Empirical Study on the Relationship between Financial Development and Economic Growth in China Based on Maximum Flow Algorithm

Qiao Wang, M.Sc
Qiao Wang, Lecturer, School of Economics and Management, Chuzhou University, Chuzhou, 239000, Anhui, China
Correspondence LecWang;coidnj@163.com

Objectives: The relationship between finance and economic growth has always been one of the hot issues in theoretical research and empirical analysis. As one of the important factors affecting economic growth, finance has long been recognized by the majority of scholars.Methods: In the context of the development of Internet e-commerce, empirical research on the relationship between China's financial development and economic growth is conducted based on the maximum traffic algorithm. Results:Based on this, this paper constructs the Probit and Logistic binary discrete selection model for economic growth, and the discrete particle swarm algorithm is used to solve the sequence of influencing factors, estimating the model parameters, and the degree of influence of each influencing factor is calculated. Conclusion: The degree of concurrent employment is a decisive factor in economic growth.

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For a long time, the theoretical research on the relationship between financial development and economic growth has been one of the hot topics in the Western academic community. As an important factor affecting economic growth, financial development has long been recognized by the majority of scholars. Western scholars are looking for issues such as whether finance promotes the economy or whether the economy drives finance and what kind of financial structure is more suitable for the long-term stable growth of the economy [1]. Finance is at the core of national economy, its importance has long been recognized by scholars, and the research on the relationship between finance and economic growth has been one of the hot topics in academia at home and abroad. Under the Environment of socialist market economy, how to carry out financial reform, give full play to its core role, and actively promote China's macroeconomic growth has become a key issue in recent years, so it is of great significance to study the impact of financial development on economic growth [2].

Economic growth is an important goal of human social and economic development. The factors that affect economic growth, starting from Adam Smith, are the core issues in economics research [3]. Looking at the development course of economic growth theory, specialization and division of labor, capital, technology and knowledge, human capital, and systems have become the focus of economists' attention[4]. Some scholars believe that the financial system and financial market have played an important role in the British industrial revolution. [5]. Since 1911, when some scholars proposed that a financial service provided by the developed financial sector can promote productivity and economic growth, a lot of theoretical and empirical literature has emerged. Since the reform, the Chinese economy has maintained an average annual growth rate of nearly 10%, and has made remarkable achievements. Some economists attributed it to insisting on reform and opening up and implementing appropriate macro-control policies. This paper intends to build a theoretical analysis framework for the relationship between financial development and economic growth based on the latest research results of domestic and foreign economic growth theory, and to theoretically explain the role of financial development in promoting economic growth [6]. A relatively scientific index system was selected to construct a Vector Error Correction Model (VECM) and a multiple regression model. The data from 1978 to 2006 were used for empirical research to explore the internal relationship between China's financial development and economic growth, exploring the strength and direction of influence between the variables such as the degree of financial development, investment conversion rate, proportion of medium and long-term loans, real interest rate, and actual per capita GDP. It also studies the results and analyzes the reasons that restrict the development of China’s finance. According to China’s national conditions, it proposes the rationalization of China’s financial reform to make it more fully play its due role and better meet the needs of economic growth in order to promote macroeconomic development. Economic long-term health, stability and sustainable development [7].

METHODS

Maximum Flow Algorithm

For the maximum flow algorithm, we set $Y = \chi\beta + \varepsilon = \beta_0 + X\beta_{\sum} + \varepsilon$, where Y is the response variable of $n \times 1$, χ is the order matrix of $n \times (p+1)$,where the elements of the first column are all 1, X is the matrix after the first column is removed in χ, and $\beta = (\beta_1, \beta_2, ..., \beta_p)$ is the regression coefficient vector. ε is a random error vector $n \times 1$ with a distribution of $N(0, \sigma^2 I)$. Let the data of matrix $Z = (Y, X)$ be missing, that is, some of the data of some variables are incomplete. The coffee algorithm proposed by Dempster, Larid, and Rubin in 1977 is an iterative method that has been widely used to deal with missing data problems. Each iteration of the maximum flow algorithm consists of two steps: expectation (E-step) and maximization (M-step). A similar maximum flow algorithm can be established for the missing of the missing matrix, the matrix $Z = (Y, X)$ (Zou J et al. 2017) [8]. Let $Z = (Y, X)$ be multivariate normal distribution, which is:

$$Z_i(y_i, x_i) \sim N_P(\mu, \textstyle\sum) \quad (1)$$

Among them:

$$\mu = \begin{pmatrix} \mu_x \\ \mu_y \end{pmatrix}, \sum = \begin{pmatrix} \sum_{yy} & \sum_{yx} \\ \sum_{xy} & \sum_{xx} \end{pmatrix} \quad (2)$$

And set the matrix $Z = (Y, X)$, Z_{obs} is a known value, then E step to get the logarithm of the maximum likelihood function of the parameter $\theta = (\mu, \sum)$:

$$\begin{aligned} Q(\theta / \theta^{(t-1)}) &= E[\log f(Z_{obs}, Z_{mis} / \theta) / Z_{obs}, \theta^{(t-1)}] \\ &= \int_{Z_{mis}} \log f(Z_{obs}, Z_{mis} / \theta) f(Z_{mis}, Z_{obs} / \theta^{(t-1)}) dZ_{mis} \quad (3) \\ &= \int_{Z_{mis}} \log f(X, Y / \theta) f(Z_{mis}, Z_{obs} / \theta^{(t-1)}) dZ_{mis} \end{aligned}$$

Where $\theta^{(t-1)}$ is the estimate of parameter θ obtained from iteration t-1, $Q(\theta / \theta^{(t-1)})$ represents the logarithm maximum likelihood function of parameter θ under $\theta^{(t-1)}$, that is, the conditional expectation of $\log f(Z_{obs}, Z_{mis} / \theta)$ under $\theta^{(t-1)}$ and Z_{obs}, and $f(*)$ is the probability Distribution function. In the next M step, the desired function $Q(\theta/\theta^{(t-1)})$ is maximally transformed to obtain an estimate θ of the parameter $\theta^{(t)}$ of the iteration t.

$$\theta^{(t)} = \text{argmax}\, Q(\theta/\theta^{(t-1)})(4)$$

Then use the new maximum value $\theta^{(t)}$ to update $\theta^{(t+1)}$ in the predictive distribution of the component, and obtain an estimate $\theta^{(t+1)}$ of the parameter θ in iteration t+l through (1)-(2), and repeat the algorithm until it converges. After convergence, we take the converged θ as an estimate of the parameter θ. As for the convergence of the maximum flow algorithm, there are many articles that are discussed and are not described here. The following gives the specific steps for the maximum flow algorithm for the matrix $Z=(Y,X)$. The maximum flow algorithm is implemented by iteratively updating θ until it converges. Therefore, the key to the algorithm is to establish the relational formula between $\theta^{(t-1)}$) and $\theta^{(t)}$. Let $\theta^{(0)}$ be the initial value of $\theta=(\mu,\sum$), let $\hat{\mu}_{i,t}$ be the estimated value of the i-th element of μ obtained in step t, and $\hat{\Sigma}_{j,k,t}$ be the estimated value of the k-th column element of the jth row of Σ obtained from step t, according to Atkinson and Cheng's formula yields the relationship between $\theta^{(t-1)}$) and $\theta^{(t)}$. Equations (5)-(6), where (5) and (6) are each an estimate of μ and Σ in $\theta^{(t)}$ at step t:

$$\hat{\mu}_{i,t} = \sum_{i=1}^{n} \hat{Z}_{ij,t-1} \Big/ n, \qquad i=1,\dots p \ (5)$$

$$\hat{\Sigma}_{j,k,t} = \sum_{i=1}^{n} \left\{ \left(\hat{Z}_{ij,t-1} - \hat{\mu}_{ij,t-1}\right)\left(\hat{Z}_{ik,t-1} - \hat{\mu}_{k,t-1}\right) + \hat{\Sigma}_{j,k,t-1} \right\} \Big/ n,\ j,k=1,\dots p \ (6)$$

Where：

$$\begin{aligned} \hat{Z}_{ik,t-1} &= E\left(Z_{ij} \big/ Z_{obs,i}, \theta^{(t-1)}\right) \quad Z_{ij}\ Unknown \\ &= Z_{ij} \qquad\qquad Z_{ij}\ Known \qquad i=1,\dots n,\ j=1,\dots p \end{aligned} \quad (7)$$

$$\begin{aligned} \hat{\Sigma}_{ik,t-1} &= \text{cov}\left(Z_{ij}, Z_{ik} \big/ Z_{obs,i}, \theta^{(t-1)}\right) \quad Z_{ij}, Z_{ik}\ Unknown \\ &= 0 \quad Z_{ij} or Z_{ik}\ Known \quad i=1,\dots n,\ j=1,\dots p \end{aligned} \quad (8)$$

$Z_{obs,i}$ Is the known component of the i-th set of data， $\hat{Z}_{ij,t}$ is the value of the element of row i and column j of matrix Z obtained by iterating in step t， Z_{ij} is the value of the i-th row j-th column element of matrix， In the formula(6), $\hat{\Sigma}_{ik,t-1}$ is the j-th row and k-th column elements of the conditional covariance matrix $\hat{\Sigma}_{i,t-1}$ of the i-th data at the iteration of t-1. For (7) and (8), it is undoubtedly very cumbersome to use complex calculations that involve complex calculations. To simplify the calculation, let y be the dimension vector of m, y_1 be the dimension component of p, and y_2 be the dimension component of q, $y \sim N(\mu,V), V>0$, where μ is the mean and V is the covariance matrix, and

$$y=\begin{pmatrix} y_1 \\ y_2 \end{pmatrix}, \mu=\begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, V=\begin{pmatrix} V_{11} & V_{12} \\ V_{21} & V_{22} \end{pmatrix} \ (9)$$

Then when given y_2, the conditional distribution of y_1 is normal, and the conditional mean and conditional covariance are：

$$E\left(y_1/y_2\right) = \mu_1 + V_{11}V_{22}^{-1}\left(y_2-\mu_2\right) \ (10)$$

$$V\left(y_1/y_2\right) = V_1 - V_{11}V_{22}^{-1} \ (11)$$

The above results are applied to each observation with missing variables (each row of matrix Z), as long as we reorder the vectors of each row of matrix Z, and combine the unknown quantities together as y_1, the known quantity as y_2. According to the sequence of elements in the corresponding transposition mean value and conditional covariance in the order of precedence, the conditional expectation (7) and the conditional covariance (8) can be obtained by calculating (10)-(11). Let $Z_{i,t}$ be the ith row vector (i-th observation data) of the matrix Z at the t-th iteration. According to the absence of the i-th row, rearrange the elements of $Z_{i,t}$, and let Z_i^1 be the component of the unknown vector. Z_i^2 is the component in which the vector is known. After getting the following formula $(i=1,\dots p)$:

$$Z_{i,t}=\begin{pmatrix} Z_i^1 \\ Z_i^2 \end{pmatrix}, \mu_{i,t}=\begin{pmatrix} \mu_{i,t}^1 \\ \mu_{i,t}^2 \end{pmatrix}, \Sigma_{i,t}=\begin{pmatrix} \Sigma_{i,t}^{11} & \Sigma_{i,t}^{12} \\ \Sigma_{i,t}^{21} & \Sigma_{i,t}^{22} \end{pmatrix} \quad (12)$$

Where $\mu_{i,t}$ and $\Sigma_{i,t}$ are the vectors resulting from rearranging the combination of μ and Σ obtained from the iteration of step t according to the order of the elements of Z_i^1 and Z_i^2. That is:

$$E\left(Z_i^1/Z_i^2\right)=\mu_{i,t}^1+\Sigma_{i,t}^{12}\left(\Sigma_{i,t}^{22}\right)^{-1}\left(Z_{i,t}^2-\mu_{i,t}^2\right) \quad (13)$$

$$Cov\left(Z_i^1/Z_i^2\right)=\mu_{i,t}^1+\Sigma_{i,t}^{12}\left(\Sigma_{i,t}^{22}\right)^{-1}\Sigma_{i,t}^{21} \quad (14)$$

Then the missing values are filled in the matrix Z, and the resulting covariance can be rearranged in the order of the original rows and columns. The advantage of (13) and (14) is that each time one can quickly estimate the missing value of a set of data, it is naturally better than (7) and (8) to estimate only one missing value at a time, and the calculation is simple. Iteratively calculate (5), (6), (13), (14) until $\theta^{(t)}$ converges. In the case of convergence, we fill the matrix with the estimated values obtained, and also denote the conditional covariance matrix of the i-th set of data by $\hat{C}$. The regression parameters β and s^2 are obtained by the following transformation:

$$\hat{\beta}_\Sigma=\hat{\Sigma}_{xx}^{-1}\hat{\Sigma}_{xy}, \hat{\beta}_0=\hat{\mu}-\hat{\beta}_\Sigma^T\hat{\mu}_x, \hat{\sigma}_2=\sigma_y^2-\hat{\Sigma}_{yx}\hat{\Sigma}_{xx}^{-1}\hat{\Sigma}_{xy} \quad (15)$$

For the M1 algorithm, similarly, we can extend Atkinson's MI (multiple factorization) multiple imputation to the mixed missing mode, which is the missing mode of the matrix $Z=(Y,X)$. Let Z_{obs} be the set of known values and Z_{mis} be the set of missing values. The posterior density of total Q can be written in the following form:

$$h\left(Q|Z_{obs}\right)=\int g\left(Q|Z_{obs},Z_{mis}\right)f\left(Z_{mis}|Z_{obs}\right)dZ_{mis} \quad (16)$$

Where $f(\cdot)$ is the posterior density of the missing value and $g(\cdot)$ is the posterior density of the complete data. Referring to the previous literature, the following formula is easily obtained (Y is replaced by $\hat{Y}$):

$$b_t=\left(\hat{\chi}_l^T\hat{\chi}_t\right)^{-1}\hat{\chi}\hat{Y}, l=1,\dots s, \bar{b}=\sum_{l=1}^{s}b_l \Big/ s, \quad (17)$$

$$U=\sum_{l=1}^{s}\hat{\sigma}_{yl}^2\left(\hat{\chi}_l^T\hat{\chi}_t\right)^{-1}\Big/s, B=\left(b_l-\bar{b}\right)\left(b_l-\bar{b}\right)^T\Big/(s-1), \operatorname{var}\left(\bar{b}\right)=U+\frac{s+1}{s}B. \quad (18)$$

Therefore, the estimated parameters can be obtained by (16), and the covariance estimation of the parameters can be obtained by (17).

Model Building and Variable Setting

In the economic model, when the explanatory variables are binary discrete (such as 0 and 1), the model is called binary discrete selection model (BCM for short). The Probit model proposed by Bliss is one of the common models. It is applicable to nonlinear statistical analysis with an assigned value of 0 in the independent variables. It is usually defined as follows: If Yi is a binary discrete variable of value (0,1), and have:

$$Y_i^*=\alpha_0+\beta X'_i+\varepsilon \quad (19)$$

$$Y_i=\begin{cases}0, if & Y_i^*\le\alpha_1 \\ 1, if & Y_i^*>\alpha_1\end{cases} \quad (20)$$

Where , Y_i^* , α_0 , β ε, α_1 represent latent variables, constant terms, parameters to be evaluated, random explanatory variables, and interval demarcation points respectively. Using the cumulative standard normal distribution function Φthe Probit model can be expressed as:

$$Prob(Y_i = 1|X'_i) = \Phi(\alpha + \beta|X'_i) = \int_{-\infty}^{\alpha_0+\beta X'_i} \frac{1}{\sqrt{\pi}} \exp(-\frac{t^2}{2}) dt \quad (21)$$

To estimate the parameters of the Probit model, the following likelihood functions can be constructed:

$$\ln L = \sum \gamma_i \ln[\Phi(\alpha_0 + \beta X'_i)] + \sum \gamma_i \ln[1 - \Phi(\alpha_0 + \beta X'_i)] \quad (22)$$

Where γ_i is the weights. The variables in this paper involve the respondents' income Y, the degree of concurrent employment X1, age X2, gender X3, and education level X4. Based on the above variable settings, the following binary Probit discrete selection model can be established:

$$Prob(Y_i = 1|X'_i) =$$
$$\Phi(\alpha_0 + \sum_{j=0}^{2} \beta_j X_1 + \sum_{j=0}^{3} \beta_j X_2 + \sum_{k=3}^{7}\sum_{j=0}^{1} \beta_j X_k + \sum_{k=8}^{10}\sum_{j=0}^{2} \beta_j X_k) \quad (23)$$

Discrete Particle Swarm Optimization Algorithm for Solving the Order of Influencing Factors

These positions of the elements can be seen as being able to move left and right; the particle elements move from left to right to produce their velocity, and thus the particle velocity can be interpreted intuitively and explicitly. Set the solution to A $\Pi_i(\pi_{i1}, \pi_{i2}, \ldots, \pi_{in})$ and the corresponding particle position to $x_i(x_{i1}, x_{i2}, \ldots, x_{in})$. Then the inverse operator (INV) is defined as follows:

$$X_i = INV(\Pi_i) = \{(\pi_{i1}, \pi_{i2}, \ldots, \pi_{in}) \mid x_{ij} = k if and only if \pi_{ik} = j, where j,k = 1,2,\ldots,n\} \quad (24)$$

$$\Pi_i = INV(X_i) = \{(\pi_{i1}, \pi_{i2}, \ldots, \pi_{in}) \mid \pi_{ij} = k if and only if x_{ik} = j, where k,j = 1,2,\ldots,n\} \quad (25)$$

We then set the given two solutions:

$$\Pi_i(\pi_{i1}, \pi_{i2}, \ldots, \pi_{in}) \text{and} \Pi_j(\pi_{j1}, \pi_{j2}, \ldots, \pi_{jn}) \quad (26)$$

Applying inverse operators to them gives their corresponding particle positions Xi and Xj. Next, we can define the difference between the two solutions, namely velocity V (Xi, Xj) as follows:

$$V(\Pi_i, \Pi_j) = V(X_i, X_j) = \Pi_i - \Pi_j = X_i - X_j = \{(x_{i1} - x_{j1}, x_{i2} - x_{j2}, \ldots, x_{in} - x_{jn}) \quad (27)$$

Good distance measurement is helpful to improve the efficiency of the meta heuristic algorithm, and the selection of distance measurement rules is not a trivial matter. A good distance measurement can accurately evaluate the similarity and difference between solutions. Given two solution arrangements $\Pi_i(\pi_{i1}, \pi_{i2}, \ldots, \pi_{in})$ and $\Pi_j(\pi_{j1}, \pi_{j2}, \ldots, \pi_{jn})$, we first apply the inverse operators to them to obtain their corresponding particle positions Xi and Xj. Next, it is then possible to define two solution position distances δ(Πi , Πj):

$$\delta(\Pi_i, \Pi_j) = \delta(X_i, X_j) = \sum_{k=1}^{n} | x_{ik} - x_{jk} | \qquad (the 1^{st} order) \quad (28)$$

$$or \delta(\Pi_i, \Pi_j) = \delta(X_i, X_j) = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \qquad (the 2^{nd} order) \quad (29)$$

The first-order is called the deviation distance in the literature and the Spearman distance in statistics is used to compare the disparity between the two sorted lists. In our algorithm, a continuous particle swarm algorithm is used to update the position of each element in its arrangement, which is:

$$x_{id}^{(t+1)} = x_{id}^{(t)} = \omega(x_{id}^{(t)} - x_{id}^{(t-1)}) + c_1 r_1 (p_{id}^{(t)} - x_{id}^{(t)}) + c_2 r_2 (p_{id}^{(t)} - x_{id}^{(t)}) \quad (30)$$

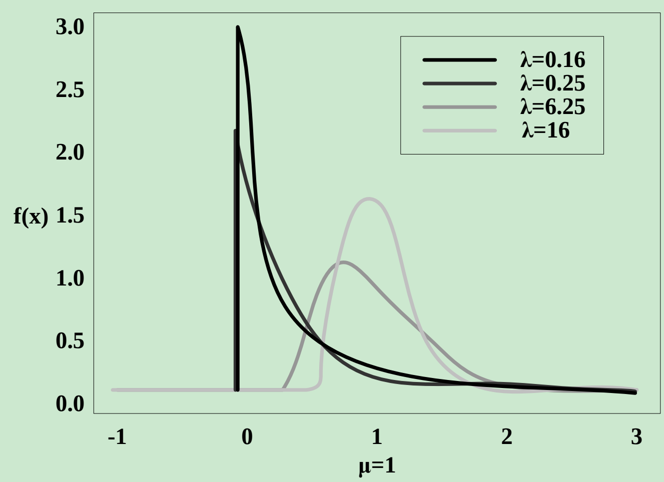
Iterating through this formula yields real-valued particle positions (intermediate results). Then use the Smallest Position Value (SPV) of the element with the smallest value to transform the intermediate result to its corresponding de-alignment. The specific steps are as follows: Let the position of the updated particle in formula (12) be a real vector $X_i(x_{i1}, x_{i2}, \ldots, x_{in})$, and the corresponding solution is an integer vector $\Pi_i(\pi_{i1}, \pi_{i2}, \ldots, \pi_{in})$. Using the principle that the element with the smallest value is scheduled first, Xi determines Πi

RESULTS

Parameter Calculation Result

According to the set model, the data of each variable is set as the initial population in the algorithm. The initial population contains the optimal solution. Then the discrete particle swarm algorithm is used in 3.2 to estimate the parameters. The frequency variable PIN=1 is specified. Choose to use the inverse function of the cumulative standard normal distribution function to convert (Figure 1), and ask to calculate the observed values, expected values, residuals, and probabilities for each independent variable with different levels of values to obtain the goodness of fit of the Probit equation and parameter estimation. In the Pearson goodness-of-fit test, the chi-squared values, degrees of freedom, and P-values of the model were 96.988, 119, and 0.999, respectively, indicating that the goodness of fit of the model was good (Table 1).

Figure 1
The Inverse Function of Cumulative Standard Normal Distribution Function



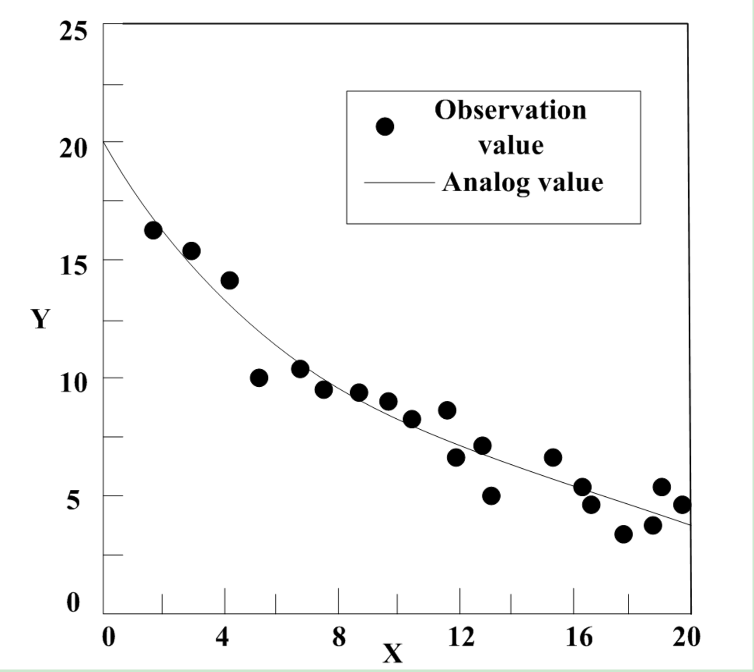
In table 1, the parameters of two probit discrete selection model is obtained by estimating the optimal parameters after 20 iterations.

Table1
Regression Coefficient and Standard Deviation Estimation of Probit Model

	Regression Coeff.	Standard Error	Coeff./S.E.
Intercept	1.298	0.815	1.592
X1	1.814	0.677	2.680
X2	0.061	0.181	0.338
X3	0.351	0.397	0.885
X4	0.139	0.425	0.327
X5	-0.039	0.707	-0.055
X6	0.250	0.642	0.388
X7	0.355	0.668	0.532
X8	-0.287	0.285	-1.008
X9	0.576	0.416	1.385
X10	0.561	0.354	1.585

Because the priori information of the parameters reflects the subjective judgment of the researcher, and it is not guaranteed that the researcher has the same subjective cognition, so how to select the prior distribution of the parameters is a controversial issue. Obviously, for the same model, given the different parameters prior distribution, it is possible to get a completely different parameter estimation results, so we will calculate the parameters fitted, get the parameter fitting curve as follows (Fig. 2), it is proved that the model has higher parameter fitting, better parameter setting, and good algorithm performance.

Figure 2
Fitting Curve of Parameter Identification



Influencing Factors Ranking Results

In the above two-dimensional Probit discrete selection model, the calculated constant term is 1.298, indicating that economic development has an initial growth momentum without being affected by other variables. Among the variables, the coefficient of the degree of double-entry was the largest (1.841), followed by the coefficient of the economic subsidy policy. The Binary Probit Discrete Choice model yields the observed values, expected values, residuals, and probabilities for each variable with different values, but because the number of covariates is greater than 1, it is not possible to draw a 95% confidence interval, taking into account both the Industry, age, direct economic supplement, and other preferential policies are multi-classification variables. Dummy variables need to be introduced. Therefore, Logistic regression is used for impact analysis.

Table2
Parameter Estimation of Logistic Regression Equation(1)

	B	S.E.	Wald
Intercept	-1.414	1.152	1.509
X1	5.333	1.612	10.948
X2			3.936
X2(1)	-1.280	1.075	1.418
X2(2)	0.755	1.063	0.505
X2(3)	-1.573	1.382	1.297
X3	0.891	0.785	1.288
X4	-0.347	0.841	0.171
X5	-0.901	1.365	0.435
X6	1.133	1.070	1.121
X7	0.168	1.112	0.023
X8	-0.905	0.606	2.232
X9	1.537	0.825	3.474
X10	0.765	0.563	1.844

The analysis results of various impression factors are shown in Table 2. First, the degree of part-time work is the decisive factor. According to the “China Economic Statistics Yearbook,” the average income of people in a certain province and city (4504 Yuan, 6232 Yuan in 2011, using the former for the consideration of the unity of variable value levels in different statistical years) is used as the criterion for dividing the income level. And according to the income of the income of the respondents in the proportion of their income from economic income to their total income, the degree of dual-employment is divided. The model shows that the variable of the degree of concurrent investment passed the test at the significant level of 1%, and the Wald value and the OR value (the odds ratio) were as high as 10.948 and 207.086 respectively. It shows that the respondents who engage in activities other than industry in a certain industry have great influence on their income. The single development of traditional industry production is no longer the main way to achieve regional economic growth.

The impact of human capital is not significant. It can be clearly seen from the model output data that the Sig. values for the employment skills, education level, and age variables are 0.509, 0.679, and 0.268, respectively, and the original hypothesis is rejected, which is related to the respondents. There is a certain relationship between the type of occupation and the level of independent variables. From the current point of view, an industry-cum-participant in the region is mainly concentrated in the labor-intensive industries (such as heavy chemicals, toys, footwear, textiles, food, construction, and associated industries, etc.) in the Yangtze River Delta and Pearl River Delta regions. The job's requirements for education and employment skills are not very high.

In general, the impact of financial development on economic growth is reflected in both positive and negative aspects: On the one hand, financial development has a positive role in promoting economic growth. For example, the emergence of credit promotes the integration of funds, the operation and operation of financial institutions to achieve a reasonable allocation of resources throughout the society; on the other hand, financial development may also have a negative impact on economic growth under certain conditions. For example, in the process of industrialization in developing countries, due to the implementation of expansionary financial policies, excessive financial liberalization has led to the rapid development of virtual economy and accumulated risks. The massive outbursts of systemic risks have destroyed the fundamentals of the economy. For the transitional economies in developing countries, how to grasp the process of financial development and how to prevent financial risks, scholars have already done a lot of research,the role of finance in the economy is manifested in four aspects. First, it promotes the circulation of commodities through the intermediary role of money, promotes the flow of funds through credit, and secondly, promotes the transformation of savings (including quantity and quality) into economic development. Provide capital investment; third, through the operation of financial institutions to achieve a reasonable allocation of resources for the entire society; fourth, directly contribute to economic growth through the financial industry's own industry growth.

DISCUSSION

Combining the increasingly mature and perfect Western theory with the actual situation in China and examining the relationship between China's financial development and economic growth is an urgent need for China's economic construction. It also provides a theoretical basis for the development of China's financial system and the adjustment of its financial structure. Whether it is the whole country or regions, no matter which equation is adopted for empirical research, the degree of financial development has a negative relationship with economic growth. Based on this, the relationship between financial development and economic growth is empirically analyzed, constructing the Probit and Logistic binary discrete selection model for economic growth. discrete particle swarm algorithm is used to estimate the model parameters and calculate the influencing factors, based on the perspective of forecasting. Excavated anomalies, formulated some excavation rules, revealed the internal mechanism of economic growth, rationally and effectively configured productivity factors, and promoted economic growth and improvement of people's living standards. After empirical analysis, the results are obtained: the degree of concurrent employment is a decisive factor for economic growth, and the impact of human capital on economic growth is not significant. Based on this, this article puts forward proposals for promoting economic growth. First, the industry is actively adjusted changing the original single primary industry into a multi-industry combination and common development, and the land system is adjusted to improve the allocation efficiency of land resources.

Human Subjects Approval Statement

This paper did not include human subjects.

Conflict of Interest Disclosure Statement

None declared.

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