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Research Article

An E-Commerce Economic Dynamic Data Evaluation Model Based on Multiuser Demand Constraints

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Forecasting the future earnings of listed companies based on multiuser constraints is the focus of investors, securities dealers, creditors, and management. Some empirical studies at home and abroad indicate that the financial reports issued by listed companies regularly contain information about future changes in earnings. On this basis, this article uses the Bayesian dynamic regression model to predict the changes in the future earnings of listed companies and compares the results with traditional analysis models. Through case analysis, it can be seen that the prediction effect of the Bayesian dynamic regression model is generally better than that of the traditional regression model. The Bayesian model can better predict the results, and through the prediction results, it can also establish an evolutionary game model of the industrial innovation replication dynamic system, which can assist enterprises in making profit decisions.

1. Introduction

The sustained profitability of a company in the future is a common concern among investors, securities firms, and creditors because only a company with sustained profitability can bring sustained dividend returns to investors. The most important and direct information that ordinary investors can get about the operating conditions of listed companies comes from the financial reports that listed companies publish regularly. Therefore, from the standpoint of ordinary investors, the following questions are worth studying. Do these financial reports contain information about the company's future profitability? If the answer is yes, can we find a better way to use this information to achieve better forecasting results [1]?

The results of scholars at home and abroad have answered the first question in a positive way. For example, we select 68 variables from the financial reports of listed companies in the United States and build a Logit regression model around the probability of earnings growth in the next year. We find that Pr is positively correlated with future earnings changes. Or nine of the basic signals commonly used by analysts are selected as predictors, and the linear regression model of cross-sectional data is used to examine their ability to predict future earnings. The analysis results also show that this prediction ability exists [2].

In China, there are also research studies on the usefulness of surplus figures in China's stock market and so on. It is generally believed that the company's current profit information is contained in the stock market price, but for long-term investors (holding more than one year of stock), it is important to look ahead. In addition to the winning figures, financial reports contain a large number of data describing the company's operating conditions. With sufficient credibility, these data should provide investors with information about the company's future profitability. This paper analyzes the annual reports of listed companies in the A-share market by using foreign scholars' methods and draws a similar conclusion: the information provided by the financial reports of listed companies can be used to predict the future profit changes of listed companies [3]. However, whether we can find a better way to use these information to obtain better prediction results is the problem to be studied in this paper. The ARMA model, exponential weighted model, and Bayesian dynamic regression model are commonly used in the economic field [4]. Compared with the mature stock markets of Western developed countries, China's stock market

(represented by the A-share market) is an emerging and developing capital market. Its main characteristics are as follows: short history, large changes (expanding scale, changing policies), and less information disclosure (except annual reports, the history of the Chinese stock market is very short, and there is no quarterly report so far) [5], not standard enough. Based on the above reasons, we believe that the ARMA model and the exponential weighted model will not have very good prediction results because both models require a long history and more stable data. The Bayesian dynamic regression model has the following advantages. First, the dynamic model assumes that the model parameters change with time, which is in line with the actual situation of the stock market. Secondly, based on the Bayesian view, the main feature of the dynamic model is to modify the distribution of model parameters according to all the past information (i.e., prior information) and the current data, obtain a posterior distribution, and then predict the future from the posterior distribution. As this correction is carried out over time, it can better simulate the stock market movement, so it is expected to get better forecasting results [6].

The rest of this paper is organized as follows. Section 2 discusses the Bayesian estimation model, followed by the empirical analysis of the Bayesian estimation model in Section 3. To the domestic city, a certain financial revenue forecast analysis is discussed in Section 4. Section 5 concludes the paper with a summary and future research directions.

2. Bias Model

The main formulas of the Bayesian estimation model are Formulas (1)–(3), Formula (1) is the observation equation, Formula (2) is the equation of state, and Formula (3) is the initial prior state. y_t is the observed value vector of the predicted variable at time t, F_t is the observed value matrix of the predicted variable at time t, t is the parameter vector of the linear regression model at time t, v_t is the normal zero mean error term, and v_t is the variance [7, 8]. Different from the traditional static linear regression model, the model parameter vector theta t is regarded as a random variable in the dynamic linear regression model, which changes with time. In the equation of state, it is assumed that theta t has a variation W_t with respect to theta $t-1$, and its distribution is normal, zero mean, and variance W_t. It is assumed that the observation and state error sequences ($\{V_t\}$ and $\{W_t\}$) are independent of each other and that the T variables are independent of each other at different times within each sequence. When $W_t = 0$, the state equation degenerates to an identity, and the dynamic linear regression model degenerates to a static linear regression model [9–11]:

$$y_t = F_t\theta_t + v_t, \quad v_t \sim N[0, V_t], \tag{1}$$

$$\theta_t = \theta_{t-1} + w_r, \quad w_r \sim N[0, W_t], \tag{2}$$

$$(\theta_0 \mid D_0) \sim N[m_0, C_0]. \tag{3}$$

The information set D_t at any time t is

$$D_t = \{y_t, F_t, D_{t-1}\}, \tag{4}$$

where D_{t-1} is the set of information at time $t-1$, and $\{Y_t, F_t\}$ is the current data. Firstly, the prior distribution D_{t-1} is obtained, then the predictive distribution Y_t/D_{t-1} is obtained, then the posterior distribution D_t is obtained, and finally, the predictive distribution Y_{t+1}/D_{t-1} is obtained. The above process continues over time [12].

Push the correction. When the observed variance V_t is known, the recurrence formula is as follows [13–15]:

The posterior distribution of $T-1$ moments:

$$(\text{theta}_{T-1}\, xD_{t-1}) \sim N[M_{T-1}, C_{t-1}]. \tag{5}$$

The a priori distribution of T moments:

$$(\text{theta}\, t \mid D_t - 1) \sim N[a_t, R_t]. \tag{6}$$

The $T-1$ moment prediction distribution:

$$(Y_T, D_{t-1}) \sim N[f_t, Q_t]. \tag{7}$$

The posterior distribution of T moments:

$$(\text{theta}\, t \mid D_t) \sim N[M_T, C_t], \tag{8}$$

where

$$\left\{\begin{array}{c} A_1 = M_T - 1 \\ R_t = C_t - 1 + W_T \\ F_t = F_t{}' a_t \\ Q_t = F_t{}' R_t\, F_t + V_T \\ E_t = Y_t - f_t \\ A_t = \dfrac{F_t R_t}{Q_t} \\ M_t = mT + 1 + A\, tet \\ C_t = R_t - A_t A_t{}' Q_t \end{array}\right\}, \tag{9}$$

where W_t is difficult to set, so R_t is usually determined by the discount method.

$$R_t - 1 = \text{delta}\, C_t - 11, \tag{10}$$

where delta is a discount factor, $0 < \text{delta} < 1$. That is, the prior accuracy is equal to the last posterior precision of the discount. By selecting different values, the best prediction model can be selected. When the observed variance V_t is unknown, a certain prior distribution should be assumed for V_t, and the model parameters are corrected recursively. The accurate distribution of the model parameters is t distribution [16].

Table 1: The forecasting variable.

Number	Variable	Formula
1	Stock	Inventory difference − difference in main business income
2	Accounts receivable	Data net accounts receivable − data main business income
3	Maori	Data main business revenue − data main business profit
4	Consumption and management costs	Data consumption and management expenses − data main business income
5	Allowance for bad debts	Data accounts receivable − data for bad debts
6	Real tax rate	Current pretax income ∗ (last year's effective tax rate − current effective tax rate)
7	Turnover of total assets	Current main business income ∗ 2/(fixed assets plus fixed assets in the previous year)
8	Asset liability ratio	Changes in pretax earnings ∗ (1 − effective tax rate in the previous year)
9	Turnover of fixed assets	Log (total assets)
10	Data PTE	Inventory difference − difference in main business income

3. Empirical Results

3.1. Prediction Models, Samples, and Variables. The Bayesian dynamic regression prediction model we use is described in the previous section [17]:

$$Y_T = (Y_{1T}, \cdots, y_{nt})'. \tag{11}$$

Subscript 1 to n is the company number, and t is the year [17]:

$$Y_{it} = \text{delta EPS } it + 1 = \text{EPS } T + 1 - \text{EPS } T, \tag{12}$$

where Y_{it} is the observed value matrix of the forecasting variable at time t and theta t is the regression coefficient vector. We should not only directly examine the prediction effect of the Bayesian dynamic model but also compare it with that of the static regression model. The basic data and literature we used are from the annual financial reports of listed companies in Shanghai and Shenzhen A-share markets from 1992 to 1999. In order to predict $T + 1$ years of income, we need to use data from $T - 2$ to $T + 2$ years [18]. The predictor variables are shown in Table 1.

Using the financial reported data for the past eight years, we can predict only four cycles, and the corresponding sample size is shown in Table 2 [19].

3.2. Analysis Results. When the Bayesian dynamic regression model is used to predict, choosing appropriate discount factors can achieve better prediction results. We try different values of delta in fitting and forecasting and find that the best result is when the value of delta equals 0.6 in most cases. We use the percentage of the actual value falling into the prediction interval to measure the prediction effect [20]. The confidence of the prediction interval is 85%, 90%, and 95%, respectively. Table 3 shows the accuracy of prediction at the time of delta = 0.6, from which we can see that the prediction effect of the Bayesian dynamic regression model is quite good. That is to say, the accuracy of the actual forecast is higher than the confidence in most cases; only in some cases is it equivalent to the confidence [21].

Table 2: The corresponding sample size (million).

Year	1995–1996	1996–1997	1997–1998	1998–1999
Shenzhen	129	207	345	365
Shanghai	132	231	356	383
Sum	262	435	642	744

Table 3: The accuracy of prediction at the time of delta = 0.6.

Year	1995–1996	1996–1997	1997–1998	1998–1999
Accuracy	98%	93%	93%	93%
95	98%	91%	91%	92%
90	98%	94%	93%	93%
85	98%	95%	95%	96%

Table 4: The results of the comparison.

Year	Index	Static regression model	Bias regression model
Predict 1995	MAD	18.4%	18.4%
1996	MSE	18.9%	18.9%
Predict 1996	MAD	20.3%	16.1%
1997	MSE	51.9%	7.4%
Predict 1997	MAD	21.5%	18.0%
1998	MSE	38.2%	10.9%
Predict 1998	MAD	19.9%	21.0%
1999	MSE	13.4%	19.3%

We use two evaluation criteria to compare the prediction results of the static regression model and the Bayesian dynamic model. One is the mean absolute error MAD = 6. The second is the mean square error MSE = 6. EN is the difference between the predicted value and the actual observed value. The smaller the value, the better the prediction effect. The results of the comparison are shown in Table 4 [22].

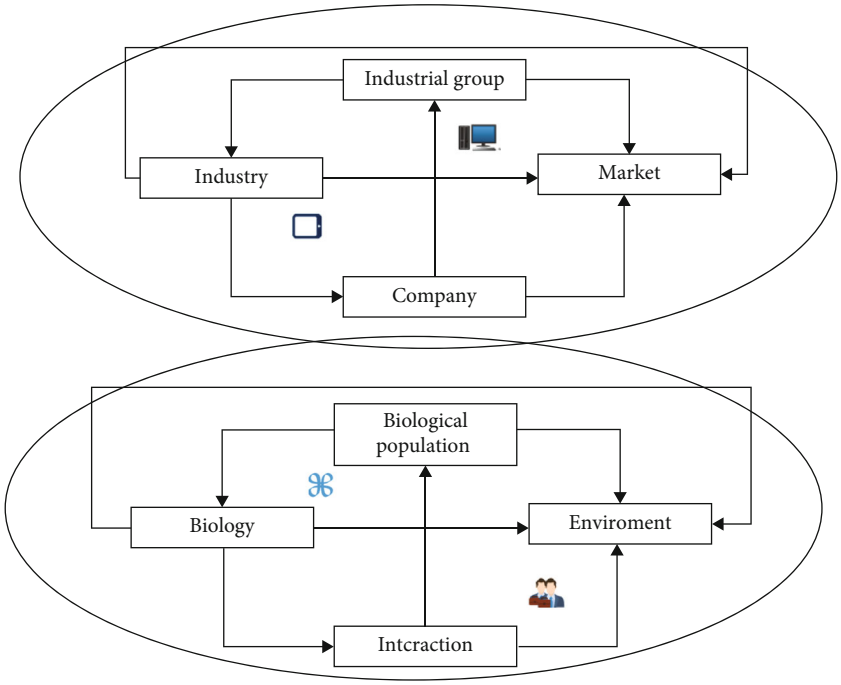

Figure 1: Certain degree of comparability between the industry and biological groups.

It can be seen that in the first forecast year, the prediction effect of the Bayesian dynamic regression model and the static regression model is equivalent. This is because, at the beginning, we have no prior information about the past, so the Bayesian dynamic regression model cannot provide better prediction results. In the next two years, the prediction effect of the Bayesian dynamic regression model is obviously better than that of the static regression model. But when the 1998 data are used to predict the 1999 profit, the prediction effect of the Bayesian dynamic regression model is not as good as that of the static regression model. The reason may be that the deterioration of the macroeconomic situation has led to a greater jump in the performance of listed companies compared with the past. Because the history of the Chinese stock market is very short, the accumulated data is very few, and our research funds and scale are limited, the current research results show the superiority of the Bayesian dynamic regression model in predicting the company's profitability to a certain extent but cannot fully show its full effectiveness [23].

4. Enterprise Innovation and Profit Constrained by Multiuser Demand

4.1. The Evolution of the Industrial Innovation Biological Population. In his 1974 monograph *The Economics of Industrial Innovation*, the British economist Freeman expounded the concept of industrial innovation systematically for the first time. Freeman believes that "industrial innovation" is "innovation" in the "industry." This definition is also the consensus of Western scholars and is basically consistent with the definition of industrial innovation in *The Handbook of Industrial Innovation*. Domestic industrial innovation research is a little late but develops rapidly. Based on the definition of industrial innovation in domestic and foreign works of literature, industrial innovation is defined as follows: industrial innovation refers to the process of technological innovation, product innovation, market innovation, or combination innovation carried out by a single enterprise or several large-scale enterprises jointly to become the common innovation of the whole industry through diffusion or through the enterprise.

The evolutionary game theory studies the repeated games of players in dynamic systems and the equilibrium state of the system. It is named after biological evolution, but it is widely used in economic and social fields. Building an innovative country has become an important strategic decision of our country. The industrial innovation system is a bridge linking the national innovation system and the enterprise innovation system and has important significance.

There are many similarities between the process of strategic choice of enterprises and the process of environmental adaptation of biological individuals. (1) The enterprise strategy is not fixed but is constantly changing in the process of interaction with the market. (2) The corporate strategy is genetically identical to biological genes. This kind of heredity shows that the strategy of enterprises is stable and sustainable in a period of time. (3) Enterprises, like organisms, are bounded rational individuals. Limited rationality of organisms is manifested in their choice behavior of seeking advantages and avoiding disadvantages and learning imitation behavior to a certain extent. The limited rationality of enterprises is rooted in the rapid change of the market environment. The completely correct and forever correct enterprise strategy is impossible to exist; the choice of the enterprise strategy is also a process of trial-and-error learning.

The industry is a collection of enterprises with similar attributes, and there is a certain degree of comparability

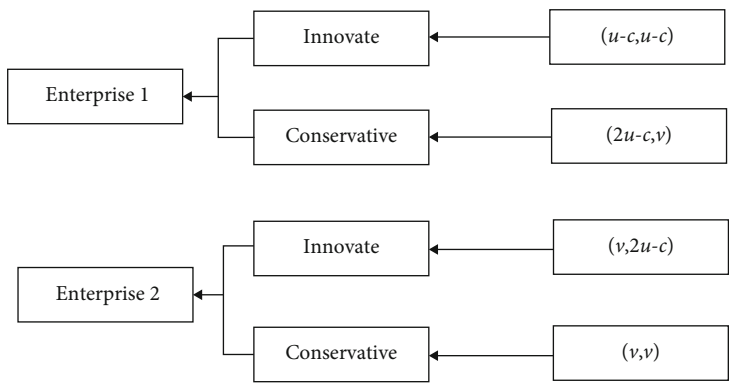

Figure 2: The matrix representation of the random pairing game.

between the industry and biological groups as shown in Figure 1. Therefore, the innovation process of the industry is similar to the evolution process of the biological population. This is the core idea of this article. The construction of the mathematical model and the analysis of the evolutionarily stable state are the core parts of this paper, which involve the evolutionary game theory, replication dynamic mechanism, dynamic system, and other theoretical knowledge.

4.2. Characteristics of Industrial Innovation under Demand Constraints. If there are demand constraints in the industry, the benefits of the enterprise innovation strategy will decrease with the increase of innovative strategy users. Taking product innovation as an example, suppose an enterprise launches a new product (product innovation), which can better meet the needs of consumers, and consumers rush to buy. The enterprise can set a higher price for the product and get excess profits. When other enterprises see that the product is profitable, they will turn to the production of the product so that the supply of the product substantially increased, and the demand for the product is limited; that is, there is a demand constraint; when the product supply exceeds demand, the price will fall, and the profits of enterprises will also be reduced. The greater the supply of products, the greater the price declines.

This phenomenon is very common in the mobile phone industry. The world's first mobile phone, Motorola's Motorola DynaTAC 8000X, was priced at $3,995. At such a high price, mobile phone manufacturers can get the excess profits brought by innovation. As the technology spreads or other companies innovate and acquire it, the number of mobile phone manufacturers increases, leading to a sharp drop in the price of mobile phones, resulting in a decrease in innovative profits. Innovations in products such as color-screen phones and camera phones have also experienced the same decline in profit margins.

4.3. The Basic Assumptions of the Model. The profit of the innovation strategy is greater than that of the conservative strategy. If the innovation strategy cannot do this, we can hardly call it innovation; gamers can only use the pure strategy; this assumption is made because the implementation of the hybrid strategy is often very complex; enterprises have the same size. This assumption is to facilitate research; the group size is large; that is, the number of players is n to infinity.

Suppose an industry is made up of n enterprises. In such an industry, 22 enterprises conduct repeated games with random pairing. Each enterprise can adopt two strategies (hereinafter referred to as strategies), that is, innovative management s1 and conservative management s2. If two enterprises adopt the conservative management strategy at the same time, they share the benefits of $2V(V > 0)$ equally. If two firms adopt an innovative strategy at the same time, they share the benefits of $2U(2U > 2V > 0)$ equally. At the same time, each firm must bear the cost of innovative operation (e.g., the cost of purchasing new equipment because of the original mechanical equipment eliminated by innovation). If an enterprise adopts the innovation strategy [8, 9], the other enterprise adopts the conservative strategy. The enterprise that adopts the innovation strategy obtains $2u - c$. The conservative enterprise still obtains v. The matrix representation of the random pairing game is shown in Figure 2.

It is assumed that the proportion of N in the total number of enterprises in the industry is X after adopting the innovation strategy s1. Because $N >$ infinity, X can be regarded as a continuous variable. Through calculation, we get

$$\frac{Dx}{dt} = x(\mathrm{PI}_1 - \mathrm{PI})(\mathrm{PI}). \tag{13}$$

To represent the average benefit of the strategy, the substitution ofPI_1, PI_2, and $\mathrm{PI}(1)$ is

$$\frac{Dx}{dt} = x(\mathrm{PI}_1 - \mathrm{PI})'' = x\left[''(2u - c - V) - ux\right]. \tag{14}$$

Formula (14) replicates the dynamic equation of $d_y n, i, e$. The point of $d_t d_x = 0$ in the dynamic equation, where $x = 0$, $1, 2u - c - vu$, and the evolutionarily stable state and the evolutionarily stable strategy of the "dynamic system of industrial innovation replication" are obtained.

4.4. Dynamic Equilibrium Analysis of Industrial Innovation Replication under Demand Constraints. It has been pointed out in the summary that when demand constraints exist, the benefits of adopting innovative strategies in industrial innovation will decrease with the increase of innovative adopters.

Under the analysis framework of Section 2, the mathematical expression of the requirement constraint $U(x)$: $(0 < x < 1)$ is a continuously decreasing function in the domain $[0, 1]$. By substituting $U(x)$ into the formula, the dynamic equation of replication under demand constraints is obtained:

$$\frac{Dx}{dt} = x(1-x) * [2U(x) - c - v] - U(x)\, x+ = F(x). \quad (15)$$

The fixed point of the equation is all x satisfying $F(x)$, which is expressed as

$$\begin{gathered} X = 0, 1, \\ X * x|2U(x) - c - v] - U(x)x = 0+. \end{gathered} \quad (16)$$

The following is the obtained function through analysis:

$$G(x) = [2U(x) - c - v] - U(x), \quad (17)$$

where x is continuously monotonically reduced in the interval $[0, 1]$, and the maximum and minimum values are

$$\left\{ \begin{array}{c} \text{Max } G(x) = 2U(0) - c - V \\ \text{Min } G(x) = U(1) - c - v \end{array} \right\}. \quad (18)$$

At the same time, according to the properties of continuous monotone functions, if

$$G(x) = [2U(x) - c - v] - U(x)x = 0, \quad (19)$$

there is a solution in the interval $[0, 1]$, and there is only one solution.

It is assumed that $X-$ is a solution of $[2U(x) - c - v] - U(x)x = 0$, and 0 is less than $x_{-1} = 1$, that is,

$$\begin{gathered} [2U(x-) - c - v] - U(x-)x- = 0, \\ \left\{ \begin{array}{c} \dfrac{Dx}{dt} = x(1-x) * [2U(x) - c - v] - U(x)x+<0 \\ \dfrac{Dx}{dt} = x(1-x) * [2U(x) - c - v] - U(x)x+>0 \end{array} \right\}. \end{gathered} \quad (20)$$

Therefore, we can get the phase diagram of the $x-$ point replication dynamic system, as shown in Figure 3.

It can be seen from Figure 3 that if the perturbation occurs to the right of $x-$, the system will automatically recover to the $x-$ point and vice versa. Therefore, $x-$ is a gradual stable state of replication of dynamic systems, that is, evolutionary stability. The evolutionary stability of the "industrial innovation replication dynamic system" under demand constraints is discussed below.

When $x-$ is $(0, 1)$, according to the above analysis, $x-$ $(0, 1)$ is the stable state of the replication dynamic system.

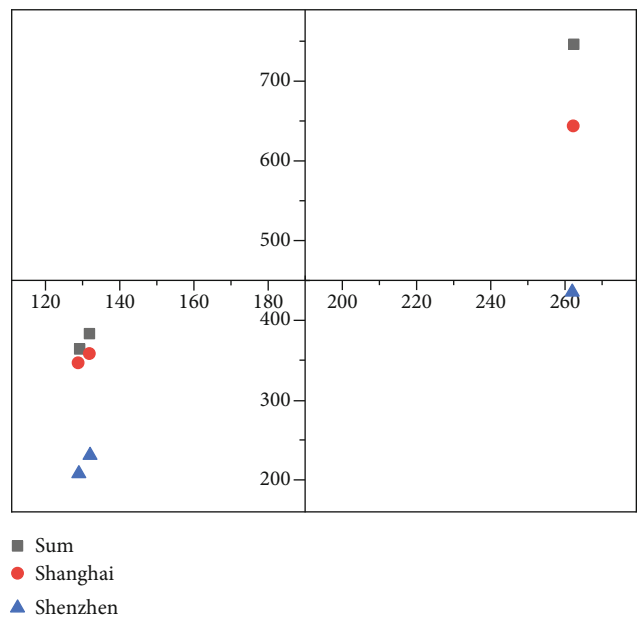

Figure 3: The phase diagram of the $x-$ point replication dynamic system.

When $x- = 0$ or 1 is based on the above analysis, $x- = 0$ or 1 replicates the steady state of the dynamic system.

There is no solution when

$$G(x) = [2U(x) - c - v] - U(x)x = 0 \text{ is in } [0, 1]. \quad (21)$$

The following two parts are discussed:

$$\left\{ \begin{array}{c} \max G(x) = 2U(0) - c - v < 0 \\ F(x) = x(1-x)G(x) \\ \dfrac{Dx}{dt} = x(1-x)G(0) = 0 \\ F(0+) = \lim x \text{ to } 0+ \\ F(x) = \lim x \text{ to } 0+ \\ X(1-x)[2U(0+) - c - v] < 0 \\ F(0-) = \lim x \text{ to } 0- \\ F(x) = \lim x \text{ to } 0- \\ X(1-x)[2U(0-) - c - v] > 0 \\ \text{Also } \max G(x) = 2U(0) - c - V \\ O \min G(x) = U(1) - c - v < 0 \\ \%F(1-) = \lim x \text{ to } 1- \\ F(x) = \lim x \text{ to } 1- \\ X(1-x)[U(1-) - c - v] < 0 \\ F(1+) = \lim x \text{ to } 1+ \\ F(x) = \lim x \text{ to } 1+ \\ X(1-x)[U(1+) - c - v] > 0 \end{array} \right\}. \quad (22)$$

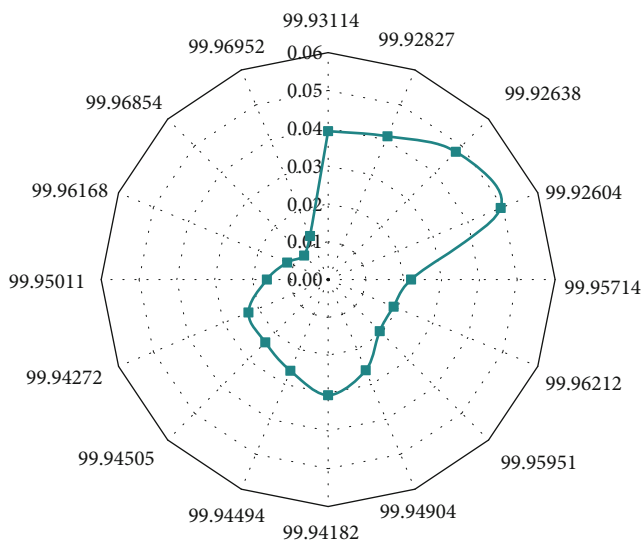

Figure 4: $x = 0$ is the equilibrium point for replication of dynamic systems.

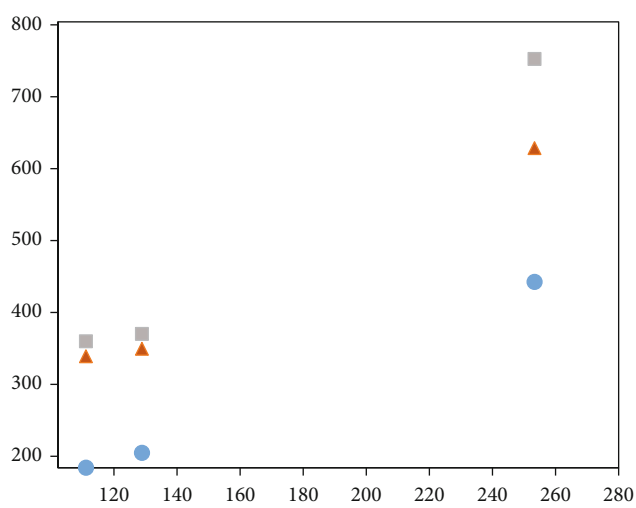

Figure 5: $x = 1$ point is the evolutionarily stable state of the replicated dynamic system.

The phase diagram of the evolutionary replication system is shown in Figure 4. Figure 4 shows that $x = 1$ is the equilibrium point for replication of dynamic systems.

The analysis procedure is similar to (1), get $F(1-) > 0$, $F(1+) < 0$, and $F(0-) < 0$. Therefore, the phase diagram of the replication system is shown in Figure 5. Figure 5 shows that the $x = 1$ point is the evolutionarily stable state of the replicated dynamic system [21–23].

In the process of simulation analysis, this paper takes a certain financial revenue of some domestic large- and medium-sized cities as the basic sample for analysis and research. Specific raw data are shown in Table 5.

It is clearly evident from Table 5 that with the passage of time, the fiscal revenue of this industry in major cities continues to increase, which also indicates that the user demand of this industry increases and the government needs to focus on this industry.

Table 5: The corresponding sample size (million).

Year	2005	2006	2007	2008
Shenzhen	136	215	345	369
Shanghai	132	231	349	378
Beijing	156	266	384	410
Guangzhou	145	236	365	385
Hangzhou	144	240	362	388
Nanjing	150	223	359	379

Table 6: Revenue forecast (million).

Year	2009	2010	2011	2012
Shenzhen	421	486	520	569
Shanghai	416	498	510	536
Beijing	409	536	540	596
Guangzhou	415	489	526	568
Hangzhou	411	485	496	529
Nanjing	408	480	526	544

The Bayesian estimation mentioned in this paper is adopted to forecast and analyze the fiscal revenue of big cities, and the results are shown in Table 6.

We compared the predicted data with the actual data from 2009 to 2012 and analyzed the error and got the error curve as shown in Figure 6.

It is clearly evident from Figure 6 that the predicted results of the Bayesian estimation model basically conform to the trend of data, which is an important data support for some conventional data prediction.

It is clearly evident from Figure 7 that the prediction results of the Bayesian estimation model are very good. The predicted results are in line with the actual results, and the errors are within the range of the theory.

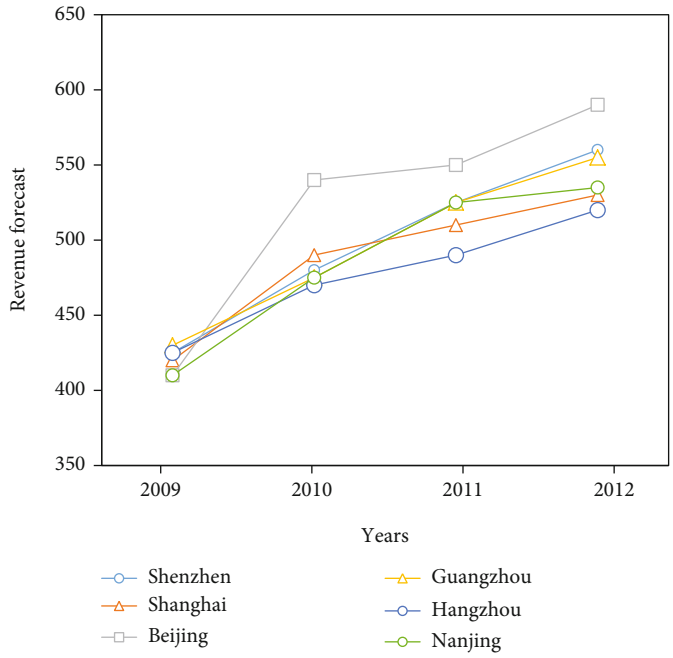

Figure 6: Revenue results.

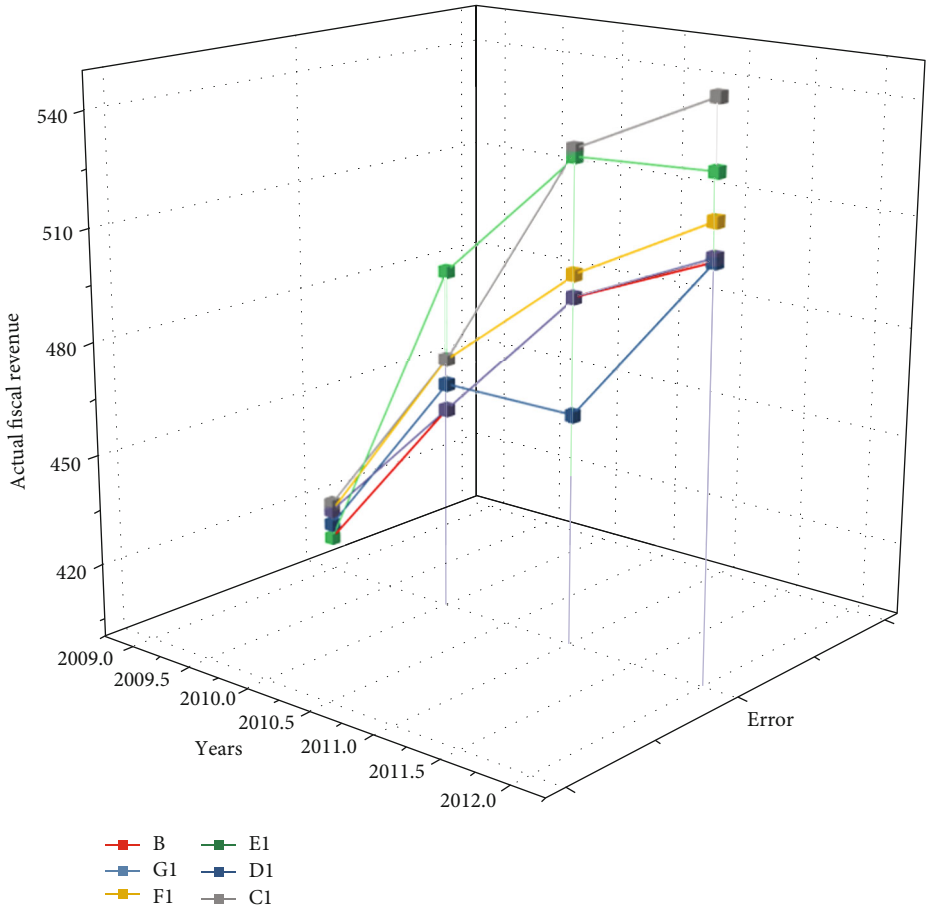

Figure 7: Comparison of error curves of financial revenue.

5. Conclusion

The forecast of the future earnings of listed companies is not only a forecast of the future development of the national economy but also a focus of investors. Through the Bayesian dynamic regression model, the information provided by the annual financial report of the listed company's A-share market is used to predict the company's future profit changes and achieve better prediction results. Compare the results with the results of the static regression model. The average absolute error and the mean square error are used as the evaluation criteria of the model. Through case analysis, it can be seen that the prediction effect of the Bayesian dynamic model is better than that of the static regression model. However, when the macroeconomic situation changes dramatically, the effect of using the Bayesian dynamic model to predict is worse than that of using the static regression model. The reason is not because of the Bayesian dynamic model itself but because we have not yet been able to introduce macroeconomic changes into the model.

Data Availability

We already included the analysis data in our manuscript.

Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

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