economies

Article

Do More Innovations Mean Less Reliance on Labor?—Evidence from Listed Chinese Manufacturing Companies in the Final Stage of Industrialization

Donghui Shi * and Ang Yang *

School of Economics, Shanghai University, Shanghai 200444, China
* Correspondence: shidonghui@shu.edu.cn (D.S.); ashtray@shu.edu.cn (A.Y.)

Abstract: This paper examines the impact of technological innovation on the role of labor within listed manufacturing companies during China's final stage of industrialization, from a factor input structure perspective. Leveraging a balanced panel dataset from 2012–2021, we find that the rising R&D intensity has increased companies' labor intensity and therefore factually slowed down the falling trend of labor intensity. This is because through R&D, the companies have both raised the relative productivity of capital and the percentage of well-educated and technically skilled personnel. Consequently, our research suggests that concerns about technological innovation leading to unemployment or diminishing the standing of workers are unnecessary. While the rising trend of labor cost will sustain for a long time, the intensified R&D activities in Chinese manufacturing companies, thanks to the fast-rising level of education for the Chinese since the 1980s, hold the potential not only to further enhance their global competitiveness, but also alleviate the pressure of employment by creating of more jobs.

Keywords: listed manufacturing companies; R&D intensity; factor structure; labor intensity; unemployment

check for updates

Citation: Shi, Donghui, and Ang Yang. 2023. Do More Innovations Mean Less Reliance on Labor?—Evidence from Listed Chinese Manufacturing Companies in the Final Stage of Industrialization. *Economies* 11: 230. https://doi.org/10.3390/economies11090230

Academic Editor: Luigi Aldieri

Received: 21 July 2023
Revised: 1 September 2023
Accepted: 3 September 2023
Published: 6 September 2023

1. Introduction

The mainstream opinion in the academic community is that China had basically achieved industrialization in 2020 (Huang 2021). In the final stage of China's industrialization from 2011 to 2020, although the annual average growth rate of industrial added value reached 5.9%, the industrial sector, especially manufacturing, still faced two major challenges. The first one is that as China increasingly approached or partly surpassed developed countries in overall technological development, its manufacturing industry depended more on indigenous innovation rather than technology introduction from foreign countries for technological progress (Zheng and Jin 2021). This posed an unprecedented test to China's independent innovation capability and the efficiency of its innovation system (World Bank, Development Research Center of the State Council, P.R. China 2013; Yu et al. 2019). The second challenge is that with the fast-rising labor cost in the manufacturing industry in 2011–2020, the average wage for urban manufacturing employees grew as much as 9.5% on annual average, rapidly wiping off the industry's comparative advantages coming from the low labor cost (Lin 2011).

In response to the twin pressures of rising labor costs and narrowing technological gaps, China aimed to shift from the extensive growth model reliant solely on factor input and scale expansion. Over the past decade, one of the primary policy objectives has been to increase enterprise research and development (R&D) investment to foster industry upgrading through technological innovation. The State Council's "Industrial Transformation and Upgrade Plan (2011–2015)", published in 2011, targeted R&D expenditure of industrial enterprises above a designated size[1] to reach 1% of their main business income and exceed 3% for key enterprises (SC 2011). The plan prioritized improving the quality and benefits of development for transformation and upgrade, optimizing input structure, and prompting a shift towards a development model centered on quality and efficiency. Similarly, "Made in China 2025", issued by the State Council in May 2015, advocated placing innovation at the heart of manufacturing development (SC 2015). As a result, from 2011 to 2020, R&D expenditure by industrial enterprises above the designated size across the country grew at an average annual rate of 11%, with R&D intensity increasing from 0.71% to 1.41%.

Factor structure, the ratio of labor and capital consumed in production, reflects the production modes and efficiency of different enterprises. Changes in the factor structure not only reveal the state of resource allocation within enterprises but also the importance of certain factors in the production process. It is widely accepted that the optimization of factor structure is crucial for industrial upgrading. Through adjusting their factor structure, enterprises can adapt production strategies to meet market changes and enhance competitiveness. Technological innovation, as a primary driver of industrial upgrading, directly affects the production process of enterprises, triggering reallocation of labor and capital, and significantly influencing the factor structure (Adams 1999). Data since 2011 indicate a rapid decline in the weight of labor in Chinese enterprises' production processes, signifying a decreasing reliance on labor. In 2020, the average staffing level in manufacturing companies above the designated size was 69.58 million, a drop of 13.6% from 2011, averaging a decrease of 1.6% per year. Concurrently, the original value and net value of fixed assets per capita rose by 7.1% and 6.5%, respectively, on an annual average (NBS 2021). This trend suggests a negative correlation between rising R&D intensity and falling labor intensity, leading to concerns that rapid technological progress may accelerate the substitution of capital for labor, diminishing the role of labor in enterprise production (Acemoglu and Restrepo 2019; Acemoglu et al. 2020). What is worse, if this inverse relationship is truly present and is confirmed as a causative link, we might soon need to navigate a delicate balance between advancing industrial upgrades and managing unemployment. However, the effect of technological innovation on the factor structure of manufacturing enterprises remains unclear due to the paucity of empirical research on the micro-level impact of technological progress on the factor structure. In the context of accelerating technological innovation in China, increasing labor costs, and the emerging issue of unemployment, understanding the effect of technological innovation on the factor structure of enterprises is essential. This insight will enable a better comprehension of the relationship between technological innovation, industrial upgrading, and labor employment, offering significant real-world implications and policy relevance.

In this paper, we review existing literature and draw from the Constant Elasticity of Substitution (CES) production function to theoretically elucidate the potential logical association between technological innovation and factor structure. We analyze potential impact mechanisms and provide hypotheses for empirical testing. Utilizing balanced panel data from Chinese manufacturing companies listed from 2012 to 2021, we conduct an empirical examination of the impact of R&D intensity on factor structure during the final stage of industrialization. We discuss possible endogeneity issues and analyze the impact mechanism of R&D intensity on factor structure. Finally, based on the conclusions of this paper, we propose policy recommendations.

Our paper contributes in the following ways: First, we confirm at a micro-level that technological advancement does not necessarily result in a decrease in the labor-intensive degree within enterprises. Instead, we find that it can enhance the capacity of firms to absorb labor. In this regard, our study provides evidence for the theory of factor structure optimization at the micro-level. Our conclusion may alleviate pessimistic views about potential unemployment caused by technological innovation and industrial upgrading and provide fresh evidence encouraging independent innovation and industrial upgrading in developing countries. Second, our findings reveal that an increase in R&D intensity can lead to greater labor intensity by improving the relative output efficiency of capital and the proportion of highly skilled and highly educated personnel, thereby further uncovering the impact mechanism of technological innovation on factor structure. Consequently, our work augments the existing literature on the relationship between technological progress, industrial upgrading, and factor structure optimization.

2. Literature Review

2.1. Measurement of Factor Structure

Theoretically, how much a company relies on labor input can be measured with labor intensity, which is the labor-to-capital ratio during production. Assuming that output is a function of capital and labor, that is:

$$Y = F(K, L) \tag{1}$$

In this equation, Y represents output, K stands for capital and L denotes labor, and $\frac{K}{L}$ is the factor structure. A smaller $\frac{K}{L}$ implies a higher labor intensity (i.e., lower capital intensity), namely the company relies heavily on labor input (Marshall 2009).

But in empirical research, researchers have chosen different indicators to reflect labor intensity owing to their varied understanding of labor input and capital input. To begin with, two indicators of labor input are usually used in existing literature: (1) the size of staff, which is taken to measure the physical amount of labor input (Dewenter and Malatesta 2001; Kim 2020); and (2) employee remuneration, which is taken to measure the value of labor input (Roca-Puig et al. 2012; Serfling 2016). The former method implies the assumption of homogeneous labor and the same per capita work hours, while the latter recognizes labor's inherent heterogeneity but tends to sideline the actual number of company employees. Thus, synthesizing both methods and simultaneously considering employee count and remuneration may more accurately reflect the differences in workers' skill and labor intensity. Secondly, regarding capital input, some researchers argue it should be counted in the total amount of capital invested in production (Desai et al. 2005), while others believe only the capital actually used during production needs to be measured (Beaulieu and Mattey 1998).

Therefore, aside from the metric of labor productivity, which has been contentious when used to gauge labor intensity, there are mainly three labor intensity indicators in empirical research. ① The first is capital input per capita or its reciprocal, such as total assets per capita, original value of fixed assets per capita, and net value of fixed assets per capita (Dewenter and Malatesta 2001; Scott 2006; Lin 2011). ② The second is the labor input value-to-capital ratio or its reciprocal, such as the ratio between employee's remuneration and total assets, that between employee's remuneration and the original value of fixed assets, and that between employee's remuneration and the net value of fixed assets (Roca-Puig et al. 2012; Serfling 2016). ③ The third is the labor input value-to-used-capital ratio or its reciprocal, such as the ratio between employee's remuneration and fixed assets depreciation (Beaulieu and Mattey 1998; Shi et al. 2023). All three indicators have their flaws, but there does not seem to be an either-or argument over them in the literature due to the availability of data. Moreover, they are also used to measure capital intensity. If one indicator denotes a rather high labor intensity in a comparison, it would simultaneously denote a rather low capital intensity.

2.2. Impact of R&D Activities on a Company's Input of Production Factors

Theoretically speaking, the impact of a company's R&D activities on its structure of factor input is never certain. While R&D activities create demand for capital and labor input, such a demand combination does not necessarily have any bias. At the same time, successful R&D inevitably leads to product innovation or process innovation, the former probably requiring a new combination of factor input and the latter inevitably changing the production function. Nevertheless, neither type of innovation will cause a definite bias in the factor input combination.

Technological innovations stemming from R&D can sometimes substitute labor through automation and other cost-saving mechanisms (Acemoglu and Restrepo 2019). They can also augment the company's labor demand, especially the demand for highly skilled or innovative labor, by fostering new products, expanding markets, establishing new positions, and so on (Harrison et al. 2014). According to the theory of biased technological progress, technological progress tends to save the scarcer production factors (Hicks 1963; Acemoglu 1998, 2002). This makes many scholars think that if a company's R&D is effective, whether that will make it less reliant on labor mainly depends on to what extent capital will replace labor because of such R&D activities (Campell 1994; Cheng et al. 2019; Acemoglu et al. 2020) and how much labor demand will be created by them (Heckman et al. 1998; Galor and Moav 2000; Hémous and Olsen 2022). If the elasticity of substitution between capital and labor is small, R&D is very likely to just trigger the self-iteration of capital, or the employment it creates surpasses the labor replaced by capital during production. As a result, innovation actually makes the company more reliant on labor (Campell 1994; Harrison et al. 2014; Acemoglu 2010). If the elasticity of substitution between capital and labor is big, more labor may be replaced by capital because of R&D than the new labor demand created by it. That means R&D apparently makes the company less reliant on labor (Acemoglu and Restrepo 2019).

In empirical research, there are diverse perspectives on how R&D affects factor intensity and employment as well. For instance, some studies, such as Adams (1999) and Su et al. (2022), found a positive impact of R&D on labor intensity and a complex interaction between patents and employment, implying a simultaneous substitution and creation of labor demand. Drawing on a comprehensive dataset from Vietnam, Le (2023) examined the technological innovation and labor structure nexus at micro level. Their findings revealed that technological innovation significantly enhances the labor force in Vietnam's SMEs. Crucially, such innovations are associated with a surge in skilled labor recruitment and a corresponding decrease in unskilled labor. Yet, this technological innovation's influence on employment predominantly resonates in sectors with lower technological emphasis. In a complementary vein, Lu et al. (2022) highlighted the pivotal importance of human capital, emphasizing its cooperative role alongside technological advancements in shaping labor dynamics amidst tech-centric innovations. Furthermore, Salehi and Alanbari (2023) determined that facilitators of knowledge sharing play a significant role in enhancing the organizational innovation of firms.

Conversely, certain studies, including those by Cirera and Sabetti (2019), have demonstrated that product innovation could have a neutral or even negative effect on employment levels, especially in high-income countries where new or upgraded products are associated with more efficient labor utilization. Moreover, Zhu et al. (2021) found contrasting effects of different types of innovation on employment in Chinese companies, with process innovation having a positive impact and product innovation a negative one.

In summary, these studies indicate that the effect of R&D and innovation on the structure of production factors is not straightforward, and it may vary depending on factors such as the type of innovation, the industry, the country's income level, and the specific measure of labor intensity used. Conclusively, there is a general agreement that innovation can both substitute and create labor demand. However, existing research has yet to specifically address how the strengthening of R&D activities in Chinese manufacturing companies in the late stage of China's industrialization has impacted their structure of production factors. And this is precisely the gap our study aims to fill.

3. Study Design

3.1. Simple Theoretical Model

To elucidate the potential influence of R&D activities on the structure of production factors, we develop a simple theoretical model in this section. Referring to Acemoglu (2003), we let the production function conform to the form of the CES (Constant Elasticity of Substitution) production function, based on Equation (2):

$$Y = \left[\alpha\left(\Gamma^{L}L\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left(\Gamma^{K}K\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

In the equation, Y denotes output, K stands for capital input, and L is labor input. Γ^L and Γ^K, respectively, signify the efficiency levels of labor and capital, illustrating labor-enhancing and capital-enhancing technological progress. $\alpha \in (0,1)$ represents the labor allocation parameter, also known as labor output elasticity; $\sigma \in [0,+\infty]$ is the elasticity of substitution between factors. Assuming each firm operates in a perfectly competitive market and takes both factor prices and product prices as given, where w is the wage rate, r is the capital price, and P is the price of the product, the firm's profit function can be represented as:

$$\pi = P \times \left[\alpha\left(\Gamma^L L\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left(\Gamma^K K\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} - wL - rK \tag{3}$$

Given that firms aim to maximize profits, taking the partial derivatives of the profit function with respect to K and L, respectively, we obtain:

$$\begin{aligned} \frac{\partial \pi}{\partial L} &= P\times\ \alpha \times \Gamma^L \times \left(\Gamma^L L\right)^{-\frac{1}{\sigma}} \times \left[\alpha\left(\Gamma^L L\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left(\Gamma^K K\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} - w = 0 \\ \frac{\partial \pi}{\partial K} &= P \times (1-\alpha) \times \Gamma^K \times \left(\Gamma^K K\right)^{-\frac{1}{\sigma}} \times \left[\alpha\left(\Gamma^L L\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left(\Gamma^K K\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} - r = 0 \end{aligned} \tag{4}$$

By simplifying Equation (4), we can derive the firm's factor structure:

$$\frac{K}{L} = \left(\frac{\Gamma^L}{\Gamma^K}\right)^{1-\sigma}\left[\frac{\alpha w}{(1-\alpha)r}\right]^{\sigma} \tag{5}$$

Based on the formula determining factor structure, i.e., Equation (5), the factor structure of a company largely hinges on the relative productivity levels of labor and capital, the relative pricing of labor and capital, the labor distribution parameter, and factor substitution elasticity, assuming all other conditions remain constant. Given that both the labor distribution parameter α and the factor substitution elasticity σ range between 0 and 1, there is an inverse correlation between a company's labor intensity and the level of labor output efficiency and labor pricing, while there is a positive correlation with the level of capital output efficiency and capital pricing.

Let us posit that a firm's R&D investment is rd. In pursuit of profit maximization, the company applies all R&D investment toward enhancing factor productivity (Grossman and Helpman 1994). Here, θ_Lrd of R&D input influences labor productivity, θ_Krd of R&D input impacts capital productivity, and θ_Frd of R&D input culminates in failure. The values θ_L, θ_K, and θ_F represent the probabilities of a successful labor-enhancing innovation, capital-enhancing innovation, and R&D failure, respectively, within the R&D input, each of these probabilities ranging between 0 and 1.

As per the practice in existing literature (Acemoglu 2002, 2003), we assume that efficiency levels of labor and capital exhibit exponential growth:

$$\Gamma^L = e^{\lambda_L},\ \Gamma^K = e^{\lambda_K} \tag{6}$$

Here, λ_L and λ_K correspond to the growth rates of labor and capital productivity respectively. R&D activities, driven by a firm's profit-seeking motive, have been highlighted in the existing literature as being able to enhance a firm's long-term profitability and added-value rate (Shi et al. 2023). From a production standpoint, R&D activities can potentially reduce production costs by altering the productivity of capital and labor (Hall and Mairesse 1995). Simultaneously, given the inherent probability of failure in R&D, the activities that do ultimately result in failure consume a firm's human and physical resources, potentially exerting a negative impact on labor and capital output efficiency (Link and Wright 2015).

For convenience and straightforwardness, let us assume that λ_L and λ_K are linear functions of $\theta_L rd$, $\theta_K rd$, and $\theta_F rd$. Therefore, we have:

$$\lambda_L = \lambda_1 + \eta_1^L \theta_L rd - \eta_2^L \theta_F rd + \varepsilon_L,\ \lambda_K = \lambda_2 + \eta_1^K \theta_K rd - \eta_2^K \theta_F rd + \varepsilon_K \tag{7}$$

Here, η_1^L denotes the impact coefficient of labor efficiency-enhancing inventions on labor efficiency, and η_1^K stands for the impact coefficient of capital efficiency-enhancing inventions on capital efficiency. Meanwhile, η_2^L and η_2^K, respectively, represent the losses inflicted on labor efficiency and capital efficiency due to the failure of R&D. By substituting Equations (6) and (7) into Equation (5), and taking the logarithm on both sides, we have:

$$\ln\left(\frac{K}{L}\right) = (1-\sigma)(\lambda_1 - \lambda_2) + \delta \ln\left(\frac{1-\sigma}{\delta}\right) + \left[\eta_1^L \theta_L - \eta_1^K \theta_K - \left(\eta_2^L + \eta_2^K\right)\theta_F rd + \sigma \ln\left(\frac{w}{r}\right) + \varepsilon_L + \varepsilon_K \tag{8}$$

From Equation (8), we can see that the impact of R&D investment on the proportion of labor inputs is negatively correlated with θ_L and η_1^L and positively correlated with θ_K, η_1^K, θ_F, η_2^L, and η_2^K. Given the probability of R&D failure, θ_F, when the impact of R&D investment on labor output efficiency is greater than its impact on capital output efficiency and the loss due to R&D failure, R&D investment can reduce the proportion of labor inputs. Conversely, when the impact of R&D investment on capital output efficiency outweighs its impact on labor output efficiency and the loss from R&D failure, R&D investment will increase the proportion of labor inputs. If the relative increase in factor efficiency brought about by R&D investment cancels out the loss from R&D investment, R&D investment will not affect the structure of production factors. Based on this, we propose:

H0. *Technological innovation can influence the factor structure of a company.*

In addition, given the loss due to R&D failure, a company's R&D investment may increase the proportion of labor inputs during the production process, or it may increase the proportion of capital inputs. This primarily depends on the success probability of labor-efficiency-enhancing inventions θ_L, the success probability of capital-efficiency-enhancing inventions θ_K, and the impact coefficients of both types of inventions on factor output, η_1^L and η_1^K, which are exogenous variables. Therefore, the direction of the impact of R&D investment on the structure of factor inputs requires discussion based on empirical analysis. To investigate the direction of the impact of a company's R&D investment on the structure of its factor inputs, we further propose:

H1. *Technological innovation can increase the proportion of labor inputs in the company.*

3.2. Sample of Study and Source of Data

To test the hypothesis, this study used data from manufacturing companies listed on China's A-share market from 2012 to 2021. Companies listed after 2012, those with special treatment for stocks (ST/ST*), those whose important data are either missing or conspicuously abnormal, and those that have changed their industrial attributes as a result of asset restructuring are excluded. That leaves 1063 companies, and the balanced panel data about them from 2012 to 2021 are used. All data are sourced from WIND database and CSMAR database.

These companies are chosen for the following reasons. First, it was after the ChiNext was officially established in 2009 that the number of listed Chinese manufacturing companies has increased notably. The samples in this paper include the majority of main companies in the industry. Meanwhile, though China Securities Regulatory Commission made specific requirement in 2007 for listed companies to disclose their R&D information, due to various reasons, it was not until 2012 that most listed manufacturing companies began to regularly disclose their annual R&D expenses. Second, observations show that between 2012 and 2021, the sample companies' average R&D intensity, labor intensity, and per capita remuneration presented a changing trend that almost coincided with that of the Chinese manufacturing industry in 2011–2020, as stated earlier. Statistics show that the sample companies' average R&D intensity rose from 2.59% in 2012 to 3.77% in 2021, an increase of 45.6% over a decade. On another note, as shown in Figure 1, their per capita remuneration rose 102.4% in 2012–2021, averaging an increase of 6.7% per year. The indicators that measure capital intensity—original value of fixed assets per capita, net value of fixed assets per capita, and the ratio between fixed assets depreciation and payable remuneration to employees—went up 86.9%, 74.2%, and 82.3%, respectively, with the annual average growth of 7.2%, 6.4%, and 6.9% each.

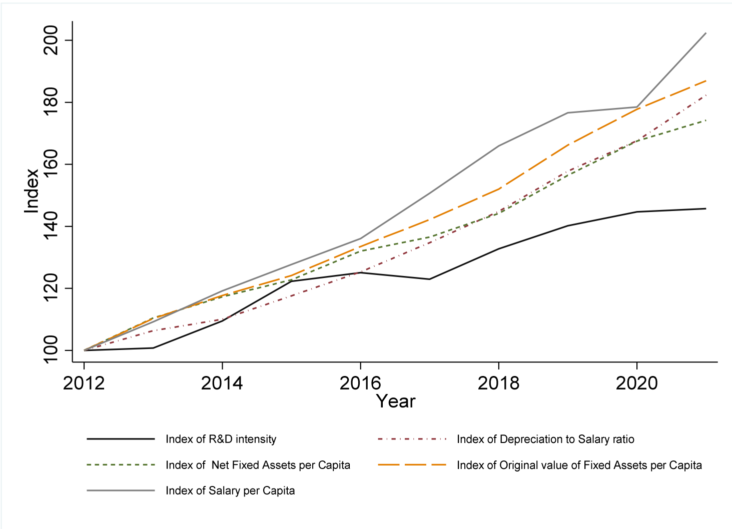

Figure 1. Index of important indicators of sample companies from 2012 to 2021 (100 set for 2012).

3.3. Benchmark Model

To uncover how the sample companies' R&D intensity in 2012–2021 actually affected their labor intensity, and to verify the above-mentioned hypotheses with the data of sample companies, this paper develops the following benchmark fixed effects model according to Equation (9):

$$S_{i,t} = \alpha + \beta RD_{i,t} + \gamma X_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \tag{9}$$

In this equation, subscript i represents company and t means year. S stands for labor intensity and RD R&D intensity. X represents relevant control variables. μ_i represents the company fixed effect, which is used to control confounding factors and omitted variables that may confound the effects imposed by a company's R&D intensity on its labor intensity and that do not change with time. It may refer to the company's innovation culture, geographical location, length of existence, and so on. τ_t represents time fixed effect, which is used to control for the common changing trend faced by the companies each year, such as the price of factors w or r and the common external impacts.

3.4. Definition and Interpretation of Variables

In this paper, the explained variable is labor intensity (S), which will be measured by the logarithmic of the ratio between the depreciation of fixed assets and payable remuneration to employees ($\ln \frac{k}{l}$) and the logarithmic of the net value of fixed assets per capita[2] ($\ln \frac{K}{L}$). It is evident that a larger value of S means a higher capital intensity and a lower labor intensity, whereas a smaller value of S means a lower capital intensity and a higher labor intensity. To further discuss how the company's R&D intensity affects its labor intensity, payable employee remuneration (l), fixed assets depreciation (k), average size of staff (L), and net value of fixed assets (K) are also used as explained variables and measured with logarithmic for the purpose of analysis.

The key explanatory variable is R&D intensity (RD), which is measured with the ratio between the company's total R&D expenses and operating revenue.

To mitigate the probable endogeneity of the impact imposed by R&D intensity on labor intensity, the company effect and time fixed effect are controlled in order to control the company characteristics and external impact that do not change with time. In addition to them, the following characteristic variables that may affect labor intensity are also controlled for. They are ① Company size (Size) measured with the logarithm of operating revenue; ② Operating profit ratio (Opr) measured with the operating profit margin; ③ Cash flow (Cash) measured with the proportion of monetary funds and tradable financial assets in the company's total assets; ④ Level of liabilities measured, respectively, with the proportion of total liabilities in total assets (i.e., liability-to-asset ratio or Lev), the ratio of total liabilities to total equity (i.e., equity ratio or Equity), and the proportion of financial assets to total assets (i.e., financial liability ratio or Finlev); ⑤ Asset efficiency measured respectively with the fixed asset turnover ratio (Turnover), the proportion of net fixed assets and net inventory to total assets (Tang), and the proportion of current assets to total assets (Liq); and ⑥ Market value of assets measured by Tobin's Q, which is obtained from CSMAR database. It is calculated as the sum of the equity market value and net debt market value, divided by the total assets.

Furthermore, given the possibility of omitted variable bias resulting from the omission of a company's R&D capabilities in the regression analysis, this paper uses the citation count of invention patents filed by listed companies (PC) to serve as the proxy variable for their R&D capabilities. Compared to the number of patents filed, the number of patent citations has a stronger exogeneity. The more the patents are cited, the higher their value and the stronger the company's R&D capabilities.

3.5. Descriptive Statistics

Table 1 shows the descriptive statistics of relevant variables used in this paper.

Table 1. Descriptive statistics.

Variable	Obs	Mean	Std.Dev.	Min	Max
ln(k/l)	10,630	−1.24	0.79	−6.91	2.33
k/l	10,630	0.40	0.37	0.001	10.28
ln(K/L)	10,630	3.47	0.85	0.16	6.94
K/L	10,630	46.64	51.09	1.17	1033.58
RD	10,630	0.05	0.04	0.00003	0.76
PC	10,630	68.86	452.94	0	17616
Cash	10,630	0.19	0.123	0.003	0.84
Opr	10,630	0.06	0.22	−8.91	1.56
Size	10,630	12.43	1.35	8.06	17.41
Turnover	10,630	4.25	6.25	0.09	213.93
Equity	10,630	0.98	1.82	0.01	86.76
Lev	10,630	0.40	0.19	0.01	0.99
Liq	10,630	0.57	0.16	0.04	0.98
Finlev	10,630	0.41	0.24	0	1.15
TobinQ	10,630	2.10	1.34	0.68	21.30
Tang	10,630	0.37	0.15	0.004	0.87

Preliminary observations show a vast disparity in labor intensity among the sample companies in 2012–2021. The average ratio between fixed assets depreciation and payable remuneration to employees is 0.40, with a standard deviation of 0.37 and coefficient of standard deviation of 0.93. The average net value of fixed assets per capita is CNY 466,400, with a standard deviation of 51.09 and coefficient of standard deviation of 1.1. At the same time, the average R&D intensity of the sample companies in 2012–2021 was 4.6%, with a standard deviation of 4.2% and coefficient of standard deviation of 0.91.

4. Analytical Results

4.1. Baseline Regression Results

In Table 2, column (1) shows the regression result of R&D intensity using the logarithm of the ratio between fixed assets depreciation and the payable remuneration to employees ($\ln\frac{k}{l}$). It shows that RD's impact on $\ln\frac{k}{l}$ is negative at the significance level of 1% with the coefficient β of −0.87. This implies the addition of one standard deviation for R&D intensity will lower the ratio between fixed assets depreciation and the payable remuneration to employees by 3.67% (−0.87 × 0.04 × 100). This indicates that an increase in R&D intensity raises the proportion of labor consumption in overall cost.

Table 2. Baseline regression results.

Variables	(1) ln(k/l)	(2) ln(K/L)	(3) lnl	(4) lnk	(5) lnL	(6) lnK
RD	−0.87 ***	−0.51 **	1.87 ***	1.00 **	1.50 ***	1.00 ***
	[−3.67%]	[−2.13%]	[7.48%]	[4.00%]	[6.00%]	[4.00%]
	(−3.52)	(−2.20)	(4.59)	(2.49)	(4.11)	(3.12)
Patents Cited	−0.00 **	−0.00	0.00	−0.00 **	−0.00	−0.00
	(−2.15)	(−1.05)	(0.45)	(−2.16)	(−0.30)	(−1.20)
Cash	0.30 ***	0.69 ***	0.08 **	0.38 ***	0.12 ***	0.82 ***
	(5.73)	(11.28)	(2.19)	(7.55)	(2.92)	(15.12)
Opr	−0.01	−0.02	−0.10 ***	−0.17 ***	−0.05	−0.07 **
	(−1.35)	(−0.55)	(−2.69)	(−4.29)	(−1.39)	(−2.31)
Size	0.03 **	0.08 ***	0.70 ***	0.73 ***	0.63 ***	0.71 ***
	(2.11)	(5.23)	(56.69)	(52.91)	(46.48)	(47.97)
Turnover	−0.00 ***	−0.03 ***	−0.01 ***	−0.03 ***	−0.01 ***	−0.04 ***
	(−4.05)	(−5.66)	(−6.63)	(−5.11)	(−4.70)	(−5.60)
Equity	0.01 **	0.01	0.00	0.01 ***	0.00	0.01
	(2.29)	(0.47)	(0.06)	(2.92)	(0.33)	(1.58)
Lev	−0.37 ***	−0.36 ***	0.18 ***	−0.18 ***	0.26 ***	−0.10 *
	(−5.14)	(−4.46)	(3.67)	(−3.21)	(4.10)	(−1.86)
Liq	−0.55 ***	−1.08 ***	−0.37 ***	−0.93 ***	−0.48 ***	−1.56 ***
	(−9.15)	(−14.82)	(−8.69)	(−14.82)	(−9.11)	(−22.13)
Finlev	0.28 ***	0.30 ***	0.05 *	0.32 ***	0.03	0.32 ***
	(7.86)	(7.46)	(1.77)	(10.17)	(0.83)	(9.41)
TobinQ	−0.02 ***	−0.02 ***	−0.01 *	−0.03 ***	−0.01 ***	−0.03 ***
	(−4.64)	(−4.22)	(−1.66)	(−6.90)	(−2.65)	(−7.47)
Tang	1.23 ***	1.96 ***	−0.02	1.21 ***	0.12**	2.08 ***
	(17.78)	(25.36)	(−0.33)	(17.87)	(2.12)	(25.20)
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Observations	10,630	10,630	10,630	10,630	10,630	10,630
Adj R^2	0.86	0.87	0.97	0.96	0.96	0.97
$\chi^2(1)$			13.61 ***		5.41 **	

Note: The first row in this table represents the regressed explained variables, and the first column from the left represents explanatory variables under regression and relevant statistics being reported. Please refer to Section 3.4 of this paper for the definition of relevant variables. In addition, square brackets report the percentage change in the outcome variable caused by one-standard-deviation change in RD. "YES" in Year FE indicates controlling for time fixed effects, and "YES" in Firm FE indicates controlling for individual fixed effects. Adj R^2 represents the adjusted R square. $\chi^2(1)$ reports the hypothesis testing of the original hypothesis that "there is no significant difference in the estimated coefficients of RD between the two regressions" under SUR estimation. $\chi^2(1)$ is significant at the significance level of 1%, which indicates the rejection of the original hypothesis and the conclusion that there is a significant difference among the estimated coefficients. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Column (2) in Table 2 shows the regression results of R&D intensity using the logarithm of the net value of fixed assets per capita. It shows that RD's impact on $\ln\frac{K}{L}$ is negative at the significance level of 5% with the coefficient β of −0.51. This means the addition of one standard deviation for R&D intensity will lower the net value of fixed assets per capita by 2.13% (−0.51 × 0.04 × 100), which is about CNY 10,000/person (46.64 × 2.13%). Given the average $\ln\frac{k}{l}$ of 0.31 and average $\ln\frac{K}{L}$ of 3.47, and in view of the estimated value of coefficient β, it can be inferred that the change in R&D intensity has a relatively large impact on the ratio between fixed assets depreciation and the payable remuneration to employees.

These two regression results indicate that when making R&D input in 2012–2021, the sample companies seemed to be biased toward saving capital. Their growing R&D intensity led to a reduced capital intensity and heightened labor intensity, which confirms hypotheses H0 and H1, i.e., technological innovation can enhance the role of labor in the production process.

4.2. Further Analysis

To further discuss how the changed R&D intensity affects a company's labor input and capital input, this paper, based on the aforesaid benchmark model (9), conducts regression on R&D intensity with lnl, lnk, lnL, and lnK as explained variables, respectively, while the other settings remain unchanged. The results are shown in column (3), (4), (5), and (6) of Table 2. Details are as follows.

First, column (3) and (4) in Table 2 show the impact of a company's R&D intensity on two distinct aspects: lnl, which represents labor cost, and lnk, which signifies fixed assets depreciation. The significant positive effects are observed at levels of 1% and 5%, respectively. Specifically, a unit increase in R&D intensity results in an increase in labor cost (lnl) by a coefficient, β of 1.87, and fixed assets depreciation (lnk) by β of 1.00. This indicates that as R&D intensity increases, labor cost surges at a rate significantly higher than that of fixed asset depreciation. Thus, it can be inferred that during this period, a higher R&D intensity made labor a larger component of total costs in the sampled companies.

Secondly, turning our attention to column (5) and (6) in Table 2, we observe the effects of R&D intensity on lnL, representing staff size, and lnK, indicating the net value of fixed assets. Here, the R&D intensity shows significant positive effects at a level of 1% for both variables. Specifically, an increment in R&D intensity relates to a β of 1.50 increase in staff size and a β of 1.00 increase in the net value of fixed assets. This suggests that while R&D intensity augments both the staff size (lnL) and net fixed asset value (lnK), the proportionate increase in staff size is more pronounced. Consequently, with rising R&D intensity, the net value of fixed assets per employee appears to decline, highlighting an increased labor intensity.

Lastly, a comparative analysis between columns (3) and (5) reveals that an increase of one standard deviation in R&D intensity leads to an approximate 7.8% ($1.87 \times 0.04 \times 100$) rise in the company's labor cost (lnl) and a 6.3% ($1.50 \times 0.04 \times 100$) increase in staff size (lnL). Both of these effects are statistically significant at the 1% level. Employing a Seemingly Unrelated Regression (SUR) model to test the difference between these effects yields a χ^2 value of 13.73, rejecting the null hypothesis that they are equal at the significance level of 1%. This means the enhanced R&D intensity drives up employee remuneration at a faster rate than it does the size of staff, leading to a higher average wage per employee.

4.3. Endogeneity Test

To address potential endogeneity issues resulting from reverse causality between R&D intensity and labor intensity, the lagged explanatory variables are included in the model, and the Sys-GMM method is adopted to estimate the following model:

$$S_{i,t} = \alpha + \beta_1 S_{i,t-1} + \beta_2 RD_{i,t} + \gamma X_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \quad (10)$$

In this equation, the subscript i represents company i, and subscript $t-1$ means the year. Like with the benchmark regression, the logarithmic of the ratio between fixed assets depreciation and payable remuneration to employees ($\ln\frac{k}{l}$) and the logarithmic of the net value of fixed assets per capita ($\ln\frac{K}{L}$) are taken as proxy variables of labor intensity (S). They are separately put in model (10) for re-estimation.

The estimates are shown in column (1) and (2) of Table 3. Firstly, the lagged item of explained variables are significantly positive at the significance level of 1%, which means the company's current labor intensity is continuous. Secondly, RD has negative effects on $\ln\frac{k}{l}$ and $\ln\frac{K}{L}$ at the significance level of 5% and 1%, respectively, which means intensified R&D intensity will boost the company's labor intensity at the significance level lower than 5%. Moreover, the regression results reject first-order serial correlation at the significance level of 1% and do not reject second-order serial correlation at the significance level of

10%, at which the Hansen J statistics cannot reject the original hypothesis that instrumental variables are exogenous, thus proving the validity of the Sys-GMM estimates.

Table 3. Endogeneity test.

Variables	**GMM**		**2SLS**	
	(1)	**(2)**	**(3)**	**(4)**
	ln(k/l)	**ln(K/L)**	**ln(k/l)**	**ln(K/L)**
L.lnk/l	0.60 ***			
	(12.87)			
L.lnK/L		0.35 ***		
		(3.82)		
			2nd Stage	2nd Stage
RD	−1.26 **	−1.34 ***	−13.31 ***	−11.39 ***
	(−2.21)	(−2.86)	(−3.55)	(−3.30)
			1st Stage	1st Stage
treat			0.01 ***	0.01 ***
			4.13	4.13
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	9567	9567	10,630	10,630
AR(1)	0.00	0.00		
AR(2)	0.13	0.41		
Hansen-J	129.12	68.65		
KP-LM			17.01	17.01
KP-F			17.03	17.03

Note: GMM and 2SLS in the first row indicate that the estimation methods used are the generalized method of moments and two-stage least square method, respectively. The third row represents the regressed explained variables. The first column represents the explanatory variables under regression and relevant statistics being reported, in which L.x is the first-order lag term of the "x" variable, and treat represents the policy of additional tax deductions for R&D expenses (experimental group = 1); "YES" in Controls indicates that the control variables mentioned previously are controlled for. Please refer to Section 3.4 for more information on control variables and their definitions. "YES" in Year FE indicates controlling for time fixed effects, and "YES" in Firm FE indicates controlling for individual fixed effects. AR(1) and AR(2) are tests for first-order and second-order serial correlation. Hansen-J represents the HansenJ statistic, which is used to test the validity of instrumental variables. KP-LM represents the under-identification test of the Kleibergen–Paap rk LM statistic. KW-F indicates the weak identification test of the Kleibergen–Paap rk Wald F statistic. z-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To make the estimates more robust, we employ the 2018 revision by the Chinese Ministry of Finance regarding additional tax deductions for R&D expenses as an instrumental variable for R&D intensity. This approach further clarifies the impact of R&D intensity on labor intensity. The policy of additional tax deduction for R&D expenses is a preferential policy applicable for corporate income tax. It allows companies to deduct a certain percentage of their actual R&D expenses before taxation as a way to encourage innovations. In 2018, the Ministry of Finance, Ministry of Science and Technology, and State Taxation Administration launched a major revision of the policy. According to the revised policy, if the R&D expenses, incurred during a company's R&D activities, do not result in intangible assets that can be recognized as current-period income or expenses, an additional 75% of the actual R&D expenses can be deducted before taxation on top of the deduction of the actual amount. If the expenses have already resulted in intangible assets, 175% of their cost shall be amortized before taxation (STA (State Taxation Administration) 2018). This major revision was aimed at giving a further boost to companies' R&D input through tax concessions rather than changing their structure of production factors, nor was there any bias related with the difference in factor structure. Therefore, the revision satisfied the exogeneity conditions for an instrumental variable. At the same time, if the new policy was able to effectively uplift the companies' R&D intensity, it also satisfied the correlation conditions for an instrumental variable.

Considering that the policy of additional tax deduction for R&D expenses might have a stronger effects on high-tech companies with a high reliance on R&D, the sample companies in this paper are categorized into high-tech (treatment group, coded as HighTech = 1) and non-high-tech (control group, coded as HighTech = 0) companies according to the Categorization of High-tech Industries (Manufacturing) 2017 issued by the National Bureau of Statistics (NBS 2017). In alignment with the release timeline of the R&D expense tax deduction policy, the samples are bifurcated using 2018 as the demarcation point. Specifically, samples from before 2018 are coded as Post = 0, while those from 2018 and onwards are coded as Post = 1. Our instrumental variable, defined as treat = HighTech $\times$ Post, is formulated by interacting the high-tech designation with the policy's temporal demarcation, capturing the differential response of high-tech companies to the policy change relative to other firms. Using this instrumental variable, we adopt the 2SLS method to re-estimation benchmark model (9).

The first-stage regression results as shown in column (3) and (4) of Table 3 indicate that the revised policy significantly increases the R&D intensity of the companies at a 1% significance level. The Kleibergen–Paaprk Wald F statistic is 17.03, which significantly rejects the weak instrument variable hypothesis, indicating a strong correlation between the instrumental variable and R&D intensity. In addition, to further verify the exogeneity of the policy's impact and the robustness of the estimation, a parallel trend test is conducted on the revised policy's effects on R&D intensity in the first-stage regression. The results, as shown in Figure 2, indicate a significant increase in the R&D intensity of high-tech companies during the three years after the revision was implemented.

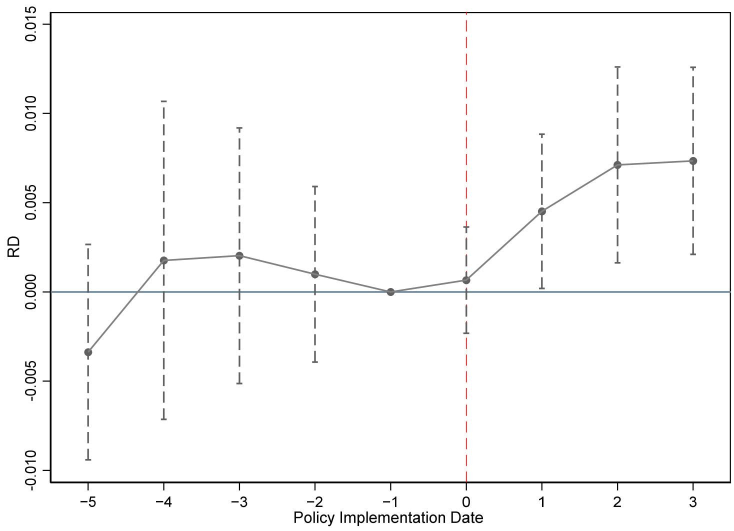

Figure 2. The impact of policy of additional tax deductions for R&D expenses on R&D intensity.

The second-stage estimation as shown in column (3) and (4) of Table 3 indicates that when the policy revision is used as an instrumental variable for re-estimation, the impact of R&D intensity on the two indicators of labor intensity remains negative—both at the 1% significance level. This once again confirms the robustness of the benchmark regression conclusions shown in Table 2, namely the increase in the companies' R&D intensity reduces capital intensity and intensifies labor intensity.

5. Mechanism Analysis

According to the statistics in Section 3.2, the labor intensity in the sample companies from 2012 to 2021 displayed a general downward trend, while the R&D intensity displayed an upward trend. However, it is noteworthy that the benchmark regression results indicate that the companies' R&D intensity during that period had significant positive effects on labor intensity. In other words, the increase in R&D intensity actually slowed down the declining trend of labor intensity. Therefore, it is obviously necessary to further discuss how the R&D intensity affects the factor structure of the companies.

5.1. Relative Productivity of Labor and Capital

As stated in Section 3.1, since R&D activities may affect the production factor structure by changing the relative productivity of labor and capital, the relative productivity may have played an intermediary role in this process. To verify this possibility, the relative productivity of labor and capital are put in the benchmark regression model. Given the possible multicollinearity between variables, labor productivity is measured with the ratio of operating revenue to the payable employee remuneration, and capital productivity with the ratio of operating revenue to fixed assets depreciation. The relative productivity of labor and capital is expressed by the ratio of the logarithm of labor productivity (LP) to the logarithm of capital productivity (CP).

The regression results in Table 4 present the intermediary effects of the relative productivity of labor and capital in the main regression. Column (1) shows that an increase in R&D intensity reduces labor productivity relative to capital at the significance level of 1%, which means that the technical progress of the sample companies from 2011 to 2021 was more biased towards improving capital productivity. Since the relative improvement in capital productivity can reduce the proportion of capital input on which the company depends for its unit output while raising the proportion of labor input, the negative effects of R&D intensity on the relative productivity of labor and capital during this period means that it will lead to a corresponding increase in the company's labor intensity. To make the logic clearer, the relative productivity of labor and capital is put in the main regression as control variable for re-estimation. The results are shown in column (2) and (3) of Table 4, which indicate that the effects of R&D intensity on the two indicators of labor intensity are no longer significant. This attempt is somewhat controversial, but it indirectly verifies the robustness of the relative productivity of labor and capital as intermediary variables.

Table 4. Analysis of intermediary effects.

	(1)	**(2)**	**(3)**
Variables	LP/CP	ln(k/l)	ln(K/L)
RD	−0.85 ***	0.74	0.16
	(−3.86)	(1.30)	(0.39)
LP/CP		1.90 ***	0.79 **
		(3.49)	(2.16)
Observations	10,629	10,629	10,629
Adj R^2	0.75	0.93	0.88
Controls	YES	YES	YES
Year FE	YES	YES	YES
Firm FE	YES	YES	YES

Note: The first row represents the regressed explained variables. The first column represents the explanatory variables under regression and relevant statistics being reported, in which LP/CP represents the relative productivity of labor and capital. "YES" in Controls indicates that the control variables mentioned previously are controlled for. Please refer to Section 3.4 for more information on control variables and their definitions. "YES" in Year FE indicates controlling for time fixed effects, and "YES" in Firm FE indicates controlling for individual fixed effects. Adj R^2 represents the adjusted Rsquare. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2. Labor Input and Structure

The analysis in Section 4.2 shows that the sample companies' R&D intensity in 2012–2021 has positive effects on both the size of staff and total employee remuneration. To further analyze how the R&D intensity affects the company's labor input, the benchmark regression model is used. The proportion of employees of different educational level and the proportion of employees in different positions are considered explained variables, the company's R&D intensity remains the key explanatory variable, while the other settings remain unchanged. Then, the effects of R&D intensity on the composition of employees of different educational level and in different positions are calculated. The regression results are shown in Tables 5 and 6.

Table 5. The impact of R&D intensity on the proportion of employees with different levels of education.

Variables	(1) Master and Above	(2) Bachelors	(3) Specialty	(4) High School and Below and Others
RD	8.23 ***	16.70 ***	−8.07 ***	−16.86 **
	(3.37)	(3.17)	(−2.64)	(−2.43)
Observations	9488	9488	9488	9488
Adj R^2	0.88	0.85	0.63	0.80
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Note: The estimated coefficients of RD in columns (1) to (4) represent the impact of R&D intensity on the proportion of postgraduates, undergraduates, specialty junior college graduates, senior high school graduates, and personnel with other educational background. The sample is obtained based on the observations by removing the part in which the total number of employees with various degrees accounts for less than 95% of the total number of employees in the enterprise. "YES" in Controls indicates that the control variables mentioned previously are controlled for. Please refer to Section 3.4 for more information on control variables and their definitions. "YES" in Year FE indicates controlling for time fixed effects, and "YES" in Firm FE indicates controlling for individual fixed effects. Adj R^2 represents the adjusted R square. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6. The impact of R&D intensity on the proportion of employees in different positions.

Variables	(1) Technicians	(2) Production Staff	(3) Sales	(4) Executives	(5) Finance
RD	29.02 ***	−0.13 ***	−8.43 ***	−8.99 ***	−3.36 ***
	(4.97)	(−2.66)	(−3.10)	(−4.16)	(−6.00)
Observations	10,546	10,391	10,546	10,546	10,546
Adj R^2	0.82	0.87	0.81	0.56	0.63
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES

Note: The estimated coefficients of RD from columns (1) to (5), respectively, represent the impact of R&D intensity on the proportions of technicians, production staff, sales personnel, executives, and finance staff. "YES" in Controls indicates that the control variables mentioned previously are controlled for. Please refer to Section 3.4 for more information on control variables and their definitions. "YES" in Year FE indicates controlling for time fixed effects, and "YES" in Firm FE indicates controlling for individual fixed effects. Adj R^2 represents the adjusted R square. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

To begin with, the R&D intensity has a positive effect on the proportion of employees with a master's degree and those with a bachelor's degree at the significance level of 1%, with the coefficient of 8.23 and 16.70, respectively. This means that with the addition of one standard deviation for R&D intensity, the proportion of those two groups of employees would rise by 0.34 (8.23×0.04) and 0.70 (16.70×0.04) percentage point each. In contrast, the R&D intensity has significantly negative effects on the proportion of employees with a specialty junior college's degree and those with a high school degree and other educational background at the significance level of 1% and 5%, respectively. This means that while the intensified R&D intensity in the sample companies between 2012 and 2021 expands the size of staff in general, the increase in the number of employees with college or higher education—out of the four groups of employees mentioned above—is more conspicuous than the increase in the rest. As higher-educated employees are better paid than lower-educated ones, total employee remuneration grows at a higher rate than the size of staff, though both are on the rise as a result of the enhanced R&D intensity.

Secondly, Table 6 shows the R&D intensity has a significantly positive effect on the proportion of technical personnel at the significance level of 1% with the coefficient of 29.02. This means that with the addition of one standard deviation for R&D intensity, the proportion of technical personnel rises by approximately 1.22 percentage points (29.08×0.04). At the same time, R&D intensity has a significantly negative effect on the proportion of production personnel, sales personnel, administrative personnel, and financial personnel at the significance level of 1%. This means that between 2012 and 2021, while the enhanced R&D intensity in the sample companies expands the size of staff, only the number of technical personnel—out of the five groups mentioned above—grows at a higher rate than it. As technical personnel are better paid than the other four groups of employees, total employee remuneration grows at a higher rate than the size of staff, though both are on the rise as a result of the enhanced R&D intensity.

6. Heterogeneity Analysis

The listed manufacturing companies vary in such aspects as the ownership structure, production approach, factor structure, and technological progress. Therefore, this section, based on the benchmark regression results, will further analyze the possible heterogeneity regarding the impact of R&D intensity on labor intensity. It will also make necessary supplementary explanations for the empirical conclusions mentioned earlier.

6.1. State Holding Companies and Non-State Holding Companies

It has been indicated by a large amount of empirical research that in China, it is easier for state-owned companies and state holding companies to obtain financing, and they have the persistent problem of redundancy of personnel (Zheng et al. 1998; Wu 2012; Yu et al. 2019; Sun et al. 2017). In this paper, the sample companies are divided into two groups according to the nature of their actual controllers—state holding companies and non-state holding companies, and group regression is performed using model (9). The results are shown in column (1) and (2) of Table 7. The research finds that the R&D intensity in state holding companies has insignificant effects on both $\ln \frac{k}{l}$ and $\ln \frac{K}{L}$, while the R&D intensity in non-state holding companies has significant negative effects on $\ln \frac{k}{l}$ and $\ln \frac{K}{L}$ at the significance level of 1% and 10%, respectively. This means that compared with state holding companies, non-state holding companies that have relatively limited capital are inclined to save capital by strengthening R&D. This corroborates the theory of biased technological progress, and also proves that although listed Chinese manufacturing companies have seen their labor cost consistently rising since 2012, capital seems to be the scarcer production factor in comparison.

6.2. Labor-Intensive Companies and Non-Labor-Intensive Companies

Companies in different industries have inherently different needs for capital and labor, so the effects of R&D intensity on factor structure may vary from industry to industry. According to the classification of labor-intensive industries in China as stated in current literature (Zhang and Li 2017), the sample companies in this paper are divided into those in labor-intensive industries and those in non-labor-intensive industries, and model (9) is used again for group regression. The results are shown in column (3) and (4) of Table 7. Labor-intensive industries include textile, garment, leather, fur, plume and its products, shoemaking, culture and education, arts and crafts, sports and entertainment products, furniture making, metal products, apparatus and instruments, and other manufacturing sectors. The results show that for companies in labor-intensive industries, the effects of R&D intensity on either $\ln \frac{k}{l}$ or $\ln \frac{K}{L}$ are insignificant; for companies in non-labor-intensive industries, the R&D intensity has significant negative effects on $\ln \frac{k}{l}$ and $\ln \frac{K}{L}$ at the significance level of 1% and 5%, respectively. This means that for companies in non-labor-intensive industries, the rising R&D intensity will boost labor intensity.

Table 7. Heterogeneity analysis.

	State Holding Companies (1)	Non-State Holding Companies (2)	Labor-Intensive Companies (3)	Non-Labor-Intensive Companies (4)	High-Tech Companies (5)	Non-High-tech Companies (6)
Variables1	ln(k/l)	ln(k/l)	ln(k/l)	ln(k/l)	ln(k/l)	ln(k/l)
RD	−0.37	−1.31 ***	−1.24	−0.93 ***	−0.87 ***	−0.79 ***
	(−1.43)	(−4.13)	(−1.41)	(−3.73)	(−2.72)	(−3.45)
Observations	3578	6997	944	9668	4040	6590
Variables2	ln(K/L)	ln(K/L)	ln(K/L)	ln(K/L)	ln(K/L)	ln(K/L)
RD	−0.15	−0.70 *	−0.12	−0.59 **	−0.45 **	−0.54
	(−0.86)	(−1.86)	(−0.14)	(−2.51)	(−2.00)	(−1.39)
Observations	3578	6997	944	9668	4040	6590
Controls	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES

Note: "YES" in Controls indicates that the control variables mentioned previously are controlled for. Please refer to Section 3.4 for more information on the definitions of the variables. "YES" in Year FE indicates controlling for time fixed effects, and "YES" in Firm FE indicates controlling for individual fixed effects. Robust t-statistics in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6.3. High-Tech Companies and Non-High-Tech Companies

Generally speaking, the R&D intensity in the high-tech industry is apparently higher than in other industries, which means its effects on factor structure may also differ between high-tech industry and other industries. According to the Categorization of High-tech Industries (Manufacturing) 2017 issued by China's National Bureau of Statistics, the sample companies are divided into two groups—those in the high-tech industry and those in non-high-tech industries, and model (9) is still used for group regression. The results are shown in column (5) and (6) of Table 7. The high-tech industry consists of six sectors: pharmaceuticals; aviation, aircraft, and equipment manufacturing; electronic and communications equipment making; computer and office equipment making; medical instruments, equipment, and apparatus manufacturing; and photographic equipment manufacturing. The results show that for companies in the high-tech industry, the R&D intensity has significant negative effects on $\ln\frac{k}{l}$ and $\ln\frac{K}{L}$ at the significance level of 1% and 5%; for those in non-high-tech industries, the effects of R&D intensity on $\ln\frac{k}{l}$ are significantly negative at the significance level of 1%, but the effects on $\ln\frac{K}{L}$ are insignificant. This means for companies in the high-tech industry, the higher R&D intensity raises labor intensity, whereas for those in non-high-tech industries, the higher R&D intensity only increases the ratio between labor cost and capital expenses without driving up the relative labor input, which is probably why their human capital grows with the rising R&D intensity.

7. Conclusions

Against the background that the Chinese manufacturing industry and all the sample companies in this paper see their R&D intensity continuously rising and labor intensity continuously falling, this paper, based on the balanced panel data of listed Chinese manufacturing companies in 2012–2021, finds that the increase in R&D intensity has made the companies more reliant on labor input, and consequently cushioned the falling trend of their labor intensity in that period. It is also found that the increase in R&D intensity has driven up the companies' employee remuneration, size of staff, fixed assets depreciation, and net value of fixed assets, with the first indicator growing the most, followed by the second indicator, and the last two indicators growing at a relatively lower rate. This underscores the idea that technological innovation has propelled the average wage level upwards in enterprises. Consequently, this highlights the potential to bolster the firm's share of labor income—a topic that has been at the forefront of discussions in the Chinese academic community, especially with its observed decline in recent times. To tackle the endogeneity concern, this study employed two methodologies: the Sys-GMM method and the two stage least square (2SLS) method with the policy of additional tax deduction for R&D expenses as the instrumental variable, and the robustness of the findings is confirmed.

The mechanism analysis shows that there are two fundamental reasons leading to this finding. The first is that in the reporting period, the sample companies, through their R&D activities, are biased toward raising the relative productivity of capital, thus creating the effect of saving capital. The second is that the enhanced R&D intensity has notably elevated the firms' human capital level by increasing the proportion of well-educated and technical personnel. Consequently, the increased presence of these high-caliber, well-paid individuals has intensified the companies' reliance on labor input. Furthermore, the heterogeneity analysis indicates that for non-state holding companies and those in non-labor-intensive industries and high-tech industry, the higher R&D intensity seems to have heightened labor intensity. Given these findings, it is crucial for policymakers to recognize the unique interplay between R&D investments and labor dynamics within different sectors and ownership structures. As a policy implication, targeted incentives could be provided to non-state holding companies and firms in non-labor-intensive and high-tech industries to further encourage R&D activities. This would not only foster innovation but also potentially bolster employment opportunities and enhance the skillset of the workforce in these sectors. Additionally, training programs and educational initiatives could be introduced to ensure that the labor force is equipped to engage in high-tech, R&D-driven roles, ensuring a symbiotic growth of both technological advancements and labor productivity.

8. Discussion

Based on the conclusion, this paper argues that while the rising trend of labor cost will sustain for a long time, the intensified R&D activities in Chinese manufacturing companies, thanks to the fast-rising level of education for the Chinese since the 1980s, will not only further enhance their global competitiveness, but also help create more jobs and enhance human capital. Moreover, for those developing nations transitioning into the advanced stages of industrialization, fears that technological progress might induce unemployment or undermine the status of workers are unnecessary. Instead, promoting technological innovation not only catalyzes a heightened demand for capital and creates additional employment opportunities, but it also optimizes the caliber of human capital and elevates the status of workers.

Author Contributions: Conceptualization, D.S. and A.Y.; methodology, D.S. and A.Y.; software, A.Y.; validation, D.S. and A.Y.; formal analysis, D.S. and A.Y.; investigation, D.S.; resources, D.S.; data curation, A.Y.; writing—original draft preparation, D.S. and A.Y.; writing—review and editing, D.S. and A.Y.; visualization, D.S. and A.Y.; supervision, D.S.; project administration, A.Y. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: Restrictions apply to the availability of these data. Data were obtained from CSMAR and are available https://cn.gtadata.com/with the permission of CSMAR (accessed on 1 January 2023).

Conflicts of Interest: The authors declare no conflict of interest.

Notes

1. "Industrial enterprises above a designated size" refers to industrial enterprises with main business revenue exceeding 20 million yuan.
2. We use the net value of fixed assets per capita to measure labor intenisty, considering both asset devaluation over time and technological advancements that might reduce asset costs, to avoid potential overestimation inherent with the original value of fixed assets per capita.

References

Acemoglu, Daron. 1998. Why do new technologies complement skills? Directed technical change and wage inequality. *The Quarterly Journal of Economics* 1134: 1055–89. [CrossRef]

Acemoglu, Daron. 2002. Directed technical change. *The Review of Economic Studies* 69: 781–809. [CrossRef]

Acemoglu, Daron. 2003. Labor-and capital-augmenting technical change. *Journal of the European Economic Association* 1: 1–37. [CrossRef]

Acemoglu, Daron. 2010. When does labor scarcity encourage innovation? *Journal of Political Economy* 118: 1037–78. [CrossRef]

Acemoglu, Daron, and Pascual Restrepo. 2019. Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives* 33: 3–30. [CrossRef]

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo. 2020. Competing with robots: Firm-level evidence from France. *AEA Papers and Proceedings* 110: 383–88. [CrossRef]

Adams, James D. 1999. The Structure of Firm R&D, the Factor Intensity of Production, and Skill Bias. *The Review of Economics and Statistics* 81: 499–510. [CrossRef]

Beaulieu, J. Joseph, and Joe Mattey. 1998. The Workweek of Capital and Capital Utilization in Manufacturing. *Journal of Productivity Analysis* 10: 199–223. [CrossRef]

Campell, John. 1994. Inspecting the mechanism: Analytical approach to the stochastic growth mode. *Journal of Monetary Economics* 33: 463–506. [CrossRef]

Cheng, Hong, Ruixue Jia, Danan Li, and Hongbin Li. 2019. The rise of robots in China. *Journal of Economic Perspectives* 33: 71–88. [CrossRef]

Cirera, Xavier, and Leonard Sabetti. 2019. The effects of innovation on employment in developing countries: Evidence from enterprise surveys. *Industrial and Corporate Change* 28: 161–76. [CrossRef]

Desai, Mihir A., C. Fritz Foley, and James R. Hines Jr. 2005. Foreign direct investment and the domestic capital stock. *American Economic Review* 95: 33–38. [CrossRef]

Dewenter, Kathryn L., and Paul H. Malatesta. 2001. State-owned and privately owned firms: An empirical analysis of profitability, leverage, and labor intensity. *American Economic Review* 91: 320–34. [CrossRef]

Galor, Oded, and Omer Moav. 2000. Ability-biased technological transition, wage inequality, and economic growth. *The Quarterly Journal of Economics* 115: 469–97. [CrossRef]

Grossman, Gene M., and Elhanan Helpman. 1994. Endogenous Innovation in the Theory of Growth. *Journal of Economic Perspectives* 8: 23–44. [CrossRef]

Hall, Bronwyn H., and Jacques Mairesse. 1995. Exploring the relationship between R&D and productivity in French manufacturing firms. *Journal of Econometrics* 65: 263–93. [CrossRef]

Harrison, Rupert, Jordi Jaumandreu, Jacques Mairesse, and Bettina Peters. 2014. Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. *International Journal of Industrial Organization* 35: 29–43. [CrossRef]

Heckman, James J., Lance Lochner, and Christopher Taber. 1998. Explaining rising wage inequality: Explorations with a dynamic general equilibrium model of labor earnings with heterogeneous agents. *Review of Economic Dynamics* 1: 1–58. [CrossRef]

Hémous, David, and Morten Olsen. 2022. The rise of the machines: Automation, horizontal innovation, and income inequality. *American Economic Journal: Macroeconomics* 14: 179–223. [CrossRef]

Hicks, John. 1963. *The Theory of Wages*, 2nd ed. New York: Springer. [CrossRef]

Huang, Qunghui. 2021. China Basically Realized Industrialization in 2020—Great Achievements in the Centennial Struggle of the Communist Party of China. *Economic Perspectives* 11: 3–9.

Kim, Hyunseob. 2020. How does labor market size affect firm capital structure? Evidence from large plant openings. *Journal of Financial Economics* 138: 277–94. [CrossRef]

Le, Dam Duc. 2023. The impact of technological innovation on labor structure: Evidence from Vietnam SMEs. *Bulletin of Monetary Economics and Banking* 26: 251–88. [CrossRef]

Lin, Justin Yifu. 2011. New structural economics: A framework for rethinking development. *The World Bank Research Observer* 26: 193–221. [CrossRef]

Link, Albert N., and Mike Wright. 2015. On the failure of R&D projects. *IEEE Transactions on Engineering Management* 62: 442–48. [CrossRef]

Lu, Qiang, Chao Hua, and Jianjun Miao. 2022. The Impact of Factor Market Distortion on the Efficiency of Technological Innovation: A Spatial Analysis. *Sustainability* 14: 12064. [CrossRef]

Marshall, Alfred. 2009. *Principles of Economics: Unabridged*, 8th ed. New York: Cosimo, pp. 116–43.

NBS (National Bureau of Statistics). 2017. Categorization of High-Tech Industries (Manufacturing) 2017. Available online: http://www.stats.gov.cn/xxgk/tjbz/gjtjbz/202008/t20200811_1782329.html (accessed on 1 August 2023).

NBS (National Bureau of Statistics). 2021. *2021 China Industry Statistical Yearbook*. Beijing: China Statistics Press.

Roca-Puig, Vicente, Inmaculada Beltrán-Martín, and Mercedes Segarra-Ciprés. 2012. Commitment to employees, labor intensity, and labor productivity in small firms: A non-linear approach. *International Journal of Manpower* 33: 938–54. [CrossRef]

Salehi, Mahdi, and Sami Abdulridha Sadeq Alanbari. 2023. Knowledge sharing barriers and knowledge sharing facilitators in innovation. *European Journal of Innovation Management*, ahead-of-print. [CrossRef]

SC (State Council). 2011. Notice of The State Council on the Issuance of Industrial Transformation and Upgrading Plan (2011–2015). Available online: https://www.gov.cn/zwgk/2012-01/18/content_2047619.htm (accessed on 1 August 2023).

SC (State Council). 2015. Notice of the State Council on the Issuance of Made in China 2025. Available online: https://www.gov.cn/zhengce/content/2015-05/19/content_9784.htm (accessed on 1 August 2023).

Scott, Allen J. 2006. The changing global geography of low-technology, labor-intensive industry: Clothing, footwear, and furniture. *World Development* 34: 1517–36. [CrossRef]

Serfling, Matthew. 2016. Firing Costs and Capital Structure Decisions. *The Journal of Finance* 71: 2239–86. [CrossRef]

Shi, Donghui, Hua Zhuang, and Ang Yang. 2023. Innovation, Profit-Seeking, and the Formation of High Value-Added Companies: An Empirical Study on China's Listed Manufacturing Companies. *Emerging Markets Finance and Trade* 59: 1262–80. [CrossRef]

STA (State Taxation Administration). 2018. Notice on Improving the Proportion of Pre-Tax Deduction of R&D Expenses. Available online: http://www.chinatax.gov.cn/chinatax/n810341/n810825/c101434/c18353158/content.html (accessed on 19 July 2023).

Su, Chi-Wei, Xi Yuan, Muhammad Umar, and Oana-Ramona Lobont. 2022. Does technological innovation bring destruction or creation to the labor market? *Technology in Society* 68: 101905. [CrossRef]

Sun, Zhe, Tsvi Vinig, and Thomas Daniël Hosman. 2017. The financing of Chinese outbound mergers and acquisitions: Is there a distortion between state-owned enterprises and privately owned enterprises? *Research in International Business and Finance* 39: 377–88. [CrossRef]

World Bank, Development Research Center of the State Council, P.R. China. 2013. *China 2030, Building a Modern, Harmonious, and Creative Society*, 1st ed. Washington, DC: The World Bank, vol. 1, pp. 34–39. [CrossRef]

Wu, Yanbing. 2012. A Study on the Double Efficiency Loss of State-owned Enterprises. *Economic Research Journal* 3: 15–27.

Yu, Liping, Huiyang Li, Zuogong Wang, and Yunlong Duan. 2019. Technology imports and self-innovation in the context of innovation quality. *International Journal of Production Economics* 214: 44–52. [CrossRef]

Zhang, Qizai, and Lei Li. 2017. Transformation and Upgrading of Manufacturing Industry and Regional Economic Growth. *Research on Economics and Management* 2: 97–111. [CrossRef]

Zheng, Jianghuai, and Jing Jin. 2021. Technology Gap and the Change of Industrial Technology Progress Direction in China. *Economic Research Journal* 56: 24–40.

Zheng, Jianghuai, Xiaoxuan Liu, and Arne Bigsten. 1998. Ownership structure and determinants of technical efficiency: An application of data envelopment analysis to Chinese enterprises (1986–1990). *Journal of Comparative Economics* 26: 465–84. [CrossRef]

Zhu, Chen, Zhiyi Qiu, and Fengjun Liu. 2021. Does innovation stimulate employment? Evidence from China. *Economic Modelling* 94: 1007–17. [CrossRef]