Research Article

Impact of Enterprise Financing Constraints on Labor Income Share Based on Internet of Things Data Analysis Technology

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Although the Chinese economy has developed rapidly since the reform and opening up, the income distribution gap is widening year by year. The final social income distribution pattern is highly dependent on the primary distribution pattern. Therefore, the changing trend and influencing factors of labor income share have become the focus of academic research and the focus of government attention. Based on this, this article proposes enterprise financing based on Internet of Things data analysis technology. Studies on the impact of restraints on labor income shares will help further research on the impact of corporate financial restraints on future labor income shares. Based on the financial data reports published in the CCER database and the company's IPO prospectus and annual report, this paper discusses whether the company's key business products belong to the Internet of Things' key technology application categories. Take 226 IoT companies as the research objects of this article, and conduct a secondary screening. The final survey sample is used to investigate the impact of corporate funding constraints on labor income share. Tests have proved that among the 179 resource-based enterprises undergoing transformation, 109 enterprises have undergone intraindustry transformation, accounting for 48.23% of the overall sample and 60.89% of the sample of transformed enterprises. Downstream expansion makes the business industry expand. This shows that funding constraints have a negative impact on labor income share. This is primarily the result of the impact of the long-term debt-to-asset ratio on labor income share.

1. Introduction

The share of labor income in the primary distribution plays an important role in the economy and society that cannot be ignored. At the same time, during the new normal period of economic change, my country's economy emphasizes structural optimization and upgrades and advocates supply-side reforms. Adjusting and upgrading the industrial structure is becoming more and more important. Declining labor income shares affect consumer demand and threaten social harmony, stability, and sustainable development. Therefore, in the context of inconsistent understanding of the evolution trend of labor income share in existing research, and the increasingly important and urgent industrial structure transformation and upgrading, it is necessary to further examine the changing trend of labor income share in China and thoroughly study the impact of corporate financing constraints on labor income share path.

SMEs are the fundamental force for building a market economy and play an important role in the prosperity of the market economy. They are close to users, serve users, and generally operate in the most competitive areas of the market. A series of properties make it innovative in research and development. In this respect, it has the unparalleled innate advantage of large- and medium-sized businesses. The Ministry of Industry and Information Technology of China pointed out that the contribution rate of SMEs in national invention patents, enterprise innovation, and new product research and development can reach approximately 65%, 75%, and 80%, respectively. They are the main implementers of research, development, and innovation. In the main body and main force of my country's scientific and

technological progress, its R&D investment level is closely related to the speed of my country's economic development, overall innovation capability, and competitiveness [1, 2].

In the past ten years, scholars at home and abroad have conducted a lot of pioneering and fruitful research on the impact of corporate financing constraints on labor income share based on Internet of Things data analysis technology and accumulated rich research results and research experience. From the perspective of the influence of financialization on the market power of enterprises and the degree of labor market competition, Tian and Nie link financialization with the proportion of labor income through theoretical derivation and analyze whether the financialization of physical enterprises will affect labor income. In addition, he also used the empirical data of Chinese listed companies from 2008 to 2016 to conduct empirical tests. The results show that the increase in the degree of financialization has reduced the price increase and the rate of return. In addition, in the eastern region, during the period of capital and technology-intensive industries and monetary policy tightening, the degree of financialization has a greater negative impact on labor income. However, its overall research lacks data support, and more data is needed to support its conclusions [3]. Yin pointed out that the increase in the shareholding of institutional investors will have a greater impact on corporate governance. Therefore, the asymmetry of information and agency costs of listed companies can be improved. Based on Almeida's financing constraint model, it verifies the relationship between institutional investors and financing constraints from the perspective of heterogeneity. The results show that financing constraints are common in enterprises. In non-state-owned enterprises, stress-resistant institutional investors can significantly alleviate financing difficulties. The experimental results lack more data support so that the results obtained through Almeida's financing constraint model are irrelevant. However doubtful [4], Fang pointed out that in corporate debt financing, the combination of information asymmetry, agency issues, and transaction costs leads to the difference between the internal and external financing costs of the company, which leads to constraints on corporate debt financing. It uses models to study debt financing constraints and analyzes its impact on corporate investment behavior choices to help companies respond more reasonably to debt financing constraints, optimize investment behavior choices, fully enhance corporate value, and enhance competition between companies. However, the research did not clearly put forward the different factors between the internal and external financing costs of enterprises [5, 6].

This paper analyzes the effect of corporate financing constraints on labor income share through empirical analysis, reveals the impact of corporate financing constraints on primary income distribution, provides a better theoretical explanation and model basis for quantitative research on income distribution, and provides a new way to solve the problem of income disparity thoughts and enrich the theory of the primary distribution of labor income. In this paper, we qualitatively and quantitatively analyze the effects of corporate financial constraints on labor income shares and break down

fluctuations in labor income shares into interindustry effects and intraindustry effects. It is hoped that the government will be able to adopt relevant policies in developing constraints on corporate financing. Develop and innovate systems, take into account corporate funding constraints and increasing labor income shares, and reasonably adjust income distribution to provide a useful policy base.

2. Corporate Financing Constraints and Labor Income Share

2.1. IoT Data Analysis Technology. Entering the era of the Internet of Things, data on the Internet will explode at an unprecedented rate. To retrieve the information people need from massive data, some other related knowledge is needed, such as the popular statistical machine learning. Data mining, recommendation systems, etc. are all based on massive user data and modeling user data and then used to predict new users or give relevant recommendations to achieve the purpose of data commercialization; that is, use known data to obtain related business profits [7, 8].

Suppose that n sensors are deployed in the grid, and the surrounding environment is periodically monitored for data collection. The calculation IED node is located in the center of the area. At this time, the network can cover the entire monitoring area [9]. Let s_i denote the i sensor node, then the set of nodes is $S = \{s_i | 1 \le i \le n\}$, and the energy consumption of the node sending bit data to a position with a distance of d is as follows:

$$E_{Tx}(l, d) = \begin{cases} lE_{\text{elec}} + l\varepsilon_{fs}d^2, & d < d_0, \\ lE_{\text{elec}} + l\varepsilon_{mp}d^4, & d \ge d_0, \end{cases} \tag{1}$$

where E_{elec} represents the energy consumption of the transmitting circuit. If the transmission distance is less than the threshold d_0, the power amplification loss adopts the free space model; if the transmission distance is greater than or equal to the threshold d_0, the multipath attenuation model is adopted.

The collection of n sensing data sampled by nodes in the monitoring network in chronological order is denoted as follows:

$$TS = \{(t_1, \alpha_1), (t_2, \alpha_2), \cdots, (t_n, \alpha_n)\}, \tag{2}$$

where t represents the acquisition time and α' represents the predicted value corresponding to t.

In order to minimize the sum of squares of errors between the sampled data and the fitted curve, let

$$D = \sum_{i=1}^{n} d_i^2 = \sum_{i=1}^{n} [\alpha_i - (a + bt_i)]^2. \tag{3}$$

At the same time, in order to make the predicted data closer to the true value, D finds the second-order partial derivative of a and b. Solutions have to

$$\begin{cases} a = \bar{\alpha} - b\bar{t}, \\ b = \dfrac{\sum_{i=1}^{n} t_i \alpha_i - nt\bar{\alpha}}{\sum_{i=1}^{n} t_i^2 - n\bar{t}^2}. \end{cases} \quad (4)$$

The heuristic mathematical expression of CFS is as follows:

$$\text{Merits}(K) = \frac{k\bar{r}_{cf}}{\sqrt{k + k(k-1)\bar{r}_{ff}}}, \quad (5)$$

where Merits represents an evaluation score containing K feature subset S. The larger the value, the greater the correlation between the feature subset S and the classification result [4, 10].

Assuming that an information source continuously emits a series of uncertain source symbols, if these source symbols C have a value $C_1, C_2, \cdots, C_n$, the corresponding uncertainty probability is $P_1, P_2, \cdots, P_n$, and these source symbols are independent of each other [11, 12]. Then, the information entropy of these information source symbols can be defined as follows:

$$H(C) = -\sum_{i=1}^{n} P(C_i) \log_2 P(C_i), \quad (6)$$

where n is the sample set, class C_i means that n sample sets contain individual samples, and $H(C)$ means the degree of uncertainty of the source samples C divided into n classes [13, 14].

Assuming that a certain feature F in the sample set S has multiple values $\{F_1, F_2, \cdots, F_v\}$, the conditional entropy of dividing S under the precondition of a given feature F can be expressed as $H(C \mid F)$; then,

$$\begin{aligned} H(C \mid F) &= -\sum_{i=1}^{m} \sum_{j=1}^{v} P(F_j) P(C_i \mid F_j) \log_2 P(C_i \mid F_j) \\ &= \sum_{j=1}^{v} P(F_j) H(C \mid F = F_j), \end{aligned} \quad (7)$$

where $H(C \mid F = F_j)$ represents the conditional entropy when the feature F takes the value F_j:

$$\begin{aligned} H(C \mid F = F_j) &= -\sum_{i=1}^{m} P(C_i \mid F = F_j) \log_2 P(C_i \mid F = F_j) \\ &= -\sum_{i=1}^{m} P_{ij} \log_2 P_{ij}. \end{aligned} \quad (8)$$

Given the large-scale polymorphic and multidimensional properties of the Internet of Things perception data in real time, the storage, calculation, and analysis of the perception data at the bottom of the Internet of Things are not only fully utilized, increasing the number of intelligent heterogeneous network elements and intelligence in the perceptual layer of the Internet of Things. It can also reduce the network transmission consumption brought by the application layer of a large amount of sensing data uploading and solve the problem of large processing feedback delay at the application layer [15, 16]. After the IoT terminal device perceives the surrounding environment data, it needs to transmit these data. Therefore, it needs the support of the network layer. Through the connection of the network layer, the objects can be connected in series to form a mesh structure. In addition to transmission, the confidentiality and correctness of data transmission must be ensured, while stability and continuity are required. The higher-level requirement is to occupy less bandwidth, and the transmission process requires less energy consumption.

2.2. Corporate Financing Constraints. The investment decision of an enterprise is closely related to the financing situation. Asymmetric information will increase the cost of external financing of the enterprise. It is difficult for enterprises facing financing constraints to obtain the required funds from the outside, so they have to give up good investment opportunities. The financial market is the basic environment for the economic activities of enterprises, and its degree of development will undoubtedly affect the investment and financing behavior of enterprises [17, 18]. In the actual capital market, a single investor cannot understand the business situation of the company due to lack of information, and the cost of evaluating the company is very high. Therefore, investors with idle funds are not willing to invest their funds in companies and projects that they do not understand. The existence of information asymmetry is not conducive to corporate financing, so that the best investment opportunity is missed.

The R&D activities of enterprises have a strong demand for funds. It is necessary not only to ensure that there are sufficient funds to carry out activities but also to ensure that funds can be supplied in time to support the continued activities [19]. However, based on the various characteristics of R&D investment itself, such as information asymmetry between the supply and demand sides of funds caused by the confidentiality of R&D core information, the uncertainty of the income results caused by the long R&D cycle, and the low guarantee value of the limited collateral in R&D, all make it difficult for enterprises to obtain funds for R&D from the outside, or although they can obtain funds, the cost is relatively high, and the use of funds is also subject to greater restrictions.

If the company's capital liquidity is insufficient, it will cause the company to be unable to pay the initial fixed costs necessary for export, and this cost is an indispensable condition for the company to conduct foreign trade. Even for companies, they have higher labor productivity and expect that exports will bring certain profits to the company, but if the company's funds are not enough to pay the fixed costs in the early stage, then they will not be able to carry out export trade. Therefore, from this perspective, the financing constraints faced by enterprises will be limited to whether they can participate in export trade [19].

2.3. Labor Income Share. China has always been at the low end of the world's industrial chain. Many multinational

investment companies have transferred some industries to China in order to save costs in order to seek advantages in labor costs. For China, different industries transferred from developed countries to my country will also cause corresponding changes in my country's labor income share. If the transfer is capital-intensive industries, then the high wages in these industries will drive the increase in China's overall labor income share and increase the wage gap in my country with different skills; if the transfer is labor-intensive industries, it will inevitably lead to low-end industry competition intensified, thereby reducing the labor income share [20, 21].

Based on this model, this paper adds a set of control variables that may affect labor income shares. The mathematical expression of the model is as follows:

$$LS_{it} = C + \alpha \text{Trade}_{it} + \gamma_i + \delta_t + \mu_{it}, \tag{9}$$

$$LS_{it} = C + \alpha \text{Trade}_{it} + \theta X_{it} + \gamma_i + \delta_t + \mu_{it}. \tag{10}$$

In the formula, LS_{it} represents my country's labor income share as the explained variable of the regression equation. Trade_{it} represents the total amount of foreign trade, as the main explanatory variable of the model, because trade involves imports and exports. In order to further analyze the impact of imports and exports on the labor income share, this variable is specifically divided into import trade and export trade species [22, 23].

The elasticity of capital output is as follows:

$$e_{Kt} = \frac{\partial Y_t}{\partial K_t} \cdot \frac{K_t}{Y_t} = MP_{Kt}^{1-\sigma} \pi^\sigma \left(\Gamma_t^K\right)^{\sigma-1}. \tag{11}$$

The labor output elasticity is as follows:

$$e_{Lt} = \frac{\partial Y_t}{\partial L_t} \cdot \frac{L_t}{Y_t} = MP_{Lt}^{1-\sigma} (1-\pi)^\sigma \left(\Gamma_t^K\right)^{\sigma-1}. \tag{12}$$

In the process of industrial transfer, foreign direct investment is the most direct manifestation. There are also differences in propensity to consume between capitalists and workers. Workers and capital owners have different marginal propensity to consume. As the labor income share increases, workers' incomes generally increase, capital owners' profits decrease, and workers' consumption increases. The magnitude is greater than the decrease in capitalist consumption, total consumption increases, and income increases [24, 25]. The increase in the labor income share reduces the average propensity to save in the whole society, and the total amount of loanable funds for investment decreases, which has a restraining effect on investment. However, considering China's high public investment rate and overcapacity, China's high investment problem should not be a problem of total volume, but a problem of investment structure. The reduction of total investment and the optimization of investment structure can also promote rapid economic development. The increase in the income share is conducive to increasing the income of laborers and promoting private investment.

In terms of labor income share, the technology contribution of the capital-intensive sector is higher than the average contribution of the labor-intensive sector, the technological progress in my country is still the introduction of technology, and independent innovation is second. When industrialization develops to some extent, after developing countries acquire a certain amount of capital accumulation and technological research ability, the rate of capital accumulation tends to decrease to some extent, and the production efficiency of capital tends to be balanced. In the intensive industrial development that is heading, the current technological progress is dominated by independent R&D and innovation. The demand for human capital has increased, and the output efficiency of human capital has gradually improved. This is manifested as capital-saving technological progress, which leads to an increase in labor income [26, 27]. With the development of the economy, the labor income share is showing a pattern of changes, and my country is in a downward stage of declining labor income share.

3. Experimental Design of the Influence of Enterprise Financing Constraints on Labor Income Share

3.1. Data Sources. Based on the financial data report published by the CCER database and the company's IPO prospectus and annual report, this article will conduct a secondary screening based on whether the company's main business products belong to the Internet of Things key technology application classification and exclude those that do not meet the requirements of the Internet of Things technology concept and belong to ST or companies with missing data, finally got 226 IoT listed companies as the final research sample of this article.

3.2. Sample Index Selection. This paper selects dividend payment rate, interest guarantee multiple, and enterprise size as the main proxy variable indicators when judging the degree of corporate financing constraints. The maximum percentage of dividends in a company's net earnings per share is 100%, and the minimum is 0%. A low dividend payout ratio means that companies have to face higher external financing constraints. The data on the company's dividend per share and net income selected in this article are derived from the company's annual financial income statement and owner's equity statement. In this paper, based on the basic characteristics of my country's Internet of Things listed companies and considering the availability of index data, the independent variables of the binary logistic regression model are selected as return on equity (ROE), asset-liability ratio (LEV), working capital allocation ratio (WCAR), and cash flow ratio (CFR). It is measured by the ratio of accounts receivable to the total assets of the enterprise. It indicates the amount of commercial loans that a company can provide to other sellers as a supplier. It is also a key indicator that reflects the ability of enterprises to obtain financing in commercial credit. The value of this indicator is also inversely related to financing constraints.

3.3. Model Building. The system GMM estimation method sends the difference equations and levels as equations and uses more information than the first-order GMM to control intrinsic problems and improve the effectiveness of the estimation results. If the cash flow coefficient CF/K is significantly positive, it indicates that the investment scale of the company is positively correlated with the internal cash flow, and that the investment activity of the company faces the constraint of external financing. It reflects the reality. If the coefficients of the lagging variable of investment expenditures are all significantly positive, it means that there is obvious continuity of corporate investment behavior. At the same time, in order to prevent the overseas financing behavior of the enterprise after the foreign direct investment from forming a certain mitigation effect on the financing constraints of the enterprise, only the first foreign direct investment behavior of the enterprise is considered in this regression. In addition, in order to avoid the influence of endogeneity on the estimation results, the explanatory variable adopts a lagging approach.

3.4. Data Processing. In order to test the applicability of the regression model of each model variable and the multicollinearity of the independent variables, this paper uses STATA/SE12.0 software to perform the Pearson correlation test on the above three different regression model variables based on the specific data calculated by each indicator variable. Here, this article has carried out a transformation on the measurement of the comprehensive index of financing constraints, replaced the comprehensive index of financing constraints score A with score B, and used the probit model to conduct further robustness tests. And the logit model is still used for regression verification again.

4. Influence of Enterprise Financing Constraints on Labor Income Share

4.1. Analysis Based on the Regression Results of the Logit Model. The larger the KZ index value, the more severe the financing constraints the enterprise faces. The regression results based on the logit model are shown in Table 1.

It can be seen from Table 1 that the coefficient of cash dividend is -36.2548, which shows that companies with fewer dividend distributions face higher financing constraints. The smaller the company's dividend distribution, the more net profit will be reserved for own use in the profit distribution. This reflects that companies are facing a relatively high degree of financing constraints and need to use most of their net profits to meet the capital needs for corporate development. The coefficient of Tobin's Q is 0.522, which shows that companies with more growth opportunities face higher financing constraints. Companies with more growth opportunities generally need more capital to meet their development needs, and the higher the degree of financing constraints they face. The above coefficients all reject the null hypothesis that the coefficient is 0 at the 1% probability level, indicating that these five indicators are a good measure of the degree of financing constraints of Chinese enterprises.

Table 1: Regression results based on the logit model.

Evaluation coefficient	CF/A	DIV/A	C/A	LEV	Q
KZ	-13.9816	-36.2548	-5.5084	3.8642	0.5220
	(0.3729)	(1.0295)	(0.1534)	(0.1135)	(0.0180)

4.2. Analysis Based on Individual Indicators

4.2.1. Analysis Based on KZ Index. From 2011 to 2020, the KZ index of sample companies is shown in Figure 1.

From Figure 1, we can see that between 2011 and 2020, the sample company's KZ index rose from 1.22 in 2011 to 2.23 in 2020, an increase of 80.07% compared to 2011. This shows that the funding constraints companies are facing are becoming more and more stringent. It is serious. From 2013 to 2020, the KZ index is on a downward trend, gradually declining to 1.86 in 2011 and 1.66 in 2012. Compared to 2011, it is still up 50.86% and 36.29%, indicating that corporate funding constraints have not improved. From 2013 to 2017, the KZ index was still fluctuating. It went through a process of rising first and then falling. It increased from 1.67 in 2013 to 2.16 in 2015 and decreased to 1.57 in 2017, but it had increased by 76.98% and 29.02% respectively from 2011. The above analysis also further illustrates the current situation in which Chinese companies are widely affected by funding constraints.

4.2.2. Analysis Based on R&D Funding. My country's R&D funding investment is shown in Figure 2.

It can be seen from Figure 2 that the intensity of R&D investment in my country (the ratio of total R&D expenditure to gross domestic product) has also shown a trend of increasing year by year. In 2010, my country's R&D investment intensity was 1.37%; in 2020, the R&D investment intensity exceeded the 1.5% mark, reaching 1.66%; as of 2020, my country's R&D investment intensity was 2.13%. The main bodies of technological innovation in my country are mainly divided into enterprises, colleges and universities, and scientific research institutions. The overall R&D investment situation cannot accurately represent the research and development investment situation of each subject. Therefore, this article further discusses the R&D investment status of enterprises as one of the main technological innovation subjects.

4.2.3. Microenterprise R&D Investment. Figure 3 shows the R&D expenditures of microenterprises.

It can be seen from Figure 3 that, as the backbone of my country's technological innovation, microenterprises' total R&D expenditures have shown an increasing trend, but the proportion of R&D expenditures in the country has fluctuated slightly, reflecting the possibility of financing constraints from the side. This has had an impact on corporate R&D expenditures. In 2007, Chinese enterprises invested 268.1 billion yuan in R&D expenditures, accounting for 72.28% of the total R&D expenditures of the country, far exceeding the proportion of R&D expenditures of colleges and universities and
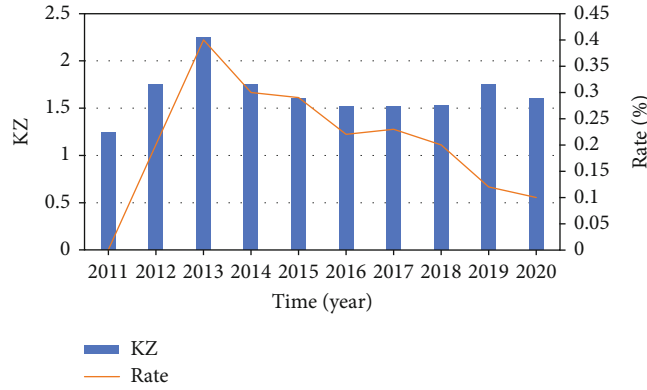
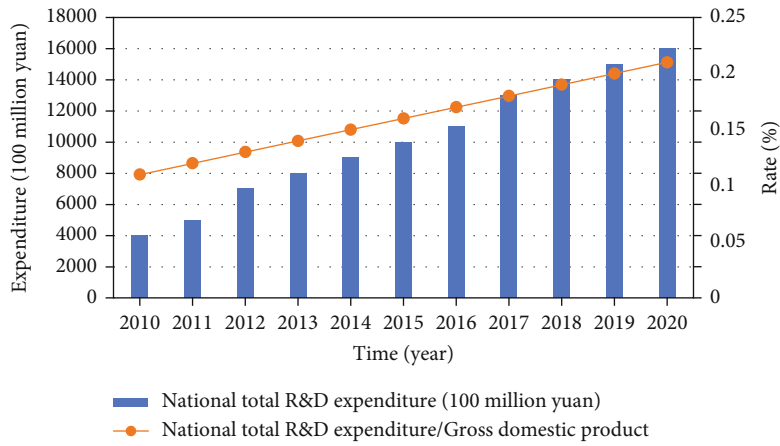FIGURE 1: The KZ index of sample companies from 2011 to 2020.

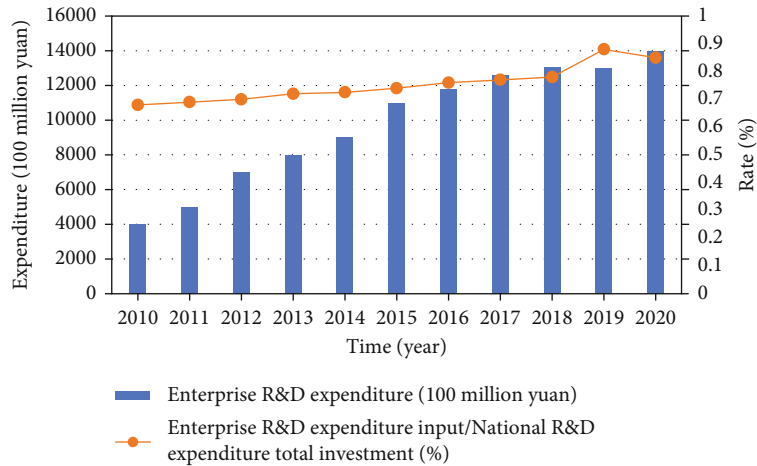FIGURE 2: Our country's R&D funding input.

FIGURE 3: Microenterprise R&D expenditures.

professional scientific research institutions in the total R&D expenditures of the country, and it further proves the dominance of microenterprises in our country's technological innovation. From 2013 to 2014, the proportion of corporate R&D expenditures in the total R&D expenditures of the country increased significantly, from 73.42% in 2013 to

75.74% in 2014, an increase of 2.32%. In 2014, corporate R&D expenditures also broke through the trillion yuan mark, reaching 1.01 trillion yuan, accounting for 77.30% of the country's total R&D expenditures. But by 2015, the proportion of corporate R&D investment in the total R&D expenditure of the country has declined, to 76.79%. As of 2017, the

TABLE 2: Variable descriptive statistics.

Variable	Mean	Standard deviation	Minimum	Median
Total number of patent applications	101.2165	490.9228	1.0000	24.0000
Invention patent application	47.9385	290.2382	0.0000	9.0000
Utility model application	44.3933	211.3312	0.0000	10.0000
Design application	8.8846	41.6548	0.0000	0.0000
Financing constraints	1.7756	1.5451	-2.7538	1.8065
R&D	5.0603	5.4002	0.0000	3.8000
Credit market development	1.3645	0.4985	0.5372	1.2111
Stock market development	0.3103	0.3205	0.0299	0.1809
Company size	21.8286	1.2328	18.3308	216136

R&D expenditure of Chinese enterprises was 137 million yuan, accounting for 77.59% of the national R&D expenditure.

4.3. Analysis Based on Variable Descriptive Statistics.

The descriptive statistics of the variables used in this paper are shown in Table 2. The minimum value of the total number of patent applications of the explained variable enterprises is 1, and the maximum value is 20,007. This shows that there are large differences in technological innovation capabilities between different companies. Some companies have strong innovation capabilities and can apply for more patents within a year, while some companies are obviously lacking in innovation capabilities and have almost no patent applications.

Based on the socialist market economy system with Chinese characteristics, state-owned enterprises enjoy the hidden protection of all aspects of the government, and at the same time, they undertake a heavier historical mission than private enterprises. On the one hand, the stable development of state-owned enterprises reflects the prosperity and stability of my country's economy and society to a certain extent. People may be extra conservative in their investment policies and tend to invest in projects that have shorter investment cycles and faster returns and can improve the current capital situation of the enterprise. On the other hand, in the process of my country's transition from a technological power to a technological power, state-owned enterprises have assumed the responsibility of playing a pioneering role. Even in the face of financing constraints, state-owned enterprises still have the motivation to devote themselves to higher technological content and stronger technological innovation activities. This article further explores the impact of financing constraints on the technological innovation activities of state-owned and non-state-owned enterprises. The specific regression results are shown in Table 3.

Technological innovation activities are closely related to the level of financing constraints. Companies with different levels of financing constraints have greater differences in technological innovation activities. Companies with high financing constraints have low investment in technological innovation, while companies with low financing constraints have higher investment in technological innovation. In order to more clearly illustrate the correlation between the degree of financing constraints and technological innovation activi-

TABLE 3: Specific regression results.

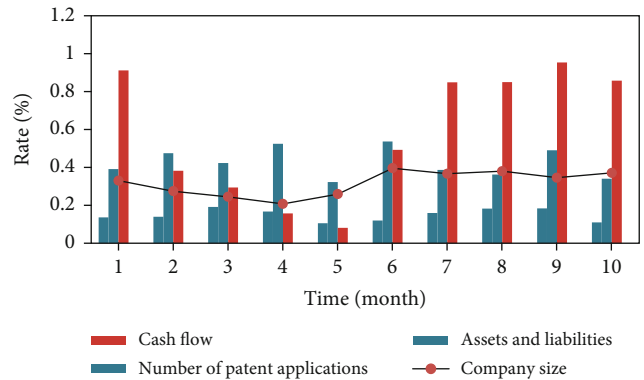| Parameter	Total number of patents	Patent	Practical	Exterior
Financing	-0.0155	-0.0041	-0.0207	-0.0084
	(0.0072)	(0.0081)	(0.0091)	(0.0147)
Constraints	0.0983	0.1114	0.1308	0.1769
	(0.0196)	(0.0220)	(0.0226)	(0.0388)
Company age	-0.0025	-0.0088	-0.0046	0.0210
	(0.0064)	(0.0070)	(0.0071)	(0.0100)

FIGURE 4: KW inspection result.

ties, this article continues to conduct a multisample bilateral test and KW rank sum test on the samples to analyze whether the innovation activities of enterprises with different financing constraints are significant. This can be seen from the inspection results in the third row to the fifth row. At the same time, the overall difference in asset-liability ratio and cash flow, the difference between the first two groups and the latter two groups, and the difference between groups have also passed the significance test, again confirming that the degree of financing constraints is positively correlated with the asset-liability ratio, and cash flow is negatively correlated. The KW inspection result is shown in Figure 4.

The result of variance decomposition is shown in Figure 5. It can be seen that the variance decomposition of technological innovation investment is basically stable after the fourth period. From the perspective of the variance
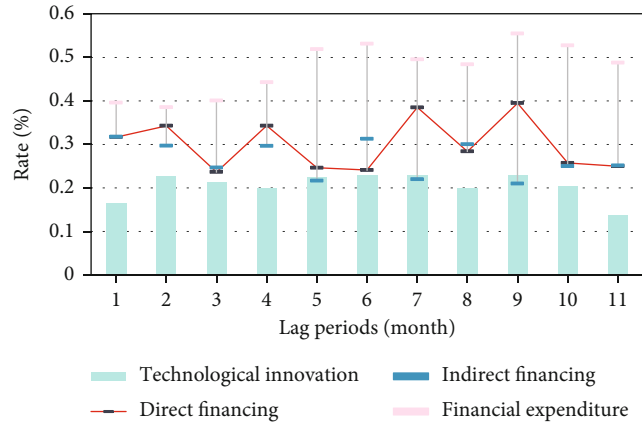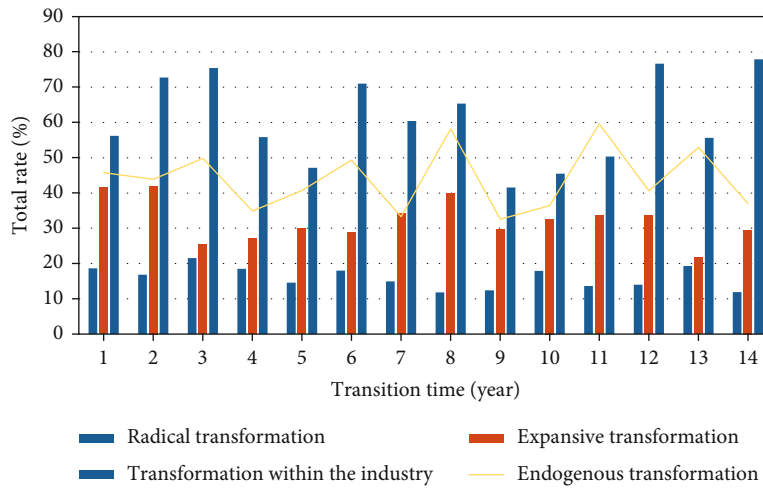
Figure 5: Variance decomposition result.

Figure 6: Resource-based enterprises account for the sample of transformed enterprises.

contribution rate of each variable, the fluctuation of technology innovation investment is mainly due to its own inertia, whether it is short term or long term. The variance contribution rate has always been dominant. The contribution rate reached 100% in the first period and then slowly declined. After the fourth period, it stabilized at 97.3%. The contribution of indirect financing to technological innovation investment volatility is relatively small, and it is basically stable at 0.4% after the fourth period, indicating that the impact of indirect financing on technological innovation changes is very weak. The variance contribution rate of direct financing is rising and stabilized at 2.2% after the fourth period, indicating that compared with the contribution of indirect financing, direct financing has a greater impact on technological innovation and can have a greater impact on technological innovation investment, mainly because the external financing channel for technological innovation in my country's strategic emerging industries is equity financing; that is, it is mainly affected by the direct financing market, while the indirect financing market with bank loans as the main method is not its main financing channel. The impact of technological innovation is relatively small. Fiscal science and technology expenditures have a small contribution to

technological innovation investment volatility, which shows that compared with the main external financing methods of enterprises, the policy guidance effect and financial support of fiscal science and technology expenditures are weak and can only be used as a supplement to the source of technological innovation funds. In general, the variance decomposition results show that the fluctuation of regional technological innovation investment mainly comes from its own inertia, followed by direct financing market, indirect financing market, and fiscal expenditures on science and technology.

There are a total of 226 listed resource-based companies studied in this article, of which 179 have undergone transformation, accounting for 79.20% of the overall sample, and 47 have not undergone transformation, accounting for 20.80% of the overall sample. This shows that, in the context of increasingly prominent resource environment, industrial structure reform, and fierce market competition, most companies are changing their original survival mode. Among the 179 resource-based enterprises that have undergone transformation, 109 of them have undergone intraindustry transformation, accounting for 48.23% of the overall sample and 60.89% of the sample of transformed enterprises. That is, most of them are keeping the main business unchanged.

Enterprise transformation chooses to expand upstream or downstream of the industry, which makes the enterprise industry expand. The sample of resource-based enterprises accounted for in transformation enterprises is shown in Figure 6.

5. Conclusions

This paper adopts the logit model to conduct empirical research on the impact of corporate financing constraints on labor income share after controlling the capital output ratio, technological progress, opening factors, and state-owned enterprise restructuring, and conducts a robustness test of the model; finally, adopts the decomposition method that measures the fluctuation of labor income share in China and decomposes the fluctuation of labor income share into interindustry effects and intraindustry effects. From the perspective of the fluctuation characteristics of labor income share, it examines the influence of industrial structure upgrading and changes in labor income share of various industries on the overall labor income share. Affected by the inherent characteristics of R&D investment and the limitations of SMEs, my country's SMEs have significant R&D input-cash flow sensitivity, and their R&D input level obviously depends on internal cash flow, and there are financing constraints. For non-state-owned enterprises and smaller enterprises, the degree of funding constraints they face is even more serious. The impact of funding constraints on labor income share is negative, primarily as a result of the impact of long-term debt-to-asset ratios on labor income share. This study still has some drawbacks, which are mainly reflected in the following: Many companies are not willing to disclose R&D input information, and it is difficult to obtain R&D input data. After screening, the sample size will be limited. Follow-up surveys should strive to increase the sample size to improve the universality of the survey results.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] I. Kitouni, D. Benmerzoug, and F. Lezzar, "Smart agricultural enterprise system based on integration of Internet of Things and agent technology," *Journal of Organizational and End User Computing*, vol. 30, no. 4, pp. 64–82, 2018.

[2] S. B. Tsai, "Using the DEMATEL model to explore the job satisfaction of research and development professionals in China's photovoltaic cell industry," *Renewable and Sustainable Energy Reviews*, vol. 2018, no. 81, pp. 62–68, 2018.

[3] X. Tian and P. Nie, "Econometric analysis of political connection affect corporate credit financing constraints based on fuzzy logic and SEM model," *Journal of Intelligent & Fuzzy Systems*, vol. 37, no. 1, pp. 441–454, 2019.

[4] Z. Yin, "Research on the relationship between China's supply-side structural reform and enterprise innovation–from the perspective of financing constraints," *World Scientific Research Journal*, vol. 6, no. 5, pp. 130–135, 2020.

[5] J. Fang, C. Liu, and C. Gao, "The impact of environmental regulation on firm exports: evidence from environmental information disclosure policy in China," *Environmental Science and Pollution Research International*, vol. 26, no. 36, pp. 37101–37113, 2019.

[6] S. B. Tsai and K. Wang, "Using a novel method to evaluate the performance of human resources in green logistics enterprises," *Ecological Chemistry and Engineering S*, vol. 26, no. 4, pp. 629–640, 2019.

[7] H. Agyei-Boapeah, "Easing financing and M&A investment constraints: the role of corporate industrial diversification," *Annals of Economics and Finance*, vol. 18, no. 2, pp. 277–290, 2017.

[8] F. Luo, "The impact of foreign direct investment on the labor income share of listed companies," *Modern Economy*, vol. 11, no. 2, pp. 541–560, 2020.

[9] Y. Liu and J. Wang, "Environmental pollution, environmental regulation, and labor income share," *Environmental Science and Pollution Research*, vol. 27, no. 36, pp. 45161–45174, 2020.

[10] N. Phaosathianphan, A. Leelasantitham, and H. K. Tang, "Understanding the adoption factors influence on the use of Intelligent Travel Assistant (ITA) for eco-tourists: an extension of the UTAUT," *International Journal of Innovation and Technology Management*, vol. 16, no. 8, article 1950060, 2019.

[11] M. Mehrabanpour, O. Faraji, R. Sajadpour, and M. Alipour, "Financial statement comparability and cash holdings: the mediating role of disclosure quality and financing constraints," *Journal of Financial Reporting and Accounting*, vol. 18, no. 3, pp. 615–637, 2020.

[12] P. Gonzalez-Gil, J. A. Martinez, and A. F. Skarmeta, "Lightweight data-security ontology for IoT," *Sensors*, vol. 20, no. 3, pp. 801–819, 2020.

[13] S. Yadav, S. Luthra, and D. Garg, "Modelling Internet of Things (IoT)-driven global sustainability in multi-tier agri-food supply chain under natural epidemic outbreaks," *Environmental Science and Pollution Research*, vol. 28, no. 13, pp. 16633–16654, 2021.

[14] W. Zhao, G. Wang, S. Atapattu, T. A. Tsiftsis, and X. Ma, "Performance analysis of large intelligent surface aided backscatter communication systems," *IEEE Wireless Communications Letters*, vol. 9, no. 7, pp. 962–966, 2020.

[15] Y. Wu, Y. Liu, S. H. Ahmed, J. Peng, and A. A. Abd el-Latif, "Dominant data set selection algorithms for electricity consumption time-series data analysis based on affine transformation," *IEEE Internet of Things Journal*, vol. 7, no. 5, pp. 4347–4360, 2020.

[16] B. Y. Ooi, Z. W. Kong, W. K. Lee, S. Y. Liew, and S. Shirmohammadi, "A collaborative IoT-gateway architecture for reliable and cost effective measurements," *IEEE Instrumentation and Measurement Magazine*, vol. 22, no. 6, pp. 11–17, 2019.

[17] M. Khan and D. H. Kim, "Service process modelling and performance analysis for composite context provisioning in IoT," *The International Arab Journal of Information Technology*, vol. 15, no. 1, pp. 141–147, 2018.

[18] C. Malathi and M. Nithyavelam, "IoT based access and analysis of wireless sensor node protocols with low power host

connectivity," *International Journal of Civil Engineering and Technology*, vol. 8, no. 12, pp. 89–95, 2017.

[19] J. A. Uqaili, S. Memon, H. M. Bilal et al., "Implementation of scalable and energy efficient WSN platform for IoT applications," *Indian Journal of Science and Technology*, vol. 13, no. 36, pp. 3725–3737, 2020.

[20] P. Sandner, A. Lange, and P. Schulden, "The role of the CFO of an industrial company: an analysis of the impact of blockchain technology," *Future Internet*, vol. 12, no. 8, pp. 128–131, 2020.

[21] L. Feng, J. Yu, F. Zhao, and H. Jiang, "A novel analysis of delay and power consumption for polling schemes in the IoT," *Tsinghua Science and Technology*, vol. 22, no. 4, pp. 368–378, 2017.

[22] Z. Qian and J. Gong, "Research on monitoring system of underground gas pipeline network based on Internet of Things and GIS," *Journal of Geomatics*, vol. 44, no. 1, pp. 111–114, 2019.

[23] Z. Meng, Z. Wu, C. Muvianto, and J. Gray, "A data-oriented M2M messaging mechanism for industrial IoT applications," *IEEE Internet of Things Journal*, vol. 4, no. 1, pp. 236–246, 2017.

[24] F. Conti, R. Schilling, P. D. Schiavone et al., "An IoT endpoint system-on-chip for secure and energy-efficient near-sensor analytics," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 64, no. 9, pp. 2481–2494, 2017.

[25] X. Yao, J. Wang, M. Shen, H. Kong, and H. Ning, "An improved clustering algorithm and its application in IoT data analysis," *Computer Networks*, vol. 159, no. AUG.4, pp. 63–72, 2019.

[26] A. Ait-Mlouk, F. Gharnati, and T. Agouti, "Application of big data analysis with decision tree for road accident," *Indian Journal of Science and Technology*, vol. 10, no. 29, pp. 1–10, 2017.

[27] W. Wu, S. An, C. H. Wu, S. B. Tsai, and K. Yang, "An empirical study on green environmental system certification affects financing cost of high energy consumption enterprises-taking metallurgical enterprises as an example," *Journal of Cleaner Production*, vol. 244, p. 118848, 2020.