Simulation of Financial Market Performance and Algorithmic Economic Model based on Complex Network

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Abstract. At present, traditional macro-financial models such as random walk model and log-periodic power law model in academia cannot explain the stylized characteristics of financial markets. So, we propose a microscopic model that produces stylized characteristics of real financial markets. The model integrates the herding effect, the non-linear relationship of investors and the non-linear structure of the system very well. The research results show that the financial market model established in this paper can simulate most of the characteristics of the real financial market price time series relatively accurately. The model helps to understand the internal operating mechanism of the financial system and provides some basis and reference for the establishment of financial market forecasting models.

Keywords: Complex Network; Financial Market; Algorithmic Model; Time Series.

1. Introduction

In the process of studying complex theories, scholars have discovered complex networks, which are an important part of complex theories. Its appearance has led to the study of complex problems and has helped the research of complexity science and systems. All complex networks are derived from reality, but their research purposes are different, as long as they are regarded as networks composed of interacting individuals according to the research motivation. Therefore, we can say that complex networks exist around us all the time, and provide a new and relatively simple research platform for the study of complex systems. Studying the network structure and evolution mechanism of financial market is the basis for exploring the development trend of financial market and an effective means to capture financial risks [1]. Although many literatures have studied the topology and evolution of financial market networks, they are scattered in different disciplines, research groups, and journals, so there is no clear picture of financial network research [2]. Although some early literature reviews covered a large number of studies, they did not systematically aggregate this knowledge based on a research tenet.

2. The Concept of Financial Market Network

The financial market is a complex system that is composed of multiple sub-markets such as the currency market, foreign exchange market, and securities market, and is constantly evolving in time and space with the participation of multiple subjects such as financial institutions, governments, corporate organizations, and individuals (Figure 1). From the perspective of complex network, this paper defines the complex correlation structure among participants in various financial sub-markets as financial market network [3].

Therefore, according to the differences between financial sub-markets, financial market can be abstracted into inter-bank market network, stock market It is a complex network structure in which multiple sub-networks such as network and foreign exchange market network are interconnected. Financial market network is a collective concept, which refers to a type of network in which financial market participants are interconnected. In the financial market network, nodes generally represent financial market participants such as governments, financial institutions, enterprise organizations, and individuals; edges represent the connection between financial market participants. Specifically, in the inter-bank market network, the edge refers to the interbank lending relationship between banks; in the foreign exchange market network, the edge refers to the correlation between exchange rate fluctuations among countries' currencies; in the stock market network, the edge refers to the correlation between corporate stocks; and in the securities text network, the edge is the interaction between the text information between securities companies.

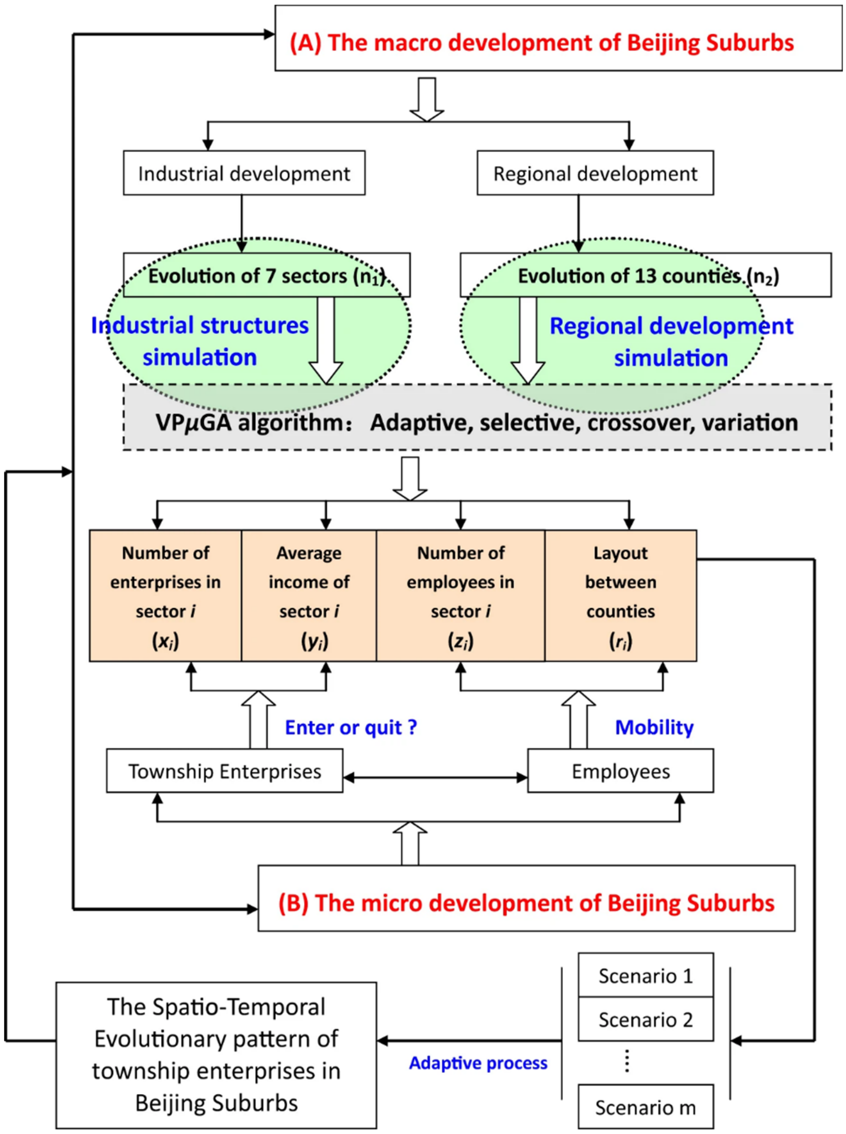

Figure 1. The spatial and temporal evolution of financial markets

The current research on financial market networks is mostly based on undirected networks, and less consideration is given to dynamics, directionality, weights, and node heterogeneity. However, dynamic networks, directed networks, weighted networks, and bipartite networks are closer to the actual evolution of financial market networks. For example, in the bank-enterprise credit network, the entire network is composed of two different types of nodes, the bank and the enterprise, which is a typical dichotomy [4]. The network has obvious dynamics on the time scale. The difference in the connection strength between the corporate banks in the network makes the connection weight of the entire network inconsistent, and has obvious weighted network characteristics. Therefore, in the evolution of the financial market network, it is more realistic to take into account the orientation, weighting, dynamic, dichotomy or diversity, and we should focus on these aspects in the future.

Based on the scale-free network topology and percolation theory, an effective stock market model is established. In this model, investors of different sizes have different positions, and the model integrates the herd effect, the nonlinear relationship between investors and the nonlinear structure of the system. At the same time, due to the mutual dependence between investors when making decisions, the self-organization characteristics of the herd effect and the nonlinear structure of the system during the entire evolution process are determined. The model itself has many advantages. It has a dynamic heterogeneous investment group structure, overcomes the difficulty of fixed relationship between investors in the cellular automata theory, and also solves the problem that the relationship between investors can be artificially regulated in the statistical physical model. Investors in this model have self-organizing evolution; the entire population can be fully covered by social networks. The percolation theory and the dynamic investment group structure theory are integrated, and a research model is established to analyse the correlation of price fluctuations and the characteristics of multifractality and income distribution in the financial market. The relevant statistics, including the volatility autocorrelation function, the scale index of the income distribution, etc., obtained through research are all in line with the real market. Therefore, it can be said that the market model based on the percolation theory has withstood the actual test and is one of the best theories for simulating market price fluctuations.

3. Measure Method of Market Risk

3.1 Sensitivity Analysis Method

The method is to use the sensitivity of financial asset value to its market factors to measure market risk. Standard market factors include interest rates, exchange rates, stock indices, and commodity prices. Assuming the value of the financial asset is P and the market factor is $x_1, x_2, ..., x_n$, then

$$\frac{\Delta P}{P} = \sum_{i=1}^{n} D_i \Delta x_i \tag{1}$$

Among them, $D, D_2, ..., D_n$ is the sensitivity of asset value to response market factors, which is called sensitivity. The premise of the establishment of formula (1) is that the change of financial asset value and its market factor change has a linear relationship, but in practice many financial assets have nonlinear dynamic behaviour, so only when the market factor changes slightly, the asset value and the market factor change. The linear relationship shown in (1) is presented. Sensitivity is thus a linear approximation, a local measure of risk.

3.2 Volatility Analysis Methods

Risk refers to the uncertainty of future returns, and the degree to which the actual result deviates from its expected result is volatility, which can be quantified by standard statistical methods. Of these, variance or standard deviation is the most commonly used method, which estimates the possible deviation between actual and expected returns. In use, volatility is often equated with standard deviation [5]. Assuming that the investment income of investing in the i-th asset is r_i, and the investment ratio is w_i, then the rate of return of the portfolio is $\sum w_i r_i$, and the risk of the portfolio is expressed by the variance of the portfolio, then

$$\sigma_p^2 = V(\sum_{i=1}^{n} w_i r_i) = \sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_{ij} w_i w_j \tag{2}$$

In the formula, $\sum_{i=1}^{n} w_i = 1$, $0 \le w_i \le 1$, $V(\cdot)$ represent the variance, and σ_{ij} is the covariance of the i and jth asset returns. The researchers wanted to verify that the return volatility and Rui Liu could be compared, so they used a variety of methods, and finally found that the multifractality and aggregation of price volatility can be supported. There is a correspondence between the two observables, such as revenue and velocity, time and length. An analogy can be drawn between the Kolmogorov energy ladder and the information ladder. In the former ladder, the big whirlwind was broken into a small whirlwind in Rui Liu. In the information ladder of the financial market, brokers are divided into two categories, one is investors who hold a large amount of capital for a long time, and the other is an investor who holds a small amount of capital for a short period of time. The volatility ladder of price fluctuations arises from their interaction. In the study of Arnoldo et al., through wavelet decomposition volatility and exchange information analysis, it can be seen that the volatility ladder actually has a scale transition. Various properties of price volatility are interconnected, such as the multifractality and volatility aggregation mentioned above. In addition, the aggregation of volatility causes the appearance of fat tails in the distribution of the return function. The autoregressive conditional heteroskedasticity model is one of the more mature models to study the aggregation of price fluctuations. VaR can be divided into relative loss and absolute loss: the loss relative to the mean is the relative loss; the loss relative to the beginning value is the absolute loss.

Relative loss:

$$VaR = E(P) - P^* = -P_0(R^* - \mu) \tag{3}$$

Absolute loss:

$$VaR = P_0 - P^* = -P_0 R^* \tag{4}$$

$$1 - a = \int_{p^*}^{+\infty} f(p)\,dp \tag{5}$$

The value of P^* is called the quantile of the distribution, which is the critical value of excess using a fixed probability of being exceeded [6]. This method works for any distribution, whether continuous or discrete, thick-tailed or thin-tailed.

4. Simulation Experiment

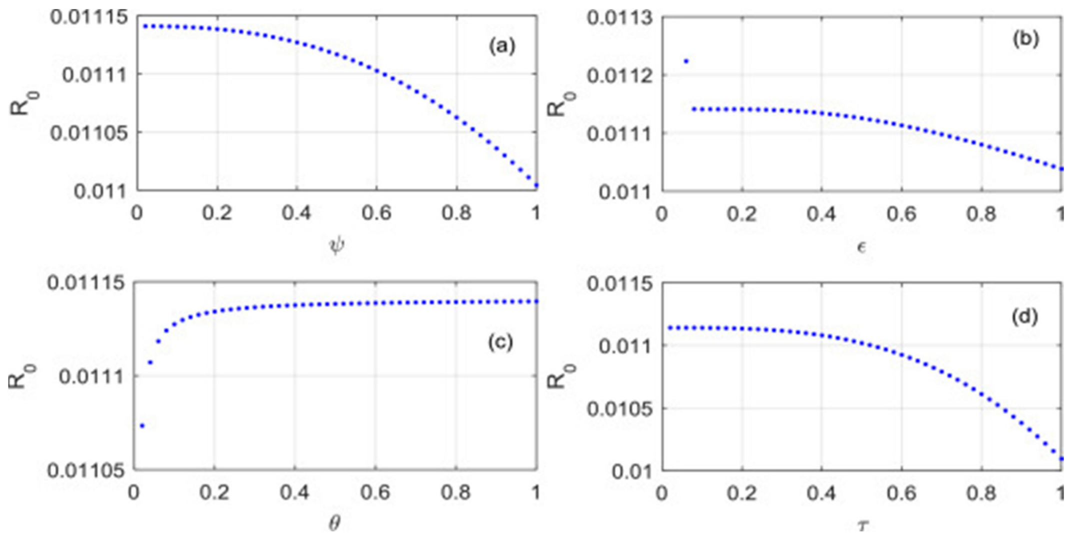

Figure 2. The impact of behavioural factors on credit risk contagion

In order to further describe the law of credit risk contagion and its evolution characteristics, this paper selects three types of networks to conduct simulation experiments according to the network heterogeneity [7]. In this model, investors will randomly choose a simple transition between fundamentalist strategies and noise traders' strategies with a certain probability. The quality of the strategy determines the size of the specific probability. That is to say, the choice of strategy will produce a follow-up effect, and stock investors will follow other investors to choose similar strategies. At the same time, investors also have mixed behaviour. In a certain parameter space, the time-series behaviours of a stock's return in the mixed-equity attractor is similar to the actual return-series behaviours. In particular, the time series and the real return series have partially identical moment properties, egg, both will have positive excess kurtosis, at which point the kurtosis will disappear. Under the influence of factors such as the risk resistance ability of financial market regulators, the monitoring intensity of financial market regulators, and the characteristics of network structure, the changes in the scale of individuals infected by credit risk over time are shown in Figure 2.

(1) In the BA network, most individuals have a small number of directly related connection edges, the speed and opportunity of mutual communication or information dissemination between individuals are relatively small, and the inhibition of credit risk contagion is high. The speed is relatively slow. (2) The ability of individual risk resistance and the intensity of financial market supervision have a strong inhibitory effect on the contagion of credit risks. Moreover, this inhibitory effect was most significant in the BA network and weaker in the WS network. This is because most individuals in the BA network have few directly related connection edges, and a small force can exert a strong inhibitory effect on the transmission of information and fear on the network. However, in the WS network, there are relatively many directly related connecting edges and high similarity between individuals, and it is difficult for weak forces to exert a large inhibitory effect on the network.

5. Conclusion

In an incomplete financial market, the credit risk contagion system has a unique positive equilibrium point, and the scale of credit risk contagion is a monotonically increasing concave function of the degree of correlation between individuals, risk attitudes and the influence of credit events, it is a monotonically decreasing convex function of the regulatory strength of the financial market and the individual's risk resistance.

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