distance is calculated from the “geodesic distance between individuals that are interconnected”. In other words, when the interconnection between two individuals belonging to two subgroups disappears, the geodesic distance between them becomes infinite.

The trends of network entropy and average geodesic distance are that there is a process of convergence to the equilibrium point before the critical point of subcluster behavior, followed by a jump phenomenon after the critical point of subcluster behavior, and then converge to a new equilibrium state that is different from the previous equilibrium state. It is also very meaningful to figure out the intrinsic mechanism in the cluster movement mentioned above, and it also allows us to better understand the interaction mechanism between human behaviors.



(a) Cluster behavior (b) Group behavior

Figure 1: Changes in various network characteristics

The individual out-degree distribution under different N and K combinations with the number of simulation steps is shown in Fig. 2. Before the critical point of subgroup behavior, the whole group has already converged to a stable state, because the out-degree distribution of individuals in the group conforms to the out-degree distribution law in the stable state mentioned before. After the critical point of subgrouping behavior, the whole group splits into two subgroups, and eventually each subgroup tends to its respective steady state. These phenomena are consistent with Haken's view in the synergetics mentioned before.

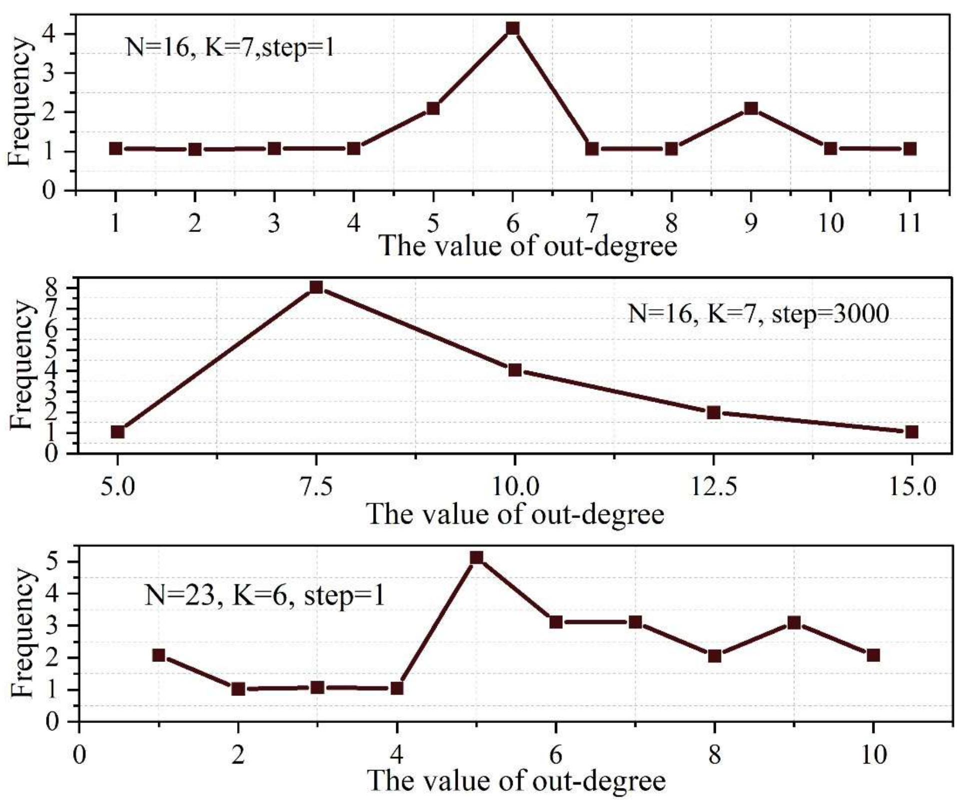


Figure 2: Individual distribution of different combinations and simulation steps

The size of the network density D is completely determined by the values of N and K and remains constant throughout the evolution. However all other network characteristics are always changing. The trends of multiple network characteristics are shown in Fig. 3 for N = 20, $1 \leqslant K \leqslant 10$. The population size N is fixed and the data in this figure are derived from the steady state in the case of multiple initial parameter settings. When the topology number K is equal to 1, there is a special case that makes the network graph disconnected, which makes the average geodesic distance and network density data in this case significantly different from the data in other cases. In addition to this, the average geodesic distance g is roughly inversely proportional to the topology number K when the topology number $K \geqslant 5$. The reason for this is that the threshold for the emergence of clustering behavior is 5, beyond which the variation of the average geodesic distance also becomes greater, and the average clustering coefficient increases with the topology number K, suggesting that higher degrees of topological interconnectivity represent better clustering effects.

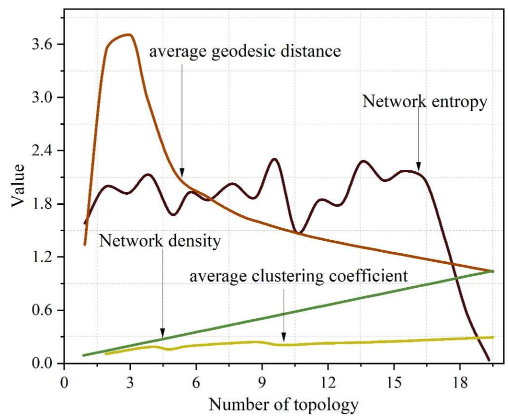


Figure 3: Changes in various network characteristics

III. A. 2) Reasonableness analysis

The rationality and feasibility of the communication topology model mentioned in this paper will be specifically analyzed in the context of the references. The value of the topological number K also determines whether or not the system will converge to a stable state, since a stable state of the system is a necessary prerequisite that can enable the emergence of cluster movements. When K is equal to 1 and 2, the topological interconnections in the system will remain disconnected, whereas it is when K is equal to 5 that an almost fully interconnected state is reached, and when K is equal to 6 or 7 that the average robustness of each neighbor will reach its peak. In fact, the above findings are linked to the communication topology model mentioned in this paper. From the results, it can be found that when K is less than 5, the individuals in the group system will not emerge cluster behaviors, while when K is equal to 5, many types of cluster movements begin to emerge, and 5 is exactly the minimum value of K that enables the group to emerge cluster behaviors. After analyzing the results of multiple simulations, I also found that with the gradual increase of K, when K is in the range of 5 to 7, the group system tends to emerge cluster behavior for the first time, and this range is also known as the emergence threshold of cluster behavior. Therefore, the communication topology interconnection model can be used to study the potential mechanisms at play in the interactions between traders in the stock market, such as the prerequisites for the emergence of the herd effect and the methods to prevent and inhibit the emergence of this kind of harmful cluster behavior. In summary, I believe that the interaction rules between individuals in the communication topology model are suitable for modeling and explaining the real interaction mechanisms between people in a crowd.

III. B. Computational experiment on the emergence of flocking behavior of green certificate trading subjects

III. B. 1) Experimental design

Based on the constructed system dynamics model of flock behavior emergence, this section designs a multi-scenario computational experiment to explore the emergence law of flock behavior of various types of subjects by simulating the emergence process of flock behavior under multiple scenarios in Vensim software. In this chapter, the data of China's renewable energy industry development is selected to simulate the emergence process of flock behavior at the early stage of green certificate trading, and the initial values and sources of each parameter are shown in Table 2. The baseline scenario in this section is the emergence of herd behavior of quota subjects considering heterogeneous information and beliefs. In this scenario, the initial imitation probability of all types of subjects is 0.5, the number of quota subjects with low-quality and high-quality information is equal, and the number of fundamental strategy subjects, momentum strategy subjects and inverse strategy subjects is also the same.

Table 2: The initial value of each parameter

Main parameter	Value	Unit
RPS quota	25	%
RPS quota monthly growth rate	0.005518	%
Increase in demand for electricity	0.0025	%
Base time renewable energy generation	2.05×10^{9}	MWh
Monthly growth rate of renewable energy generation	0.0075	%
Green certificate base price	60	Yuan
Penalty	200	Yuan
The adjustment time of the TGC price fluctuation	2.5	Day

III. B. 2) Validity tests

The validity of the model is first validated based on the results of the baseline scenario. According to the Werker-Brenner method for validation of computational experimental model validity, the validity of the model is verified based on the comparison between the computational experimental results and the actual worth. Currently, China's green certificates include green certificates for stock renewable energy projects, levelized green certificates, and green certificates for green power trading, and there are differences in the prices of the three types of certificates, and since the latter two types of certificates are able to reflect the current level of development of the renewable energy industry, the prices of the latter two types of certificates serve as a reference for the actual values.

In September 2024, 309 market players from 22 provinces in China completed 9,875.26 million kWh of green power transactions in an online and offline manner, with the average price of the transactions at a premium of 2.5-6 cents/kWh over the medium- and long-term agreements, which represents the environmental value of green power, i.e., the value of the green certificates. According to the transaction data of China's green power certificate subscription and trading platform, the price of China's affordable green certificates is 25-60 yuan/MWh, which is basically the same as the environmental premium in the green power transaction, thus, the actual value of China's green certificates is basically in the range of 25-60 yuan, and the actual value of green certificate price and the simulation value are shown in Fig. 4, which shows that the deviation of simulation value from the actual value is less than 0.05, and the validity of the model can be verified. The validity of the model can be verified.

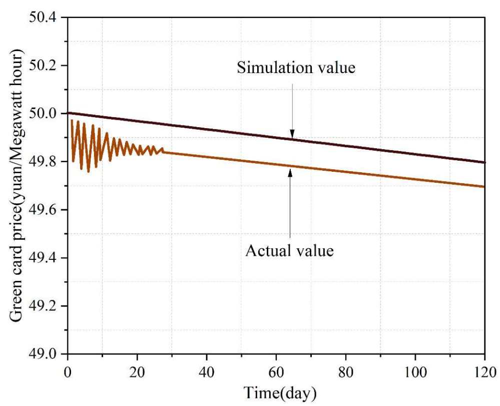


Figure 4: The price simulation value is compared to the actual value

III. B. 3) Dynamics of flock behavior emergence

Under the benchmark scenario, various types of subjects emerge from the herd behavior emergence depth, compliance costs and green certificate market price. The simulation results of the benchmark scenario are shown in Figure 5. As can be seen from the figure, the proportion of flocking behavior of low-quality information quota subjects increases significantly, while the level of flocking behavior of high-quality information subjects also rises gradually and tends to 1. The difference in the fulfillment cost of the two types of subjects shows that, among low-quality information quota subjects, the fulfillment cost of the subjects that adopt imitation strategy is significantly lower than that of the subjects that adopt no imitation strategy, which is because the subjects with low-quality information, due to the inaccurate judgment on the value of green certificates, result in purchasing fewer green certificates or hoarding too many green certificates. This is because the subjects with low-quality information, due to their inaccurate judgment of the value of green certificates, buy fewer green certificates or hoard too many of them, which raises the overall compliance cost.

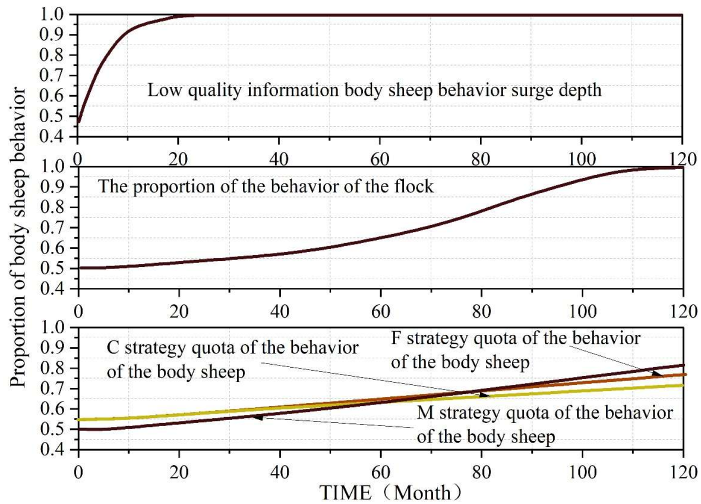
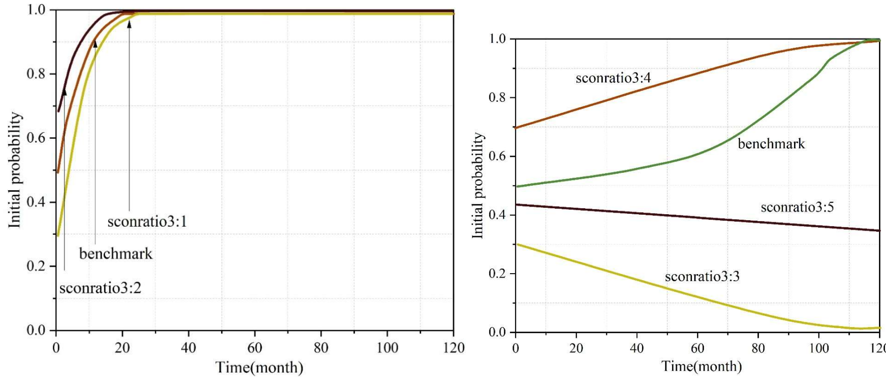


Figure 5: Benchmark scenario simulation results

III. B. 4) Scale effects emerging from herd behavior

In order to study whether there is a critical point for the emergence of herd behavior between the initial imitation scale of low-quality information subjects and high-quality information subjects, this chapter sets a variety of initial imitation scale levels (proportions) for the two types of subjects, and the other settings are the same as the benchmark scenarios, and the simulation experimental results of different scenarios are shown in Figure 6, where (a) and (b) represent the emergence depth of herd behavior of low-quality and high-quality information quota subjects, respectively. The results show that only when the initial probability of high-quality information subjects adopting imitation behavior is lower than 0.439, this type of subjects will not emerge from the flocking behavior, while low-quality information subjects, in order to save the cost of collecting information, will always exchange information with high-quality information subjects, imitating each other's decisions, and improving the accuracy of price prediction, which will cause the emergence of flocking behavior. In all of the above scenarios, the level of flocking behavior of low-quality information subjects rises, while the level of flocking behavior of high-quality information subjects rises only when the initial imitation scale is higher, and no flocking behavior emerges when the initial willingness is lower. It can be seen that the level of flocking behavior emergence of quota subjects is related to the individual to the initial imitation scale. In the low-quality quota subject, the higher the individual to initial imitation scale, the higher the level of emergence of herd behavior of the group; while in the high-quality information quota subject, only when the individual to initial imitation scale is higher, the herd behavior will further emerge. If the individual to the initial imitation scale is low, the level of flocking behavior will remain at the initial level or even converge.

On the whole, the low-quality information group will realize the disadvantage of its own strategy through interaction with the high-quality information group, so it will gradually adopt the imitation strategy, which leads to the emergence of flocking behavior in the low-quality information group. On the other hand, high-quality information groups will only adopt imitation strategies when interacting with subjects with more accurate information than their own, so the emergence of flocking behavior in high-quality information groups depends on the heterogeneity of information of subjects in high-quality information groups.



(a) The low quality information quota is the main body of sheep

(b) The high quality information quota is the main body of sheep

Figure 6: Simulation results of different scenarios

IV. Conclusion

The study shows that the emergence of flocking behavior is not only affected by investors' imitation tendency, but also closely related to the quality of information in the market and the initial imitation scale. In the simulation of green certificate market, the depth of emergence of flocking behavior of low-quality information subjects is significantly higher than that of high-quality information subjects. When the initial imitation size of high-quality information subjects is lower than 0.439, the flocking behavior does not emerge, while low-quality information subjects always exacerbate market volatility through imitation strategies.

The experimental results also show that imitation behavior has a significant impact on the prediction accuracy of market prices, and the imitation strategy of low-quality information subjects can significantly reduce the cost of compliance, while high-quality information subjects gradually converge to the imitation behavior through the interaction with low-quality information subjects. The simulation data show that in the group size N = 20, with the increase of K value, the group system will experience the transition from no flocking behavior to flocking behavior, and the flocking behavior of the group is most significant when the K value is between 5 and 7.

By comparing with the actual market data, the simulation results are consistent with the actual price fluctuations in China's green certificate market, which verifies the validity of the model. This study provides a new perspective for understanding the herd behavior in the green certificate market and its impact on market volatility, and provides a theoretical basis and empirical support for policy makers in regulating the green certificate market.

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