Marketing Strategy of Private Enterprises Based on Bayesian Dynamic Panel Model of Machine Learning Algorithms

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ABSTRACT

Machine learning algorithms have attracted widespread attention in both industry and academia. This article mainly studies the marketing strategy decision-making of private listed enterprises based on Bayesian panel data model. By constructing a Bayesian static panel data model and a Bayesian dynamic panel data model, an empirical analysis was conducted on the debt financing decisions of private enterprises from two aspects: external financial environment and internal governance. The experimental results show that the MC error and standard deviation of parameter estimation for Bayesian static panel data model and Bayesian dynamic panel data model are both very small. This method contains more information, increases observation data and degrees of freedom. This article provides important theoretical guidance for the coordinated development of private listed enterprises and state-owned enterprises. It is conducive to promoting the coordinated development of the entire national economy.

KEYWORDS

Bayesian Template, Dynamic Panel Model, Machine Learning Algorithms, Marketing Strategy, Private Enterprise

In recent years, the development of private listed enterprises has received increasing attention. However, the issue of debt financing has always plagued these enterprises, and how to effectively improve the level of debt financing has become an urgent problem to be solved. This article conducts empirical research on the influencing factors of debt financing of private listed enterprises using Bayesian methods to address this issue. In panel data modeling research, the random effects model is one of the commonly used methods. Considering that the research sample was randomly selected from numerous private listed companies, it is more reasonable to establish a random effects model. Based on Bayesian inference theory, this paper analyzes a panel data model with dynamic random effects of exogenous variables. This model can not only improve the accuracy and precision of parameter estimation, but also better reflect the dynamic evolution process of data. The academic contributions of this article are mainly reflected in two aspects. First, this article systematically studies the factors that affect the debt financing level of private listed enterprises from two aspects: external financial environment and internal financial indicators. Second, this article proposes a new model to analyze

DOI: 10.4018/IJITWE.344834
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the determinants of debt financing in private listed enterprises, namely, a Bayesian dynamic random effects panel data model with strict exogenous variables. And empirical research was conducted on the influencing factors of debt financing of private listed enterprises using this model. The research results have been validated. Specifically, this study found that the debt financing level of private listed enterprises is significantly negatively correlated with the external financial environment, and the debt level of enterprises has inertia. This article provides new theoretical guidance for the research on debt financing of private listed enterprises and also provides a new understanding of the influencing factors of debt financing of private listed enterprises in the academic community, which is conducive to helping enterprises and governments formulate more scientific and effective debt financing strategies.

This article is divided into five parts. The first section of the introduction introduces the main content of the article. The second section elaborates on the impact of the external macro environment on the marketing strategy of private listed enterprises. At the same time, it is pointed out that a panel data model should be established for analysis. Section three introduces marketing theories based on machine learning algorithms. And based on machine learning algorithms, the static panel data model of machine learning algorithms is analyzed. A fixed effect Bayesian model based on machine learning algorithms is constructed. Section four analyzes the experimental results and related analysis based on machine learning algorithms. The fifth section summarizes the entire text. The research results indicate that the debt financing level of private listed enterprises is positively correlated with early debt level, enterprise size, political background of corporate executives, and corporate growth. It is negatively correlated with the external financial environment, company profitability, and short-term solvency.

LITERATURE REVIEW

Machine learning algorithms have attracted much attention from researchers of industry and academia, involving the application of machine learning algorithms. Over the past 40 years of reform and opening up, China has rapidly developed into a world economic and trade power. From the perspective of the global value chain, most of the work undertaken by Chinese enterprises is still low value-added. China's 13th Five Year Plan for National Science and Technology Innovation pointed out that compared with innovative countries and world science and technology powers, China still has a big gap in its original ability. Core technologies in key areas are still under the control of others. Many industries are still at the middle and low end of the global value chain, which is a weak link in China's science and technology innovation. How to seek the scientific and technological innovation path of Chinese enterprises and cultivate some world-class advanced manufacturing clusters is a high-end concern in China's current industry.

With the trend of economic and financial globalization and investment liberalization gradually strengthening, the economic, political, and social environments of various regions (countries) are increasingly closely linked (Mahesh, 2020). Economic activities such as capital flows, international trade, and technology spillovers have greatly increased the economic dependence of countries (Taha et al., 2023). Therefore, when studying the economic behavior of a region, the impact of economic behavior of other regions should be considered at the same time (Pires, 2023). Topler's first law holds that "everything is related, and things that are close to each other are more related than things that are far away" (as cited in Thalita et al., 2023,p.6). Based on this, it is very important to properly introduce the spatial dependence among regions into the regression model. At the same time, in the study of practical problems, researchers often pay more attention to both ends of the conditional distribution of dependent variables than the average impact of independent variables on dependent variables. Georgiou (2023) pointed out that high concentrations of pollution have a more serious impact on human beings and ecosystems. Therefore, it is essential to study this group of countries to formulate effective environmental protection policies. Quantile regression theory can provide strong support for solving this problem. However, most of the existing literature often only considers one aspect.

Information economics, contract economics, and principal-agent theory are widely used in the field of enterprise financing research (Georgiou, 2023). These theories mainly study the changes of corporate financing structure and the impact of different financing methods on corporate performance, cash flow, and corporate internal governance (Alabdullah & Naseer, 2023). Comparatively speaking, there is less research on the marketing strategy decision-making of enterprises, which makes it an urgent area to be improved in the empirical research of enterprise financing. China's economy is in a rapid transition period. With the increasingly open economy and increasingly fierce competition at home and abroad, both the external environment and the internal governance structure of enterprises are undergoing tremendous changes. China's market economy has been transformed into a planned economy. The traces of planned economy, such as administrative approval and government intervention, formed over a long period of time, have a great impact on private listed enterprises. Moreover, the formation of China's market economy is relatively short, and many aspects are not perfect, which aggravates the impact of the external environment on the marketing strategy decisions of private listed enterprises. The private economy has only developed in recent decades. Due to the restrictions of the institutional environment and market environment, compared with the public economy, the development of private enterprises is more vulnerable to the impact of the external macro environment. Therefore, it is of great practical significance to study the impact of the external macro environment on the marketing strategies of private listed enterprises. However, the following problems exist in the research on the marketing strategy decision-making of private listed enterprises:

1. It only studies the influence of internal governance on marketing strategy but does not study the marketing strategy in combination with the external macro environment. The enterprise's marketing strategy is not only affected by the enterprise's internal financial strength, but also by the maturity of the external macro financial environment, which affects the enterprise's operating performance. Therefore, it is not perfect to ignore the external macro financial environment and only consider the influencing factors of marketing strategies from within the enterprise, which may lead to incorrect conclusions.
2. Cross section (time series) data are used to build the model, and the data characteristics of samples in time series (cross section) cannot be analyzed. The panel data integrates sectional data and time series data, so it can better identify and measure the influencing factors that cannot be found in pure sectional data or time series data, ensure the unbiased estimation results, and analyze marketing strategy problems from multiple levels.

Due to the complexity and variability of economic activities, researchers often face the problem of high-dimensional numerical calculation when building panel data models. However, the existing panel data numerical calculation methods are difficult to effectively solve high-dimensional integration and other numerical calculation problems, which hinders the development of panel data model research. Bayesian analysis theory and Markov Chain Monte Carlo (MCMC) sampling algorithms provide tools and methods to solve high-dimensional numerical calculation problems. Bayesian analysis adds prior information to the model, which can further improve the accuracy and precision of model parameter estimation. The studies in this paper provides an important theoretical guidance to machine learning algorithms.

RELATED MATERIALS AND METHODS

Overview of Marketing Related Theories Based on Machine Learning Algorithms

Through machine learning algorithms, Porter's five forces analysis model in the early 1980s included suppliers' opinions, price ability, bargaining power of buyers, ability of potential competitors to enter, ability of substitutes, and current competitiveness of competitors in the industry (as cited in Alshurideh et al., 2023). The changes in the industry's profit potential are ultimately affected by the different combinations and changes of these five forces. Porter's analysis model has a broad and far-reaching impact in the field of enterprise strategy formulation (Ahmad Sobri et al., 2023). At the same time, it is also widely used in competitive strategy analysis, especially global strategy analysis, and it can also make a more effective and feasible analysis of the competitive environment. Porter's model contains some different factors in a simple model, which can be used to analyze the basic competitive situation of the industry (Llorente et al., 2023). Porter's model corresponds to five main sources of competition, namely, the bargaining power of suppliers, bargaining power of buyers, threat of new entrants, threat of substitutes, and degree of competition of competitors in the same industry (Wang et al., 2023). Whether a strategy is feasible requires testing and confirming the five sources. The characteristics and importance of different sources will vary with different industries or companies.

The bargaining power of suppliers. If suppliers want to affect the profitability of existing enterprises in the industry and the competitiveness of products, they generally achieve this by improving the price of input factors and reducing the quality of unit value (Ramli et al., 2023). However, what input factors it provides to the buyer can mainly determine the strength of the supplier in the competition. When a large part of the total cost of the goods the supplier needs to purchase is occupied by the value of the input factors it provides, at the same time, it has a very important impact on the production process of the buyer's products, or it has a serious impact on the quality of the buyer's products. The potential bargaining power of the supplier for the buyer's product price increases significantly.

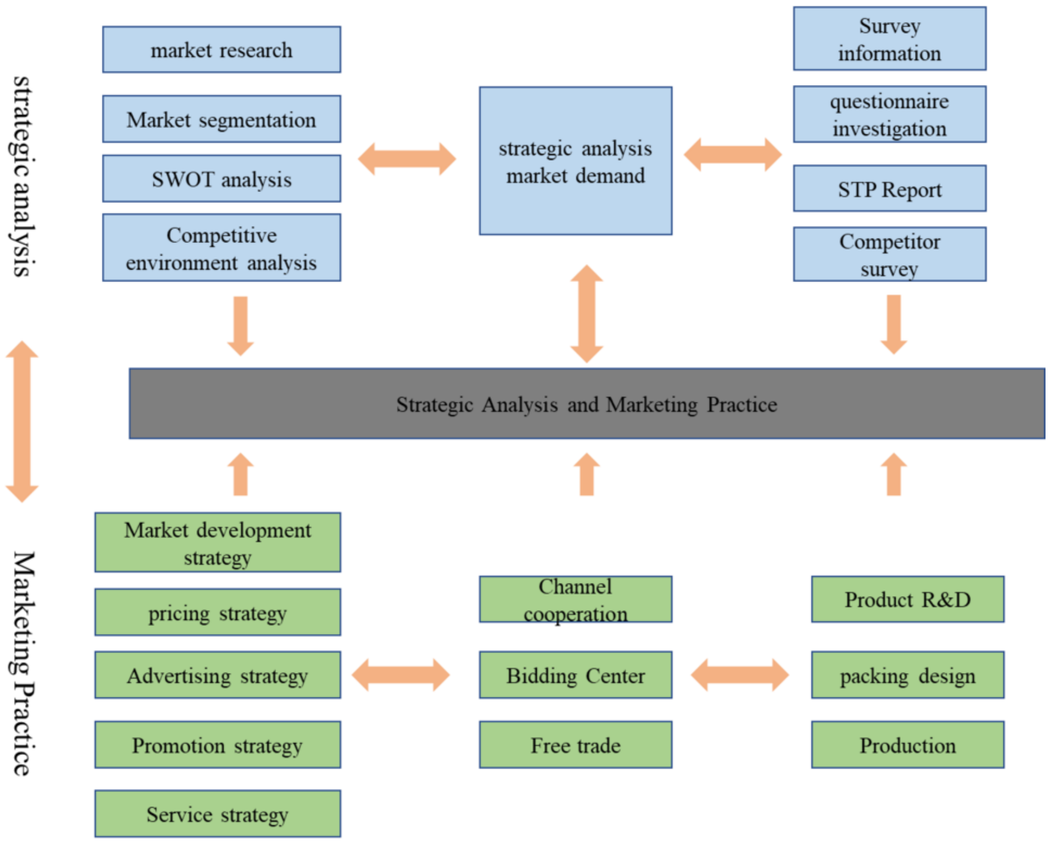
The bargaining power of buyers and ways that buyers can affect the profitability of existing enterprises in the industry mainly include the ability to lower prices and require suppliers to provide relatively high-quality products or services (Bull et al., 2023). Generally speaking, if the buyer meets the following series of conditions, it may have strong bargaining power:

1. In the industry where the supplier is located, the number of buyers is relatively small, a single buyer will buy more, and the purchase volume of a single buyer accounts for a higher proportion of the total sales volume. There are many members in the seller's industry, and they are basically small enterprises with relatively small scale.
2. The commodities provided to shoppers by the supplier's industry are basically standardized products with high substitutability. For buyers, if they buy products from multiple sellers at the same time, it is completely feasible in terms of economy, aspect, and method.
3. For the buyer, if it is large, it is more likely to achieve backward integration, but for the seller it may not be able to achieve forward integration.

The obstacles that new enterprises will encounter can be diversified, mainly including macro-control or a series of government actions and policies (Barigou et al., 2023). On the other hand, it is not easy to predict the reaction of existing enterprises to new enterprise entrants after entry, which is mainly reflected in the possibility of retaliation. For the possibility of a new enterprise entering an existing industry, the relevant factors are the combination of the potential benefits that the new enterprise entrants hope to obtain after entering the existing industry according to their subjective estimates and their efforts to deal with various competitive barriers and risks, that is, potential peer followers.

In general, the intensification of competition among existing enterprises in the industry is often due to the following situations: There are many competitors, and many competitors enter the industry with few barriers, or the market related to lower products is mature (Howord & Putri, 2023). There is a market for existing products, and it is difficult to replace them in a short time (Sitinjak et al., 2023). In addition, the demand for new products is growing slowly. Competitors try to use vicious price wars to win competitive advantages in the market of the same industry, The product similarity of each competitor is too high or identical, and there is no difference in services, which will cause

Figure 1. Machine Learning Algorithm Based Enterprise Marketing Strategy Process



users to have very low switching costs between products. If only one strategic action succeeds, the revenue it can bring is very objective. The weak enterprises in the industry are merged or supported by powerful enterprises. After entering the industry and entering the market, the main competitors who have taken offensive actions and become the market at one fell swoop have higher exit costs and more obstacles, that is, the cost of exiting the market competition is relatively higher than that of remaining in the market.

Strengths, Weaknesses, Opportunities, Threats (SWOT) analysis is the most commonly used strategic planning analysis tool (Harini et al., 2023). This method was proposed by A. Humphrey; SWOT analysis is the comprehensive analysis method of strength, weakness, opportunity, and danger (as cited in Wuisan & Handra, 2023). It can analyze the competitive situation of enterprises and is also the basic method of marketing analysis (Zhong et al., 2023). By evaluating the strengths, weaknesses, and competitive markets of enterprises opportunities and threats are used to help formulate the development strategy of the enterprise through comprehensive and in-depth analysis of the enterprise and positioning of the competitive situation. Figure 1 shows the enterprise marketing strategy process.

Enterprise Marketing Strategy Analysis and Marketing Strategy Evaluation Method Based on Machine Learning Algorithms

Through machine learning algorithms, in theory politics, economy, society, and technology (PEST) analysis is aimed at the macro environment in which the enterprise is located and analyzes the impact on the enterprise. The development of the enterprise cannot be separated from the impact of the macro environment. Only by determining the external macro environment can the enterprise make strategic decisions (Seshadri et al., 2023). On the one hand, the macro environment of the enterprise includes the national policy environment, and, on the other hand, the industry environment of the enterprise is considered (Zanubiya et al., 2023). In the analysis, the uniqueness of the enterprise itself should also be considered, and the impact of the external environment should be analyzed according to the different goals and needs of the enterprise itself. At present, the macro environment is generally divided into four categories: politics, economy, society, and technology. These four aspects are what we call PEST analysis, which is the most critical factor affecting the external environment of enterprises.

The political environment is a form of social organization. Different countries have different organizational forms. The differences between countries include social systems, the nature of political parties, and relevant policies and regulations. These differences have different impacts on the survival and development of enterprises. They affect the organizational structure, nature of enterprises, development limitations, and other aspects of enterprises. The economic environment is generally considered from two aspects. On the one hand, it is the national economic level (macroeconomic environment), including the national economic level, Gross Domestic Product (GDP) growth rate, population change, per capita income level, and other aspects to illustrate the current state of the national economic environment. On the other hand, the regional economic development level (microeconomic environment) should analyze the per capita income, consumption level, education level, employability, per capita disposable income of families, and living environment. There are many and complex factors affecting the social environment. It is necessary to consider that the educational levels, gender structures, habits and preferences, consumption keys, value driven characteristics, cultural orientations, and other aspects of the local population reflect the characteristics of different groups of people.

In order to further develop enterprise strategic management theory, an American scholar proposed the SWOT analysis method. The proposal of this method has directly promoted people's understanding of strategy to a new height. SWOT analysis is a comprehensive analysis and evaluation of the strengths, weaknesses, opportunities, and threats of an enterprise. This method is often used by scholars to analyze internal resources, competitors, and overall strategy. This method starts from the inside of the enterprise and integrates the advantages and disadvantages of the enterprise environment to form an intuitive two-dimensional matrix to help enterprise managers make better strategic decisions, the internal and external (IE) matrix. That is, on the basis of the analysis of the internal and external environments of a company, a comprehensive analysis of the development of the enterprise is carried out considering a variety of factors to help the enterprise understand the current developmental situation and find out the problems in production and operation. IE matrix has been cited many times. Figure 2 shows the market changes of the e-commerce industry using marketing strategies.

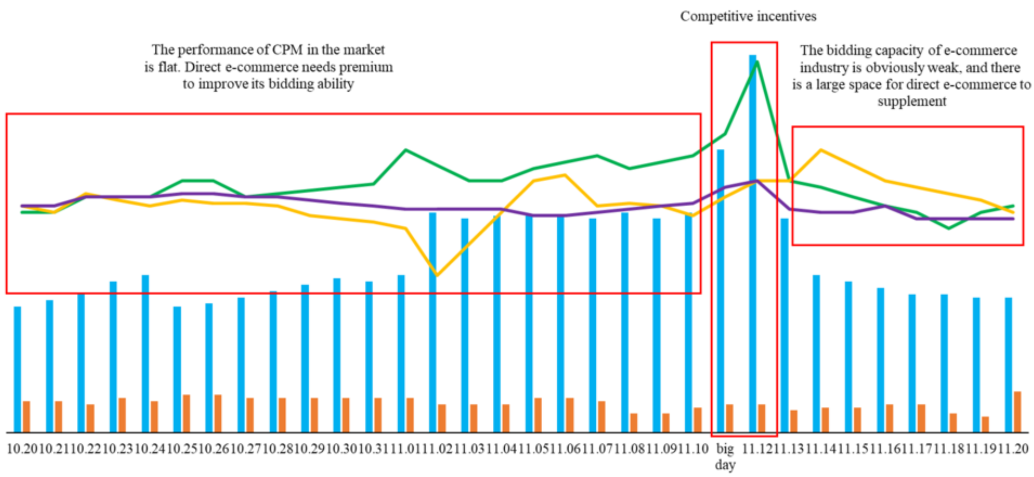
Static Panel Data Model for Machine Learning Algorithms Based on Machine Learning Algorithms

Panel data refers to the data that take multiple sections on the time series, that is, the data that combine the time series data and section data (Rosário & Dias, 2023). The difference between panel data, time series data, and section data is that the variables of panel data have double subscripts. The general expression is shown in Equation (1).

$$y_{it} = \alpha + X_{it}^{'}\kappa + \varepsilon_{it} \qquad 1 = 1,2,\cdots,N; t = 1,2,\cdots,T \tag{1}$$

where i represents an individual, t represents time, x is a constant, K is a constant vector of Kx1 order, and Xit is the ith observation value. Most panel data applications use one-way error component models, as shown in Equation (2).

Figure 2. Machine Learning Algorithm Based Market Changes of E-Commerce Industry Using Marketing Strategies



$$\varepsilon_{it} = \mu_i + v_{it} \tag{2}$$

among μ I represents unobservable individual effects, and vit is a random disturbance term. Equation (1) can be written in the vector form shown in Equation (3).

$$y = \alpha t_{NT} + X\kappa + \varepsilon = Z\delta + \varepsilon \tag{3}$$

where y is a vector of NTx1 order, X is a matrix of NTxK order, Z=[Lnt, X], δ'= (at ', K'), IvT is a vector of NT order whose elements are all 1. Equation (2) can be written in the vector form shown in Equation (4)

$$\varepsilon = Z_{\mu}\mu + v \tag{4}$$

$$u' = \left(u_{11}, \cdots, u_{1T}, u_{21}, \cdots, u_{2T}, \cdots, u_{N1}, \cdots, u_{NT}\right) \tag{5}$$

In the fixed effect model, μ I is a fixed parameter, vit is a random perturbation term, and vit is independent and identically distributed, that is, vit~N (0, σ 3). For all i and t, Xit and vit are independent. The authors substitute Equation (4) into Equation (3) to get Equation (6).

$$y = \alpha v_{NT} + X\kappa + Z_{\mu}\mu + v = Z\delta + Z_{\mu}\mu + v \tag{6}$$

For Equation (6), the ordinary least squares (OLS) method can be used to estimate a, β and μ. Z is NTx (K+1) order matrix, z is (NTxN) order individual dummy variable matrix. When N is large, Equation (6) contains too many dummy variables. Because the matrix dimension of (N+K) dimension is too large, its inverse matrix is difficult to solve, so using OLS will lead to large deviation. At this time, the authors use Q to multiply Equation (6) left and then apply OLS to the converted model to obtain the least squares dummy variable (LSDV) estimate of the parameter. The converted model is shown in Equation (7).

$$Qy = \alpha Qt_{NT} + QX\kappa + QZ_{\mu}\mu + Qv \tag{7}$$

Matrix Q eliminates the individual effect. At this time, the authors allowed for what is shown in Equation (8).

$$\tilde{y} = Qy, \tilde{X} = QX \tag{8}$$

The OLS estimator of Equation (7) is shown in Equations (9) and (10):

$$\tilde{\kappa} = \left(X'QX\right)^{-1} X'Qy \tag{9}$$

$$\mathrm{var}(\tilde{\kappa}) = \sigma_{v}^{2}\left(X'QX\right)^{-1} = \sigma_{v}^{2}\left(\tilde{X}'\tilde{X}\right)^{-1} \tag{10}$$

Equation (11) represents the regression model.

$$y_{it} = \alpha + \kappa x_{it} + \mu_{i} + v_{it} \tag{11}$$

The authors calculate the mean value of all observations according to Equation (11) and the results are shown in Equation (12).

$$\overline{y}_{it} = \alpha + \kappa\overline{x}_{it} + \overline{\mu}_{i} + \overline{v}_{it} \tag{12}$$

F test was used to test the significance of fixed effects, and the original hypothesis was used. OLS is used to regress the mixed model to obtain the constrained residual sum of squares (RRSS), and LSDV regression is used to obtain the unconstrained residual sum of squares (URSS). When N is large, the sum of squares of residuals can be used as URSS by means of intra group mean conversion. At this time, the test statistic is shown in Equation (13).

$$F_{0} = \frac{(RRSS - URSS)\,/\,(N-1)}{URSS\,/\,(NT - N - K)} \sim F_{(N-1),N(T-1)-K} \tag{13}$$

If the regression is estimated within the group of Equation (11), it should be noted that since there are no intercept items and dummy variables in the standard regression model, the estimated value s2 of the random error item is equal to the sum of residual squares divided by (NT-K). However, s * 2 estimated by LSDV from Equation (5) uses the same residual square.

For the intra group estimator, a simple method can be used to test the robustness of the standard deviation. This method needs to calculate the generalized variance covariance matrix of vit. For each individual, the panel data model can be written in the form shown in Equation (14).

$$y_i = Z_i\delta + \mu_i v_T + v_i \tag{14}$$

The matrix form is shown in Equation (15).

$$\begin{pmatrix} y_{i1} \\ y_{i2} \\ \vdots \\ y_{iT} \end{pmatrix} = \begin{pmatrix} 1 & x_{i11} & \cdots & x_{i1K} \\ 1 & x_{i21} & \cdots & x_{i2K} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{iT1} & \cdots & x_{iTK} \end{pmatrix} \cdot \begin{pmatrix} \alpha \\ \kappa_1 \\ \vdots \\ \kappa_T \end{pmatrix} + \begin{pmatrix} \mu_i \\ \mu_i \\ \vdots \\ \mu_i \end{pmatrix} + \begin{pmatrix} v_{i1} \\ v_{i2} \\ \vdots \\ v_{iT} \end{pmatrix} \tag{15}$$

Bayesian Analysis of Fixed Effect Model Based on Machine Learning Algorithms

The fixed effect model of static panel data can be expressed as a model consisting of a matrix composed of explanatory variable X and an individual dummy variable vector, as shown in Equation (16).

$$y_i = X_i\kappa + \gamma_i j_T + \varepsilon_i, \varepsilon_i \left| X_i, \kappa, \varepsilon_i \sim N\left(0, \tau I_T\right)\right. \tag{16}$$

Here, y_i represents the vector of the ith individual with a time length of T, X_i is a matrix of order Txk, κ is a vector of order k, and j_T is a vector of order T with all elements of 1, ε It is a random disturbance term, obeys normal distribution and is unique with X_i , K, γ_i And Ii is the identity matrix of order T. Equation (17) can be expressed in the matrix form as shown including all individuals.

$$y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{pmatrix} = \begin{pmatrix} X_1 & j_T & 0 & \cdots & 0 \\ X_2 & 0 & j_T & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 \\ X_N & 0 & \cdots & 0 & j_T \end{pmatrix} \begin{pmatrix} \kappa \\ \gamma_1 \\ \vdots \\ \gamma_N \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_N \end{pmatrix} \tag{17}$$

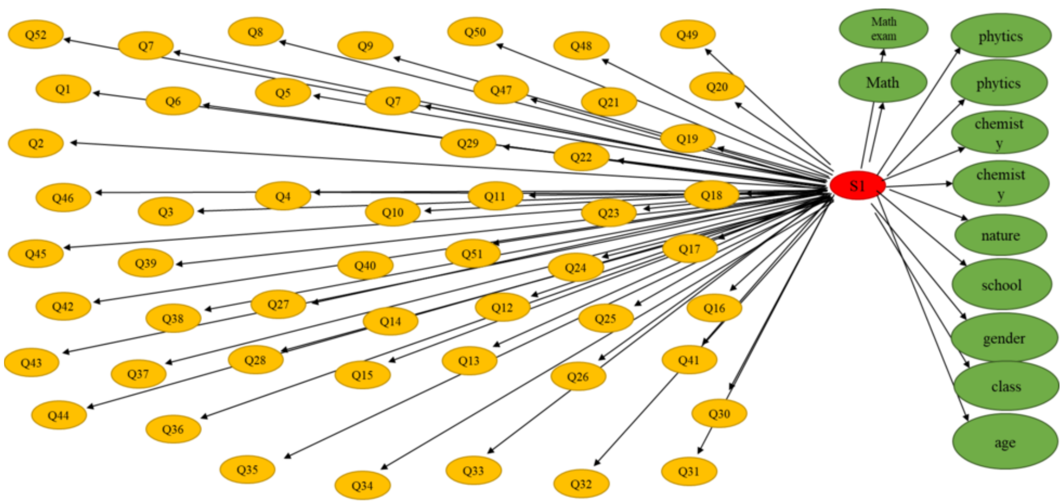
Here, the explanatory variable matrix is NTx (k+N) order, and the coefficient vector is (k+N) order because the fixed effect model assumes individual effects γ I is uniformly distributed, and this assumption is not estimated γ. The mean value of i belongs to a prior distribution without information, that is, the parameter has no constraints. At this time, the posterior distribution of the parameter is almost completely determined by the sampled sample. This setting only applies to parameter information 1 before sampling and applicable when unknown. When some parameter information can be obtained before sampling, it can be added to the prior distribution. Since the posterior distribution and prior information are proportional to the product of the likelihood function, Bayesian inference can be performed. By analyzing the structure of the panel data model, the specific form of the panel data model likelihood function is deduced. On this basis, the prior distribution of each parameter of the model is constructed, and then the posterior distribution of the corresponding parameters is deduced using Bayesian theorem. Figure 3 shows the Bayesian model.

RESULTS AND ANALYSIS

Analysis of Experimental Results

From machine learning algorithms, Monte Carlo (MC) simulation is a method to obtain numerical results through a large number of repeated random samples, so as to simulate and depict the real

Figure 3. Bayesian Model Machine Learning Algorithm



(Wu & Monfort, 2023). With the development of computer technology and the improvement of computing speed, it has been widely used in practical application analysis. Its basic idea: First, set the data generation process according to the model. Second, set a specific distribution for the variables involved in the model to generate random numbers. Finally, according to the set model and the corresponding distribution of model variables, it can be used to estimate the parameters, quantiles, mean square error, MC error, and confidence interval in the statistical distribution.

Small MC error: Small MC error refers to the variance of the results obtained when using MC simulation methods for parameter estimation. MC simulation is a method of approximating certain numerical values or making inferences through random sampling and repeated experiments. The small MC error represents the degree of variation in the estimated results during repeated experiments. Usually, the smaller the error of a small MC, the closer the estimated result is to the true value.

Standard deviation: Standard deviation is a measure of the degree of dispersion of a set of data. In parameter estimation, standard deviation is used to measure the difference between the estimated value and the true value. A smaller standard deviation indicates higher stability and accuracy of the estimation results, while a larger standard deviation indicates higher uncertainty of the estimation results.

Therefore, both small MC error and standard deviation are used to evaluate the reliability and accuracy of parameter estimation results. The small MC error mainly focuses on the variance of MC simulation methods, while the standard deviation measures the overall dispersion of the estimation results.

After an initial value of the parameter to be estimated is randomly given, a new value of the parameter is generated. New values of other parameters are generated according to the new values. In this way, for each parameter to be estimated, a set of generated S values will be obtained. The mean value is calculated as the Bayesian estimate of the parameter to be occupied. According to the parameter significance and maximum likelihood value, the specific types of general spatial econometric models are determined. Then, for the determined type, judge whether it is necessary to further use Bayesian estimation method. For a more comprehensive analysis, this paper simulates the estimation effect of Bayesian spatial econometric model in the presence of positive and negative spatial effects. It can be found that whether in the case of positive spatial effect or negative spatial effect, the posterior estimation results of parameters are good, and the estimated values are close to the true values. According to the symbols of Q0.025 and Q0.975 values, it can be judged that all coefficient values are significantly different from 0 at the 95% level, indicating that all parameters to be estimated are valid.

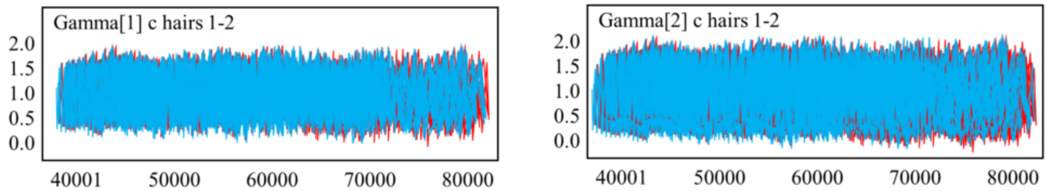
Spatial dynamic panel data model includes both spatial correlation and sequence correlation (Saura et al., 2023). Before model estimation, a key step is to separate spatial correlation and sequence correlation, which is often called "filtering," and then estimate the transformed model (Khan & Al-Ghamdi, 2023).

Through the analysis of the parameters, we can find the factors that affect the debt financing of private listed enterprises in China. As for the parameters in the Bayesian dynamic random effects panel data model β, the MC error of is far less than the standard deviation. This proves the rationality and accuracy of the model. The sign of the posterior mean of the parameters is positive, indicating that these parameters are positively correlated with the asset liability ratio and are consistent with the expected assumptions. When the investment has not realized the maximization of income, failure to repay debts in time will lead to the accumulation of liabilities. Therefore, the current debt level of enterprises with higher debt level in the previous period will also be higher, that is, the debt financing level of enterprises has inertia. The larger the size of the enterprise, the higher the asset liability ratio, which is related to the easy access of large enterprises to the credit support of the state. In addition, the business scope of large enterprises is often relatively wide, and the more funds required for business activities, the larger the amount of loans. Therefore, the larger the enterprise is, the higher the asset liability ratio is.

The MCMC method is a statistical method used to generate random samples, suitable for estimating probability distribution functions and model parameters. The MCMC method generates samples by constructing a Markov chain and uses these samples to estimate the probability distribution function and infer model parameters. Specifically, the MCMC method uses a Markov chain to simulate random walks in the parameter space, where the probability of each state in the next state depends only on the current state rather than the previous state. Each state in a Markov chain is a parameter vector, which is the value we need to estimate or infer. In the MCMC method, we generate a series of parameter vectors through the transition of Markov chains, which are sampled from the probability distribution function. The MCMC method can be applied to many statistical problems, such as parameter estimation, model selection, and Bayesian inference. By generating a series of parameter vectors and calculating their probability distributions, we can obtain information such as the posterior distribution and confidence interval of the model parameters. It should be noted that the MCMC method requires a large amount of computation and sufficient computing resources and time to obtain accurate results. In addition, for high-dimensional parameter spaces or complex models, it may be necessary to use some improved MCMC algorithms, such as the Hamiltonian Monte Carlo method. The MCMC method is a powerful parameter estimation tool suitable for various statistical models and Bayesian inference problems. By correctly applying and interpreting MCMC results, reliable estimates and inferences of parameters can be obtained. The following are the general steps for using the MCMC method for parameter estimation:

1. Determine the model and parameters: First, it is necessary to clarify the statistical model used and the parameters to be estimated. This can be determined based on actual problems, such as linear regression models and mixed models.
2. Building a probability model: Based on the selected model and parameters, construct a complete probability model, including a prior distribution and likelihood function. The prior distribution reflects prior knowledge or beliefs about the parameters, while the likelihood function specifies the relationship between the data and the parameters.
3. Initialize parameter: Set an initial value for the parameter.
4. Sampling: Using the MCMC method, generate a series of parameter sampling values through Markov chains. The most commonly used MCMC algorithms are Metropolis Hastings algorithm and Gibbs sampling algorithm.

Figure 4. Machine Learning Algorithm Aided Static Panel Parameters γ Dynamic Iterative Trajectory



(2.1.a) Dynamic iterative trajectory of γ1 (2.1.b) Dynamic iterative trajectory of γ2

5. Convergence diagnosis: After conducting MCMC sampling, convergence diagnosis is required to ensure that the sampling process has converted to a stable state. Common diagnostic methods include observing trajectory maps of parameters, autocorrelation functions, and Gelman Rubin convergence diagnosis.
6. Parameter estimation: Based on the sampled parameter values, the estimated values and confidence intervals of the parameters can be calculated. Usually, the mean of sampled parameters is used as the parameter estimate.

According to the prior distribution of the parameters set above and based on the Bayesian inference method, the MCMC method is used to estimate the parameters in the model, and 80,000 MCMC sampling iterations are conducted for the parameters. Since the method of randomly generating initial values is adopted, in order to eliminate the impact of initial values on the sampling results, the data sampled in the previous 40,000 iterations are discarded, and the simulation experiment parameters are estimated using the data of the 40,001st to 80,000th iterations. Figure 2.1 shows the parameters γ. From the dynamic iteration trajectory, it can be found that the two Markov chains of parameter y have converged, which shows that the simulation process based on MCMC method is stable. Figure 4 shows the parameters γ. It can be seen from Figure 4 that, except for γ 1 has poor convergence, γ 2, γ 3,γ. The G-R statistic of 4 gradually approaches to 1 with the increase of iteration times, which shows that the sampling method has good convergence.

According to the prior distribution of the parameters set above and based on the Bayesian inference method, the MCMC method is used to estimate the parameters in the model, and 80,000 MCMC sampling iterations are conducted for the parameters. Since the method of randomly generating initial values is adopted, in order to eliminate the impact of initial values on the sampling results, the data sampled in the previous 40,000 iterations are discarded, and the simulation experiment parameters are estimated using the data of the 40,001st to 80,000th iterations. Figure 5 shows the parameters γ. The dynamic iteration trajectories of and K, from the dynamic iteration trajectories, it can be found that the two Markov chains of parameter K have converged, indicating that the simulation process based on MCMC method is stable.

Taking the sales strategy of OLED mobile phones as an example, considering that there is often an unstable period in the early stage of new products' launch, and the fluctuations are large, for the accuracy of the model, the starting point of the BASS model can refer to the starting sequence value that is greater than or equal to pxm, and the data sequence is postponed. Therefore, the starting point sequence should start from 2010 by multiple measurements. Figure 6 shows the comparison between the original data and the fitting value of the model. This paper selects the data simulation values of 20 years from 2010 to 2029, which can clearly show the cumulative sales curve of OLED mobile phones.

During parameter estimation, the number of iterations of MCMC sampling is set to 30,000, and 5,000 instable points in the initial iteration period (burn in) are discarded. In order to weaken the correlation between the data, in the remaining chain, take one every three observations to form a Markov chain with a length of 8,334 with statistics such as parameter estimates, deviations, and

Figure 5. Dynamic Iterative Trajectory of Dynamic Panel Parameters Based on Machine Learning Algorithm

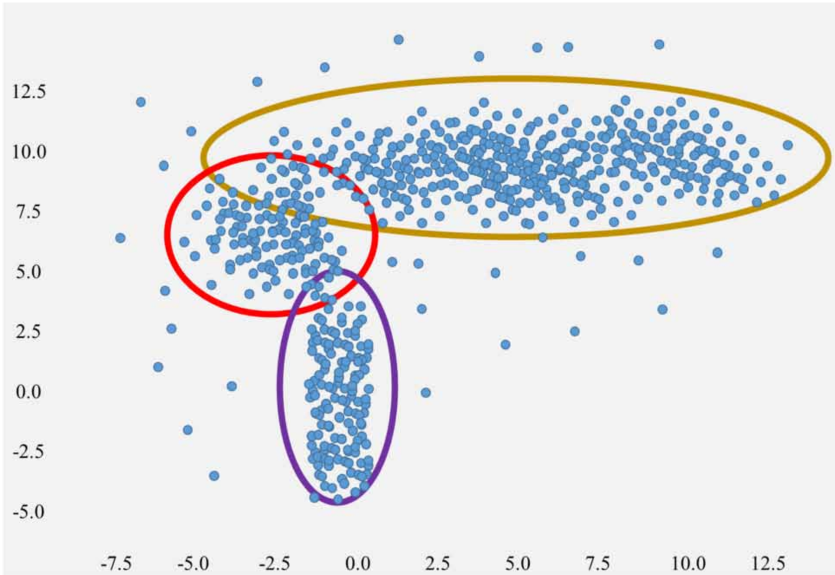
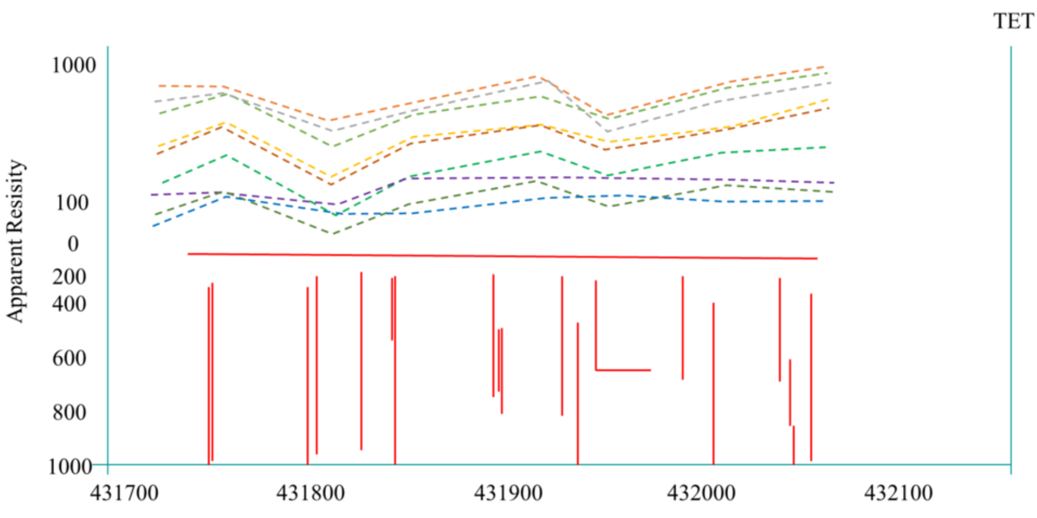
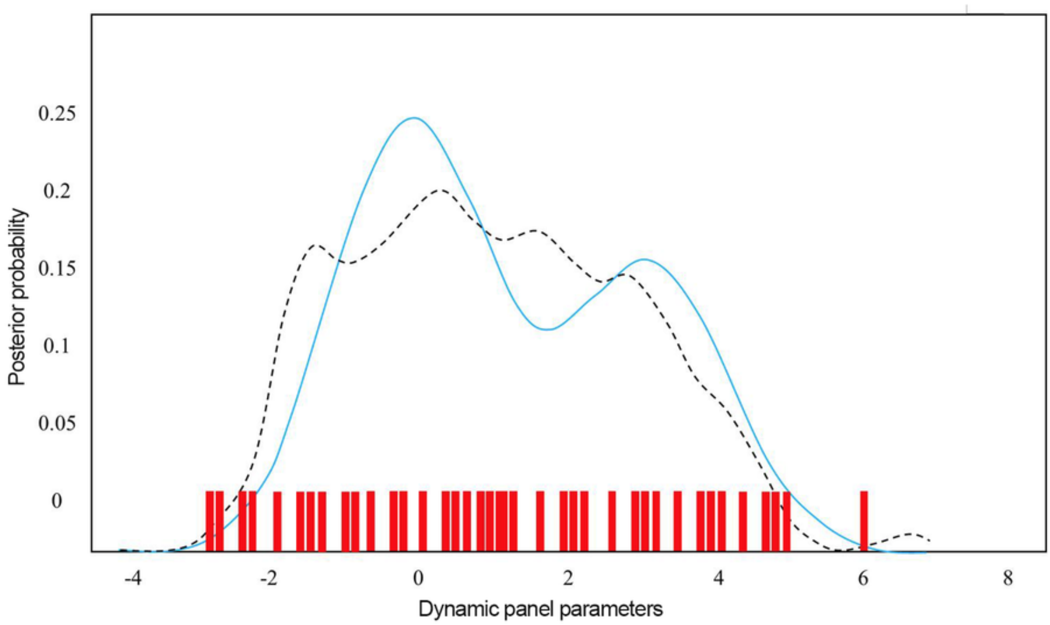


Figure 6. Comparison Between Raw Data and Model Fitting Values



standard deviations. In order to evaluate the significance of the model coefficients, a 95% confidence interval is also reported here. If the estimated value of the parameter is positive (negative), and the upper and lower bounds of the confidence interval are also positive (negative), then this parameter is significantly different from 0. According to Q0025 and Q975, all parameters are significantly different from 0 at 95% level, indicating that variables contribute to the model. In order to further evaluate the effectiveness of the model, Figure 7 shows the complete a posteriori probability density diagram of each parameter. It can be found from Figure 7 that the posterior distribution kernel density map

Figure 7. Complete Posterior Probability Density Map for Each Parameter



of each parameter is close to the normal distribution and has the property of unimodal symmetry, indicating that the model fitting effect is good.

Analysis of Practical Applications

In the current economic environment, as an important component of the national economy, the debt financing level of private listed enterprises has a significant impact on their internal governance and external financial environment. However, our understanding of this complex relationship still has certain limitations. Therefore, this article aims to establish a Bayesian dynamic random effects panel data model with strict exogenous variables based on private enterprise data, and it explores the relationship between debt financing level and various factors. However, in our research, we also need to have a full understanding of the limitations of this article, which will help to interpret and promote the research results more accurately.

1. Limitations of data sources: This article uses data from private enterprises as the basis, but there may be limitations to the data. For example, data may come from companies in specific regions or industries and therefore cannot fully represent the situation of the entire private listed enterprise. In addition, there may also be some degree of issues with data quality and reliability. To avoid limitations in data sources, it is possible to consider expanding the range and diversity of data samples. A wider range of regions and industries can be chosen to obtain more comprehensive data on private listed companies. In addition, data from different sources can be combined to improve the quality and reliability of the data.
2. Limitations of model assumptions: This article establishes a Bayesian dynamic random effects panel data model, but this model is based on a series of assumptions and may not fully capture complex real-world situations. For example, the model assumes a linear relationship between variables but, in reality, there may be non-linear relationships. In addition, the model also assumes that the random error term in the data has specific distribution characteristics, which may also have a certain impact on the results. In order to more accurately reflect the relationship between

variables, nonlinear or nonparametric models can be introduced to analyze the relationship between debt financing level and other factors. This will help identify potential nonlinear relationships and further improve the accuracy and predictive ability of the model.

3. Changes in external environment: This article studies the impact of external financial environment on the debt financing level of private listed enterprises, but the external environment is dynamic. Due to the limited time span of the data, this article may not fully reflect the impact of external environmental changes on the results. Future research can consider data with longer time spans to study the impact of external environments more accurately. In addition, macroeconomic indicators or specific events can also be combined to characterize changes in the external environment and incorporated into the model for analysis.
4. Applicability of the model: The model established in this article is applicable to the study of debt financing levels of private listed enterprises but may not be directly applicable to other types of enterprises or situations in other countries. There may be differences in the financial environment of different types of enterprises or countries, so careful interpretation and promotion of research results are necessary. In order to increase the applicability of the research, the research object can be extended to other types of enterprises or other countries. This can compare the differences between different types of enterprises and compare the research results with the situation in other countries to obtain a more comprehensive understanding.

In summary, by taking the above measures, the limitations of this article can be effectively addressed, and the reliability and applicability of the research can be improved. This will help to better understand the factors influencing the debt financing level of private listed enterprises and provide more targeted suggestions for relevant enterprises to formulate appropriate debt financing strategies.

When private listed companies understand the correlation between debt financing and various factors, they can apply these findings to optimize their marketing strategies. Here are some specific case studies that illustrate how private enterprises can actually apply these findings:

1. Industry competitiveness analysis: Private listed enterprises can use relevant data and market research to conduct in-depth analysis of the competitiveness of their respective industries. By understanding factors such as the competitive landscape, market size, and growth trends of the industry, enterprises can adjust their marketing strategies, better position their products or services, and formulate corresponding debt financing strategies.
2. Product differentiation positioning: By studying consumer needs and competitor product positioning, companies can identify their differentiation advantages and position their products based on these advantages. This positioning helps companies increase market share and profitability, thereby enhancing the level of debt financing.
3. Marketing strategy: With the help of debt financing funds, enterprises can increase their marketing investment and expand brand awareness and market share. For example, through advertising, sponsorship activities, and online and offline promotion, companies can attract more potential customers and establish long-term cooperative relationships with them.
4. Channel expansion and online marketing: Enterprises can use debt financing funds to explore new sales channels, such as online e-commerce platforms and overseas markets. In addition, companies can also use social media and digital marketing methods to increase brand exposure and attract more target customers.
5. Customer relationship management: By establishing a sound customer relationship management system, enterprises can better understand customer needs and provide personalized products and services. This helps to improve customer satisfaction and loyalty, thereby increasing the company's sales and profitability, and creating more favorable conditions for debt financing.

These examples and case studies demonstrate how private listed companies can combine debt financing with marketing strategies to optimize their market performance and competitiveness. In practical applications, enterprises can develop specific marketing strategies based on their own situation and needs, combined with relevant research results, and support and implement these strategies through debt financing. The future development direction can include the following aspects:

1. Consider more factors: In addition to existing internal governance and external financial environment factors, other factors that may affect the debt financing level of private listed enterprises can be further considered, such as industry competitiveness, policy environment, and market size. By comprehensively considering more factors, the impact mechanism of debt financing level can be analyzed more comprehensively.
2. In depth research on impact mechanisms: For existing relationship models, further in-depth research can be conducted on their impact mechanisms. For example, qualitative research or empirical analysis can be used to explore how internal governance measures affect debt financing levels, as well as how the external financial environment shapes corporate financing behavior. This will help to better understand the ways and mechanisms in which these factors affect debt financing.
3. Introducing machine learning and big data analysis: With the advent of the big data era, machine learning and big data analysis techniques can be used to mine deeper levels of information. For example, predictive analysis and risk assessment can be conducted based on large-scale enterprise data to help companies make more accurate debt financing decisions.
4. Cross border comparison and case studies: Cross border comparative studies can be conducted to compare China's private listed enterprises with similar enterprises in other countries or regions, exploring debt financing models and influencing factors in different national contexts. In addition, in-depth research can be conducted on some representative cases to analyze their successful or failed debt financing experiences, providing reference and inspiration for other enterprises.
5. Policy recommendations and practical guidance: Based on research results, relevant policy recommendations and practical guidance can be proposed to help governments and enterprises formulate more effective debt financing policies and strategies. This will help improve the financing capacity and development quality of private listed enterprises.

In short, future research can be devoted to expanding research fields, deepening analytical methods, and applying research results to practice, providing useful support and guidance for promoting the sustainable development of private listed enterprises.

CONCLUSION

As an important part of the national economy, private listed enterprises' debt financing level is not only related to their internal governance, but also has a significant impact on their asset and liability levels from the external financial environment. This paper establishes a Bayesian dynamic random effect panel data model with strict exogenous variables based on the data of private enterprises. Based on the Bayesian reasoning method, the MCMC method is used to estimate the parameters in the model, and 80,000 MCMC sampling iterations are conducted for the parameters. The iterative trajectories of the parameters converge, and the standard deviation and MC error are very small. This shows the validity and accuracy of the Bayesian dynamic random effects panel data model with exogenous variables. The model is used for an empirical test. The results show that the debt financing level of private listed enterprises is positively related to the debt level of the previous period, the size of enterprises, the political background of enterprise executives, and the growth of enterprises. It is negatively related to the external financial environment, the profitability of the enterprise, and the short-term solvency of the enterprise. These conclusions are helpful for private listed enterprises to adopt corresponding debt financing strategies according to their external financial environment and their own internal financial level and operating conditions. It has a good guiding role in the debt financing of private listed enterprises. However, the description of the political background and external financial ecological environment of corporate executives in this paper may lack comprehensiveness. Furthermore, the research object is private listed enterprises. Therefore, the conclusions of this study need to be further tested in private enterprises.

DATA AVAILABILITY

The figures and tables used to support the findings of this study are included in the article.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

FUNDING STATEMENT

This work was supported by 2020 Chongqing Municipal Education Commission Humanities and Social Sciences under grant No.20SKGH337, and the work was supported by 2020 Chongqing City Vocational College under grant No. XJSK2020010093. Project results of Collaborative Innovation Center of Smart Retail of Chongqing City Vocational College, Project No.: KYPT202200003.

PROCESS DATES

Received: October 17, 2023, Revision: January 23, 2024, Accepted: January 23, 2024

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ACKNOWLEDGMENT

The authors would like to show sincere thanks to those whose techniques have contributed to this research.

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