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Impact of the Transforming and Upgrading of China's Labor-Intensive Manufacturing Industry on the Labor Market

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Abstract: The transforming and upgrading of China's labor-intensive manufacturing sector is profoundly affecting the low-end labor market. However, there are few empirical studies that focus on labor-intensive manufacturing industries and that explore the impact of their transforming and upgrading on the labor market. Based on the wage and quantity of employment in the labor market, this paper examines the impact and the mechanism of the transforming and upgrading of China's labor-intensive manufacturing industry on the labor market, using industry panel data from 2011 to 2019. The results show that the transforming and upgrading of labor-intensive manufacturing: (1) significantly improves the average wage of labor, but reduces the quantity of employment, and that this effect varies for different industry segments; (2) improves the average wage of labor through human capital factors and reduces the quantity of employment through labor productivity. The results suggest that we should focus on the impact of the transforming and upgrading of labor-intensive manufacturing on employment to achieve the synergistic development of employment quantity and quality, and ultimately promote sustainable labor market development.

Keywords: labor market; employment quantity; wage; labor-intensive manufacturing; transforming and upgrading

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Citation: Dai, Z.; Niu, Y.; Zhang, H.; Niu, X. Impact of the Transforming and Upgrading of China's Labor-Intensive Manufacturing Industry on the Labor Market. *Sustainability* **2022**, *14*, 13750. https://doi.org/10.3390/su142113750

Academic Editor: Franklin G. Mixon

Received: 27 September 2022
Accepted: 20 October 2022
Published: 24 October 2022

1. Introduction

China's labor-intensive manufacturing industry has been losing its competitive advantage of low production factor costs, and is in urgent need of transformation and upgrading to shape new competitive advantages; its transformation and upgrading has profoundly affected the labor market. At the same time, China's labor-intensive manufacturing industry is responsible for a large amount of low-end labor employment. According to statistics, in 2020, the number of industrial enterprises above the scale of China's labor-intensive manufacturing industry accounted for 27.39% of the total number of manufacturing enterprises, and employment accounted for 52.06% of the total employment in the manufacturing industry.

Employment is a top priority for people's livelihoods and is an important support for sustainable economic development. High-quality employment can stabilize the income expectations of market subjects and improve residents' consumption expectations, which in turn can contribute to high-quality economic development [1]. In 2015, the United Nations General Assembly adopted the 2030 Agenda for Sustainable Development, which sets the goal of "promoting sustainable economic growth and full productive employment". At the same time, China's economy is moving from a stage of rapid growth to one of high-quality development, and the 14th Five-Year Plan also sets the goal of "increasing employment and increasing better quality jobs". China is the largest developing country. In China, labor-intensive manufacturing undertakes a large amount of low-end labor employment.

However, owing to the current uncertainty in the international and domestic environment, employment is facing greater challenges.

In the context of the transformation and upgrading of China's labor-intensive manufacturing industry, the question of how to achieve sustainable development in terms of the quantity and quality of employment has become a pressing issue. As one of the main objectives of individuals entering the labor market is to earn wage income through employment, wage income is one of the important references reflecting the quality of employment [2]. Therefore, focusing on China's labor-intensive manufacturing sector, this study explores the impact of the transformation and upgrading of the labor-intensive manufacturing sector on the labor market and its mechanisms, based on the dual perspective of the number of jobs and the level of wages in the labor market, using industry panel data for China over 2011–2019.

The rest of the article is organized as follows: Section 2 presents a review of the relevant literature examining industrial upgrading and employment in the labor market, Section 3 describes the data and methodology of the study, Section 4 presents the statistical analysis and econometric results, and Section 5 presents the discussion and the main conclusions.

2. Literature Review

The issue of employment in the labor market is currently a hot topic of research, and scholars have mainly studied it from three aspects: employment quantity, employment quality, and employment structure.

Regarding the quantity of employment, some scholars have argued that industrial upgrading has inhibited the quantity of employment. Banerji (1975) found that in the 1950s–1970s, Taiwan's emphasis on the development of labor-intensive industries contributed to the rate of employment growth and economic development in Taiwan, while India's preference for capital-intensive industries hindered economic development and labor specialization [3]. Hicks (1986) came to the consistent conclusion that developing countries that rely too much on capital-intensive industries and technologies may lead to enhanced employment suppression capacity in emerging industries, which is not conducive to employment [4]. Upendranadh et al. (1994), by further comparing the industrial development and employment structures of manufacturing industries in different regions of India, found that there was a reducing effect on employment, due to the gradual capital deepening of capital-intensive industries that put demands on education levels [5].

In recent years, with the development of artificial intelligence, scholars have shifted their research focus to the impact of artificial intelligence on industrial upgrading and employment adjustment. While AI has contributed to the transformation and upgrading of manufacturing, it has also brought some impact on the labor market, with low-skilled labor involving repetitive tasks being more easily replaced by AI [6]. Freya and Osborne (2017) estimated the sensitivity of 702 jobs in the US to computerization and found that approximately 47% of jobs in the high-risk category would be replaced by AI in the next 20 years [7]. However, considering the nature of the tasks in the occupation, only 9% of US employees and 12% of German employees were at risk of being replaced by automation [8,9]. Relying on machine learning technologies, approximately 55% of jobs in Japan are at risk of being replaced in the coming years, and informal jobs are more vulnerable to the proliferation of computer technology [10].

However, some scholars have found that industrial upgrading has had a positive effect on the quantity of employment. As early as 1990, Pissarides argued that there is a clear boost to economic growth from industrial upgrading, with economic growth creating new jobs, and thus, employment growth [11]. Later, Gali (1999), focusing on labor-intensive industries, found that the process of capital deepening could lead to employment growth by expanding the capital stock [12]. With the rise of new energy industries, some scholars have begun to focus on employment in new energy industries. Wei and Patadia (2010), in their study of the employment absorption capacity of the newest and traditional energy industries in the US, found that the emerging renewable and low-carbon energy industries would absorb more people in employment than the traditional industries [13]. Lehr and Lutz (2012) also conducted a similar study in Germany and came to the same conclusion [14]. Other scholars have focused on regional employment. He Zixin (2018) empirically analyzed the relationship between industry and employment in resource-based cities, and they concluded that an increase in the share of the tertiary industry has a significant positive effect on the increase in total employment in resource-based cities [15].

Regarding the quality of employment, the EU has formulated a seven-dimensional employment quality index system including employment security, and norms and labor remuneration. Some scholars also measure the quality of employment by constructing an index system. Lai Desheng et al. (2011) constructed China's regional employment quality index from six dimensions, including employment environment, employability, and laborers' remuneration [16]. Yang Haibo and Wang Jun (2021) characterized the employment quality by weighting the per capita wage incomes of farmers, the average wage of urban workers, and the social security and employment expenditure in fiscal expenditure [17]. However, due to the limitations of various conditions in empirical studies, scholars tend to measure employment quality by salary level or job security. Zhang Kangsi (2015) proposed that labor remuneration is a first-level index with the largest weight in the employment index system and drew the conclusion that the increase of labor remuneration can greatly improve China's employment quality index [18]. Li Min (2021) used the salary of practitioners in different industries to represent the employment quality, and constructed the following employment quality index, based on the two dimensions of non-private units and private units [19].

With rapid development and the widespread application of digital technology, the digital economy is a new economy, a new dynamic, and a new business model, which has triggered profound social and economic changes [20]. As a result, some scholars have begun to study the relationship between the development of the digital economy and the quality of employment. Scholars have argued that the development of the digital economy has improved the quality of employment. Autor (2015) found that digital technological advances have raised productivity levels and have increased the demand for highly skilled labor, thus contributing to overall income growth [21]. Si Xiaofei and Chen Maishou (2022) also found that the development of the digital economy triggered a change in the demand for labor with different skills, increasing the demand for high-skilled personnel while reducing the demand for low-skilled labor, and this change in demand pushed low-skilled workers to continuously learn new knowledge and skills and improve their employability, thus driving up the quality of employment [22].

At the same time, there is also interest in the relationship between smart manufacturing and employment quality, with some scholars arguing that smart manufacturing enhances employment quality, and some arguing that smart manufacturing reduces employment quality. Acemoglu and Restrepo (2018) point out that in the long run, with the adoption of industrial robots, low-skilled workers who improve their skills through continuous learning will not only increase employment opportunities, but also increase their labor remuneration [23]. Graetz and Michaels (2018) come to a similar conclusion, in that the technological upgrading brought about by AI not only affects the allocation of labor resources, but will also raise the wages of workers in all industries [6]. However, David (2017) conducted a study on the changing impact of AI on the structure of the labor market, and found that medium-skilled jobs are more likely to be replaced by robots relative to low-skilled and high-skilled jobs, with varying degrees of reduction in the number of workers and wages [10]. Qi Le and Tao Jianping (2022) also argue that industrial intelligence hinders high-quality employment by reducing the job stability and social security levels of migrant workers [24].

The development of digital economy and smart manufacturing has promoted industrial upgrading, but research on the impact of industrial upgrading on employment quality in China is still in its initial stage. Yang Haibo and Wang Jun (2018) used co-integration theory and the VEC model to analyze the employment effects of industrial restructuring dynamically, from both qualitative and quantitative perspectives, respectively, and found that both are balanced in the long run, and that industrial structure optimization can improve employment quality [17]. Li Min (2021) further explored the relationship between the platform economy, industrial restructuring, and employment quality; and found that both the platform economy and industrial restructuring significantly contributed to the increase in wage levels. However, they used industrial structure optimization to measure industrial upgrading, ignoring the other dimensions of industrial upgrading [19].

Concerning the employment structure, on one hand, scholars have found that industrial structure affects employment structure. Martin (1993) believes that employment structure is affected by industrial structure [25]. Griffith and Harisson (2004) further pointed out that the adjustment and transformation of the employment structure needs to match the change and development of the industrial structure, and that a more compatible industrial and employment structure is conducive to solving the employment problem [26]. Labor productivity and industrial structure affect employment structure. The higher the labor productivity, the more advanced the manufacturing employment structure tends to be [27]. On the other hand, some scholars have found that there is a complementary relationship between industrial structure and employment structure. The upgrading of industrial structure will promote the development of employment structure, and the optimization of employment structure will also promote the upgrading of industrial structure [28]. However, with the advanced mode of economic development, the employment structure often lags behind the change of the industrial structure [29]. At present, the relationship between China's industrial structure and employment structure is in an unbalanced state, and the change of employment structure lags significantly behind the change of industrial structure [30].

In addition to the literature on employment in the labor market, another strand of literature relevant to this paper is research on the measurement of industrial upgrading. International scholars mainly define industrial upgrading from the perspective of the global value chain [31–33]. Chinese scholars more often define industrial upgrading as industrial restructuring or industrial structure upgrading, and the main measurement indicators of industrial upgrading are industrial structure rationalization [34], industrial structure heightening [35,36], and the ratio of value added, etc. [17]. In recent years, scholars have constructed indicator systems to measure industrial transforming and upgrading. Li Lianshui et al. (2015) evaluated the degree of "newness" of China's manufacturing industry by constructing a system of indicators in five aspects: economy, technology, energy, environment, and social services [37]. Luo Xubin and Huang Liang (2020) constructed an evaluation index system for the high-quality transforming and upgrading of China's manufacturing industry from four aspects: digitalization, networking, intelligence, and greening [38]. Based on these studies, this paper measures the level of transforming and upgrading of labor-intensive manufacturing industries in four dimensions: economic efficiency, scientific and technological innovation, green development, and social services. Firstly, excluding the influence of subjective factors, the objective assignment method—entropy weighting method is used to assign weights to each indicator. Secondly, in order to evaluate the level of transforming and upgrading of the labor-intensive manufacturing industry more comprehensively, both the subjective and objective factors are considered in the robustness test, and the combined assignment method is used to measure the level again.

From the above literature, we can see that employment in the labor market has always been an important topic of concern among scholars, but few studies have focused on employment in labor-intensive manufacturing, which plays an irreplaceable and important role in absorbing low-end labor employment and social stability [39]. From the perspective of the labor supply, with the speeding up of urbanization, a certain quantity of surplus agricultural labor needs to realize transfer employment every year. In terms of labor demand, some enterprises are facing difficulties in production and operation, due to the complex and changeable internal and external/domestic and foreign environment, as well as the impact of COVID−19, coupled with technological progress and the "machine substitution tendency". All these factors will promote changes in production methods and labor productivity, which will directly or indirectly affect labor demand [40,41]. With demand turning weak under the condition of unabated supply, the total employment pressure on low-end labor is high. Labor-intensive manufacturing industries have an important effect on absorbing and transferring surplus rural labor, upgrading workers' labor skills, and building complete industrial chains [39]. Therefore, to expand the employment capacity and to improve the quality of employment, the labor-intensive manufacturing industry should play an important role. However, only a small number of scholars have analyzed the relationship between labor-intensive manufacturing and employment from the perspective of capital investment in labor-intensive manufacturing [42], ignoring the impact of the transformation and upgrading of labor-intensive manufacturing on employment.

Moreover, most of the existing literature studies employment from a single perspective of quality or quantity, and less of the literature examines employment from a dual perspective of quality or quantity in the labor market. In recent years, some scholars have begun to study the dual impact of industrial structure upgrading and optimization on the quantity and quality of employment. Studies have shown that the upgrading of industrial structure plays a positive role in both the increase of total employment and the improvement of employment quality [43,44]. In the case of labor-intensive manufacturing, the transformation and upgrading of labor-intensive manufacturing not only puts pressure on the quantity of the employment of low-end labor, but also affects the quality of employment. Achieving both quantity and quality in employment can truly address the issue of sustainable development in the labor market. Therefore, it is very important to examine the impact of labor-intensive manufacturing on the perspectives of both employment quantity and employment quality.

Therefore, this paper studies the dual impact of the transformation and upgrading in China's labor-intensive manufacturing industry on employment quantity and wage level, enriching the relevant research on the impact of industrial upgrading on the labor market, and providing a reference for the government to formulate employment policies for the labor-intensive manufacturing industry, which has important theoretical and practical significance.

3. Materials and Methods

3.1. Research Area

Industry panel data on China's labor-intensive manufacturing industry over 2011–2019 were used herein to conduct the study. The classification of the labor-intensive manufacturing industry was defined according to the definitions of Guo Kesha (2004) and Yuan Fuhua (2007) [45,46], based on the definitions of Yuan Tiantian et al. (2012) [47] and Zhu Yi (2020) [42]. Twelve labor-intensive manufacturing industry segments (agriculture and food processing industry, 13; food manufacturing industry, 14; wine, beverage, and refined tea manufacturing industry, 15; textile industry, 17; textile, clothing, and apparel industry, 18; leather, fur, feather, and feather products, and footwear industry, 19; wood processing and wood, bamboo, rattan, palm, and grass manufacturing industry, 20; furniture manufacturing industry, 21; paper and paper products industry, 22; printing and recording media reproduction industry, 23; cultural, educational, industrial, aesthetic, sports and entertainment, goods manufacturing industry, 24; and metal products industry, 34) were selected as the samples in the study of this paper.

3.2. Sources of Data

The data in this paper were mainly obtained from *China Statistical Yearbook*, *China Industrial Statistical Yearbook*, *China Science and Technology Statistical Yearbook*, *China Environmental Statistical Yearbook*, *China Energy Statistical Yearbook*, and *China Labor Statistical Yearbook*, and some missing data were supplemented via the interpolation method.

3.3. Variables

3.3.1. Dependent Variables

(1) Wage

This paper uses the average wage of urban non-private sector workers by industry from the *China Labor Statistics Yearbook*. Considering the data comparability, in order to eliminate the influence of price factors, the average wage was reduced by the CPI index in the 2011 base period. As one of the main objectives of individuals entering the labor market is to earn wage income through employment, wage income is one of the important references reflecting the quality of employment [2]. Due to the limitations of various conditions in empirical studies, scholars tend to measure employment quality by salary level or job security [18,19].

Overall, as shown in Figure 1, the average wage level in the labor-intensive manufacturing sector increased in general, with the average wage level in the labor-intensive manufacturing sector reaching RMB 39,422.74 in 2019. The wage levels in the main labor-intensive manufacturing industry segments have been shown in Table 1. In recent years, the average wage level of the wine, beverage, and tea manufacturing industry was the highest, at RMB 47,286 in 2019, followed by the printing and recording media industry, and the metal products industry. On the other hand, the average wage levels of the leather and fur products, and the wood, stationery, and entertainment products manufacturing industry were relatively low, as in 2019, when the average wages were RMB 33,690, RMB 33,695, and RMB 35,209, respectively. In general, the average wage levels of the labor-intensive manufacturing industries have also been steadily increasing among the sub-sectors, but the distribution of the average wage level among the various sectors is not balanced.

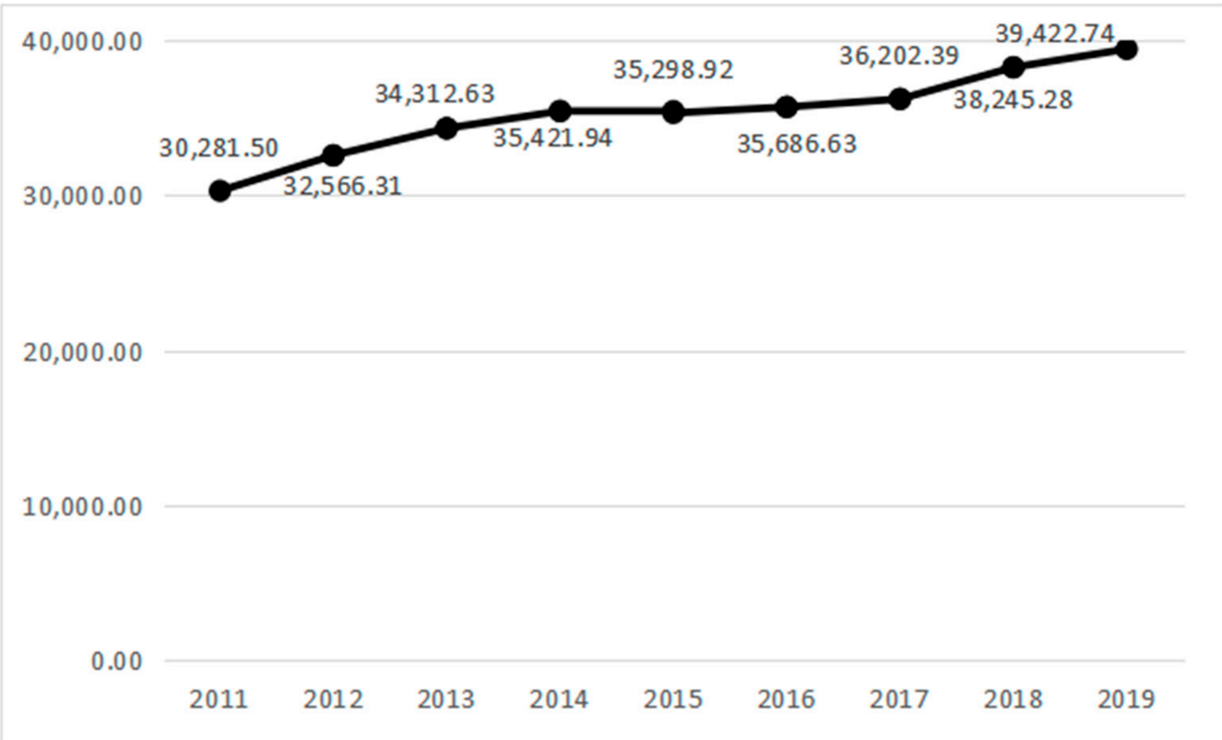

Figure 1. Average wage levels in labor-intensive manufacturing, 2011–2019 (Unit: RMB).

Table 1. Wage levels in labor-intensive manufacturing industry segments, 2011–2019 (Unit: RMB).

Industry	2011	2012	2013	2014	2015	2016	2017	2018	2019
Agricultural and sideline food processing industry	27,901	30,005	32,140	32,983	33,092	33,368	33,772	35,078	36,651
Food manufacturing	34,483	37,082	38,407	37,829	37,375	38,059	38,215	40,766	43,355
Wine, beverage and tea manufacturing industry	34,105	36,039	37,808	39,200	37,785	38,505	39,046	43,865	47,286
Textile industry	26,973	29,095	32,164	33,240	33,350	33,560	34,047	36,192	36,406
Textile and clothing, clothing industry	29,026	31,356	32,836	34,051	33,836	33,821	34,257	35,119	35,357
Fur products	27,487	29,098	30,161	31,406	31,744	32,081	31,877	33,861	33,690
Wood	25,618	28,358	29,972	31,340	31,034	31,397	31,244	32,600	33,695
Furniture manufacturing	30,700	33,498	35,411	36,493	36,469	37,217	38,373	40,252	41,091
Paper-making and paper-products industry	31,376	32,954	35,314	36,464	37,078	37,951	38,668	41,306	42,784
Printing records media industry	34,095	37,106	37,400	38,933	39,074	39,057	40,402	41,946	43,880
Cultural, educational and entertainment supplies	27,598	29,960	31,567	33,201	33,383	33,682	34,149	35,446	35,209
Metal products industry	34,016	36,245	38,572	39,923	39,367	39,543	40,380	42,514	43,668

Data source: *China Labor Statistical Yearbook* over the years.

(2) Employment Quantity

This paper uses the "total number of employed persons at the end of the year" as a measure of the number of jobs and takes its logarithm for empirical analysis, which is also one of the explanatory variables in this paper.

In recent years (as shown in Figure 2), the number of employed persons in labor-intensive manufacturing industries has been on a downward trend since 2014, with the average number of employed persons in labor-intensive manufacturing industries in 2019 being only 23,865,100. The main reason for this is that with a new round of technological revolution, the replacement of people by machines is becoming more and more obvious, and low-qualified employed people in labor-intensive manufacturing are easily fired. Another reason is that with the development of the digital economy, people are more willing to take up new occupations that offer relative freedom and more hourly wages. Detailed employment characteristics of the sub-sectors can be seen in Table 2. In general, except for the textile industry and paper-making and paper-products industry, the quantity of employment in most subsectors first showed a trend of rise, and then decline. This shows that the elimination and competition of employees in labor-intensive manufacturing has become a major trend; thus, there is an urgent need to boost the decreasing number of jobs in labor-intensive manufacturing.

Table 2. Average number of employees in labor-intensive manufacturing segments, 2011–2019 (Unit: 10,000 people).

Industry	2011	2012	2013	2014	2015	2016	2017	2018	2019
Agricultural and sideline food processing industry	360.71	379.6	418.15	439.49	424.75	416.94	371.32	314.3	288.41
Food manufacturing	176.86	183.1	200.94	206.47	212.05	211.61	197.74	179.4	176.26
Wine, beverage, and tea manufacturing industry	136.76	144.4	157.81	162.35	166.82	162.61	148.18	129.6	119.26

Table 2. *Cont.*

Industry	2011	2012	2013	2014	2014	2015	2017	2018	2019
Textile industry	588.83	495.2	486.34	490.2	464.45	436.22	391.16	331.8	348.03
Textile and clothing, clothing industry	382.41	443.9	455.14	462.19	449.49	430.49	387.15	335.6	301.66
Fur products	259.75	303	296.9	303.93	293.94	274.64	250.99	214	211.53
Wood	128.68	132.5	138.06	142.3	140.78	139.33	125.07	101.2	93.69
Furniture manufacturing	106.42	106	115.83	120.05	120.08	122.1	124.64	110.4	113.39
Paper-making and paper-products industry	146.75	143.6	140.35	138.12	134.95	127.11	119.23	106.2	115.88
Printing records media industry	70.98	72.2	92.26	95.91	98.07	98.71	95.51	84.5	85.03
Cultural, educational, and entertainment supplies	110.32	189.2	200.86	227.83	234.49	232.22	216.43	190.4	178.5
Metal products industry	311.51	346.7	371.94	380.12	380.82	364.6	351.72	340.6	354.87

Data source: *China Statistical Yearbook* over the years.

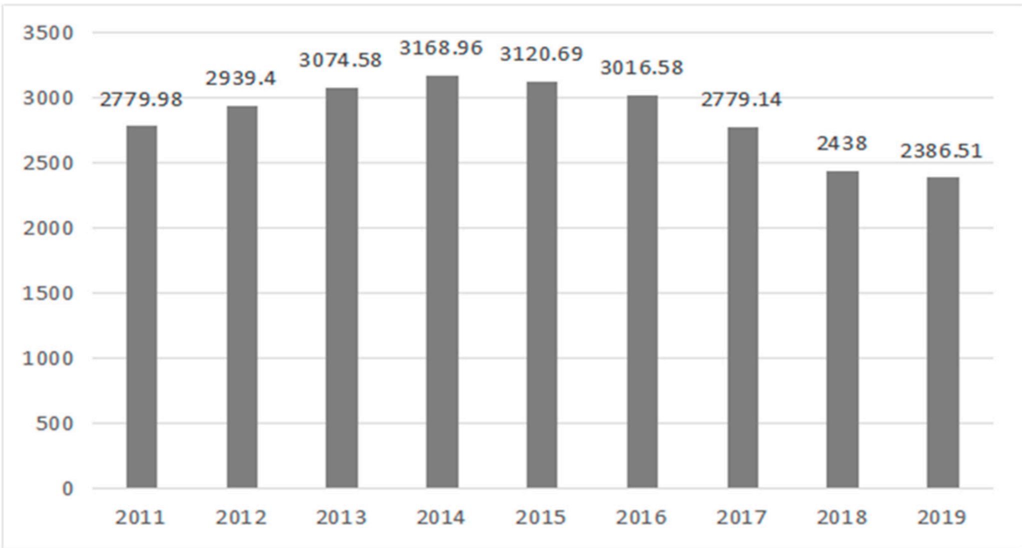

Figure 2. Average employment quantity in labor-intensive manufacturing over 2011–2019 (Unit: 10,000 people).

3.3.2. Focal Variables

This paper draws on the evaluation index system of the "newization" manufacturing industry constructed by Li Lianshui et al. (2015) [37]. It measures the level of transforming and upgrading of labor-intensive manufacturing industries in four dimensions: economic efficiency, scientific and technological innovation, green development, and social services. Different indicators are used to measure the level of each dimension. (1) Economic efficiency: the proportion of output value, the profit margin per capita, and the profit margin of product sales; (2) Scientific and technological innovation: the proportion of investment intensity in funding, the proportion of investment in R&D personnel, and the proportion of new product sales revenue; (3) Green development: the consumption of electricity and coal per unit of output value, as well as waste material and waste water emissions per unit of output value; (4) Social services: the proportion of employment in labor-intensive manufacturing. The indicator system is shown in Table 3. After standardizing the above indicators, the level of transformation of labor-intensive manufacturing can be calculated using the entropy method and is then used as the core explanatory variable in this paper.

Table 3. Construction of indicator system for transforming and upgrading level of labor-intensive manufacturing industry.

Main Indicators	Sub-Indicators	Explanation of Indicators	Indicator Unit	Indicator Attributes
Economic benefits A	Total labor-intensive manufacturing output as a proportion of total manufacturing output A1	Total labor-intensive manufacturing output/total manufacturing output	%	Positive
	Profit margin per person employed in labor-intensive manufacturing A2	Total profit of labor-intensive manufacturing enterprises/number of employed persons in enterprises	RMB/person	Positive
	Profit margin on sales of labor-intensive manufacturing products A3	Operating profit/main business income of labor-intensive manufacturing products	%	Positive
Technology Innovation B	Labor-intensive manufacturing industry investment intensity share B1	R&D expenditure/main business income	%	Positive
	Share of new product sales revenue in labor-intensive manufacturing B2	Revenue from new product sales/main business revenue	%	Positive
	Number of effective invention patents per unit of R&D expenditure in labor-intensive manufacturing B3	Number of patent applications/R&D expenditure	Pieces/RMB 10,000	Positive
Green Development C	Electricity consumption per unit of output value in labor-intensive manufacturing C1	Electricity end-use consumption/total output	Billion kWh/billion RMB	Reverse
	Coal consumption per unit of output value in labor-intensive manufacturing C2	End consumption of coal/total output	Millions of tons of standard coal/RMB billion	Reverse
	Wastewater emissions per unit of output value in labor-intensive manufacturing C3	Total Wastewater Discharge / Total Output	Million tons/RMB billion	Reverse
	Emissions per unit of output value of labor-intensive manufacturing C4	Total emissions/total output	Billion standard cubic meters/RMB billion	Reverse
Social Services D	Share of employment in labor-intensive manufacturing D1	Labor-intensive manufacturing employment/total manufacturing employment	%	Positive

Regarding the specific measurement method, this paper draws on existing literature studies. The entropy method of assigning weights and the linear weighting method are adopted for comprehensive evaluation with the following specific operational steps.

(1) Standardization of indicators

In order to eliminate the influence of different dimensions, the indicators need to be standardized before determining the weight of each indicator. The original absolute number is replaced with the standardized relative number, in order to ensure that the indicators of different units of measurement and different dimensions are comparable with each other. The specific standardization formula is as follows:

$$Y_{ij} = \frac{x_{ij} - \min\left(x_{1j}, \cdots, x_{nj}\right)}{\max\left(x_{1j}, \cdots, x_{nj}\right) - \min\left(x_{1j} \cdots, x_{nj}\right)} \text{ PositiveIndicators} \quad (1)$$

$$Y_{ij} = \frac{\max(x_{1j}, \cdots, x_{nj}) - x_{ij}}{\max(x_{1j}, \cdots, x_{nj}) - \min(x_{1j} \cdots, x_{nj})} \text{ ReverseIndicators} \quad (2)$$

where x_{ij} represents the original value of the *j* indicator of the *i* sample. Y_{ij} represents the standard value after processing. Suppose that there are n samples of evaluation subjects, m indicators exist for each sample, and x_{ij}.

(2) Determination of the entropy value of the indicator

Calculate the weight P_{ij} of the *i* sample value under the *j* indicator on the basis of the normalization of each indicator:

$$p_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{n} Y_{ij}}, i = 1, \cdots, n; j = 1, \cdots, m \quad (3)$$

The entropy value e_j for the *j* indicator is further calculated as:

$$e_j = -k\left(\sum_{i=1}^{n} p_{ij} \times \ln p_{ij}\right), i = 1, \ldots, n; j = 1, \ldots, m; e_j \geqslant 0, k = \frac{1}{\ln n} > 0$$

(3) Determination of the indicator weights

The weight W_j of the *j* evaluation indicator is:

$$W_j = \frac{\gamma_j}{\sum_{j=1}^{m} \gamma_j}, j = 1, \cdots, m \quad (4)$$

where $\gamma_j = 1 - e_j, j = 1, \cdots, m$, is the redundancy of information entropy calculated from the entropy value.

(4) Composite index determination

Finally, the weights of each indicator are re-weighted to obtain the composite index Z_i, which denotes the composite index of the *i*th evaluation object, as:

$$Z_i = \sum_{j=1}^{m} W_j \times Y_{ij}, i = 1, \cdots, n; j = 1, \cdots, m \quad (5)$$

Based on the above entropy weighting formula, we can measure the weights of the indicators of the transforming and upgrading of labor-intensive manufacturing industry, as shown in Table 4. The relative importance levels of the indicators of labor-intensive manufacturing industry in the process of transforming and upgrading are as follows: the science and technology innovation ranks first, with a weight of 0.473, among which the most influential level of science and technology innovation is the proportion of R&D investment in the labor-intensive manufacturing industry, with a weight of about 0.219. The last one is social service, with a weight of 0.078. Thus, the labor-intensive manufacturing industry still relies most on the level of scientific and technological innovation in the process of transforming and upgrading.

Table 4. Weights of all indicators for the transforming and upgrading level of labor-intensive manufacturing industry.

		A			B			C			D
Index	A1	A2	A3	B1	B2	B3	C1	C2	C3	C4	D1
Weight	0.049	0.077	0.079	0.219	0.160	0.095	0.057	0.068	0.069	0.052	0.078
Total weight		0.204			0.473			0.246			0.078

The data on the specific weighting indicators for the transforming and upgrading of the labor-intensive manufacturing industries are shown in Table 5. In general, from 2011 to 2019 (as shown in Figure 3), the level of transforming and upgrading of the labor-intensive manufacturing industries in China is transforming towards a higher level, year by year. The total weight in 2011 was only 0.003, while in 2019, it increased to 0.249. The transforming and upgrading are very rapid, which also confirms that labor-intensive manufacturing has great potential for development. Firstly, concerning the economic efficiency data of the labor-intensive manufacturing industry from 2011 to 2019, we can find that the economic efficiency creation ability of the labor-intensive manufacturing industry has always been insufficient, and that the weight has been stable at around 0.2, with slow development. This phenomenon is related to the problem of low labor productivity that has always existed in the labor-intensive manufacturing industry. Secondly, scientific and technological innovation has been developing very rapidly since 2018. Its indicator increased from 0.046 in 2017 to 0.126 in 2018, which is about 2.7 times, and in 2019, it reached 0.146. For the labor-intensive manufacturing industry, its upgrading route is mainly towards technology-intensive transformation, so that the level of scientific and technological innovation is an important indicator for the transforming and upgrading of the labor-intensive manufacturing industry. Additionally, the labor-intensive manufacturing industry has maintained a good trend in the transforming of green development, especially since the level of green development of labor-intensive manufacturing has been steadily developing towards a better trend. This has especially been so since October 2017, when General Secretary Xi once again emphasized in the report of the 19th National Congress that adhering to a harmonious coexistence between man and nature, and the concept of clean water and green mountains, are as good as mountains of silver and gold.

Table 5. Transforming and upgrading level of China's labor-intensive manufacturing industry, 2011–2019.

Time	Economic Benefits A	Technological Innovation B	Green Development C	Community Service D	Total Weight
2011	0.018	0.004	4.44×10^{-6}	1.7×10^{-6}	0.003
2012	0.023	0.023	0.013	0.006	0.043
2013	0.021	0.018	0.020	0.005	0.056
2014	0.019	0.024	0.027	0.017	0.074
2015	0.023	0.038	0.029	0.012	0.100
2016	0.032	0.048	0.032	0.011	0.124
2017	0.022	0.046	0.037	0.004	0.140
2018	0.023	0.126	0.042	0.014	0.213
2019	0.023	0.146	0.044	0.009	0.249

Finally, in terms of social services, the weight of social services in labor-intensive manufacturing has fluctuated greatly. Especially in recent years, blue-collar workers in labor-intensive manufacturing began to flee to new occupations spawned by the digital economy, leading to a steady decline in the number of jobs in labor-intensive manufacturing. The reason for this is that in the rapid development of the digital economy, thanks to the huge market size of China and the rapid rise of some internet platforms, the platform economy has spawned a new form of gig employment: application-based, on-demand work. It is mainly generated by instantly matching the supply and demand within the local scope. Most of them belong to labor-intensive services, and the common jobs include online ride-hailing drivers, food delivery riders, and designated driver. According to relevant platform data, the average monthly income of Didi ride-hailing drivers (including full-time and part-time) was RMB 2522 in 2019, while it was more than RMB 5000 in first-tier cities. For Meituan riders in 2020, the average was RMB 4950.8, of which RMB 5887, and 7.7% were more than RMB 10,000. For comparison, the relative data released by China's Bureau of Statistics show that the average monthly income of migrant workers in 2020 was RMB 4072. More labor-intensive workers are choosing to complete relatively flexible tasks while earning decently paid income [48,49].

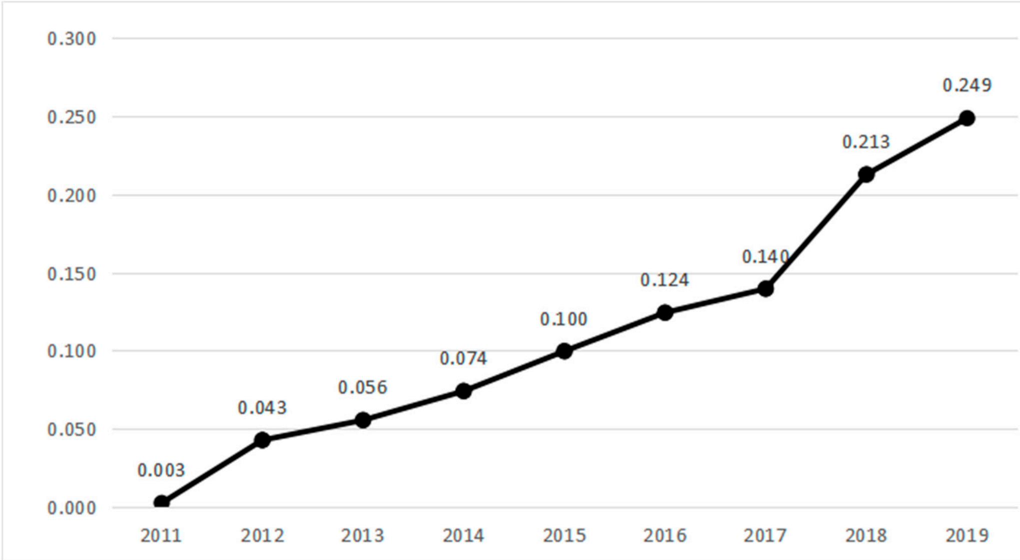

Figure 3. Overall transforming level of labor-intensive manufacturing industry, 2011–2019.

At the same time, the comprehensive score of the development of each segment of the labor-intensive manufacturing industry can be measured using the entropy weight method, as shown in Table 6. In 2011, for example, the paper and paper products industry scored only 14.75 points, the printing and recording media reproduction industry scored 21.94 points, and the timber industry scored 20.95 points. Because these industries are not the advantages of China's labor-intensive manufacturing industries, their performances are weaker in terms of economic effects and social services. The agricultural and sideline food processing industry, textile industry, and apparel industry are advantageous industries, which have a high transformation and upgrading score.

Table 6. Comprehensive score of the upgrading level of the labor-intensive manufacturing industry in subdivided industries, 2011–2019.

Industry	2011	2012	2013	2014	2015	2016	2017	2018	2019
Agricultural and sideline food processing industry	37.36	39.48	39.54	39.26	39.97	41.44	40.12	41.80	40.78
Food manufacturing	27.70	28.71	29.65	29.83	31.13	33.12	32.09	36.04	37.06
Wine, beverage and tea manufacturing industry	29.80	33.17	32.25	31.12	30.95	32.92	34.27	41.15	43.85
Textile industry	38.06	34.08	33.79	34.04	34.95	35.71	32.93	35.84	37.36
Textile and clothing, clothing industry	32.00	34.78	33.40	34.40	36.51	35.07	31.24	34.74	34.04
Fur products	27.45	27.12	27.03	28.06	30.11	32.20	36.89	45.00	49.12
Wood	20.95	21.71	20.96	20.53	19.98	21.64	20.57	23.03	23.33
Furniture manufacturing	34.24	30.12	28.41	27.15	32.66	32.85	32.18	35.14	36.19
Paper-making and paper-products industry	14.75	15.65	15.02	16.47	17.70	20.75	25.57	28.56	28.80
Print and record media reproduction industry	21.94	23.47	25.96	25.00	24.75	24.84	27.28	31.95	34.10
Culture, education and entertainment supplies manufacturing industry	30.20	33.15	33.16	33.62	33.55	33.57	33.03	35.47	36.41
Metal products industry	29.39	33.46	33.38	33.56	34.87	36.80	35.28	41.31	43.31

In addition, in terms of horizontal development, the ranking of the development level of each industry in the labor-intensive manufacturing sector did not have much fluctuation from 2011 to 2019, and the composite score of the transforming and upgrading level of each industry basically increased year by year.

3.3.3. Control Variables

To reduce the endogeneity bias arising from omitted variables, the relevant control variables that may have an impact on the wage and employment quantity are selected based on existing research, which include: (1) The level of openness to the outside world: log of the industry's export delivery value; (2) Foreign direct investment: log of the industry's foreign direct investment amount; (3) Industry net fixed assets: take the log of the industry's net fixed assets; (4) Trade competitiveness index: (imports—exports)/total imports and exports; (5) Total factor productivity (TFP): measured using the DEA–Malmquist method, the net fixed assets as capital input, the average number of employees at the end of the year as labor input, and the total industrial output as output.

3.3.4. Intermediate Variables

(1) Human Capital

"Building an army of knowledge-based and skill-based innovative workers" is an inherent requirement for the optimization and upgrading of the industrial structure, and a guarantee for human resources. Especially from the perspective of cultivating innovation capacity, human capital investment should be proactive rather than oppressive. Based on the existing research and the availability of industry data, this paper will use human capital as a mediating variable between the transformation and upgrading of labor-intensive manufacturing industries and the wage, while the ratio of R&D personnel to total employment in labor-intensive manufacturing industries is applied as a metric.

(2) Labor Productivity

In order to give full play to the important role of labor-intensive manufacturing industries in "stabilizing employment" while firmly promoting their transforming and upgrading to the middle- and high-end tiers, the relationship between improving labor productivity and creating employment needs to be effectively addressed. Based on the existing research, this paper measures labor productivity by the ratio of the output value of labor-intensive manufacturing industries to the number of people employed.

3.4. Research Hypotheses

3.4.1. Transforming and Upgrading of Labor-Intensive Manufacturing, Human Capital, and the Wage

An important part of achieving fuller and higher quality employment lies in the formation of a virtuous cycle of human capital upgrading, and industrial transforming and upgrading. Industrial upgrading enhances the level of human capital by changing the structure of skill demand and cognitive level, which in turn improves the wage. On the one hand, Barbour (2002) found that there is a consistent relationship between the industrial and occupational structures, and that occupational structures develop in tandem with industrial structures [50]. Through the industry–occupation matrix, the occupational demand and employment situation of a city can be obtained from the analysis of the industrial structure of the city. Changes in industrial structure result in a change in the allocation of labor between industries, with human capital being released from declining industries and being absorbed by thriving industries. In addition, various industries have different labor intensities, so that their requirements for labor demand and the structure of occupational categories are also different [51]. Meanwhile, industrial upgrading is considered to be conducive to the increase of human capital investment, and the structure of human capital distribution would be adjusted and optimized [52]. On the other hand, when the level of the human capital of workers is matched with the skills and wages of jobs, workers will choose those jobs, while when those factors do not match, workers will seek new jobs to achieve optimal resource allocation [53]. Human capital stock plays a mediating role in the impact of quality employment in China, and the improvement of human capital is an important factor in achieving re-employment after unemployment, as well as pay package improvement [54]. Based on this, this paper proposes hypothesis H1.

Hypothesis 1 (H1). *The transforming and upgrading of labor-intensive manufacturing improves the wage by raising the level of human capital.*

3.4.2. Transforming and Upgrading Labor-Intensive Manufacturing, Labor Productivity, and Employment Quantity

In order to give full play to the important role of labor-intensive manufacturing industries in "stabilizing employment", the relationship between labor productivity and employment creation needs to be effectively addressed. On the one hand, the "structural dividend theory" points out that industrial upgrading will lead to the transfer of factors of production from low-end to high-end industries, which contributes to the growth of the local economy and the improvement of productivity [55]. The transforming and upgrading of labor-intensive manufacturing industries is a direct manifestation of the transition towards technology-intensive and increasing production efficiency [56]. On the other hand, the increase in labor productivity creates structural unemployment [57]. Industrial upgrading implies technological progress, which brings about an increase in labor productivity. Additionally, technological development would have an obvious substitution effect on jobs, especially for some repetitive and procedural jobs. As technology progresses and the replacement of people by machines occurs, blue-collar people with relatively low skill levels will face the risk of being unemployed at any time [58]. In addition, the booming of artificial intelligence technology has brought some impact on the labor market while promoting the transforming and upgrading of the manufacturing industry. Acemoglu and Restrepo (2018) studied the impact of automation on labor productivity and employment based on endogenous growth theory and found that automation increases productivity and reduces labor demand using cheap capital [23]. Manufacturing firms will introduce a large number of robotic equipment in order to increase productivity, and thus, in the short term, there will be a certain degree of a crowding out effect on labor, and a negative impact on employment [59]. Based on this, this paper proposes research hypothesis H2 (Figure 4).

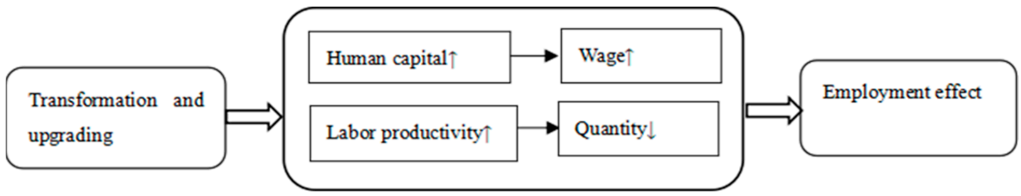

Figure 4. Theoretical mechanism analysis diagram.

Hypothesis 2 (H2). *The transforming and upgrading of labor-intensive manufacturing has reduced the number of jobs by increasing labor productivity.*

3.5. Methods

3.5.1. Benchmark Model

In order to examine the relationship between the transforming and upgrading of labor-intensive manufacturing and the labor market, a baseline econometric model was set up based on the existing literature as follows:

$$Wage_{it} = \alpha_0 + \beta_0 Upgrade_{it} + \sum_{k=1}^{n} \lambda_k X_{it} + \varepsilon_{it} \quad (6)$$

$$Quantity_{it} = \alpha_1 + \beta_1 Upgrade_{it} + \sum_{k=1}^{n} \lambda_k X_{it} + \varepsilon_{it} \quad (7)$$

where i denotes industry, t denotes year, $Wage_{it}$ denotes the average wage of labor, $Quantity_{it}$ denotes the quantity of employment, and $Upgrade_{it}$ denotes the level of transforming and upgrading of labor-intensive manufacturing. X_{it} are the control variables, and ε_{it} is the random disturbance term λ. In this paper, the sample size is limited due to the availability of industry data, so the industry fixed effects are controlled and the time effects are not fixed, referring to Liu et al. (2018), Wang and Wei (2021), and Ning Ye et al. (2021) [60–62].

3.5.2. Path Analysis Model

In order to further examine the influence channel of labor-intensive manufacturing upgrading on its wage and employment quantity, on the one hand, this paper finds that the level of labor-intensive manufacturing transforming and upgrading can act on human capital, which in turn affects the wage. In other words, an increase in the level of labor-intensive manufacturing transforming and upgrading will lead to an increase in the level of human capital, and finally induce the improvement of the wage. On the other hand, the level of transforming and upgrading of labor-intensive manufacturing can act on labor productivity, which in turn affects employment quantity. In other words, an increase in the level of labor-intensive manufacturing transforming and upgrading will lead to an increase in the level of labor productivity, and finally induce the decrease of employment quantity. In this paper, the aforementioned influence channel is tested by drawing on the estimation method of Wen Zhonglin (2004) [63]. Specifically, the following model is applied to validate the mechanism, where the subscript i denotes the industry, t denotes the year, $Human_{it}$ denotes the level of human capital, measured by the proportion of R&D personnel to employed personnel, and $Labor_{it}$ denotes labor productivity, measured through the output value of labor-intensive manufacturing as a proportion of employed persons.

$$Human_{it}(Labor_{it}) = \alpha_2 + \beta_2 Upgrade_{it} + \sum_{k=1}^{n} \lambda_k X_{it} + \varepsilon_{it} \tag{8}$$

$$Wage_{it}(Quantity_{it}) = \alpha_3 + \beta_3 Upgrade_{it} + \beta_4 Human_{it}(Labor_{it}) + \sum_{k=1}^{n} \lambda_k X_{it} + \varepsilon_{it} \tag{9}$$

4. Results

4.1. Descriptive Statistical Analysis

Table 7 shows the selection and descriptive statistical results of the main variables.

Table 7. Descriptive statistics of the main variables.

Variables	Definition	N	Mean	p50	SD	Min	Max
Wage	Average wage of labor	108	10.464	10.457	0.120	10.151	10.764
Quantity	Employment quantity	108	5.325	5.295	0.551	4.262	6.378
Upgrade	Upgrading levels of labor-intensive manufacturing	108	3.156	3.298	0.678	1.475	4.912
Open	Level of openness to the outside world	108	7.329	7.521	0.972	5.285	8.553
Foreign	Foreign Direct Investment	108	7.915	8.193	0.692	6.019	8.695
Assets	Industry net fixed assets	108	8.097	8.084	0.705	6.208	9.468
Trade	Trade Competitiveness Index	108	0.434	0.669	0.477	−0.705	0.949
Total	Total factor productivity	108	1.051	1.043	0.132	0.707	1.360
Human	Human capital	108	5.163	5.253	1.674	2.304	6.522
Labor	Labor productivity	108	13.695	13.716	0.436	12.582	14.860

4.2. Benchmark Model Results

This paper compares the fitting effect of the fixed effect model (FE) and the random effect model (RE) using the Hausman test method. The test result shows that the p-value is 0.0000, which is less than 0.05, which rejects the random effect model constructed in the original hypothesis and establishes the fixed effect model. The regression results are shown in Table 8, where columns (1) and (3) are the regression results without adding the control variables, and columns (2) and (4) are the results of adding the control variables. It can be found that the wage and the transforming and upgrading of labor-intensive manufacturing industries always shows a significant positive correlation, while a significant negative correlation is always shown between the employment quantity and the transforming and upgrading of labor-intensive manufacturing industries. Therefore, the research hypothesis proposed in this paper can be validated.

Table 8. Benchmark regression results.

	(1)	(2)	(3)	(4)
Variables	**Wage**	**Wage**	**Quantity**	**Quantity**
Upgrade	0.393 ***	0.171 ***	−0.109 ***	−0.124 ***
	(8.57)	(5.88)	(−3.23)	(−7.56)
Open		−0.418 ***		0.665 ***
		(−3.93)		(11.08)
Foreign		−0.236		0.233 ***
		(−1.64)		(2.88)
Assets		0.919 ***		−0.146 ***
		(14.20)		(−3.99)
Trade		0.252		0.050
		(1.27)		(0.45)
Total		0.596 ***		−0.192 ***
		(7.16)		(−4.08)
Constant	9.474 ***	6.923 ***	5.670 ***	0.354
	(64.96)	(11.39)	(52.78)	(1.03)
N	108	108	108	108
R^2	0.436	0.857	0.099	0.866
Fixed effects	Control	Control	Control	Control

Note: *** indicate that the results are significant at the 1% levels, with standard errors in brackets.

Furthermore, it can be seen from Table 8 that the control variables also had a significant impact on the wage and employment quantity: (1) The level of external openness significantly reduced the wage, which is in line with the expectations. It means that as the level of opening up to the outside world increases, individual labor becomes less competitive in the market, which is detrimental to the wage. In contrast, the level of opening up to the outside world significantly increases the quantity of employment, suggesting that as the level of opening up to the outside world increases, corresponding jobs will be available in the international market. Thus, the quantity of employment in labor-intensive manufacturing would be enriched with labor mobility. (2) Foreign direct investment has reduced the wage. Because foreign-invested enterprises through the "squeeze out effect" of the product market can affect the wage level of domestic enterprises, and there is competition in the product market between foreign and domestic enterprises, then the increase in foreign capital will force local Chinese enterprises to reduce their costs. In the case of unchanged technology, a direct result is to reduce the wage level [64,65]. However, the entry of FDI will bring more jobs to the host country, and thus the quantity of employment would have a significant increase. (3) Industry fixed assets significantly improve the wage at the 1% level. The main reason for is that industrial upgrading requires corresponding capital, and the wage of labor also requires corresponding capital for investment. The greater the net value of fixed assets in the industry, the more it will naturally improve the wage. (4) Trade competitiveness enhances the wage and quantity of employment. As the trade competitiveness of the labor-intensive manufacturing industry increases, more jobs will be created and a higher-level labor force will be attracted to the international market, which will improve the wage and quantity of employment. (5) An increase in the total factor productivity significantly improves the wage of employment at the 1% level. As labor-intensive manufacturing industries advance technologically, labor productivity is bound to increase, and the wage of labor will follow.

4.3. Robustness Tests

4.3.1. Endogenous Issues

Although fixed effects models can solve the bias caused by omitted variables to some extent, bi-direction causality may also lead to endogeneity problems, i.e., the transforming and upgrading of labor-intensive manufacturing affects the wage and employment quantity, and in turn, the wage and employment quantity may potentially affect the transforming and upgrading of labor-intensive manufacturing. Two approaches are adopted to address the endogeneity problem in this paper. (1) A one-period lagged regression of the explanatory variables: Upgrade, as can be seen in columns (1) to (2) of Table 9. It is shown that the one-period lagged level of the transforming and upgrading of labor-intensive manufacturing is significantly and positively correlated with the wage, and significantly negatively correlated with its employment quantity. Thus, the robustness of the research hypothesis proposed in this paper is verified. On the other hand, it also shows that the impact of transforming and upgrading of labor-intensive manufacturing industries on the wage and employment quantity is a gradual process with long-term effects. (2) Regression using the instrumental variables method. An instrumental variables-based approach was used to estimate the model. It should be noted that the choice of instrumental variables is key to effectively overcoming the problem of endogeneity. The instrumental variables should ensure the correlation with endogenous variables, as well as the exogeneity relative to the explanatory variables. The methodology for constructing the instrumental variables is illustrated below.

Table 9. Regression results for endogeneity issues.

	(1)	(2)	(3)	(4)
Variables	**Wage**	**Quantity**	**Wage**	**Quantity**
Upgrade			0.476 ***	−0.244 ***
			(6.89)	(−7.39)
L.Upgrade	0.167 ***	−0.140 ***		
	(4.74)	(−6.01)		
Open	−0.414 ***	0.714 ***	−0.275 *	0.609 ***
	(−4.15)	(10.75)	(−1.77)	(8.20)
Foreign	−0.169	0.225 **	−0.111	0.185 *
	(−1.16)	(2.33)	(−0.53)	(1.86)
Assets	0.888 ***	−0.147 ***	0.552 ***	−0.002
	(12.99)	(−3.24)	(4.83)	(−0.04)
Trade	0.031	0.185	0.827 ***	−0.175
	(0.16)	(1.40)	(2.72)	(−1.20)
Total	0.750 ***	−0.261 ***	0.437 ***	−0.130 **
	(10.14)	(−5.32)	(3.53)	(−2.20)
Constant	6.607 ***	0.121	10.65 ***	−1.840 ***
	(7.66)	(0.21)	(14.37)	(−2.88)
N	96	96	108	108
R^2	0.841	0.822	0.682	0.787
Fixed effects	Control	Control	Control	Control
Anderson canon. corr. LM			35.472	35.472
			[0.0000]	[0.0000]
Cragg-Donald Wald F			26.079	26.079
Sargan			0.6404	0.3209

Note: *, **, *** indicate that the results are significant at the 10%, 5%, and 1% levels, respectively; standard errors are in brackets and *p*-values are in boxes.

The instrumental variables in this paper refer to the most general approach, from the instrumental variable at the upper level of the analysis: agglomeration data, with specific reference to [66], where endogeneity exists within a specific industry (labor-intensive manufacturing). Then, the variables for the manufacturing sector can be considered exogenous to the labor-intensive manufacturing sector, specifically when using the competitiveness of the manufacturing sector as the instrumental variable, with the competitiveness of the manufacturing sector being specifically measured as follows [67], where manufacturing added value per capita and manufacturing added value in the proportion of GDP are used as the measurement of manufacturing competitiveness. The choice of instrumental variables must satisfy the conditions of relevance and exogeneity; the former means that the instrumental variables must be correlated with the endogenous variables, and the latter means that the instrumental variables affect the explanatory variables only through the endogenous variables. The instrumental variables in this paper firstly satisfy the correlation, because the level of competitiveness of the entire manufacturing industry often affects the level of competitiveness within specific industries due to peer effects, which in turn affect the level of transforming and upgrading of labor-intensive manufacturing. Then, for exogeneity, as the instrumental variables are chosen to study the level of competitiveness of the manufacturing industry at a higher level, they do not directly affect the wage and employment quantity in the specific industry (labor-intensive manufacturing). However, the wage and employment quantity in labor-intensive manufacturing may be further affected by the influence on its transforming and upgrading process.

The results of the regression using the instrumental variables method are shown in columns (3) to (4) in Table 9. It can be found that the level of transforming and upgrading of labor-intensive manufacturing industries still has a significant positive relationship with the wage, and a significant negative relationship with the quantity of employment, once again proving the robustness of the results of this paper. This paper also does the following three major tests on the instrumental variables: the unidentifiable test, the weak instrumental variable test, and the over-identification test. Firstly, the p-value of the Anderson canon. corr. LM statistic is 0.0000, indicating that the original hypothesis of "under-identification of instrumental variables" is significantly rejected at the 1% level; secondly, the Cragg-Donald Wald F-statistic is 49.427, which is greater than 10 and can also exclude the existence of weak instrumental variables. Finally, the p-values for the Sargan statistic are 0.4419 and 0.3209, respectively, which are greater than 0.1 and can rule out the over-identification of instrumental variables.

4.3.2. Sub-Sample Regression

According to Li Peng's (2014) approach [68], the labor input intensity of an industry is measured by the labor intensity index, calculated as

$$I_i = (L_i/V_i)/(L/V)$$

where L_i is the average number of employees in the industry, V_i is the total industrial output value of the industry, L is the average number of employees in the industry, and V is the total industrial output value of the industry. The larger the I_i index, the higher the level of labor intensity of the industry. Meanwhile, the labor intensity index is bounded by 1, in order to divide the labor-intensive manufacturing industries into two categories, according to low labor intensity and high labor intensity. The low labor-intensive industries include: food manufacturing, 14; wine, beverage, and refined tea manufacturing, 15; furniture manufacturing, 21; and metal products industry, 34, while the highly labor-intensive industries include: agricultural and sideline food processing industry, 13; textile industry, 17; leather, fur, feather, and their products, and footwear manufacturing, 19; wood processing and wood, bamboo, rattan, palm, and grass manufacturing, 20; paper and paper products, 22; printing and recording media reproduction, 23; and cultural, educational, industrial, aesthetic, and sports and recreational goods manufacturing, 24.

Next, the regressions are categorized into low- and high labor-intensive industries, as shown in Table 10; columns (1) and (2) for the wage, and columns (3) and (4) for employment quantity. It can be seen from Table 10 that there is still a significant positive correlation between the transforming and upgrading of labor-intensive manufacturing industries and the wage, and a significant negative correlation between employment quantity. This again proves to be consistent with the previous hypotheses. In addition, the impact of the transforming and upgrading of labor-intensive manufacturing on the wage and employment quantity is more pronounced in high labor-intensive industries than in low labor-intensive industries.

Table 10. Sub-sample regression results.

	(1)	(2)	(3)	(4)
Variables	Low Labor-Intensive	Highly Labor-Intensive	Low Labor-Intensive	Highly Labor-Intensive
	Wage	Wage	Quantity	Quantity
Upgrade	0.138 ***	0.191 ***	−0.044 *	−0.158 ***
	(3.08)	(5.11)	(−1.85)	(−8.45)
Open	−0.303	−0.309 **	0.539 ***	0.684 ***
	(−1.68)	(−2.01)	(5.59)	(8.89)
Foreign	0.084	−0.414 **	0.426 ***	0.193 *
	(0.36)	(−2.15)	(3.42)	(2.01)
Assets	0.835 ***	0.871 ***	−0.165 ***	−0.143 ***
	(9.16)	(8.84)	(−3.38)	(−2.91)
Trade	−0.524	0.563 *	0.856 ***	−0.077
	(−1.43)	(1.98)	(4.36)	(−0.54)
Total	0.575 ***	0.586 ***	−0.117 **	−0.234 ***
	(5.40)	(4.86)	(−2.06)	(−3.88)
Constant	4.701 ***	7.740 ***	−0.814	0.659 *
	(4.19)	(9.96)	(−1.36)	(1.70)
N	45	63	45	63
R^2	0.911	0.844	0.861	0.913
Fixed effects	Control	Control	Control	Control

Note: *, **, *** indicate that the results are significant at the 10%, 5%, and 1% levels, respectively, with standard errors in brackets.

4.3.3. Other measures of Focal Variables

In this paper, when studying the level of the transforming and upgrading of the labor-intensive manufacturing industry, in order to consider the subjective and objective factors comprehensively, the combination assignment method is selected for a more robust analysis, i.e., the assignment method of subjective and objective combination. The subjective assignment adopts the equal weight method, where the same weight is assigned to each of the 11 secondary indicators in the indicator system; in other words, the above 11 indicators measure different aspects of the upgrading of the labor-intensive manufacturing industries, and their priority levels are difficult to distinguish. The objective weighting method still adopts the entropy weighting method proposed in this paper. From Table 11, whether the control variables are added or not, the transformation and upgrading levels of the labor-intensive manufacturing industry have a significant positive correlation with the wage, and there is always a significant negative correlation between the transformation and the upgrading level of the labor-intensive manufacturing industry and the number of employments. This again verifies the correctness of the hypothesis and the robustness of the regression results.

Table 11. Regression of alternative measures of labor-intensive manufacturing upgrading.

	(1)	(2)	(3)	(4)
Variables	Wage	Wage	Quantity	Quantity
Upgrade	0.406 ***	0.209 ***	−0.103 ***	−0.125 ***
	(14.39)	(9.31)	(−3.78)	(−8.86)
Open		−0.258 ***		0.580 ***
		(−2.80)		(10.01)
Foreign		−0.275 **		0.266 ***
		(−2.29)		(3.52)
Assets		0.755 ***		−0.074 *
		(12.45)		(−1.93)
Trade		0.179		0.135
		(1.10)		(1.32)
Total		0.492 ***		−0.141 ***
		(6.85)		(−3.13)
Constant	9.115 ***	7.256 ***	5.732 ***	0.148
	(81.41)	(14.20)	(52.86)	(0.46)
N	108	108	108	108
R^2	0.685	0.899	0.131	0.883
Fixed effects	Control	Control	Control	Control

Note: *, **, *** indicate that the results are significant at the 10%, 5%, and 1% levels, respectively, with standard errors in brackets.

4.4. Path Analysis Results

4.4.1. Human Capital Mechanism Test

The existence of the mediation effect requires the following four conditions: (1) before the inclusion of the mediating variable, the independent variable has a significant effect on the dependent variable; (2) the independent variable has a significant effect on the mediating variable; (3) after the inclusion of the mediating variable, the mediating variable has a significant effect on the dependent variable; (4) after the inclusion of the mediating variable, the degree of influence of the independent variable on the dependent variable becomes lower. To verify the existence of the mediating effect, the regression results on the mediating effect are shown in Table 12. Column (1) shows that the level of transforming and upgrading of labor-intensive manufacturing has a significant effect on the wage, satisfying the first condition. Column (2) shows that the level of transforming and upgrading of labor-intensive manufacturing has a significant effect on the level of human capital, satisfying the second condition. Column (3) shows that the level of human capital has a significant effect on the wage. The coefficient of the effect of the level of transforming and upgrading of labor-intensive manufacturing on the wage is reduced from 0.171 to 0.153, after the inclusion of the mediating variable of the level of human capital, which satisfies the latter two conditions. At the same time, this paper further verifies that the mediating effect of human capital accounts for 15.34%, so it can be proven that the mediating effect of this paper does exist.

Table 12. Regression results for the mediating effect of human capital.

	(1)	**(2)**	**(3)**
Variables	**Wage**	**Human**	**Wage**
Upgrade	0.171 ***	0.366 **	0.153 ***
	(5.88)	(2.28)	(5.29)
Human			0.050 ***
			(2.69)
Open	−0.418 ***	−0.406	−0.398 ***
	(−3.93)	(−0.69)	(−3.86)
Foreign	−0.236	−0.463	−0.213
	(−1.64)	(−0.58)	(−1.53)
Assets	0.919 ***	1.317 ***	0.854 ***
	(14.20)	(3.68)	(12.72)
Trade	0.252	0.631	0.221
	(1.27)	(0.58)	(1.15)
Total	0.596 ***	0.861 *	0.553 ***
	(7.16)	(1.87)	(6.74)
Constant	6.923 ***	−1.198	6.983 ***
	(11.39)	(−0.36)	(11.87)
N	108	108	108
R^2	0.857	0.341	0.868
Fixed effects	Control	Control	Control

Note: *, **, *** indicate that the results are significant at the 10%, 5%, and 1% levels, respectively, with standard errors in brackets.

4.4.2. Labor Productivity Mechanism Test

The verification process of the mediating effect is the same as those in the previous sections, and in order to verify the existence of the mediating effect, the results of the mediating effect regression are shown in Table 13. Column (1) shows that the level of transforming and upgrading of labor-intensive manufacturing industries has a significant impact on the quantity of employment, which satisfies the first condition in Section 3.4.1. Column (2) shows that the level of transforming and upgrading of labor-intensive manufacturing industries has a significant impact on labor productivity, which satisfies the second condition. Column (3) shows that after the inclusion of labor productivity as a mediating variable, the coefficient of labor-intensive manufacturing transforming and upgrading level for employment quantity decreases from 0.124 to 0.059, which satisfies the last two conditions. Therefore, the mediation effect in this paper can be proven to exist.

Table 13. Regression results for the mediating effect of labor productivity.

	(1)	(2)	(3)
Variables	**Quantity**	**Labor**	**Quantity**
Upgrade	−0.124 ***	0.210 ***	−0.059 ***
	(−7.56)	(5.63)	(−4.32)
Labor			−0.311 ***
			(−9.42)
Open	0.665 ***	−0.760 ***	0.429 ***
	(11.08)	(−5.58)	(8.65)
Foreign	0.233 ***	−0.161	0.183 ***
	(2.88)	(−0.88)	(3.16)
Assets	−0.146 ***	1.167 ***	0.217 ***
	(−3.99)	(14.05)	(4.67)
Trade	0.050	−0.180	−0.006
	(0.45)	(−0.71)	(−0.07)
Total	−0.192 ***	0.888 ***	0.084 *
	(−4.08)	(8.31)	(1.89)
Constant	0.354	9.578 ***	3.335 ***
	(1.03)	(12.29)	(8.34)
N	108	108	108
R^2	0.866	0.844	0.933
Fixed effects	Control	Control	Control

Note: *, *** indicate that the results are significant at the 10% and 1% levels, respectively, with standard errors in brackets.

5. Discussion and Conclusions

In this study, China's labor-intensive manufacturing industry was used as the research object to measure the transformation and upgrading of China's labor-intensive manufacturing industry, by constructing an industrial indicator evaluation system. While previous studies focused on the level of transformation and upgrading of China's overall manufacturing industry [38] and measured the indicators of industrial transformation and upgrading using a single weighting method, this paper successively adopted the entropy weighting method and the combined weighting method to measure the level of transformation and upgrading of China's labor-intensive manufacturing industry more comprehensively and accurately. Through the measurement, it is found that the level of transformation and upgrading of China's labor-intensive manufacturing industry has increased year by year, from only 0.003 in 2011 to 0.249 in 2019. Among them, the transformation and upgrading levels of the agro-food processing industry, the textile industry, and the textile, clothing, and apparel industry rank in the top three, because these three sub-sectors are China's labor-intensive industries, with advantages in economic efficiency, technological innovation, green development, and social services being better developed.

Next, through data collation from the *China Statistical Yearbook*, the development trend of the number of jobs and wages in China's labor-intensive manufacturing industry from 2011 to 2019 was described. From 2011 to 2014, which was the expansion phase of China's labor-intensive manufacturing industry, the number of jobs increased year by year. From 2014 to 2019, with a new round of technological revolution, the number of jobs decreased year by year. Additionally, from 2011 to 2019, the average wage level rose year by year.

Based on the above analysis, this paper provides new evidence on the relationship between industrial upgrading and employment, namely, the impact of the transformation and upgrading of labor-intensive manufacturing industries in China on the amount of jobs and wages. In previous studies on employment in labor-intensive manufacturing, only a few scholars have analyzed the relationship between capital input and employment [42], while neglecting the impact on employment from the perspective of industrial transformation and upgrading. Meanwhile, the existing literature has mainly studied a single aspect of employment quality or employment quantity, while a few have examined employment from a dual perspective of quality or quantity, arguing that industrial restructuring and upgrading has a positive effect on both the increase in employment quantity and the improvement in employment quality [43]. This paper empirically examines the dual impact of the transformation and upgrading of labor-intensive manufacturing on the quality of employment and wage levels and finds that the transformation and upgrading of labor-intensive manufacturing increases wage levels but reduces the quantity of employment. Unfortunately, due to data limitations, it is not possible to measure the quality of employment for the time being, while the level of wages is only one dimension of employment quality. The empirical results show that the transformation and upgrading of labor-intensive manufacturing in China significantly increased the level of wages but reduced the quantity of employment. Moreover, the results remain unchanged after a series of robustness tests such as instrumental variables, sub-sample tests, and alternative measures of variables. The results suggest that the number of jobs and wage levels did not develop synergistically during the transformation and upgrading of labor-intensive manufacturing industries in China, and that although wage levels increased, there were fewer jobs for low-end labor.

When labor-intensive manufacturing industries were divided into two categories, low- and high labor-intensive, it was found that for high labor-intensive manufacturing industries, the transformation and upgrading increased the wage level and reduced the number of jobs to a greater extent; i.e., the results were more pronounced for high labor-intensive manufacturing industries than for low labor-intensive manufacturing industries.

To address the reasons behind the empirical results, this paper further explores the theoretical mechanisms by which the transformation and upgrading of labor-intensive manufacturing industries affect the number of jobs and wage levels and validates the mechanisms through a mediating effects model. It was found that the transformation and upgrading of labor-intensive manufacturing industries in China raises wages through an increase in human capital and reduces the number of jobs through an increase in labor productivity.

In the future, further research on the employment effects of the transformation and upgrading of labor-intensive manufacturing can be carried out in the following three areas. First, this paper does not control for time to observe the characteristics of changes over time, mainly because of the small sample size due to the limitations of industry data, and future research can be conducted by selecting industrial enterprise micro-data or cross-provincial panel large sample data. Second, the firm heterogeneity and regional heterogeneity of the impact of industrial upgrading on employment are further explored. Third, this paper concludes that industrial transformation and upgrading reduces the number of jobs in labor-intensive manufacturing industries and additionally, whether the labor force shifts to other industries. Therefore, the mobility of labor in labor-intensive manufacturing industries in China between industries can be further explored in the future.

In addition, this paper has important policy implications. First, a shared employment system that facilitates the continuous accumulation of human capital incentives is gradually being established. In the face of the transformation and upgrading of labor-intensive manufacturing, the formerly maintenance-based employment system is showing increasing dislocation due to the friction between the old and new paradigm shift, with a large number of workers drifting towards the low-end sectors, and a clear lock-in at the low-end. Restricting migrant workers and urban grassroots workers, who make up the vast majority of the workforce, to the low-end job market is a dangerous move, and establishing an employment system that facilitates career planning for these workers is fundamental to achieving quality development.

Secondly, the institutional advantages of modernizing China's macro-governance system and governance capacity should be used to enhance the synergistic governance capacity to establish a low-end labor-sharing employment system and to promote the transformation and upgrading of labor-intensive manufacturing industries. The labor-intensive manufacturing industry is responsible for the employment of the vast majority of low-end labor, and it lacks systematic training and learning to match the job skills needed to transform and upgrade the labor-intensive manufacturing industry. Industrial upgrading can create more high-quality jobs, but it also requires the quality of the workforce to keep up. This requires a collaborative approach between the industry and the employment sector, with a focus on "quality development".

Finally, the government should honor its policy of supporting employment in labor-intensive manufacturing. As labor-intensive manufacturing enterprises bear the social responsibility of employment pressure, the government should implement a policy of subsidies for enterprises and give tax subsidies, social security subsidies, and one-off business start-up subsidies to labor-intensive manufacturing enterprises that absorb qualified personnel. At the same time, the threshold for loans should be lowered, and the loan amount increased to help ease the financial pressure on enterprises.

Author Contributions: Conceptualization, Z.D.; Data curation, Y.N.; funding acquisition, Z.D. and H.Z.; supervision, Z.D.; writing—original draft, Y.N.; writing—review and revision of the manuscript, X.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the General Program of National Social Science Fund of China (Grant No. 20BJL048), the General Program of Philosophy and Social Science Research in Universities of Jiangsu Province (Grant No. 2020SJA1220), the Major Program of National Social Science Fund of China (Grant No. 20&ZD128), the General Program of Humanities and Social Science Research in Universities of Henan Province (Grant No. 2023-ZZJH–193), and the Innovation Funds Plan of Henan University of Technology (Grant No. 2022-SKCXTD–02).

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

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