sustainability

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Bilateral Effects of the Digital Economy on Manufacturing Employment: Substitution Effect or Creation Effect?

Chenhui Ding [1], Xiaoming Song [1,2], Yingchun Xing [2,*] and Yuxuan Wang [1]

[1] Business School, Hohai University, Nanjing 211100, China; dingchenhui@hhu.edu.cn (C.D.); songxiaoming@hhu.edu.cn (X.S.); 15161123257@163.com (Y.W.)
[2] Department of Postal Communication Management, Shijiazhuang Posts and Telecommunications Technical College, Shijiazhuang 050021, China
* Correspondence: x18903391860@163.com; Tel.: +86-189-0339-1860

Abstract: Understanding the substitution effect and creation effect of digital transformation on the manufacturing industry is crucial to safeguarding employment stability and advancing manufacturing sophistication in China's contemporary context. In this study, a bilateral stochastic frontier model is used to examine the aforementioned effects drawing on provincial panel data of China spanning 2011 to 2020. The study reveals that: Firstly, the substitution effect of digital economy development on manufacturing employment outweighs the creation effect, culminating in a 7.80% decrease below the frontier benchmark, contrasted by a 4.15% increase attributed to the creation effect. The two effects possess an inverse relationship, collectively inducing a 3.66% decline in manufacturing employment as compared to the frontier. Secondly, the prevailing influence of the digital economy upon manufacturing employment is predominantly characterized by the substitution effect. However, projected medium to long term trajectories intimate a diminishing potency of this substitution effect and the creation effect will become more pronounced. Thirdly, in terms of geographical areas, the weakening of the employment-substitution effect due to the digital economy is most evident in the central region, followed by the western, and then the eastern regions. Conclusively, the impact of the digital economy on manufacturing employment exhibits variances contingent upon distinct economic maturation and disparate human capital stratification.

Keywords: digital economy; manufacturing employment; bilateral stochastic frontier model; substitution effect; creation effect

Citation: Ding, C.; Song, X.; Xing, Y.; Wang, Y. Bilateral Effects of the Digital Economy on Manufacturing Employment: Substitution Effect or Creation Effect? *Sustainability* **2023**, *15*, 14647. https://doi.org/10.3390/su151914647

Academic Editor: Mirco Peron

Received: 1 August 2023
Revised: 5 October 2023
Accepted: 6 October 2023
Published: 9 October 2023

1. Introduction

The digital economy is anchored in economic activities where data resources are key production factors, modern information networks are essential carriers, and utilizing information and communication technologies is the primary driver for improving efficiency and optimizing the economic structure. Disruptive digital technologies, such as 5G, Internet of Things (IoT), big data, cloud computing, and artificial intelligence (AI), have catalyzed the digital transformation of global manufacturing industries. Countries around the world are integrating digital initiatives, such as artificial intelligence, to accelerate the digital and intelligent transformation of their manufacturing industries. This is to retain and refine the competitive advantage of manufacturing industries and the global division of labor in manufacturing. As a major player in global manufacturing, China grapples with fierce international competition, technological barriers, an aging population, and rising labor costs. Embracing digital technology in manufacturing offers China innovative solutions to these challenges, laying a foundation for high-quality manufacturing development [1]. The application of new-generation information technology and advanced production and manufacturing technologies, including intelligent manufacturing and robotics, is not only transforming production and organizational dynamics, but also boosting efficiency and improving the quality of products in the enterprises [2]. There are many examples of digital technology applications in the manufacturing sector. For example, augmented reality and motion-recognition sensors can help companies have the potential to not only reduce the cognitive workload of the operator but also increase productivity, improve quality, reduce defects, and, consequently, reduce costs [3]. The use of assistive technologies, such as digital instructions (Dis) and collaborative robots (cobots), can improve the productivity of the assembly system [4]. In addition, the combined use of motion-capture systems and virtual reality (VR) has been considered very promising, with many researchers showing its potential [5]. On the other hand, the adoption of digital technologies has also led to new requirements for digital literacy and skills among workers, resulting in a shift in the labor market towards skill-based jobs [6]. This phenomenon sparked discussions among scholars and policymakers regarding issues and concerns around potential technological unemployment. As a result, significant impacts on employment will be experienced as China advances its digital and intelligent transformation in manufacturing. This is attributed to China's prevalent low educational levels, an aging population, and a focus on low-end, labor-intensive manufacturing sectors. Therefore, the employment implications of digital economy development have become critical and unavoidable concerns to be addressed.

The impact of technological innovation on employment has long been debated, and there is no consensus on whether this is also true for technological innovation in the digital economy. This debate is particularly contentious when it comes to whether digitalization and intelligence contribute to or undermine employment [7]. Digitalization and intelligent technologies, akin to previous technological advancements, present challenges when evaluating their long-term implications on employment [8]. This is due to the fact that digital technologies have had a significant impact on the labor market, while at the same time exhibiting distinct employment effects within the manufacturing sector that are characteristic of the digital economy era, which have two forms: the "job substitution effect" and "job creation effect". On one side, the advent of automation and intelligent enhancements boosts productivity, leading to changes in the labor force. Specifically, jobs centered around repetitive and mundane tasks are at risk of being supplanted by these innovative technologies, a phenomenon often referred to as "machines replacing humans", signifying a shift towards job displacement. This will lead to a decreased demand in the labor market, raising the unemployment rate, which is the "job substitution effect" [9]. Conversely, the adoption of digital technology enhances both productivity and overall output for firms, enabling them to benefit from economies of scale by expanding their production capacities. In turn, this is likely to spawn additional job opportunities, which is the "job creation effect". Overall, the net effect of the digital economy on manufacturing employment remains controversial. As such, it is important for policymakers to grasp the nuances of this dynamic, ensuring a precise comprehension of the interplay between the digital economy and employment.

On the one hand, this research area facilitates a comprehensive understanding of the profound impact of technological change on employment. On the one hand, this research area facilitates a comprehensive understanding of the profound impact of technological change on employment. On the other hand, effectively addressing the job substitution and creation effects of the digital economy, while promoting the integration of digital technology and manufacturing, and balancing short-term employment structural risks with long-term overall growth, as well as effectively managing the inherent conflict between intelligent manufacturing and labor employment, have important practical implications for ensuring employment stability in China amidst the "new normal". This has immense practical significance for China's employment stability and the development of its manufacturing sector under the "new normal".

This research will offer an in-depth exploration of how technological advancements influence employment dynamics, and highlight the importance of acknowledging both the challenges and opportunities presented by the digital economy. It is essential to harmonize the effects of job substitution with job creation, encourage the merger of digital technology with traditional manufacturing, and find equilibrium between short-term employment changes and long-term growth prospects. Moreover, the ongoing tension between automated manufacturing systems and traditional labor employment requires careful management. Addressing these issues holds significant implications for China, especially as it seeks to uphold employment stability and foster manufacturing development in the context of its "new normal" economic framework.

The impact of the digital economy on employment has garnered significant academic attention because of its dual-sided implications. [10]. There have been three main perspectives on this issue. One perspective suggests that the development of the digital economy leads to an employment-substitution effect. In the 1930s, Keynes speculated that rapid technological progression would lead to technological unemployment over the next 90 years [11]. Wassily Leontief [12] suggested that the digital economy, as an emergent economic model anchored in digital technology advancements, would, in its early phases, exhibit a negative influence of ICT on the substitution of manufacturing labor [13]. That is, the digital economy could adversely impact the traditional labor market, and the broad adoption of new technologies may replace human roles, leading to a phenomenon where "machines" take over manpower [14]. Frey and Osborne (2017) predicted that 47% of the jobs would face a higher risk of being replaced by artificial intelligence [10]. In this regard, Jung and Lim (2020) used panel data from 42 countries to confirm that the extensive use of industrial robots tends to suppress employment growth [15]. Dauth et al. (2018) found that the adoption of robots resulted in job reductions within the manufacturing sector [16]. Moreover, the impact of the digital economy on employment varies based on the skill composition of the workforce. In particular, workers with medium- and low-skill levels face a heightened threat of replacement due to cutting-edge technologies. [17]. Using German plant-level data, Deng et al. (2020) found that low-skilled labor is more likely to be replaced by robots than high-skilled labor [18]. Grischa Beier et al. (2022) found that, in the context of Industry 4.0, sectors with a higher proportion of relatively low-skilled workers are anticipated to see reductions in staffing needs [19]. David et al. (2017) highlighted that jobs requiring medium skills are more likely to be replaced by industrial robots than those requiring low and high skills [20]. However, in the long term, the development of the digital economy can lead to job-creation effects. Specifically, the digital economy could enhance labor productivity, stimulate labor demand, and create a significant number of new job opportunities [21]. Supporting this notion, Dekle (2020) ascertained that robots bolster demand expansion, which in turn increases the labor demand for the industry introducing robots [22]. In addition, Meng Niu et al. (2022) found that China's ICT growth has cultivated numerous routine and nonroutine jobs, favorably tilting the employment balance towards nonroutine roles compared to routine ones [23]. In a more recent study, Anabel et al. (2023) shed light on the overall positive influence of ICT investments on aggregate employment across EU nations [24]. Furthermore, the evolution of the digital economy accelerates the demand for highly proficient workers, leading to a transformation in the total employment structure [25] and the creation of numerous high-end job positions. [26]. The third perspective argues that digitalization leads to an employment polarization effect. Existing research indicates that routine-biased technological changes can lead to employment polarization [27]. This is depicted by a "U"-shaped curve, illustrating a growth in job opportunities for both high-skilled and low-skilled workers, but a contraction for middle-skilled roles, with routine tasks being particularly vulnerable to automation [28]. In recent studies, Luca Eduardo Fierro et al. (2022) designed a multisector agent-based macroeconomic model and concluded that automation can polarize the labor market [29].

In summary, plenty of studies have explored the influence of ICT, the digital economy, and industrial robots on employment. Despite this, a clear consensus remains elusive about whether these elements promote employment substitution or creation, given the dual nature of effects that industrial robots and intelligence present. A significant gap in the current research landscape is the lack of a consistent quantitative methodology to assess these effects. This discrepancy hampers a holistic grasp of their aggregate impact on employment, resulting in a spectrum of conclusions that span both optimistic and pessimistic outcomes [30]. Moreover, focusing narrowly on just one dimension of the digital economy can lead to skewed results. The implications of the digital economy on employment are multifaceted, shaped by both the substitution and creation effects. The overall net impact depends on the balance between these effects; a dominant substitution effect might result in a net reduction in jobs. Conversely, if the effect of job creation exceeds the effect of job substitution, the overall outcome would be increased demand for labor and a net increase in jobs. A pressing unresolved question is how the cumulative effect of the digital economy on employment shifts across varying time spans, geographical areas, demographic groups, and other factors, and what drives these variances. Building on this, our research synthesizes both the substitution and creation effects of the digital economy on manufacturing employment, using an integrated analytical methodology. Using the bilateral stochastic frontier model, we measure the effects of the digital economy on manufacturing employment in China from 2011 to 2020. Additionally, we analyze the differential impacts across various dimensions within the manufacturing employment landscape.

Given the context, our paper seeks to contribute in the following areas: Firstly, this study introduces the concept of the bilateral effects of the digital economy on manufacturing employment, leveraging the intrinsic duality of the digital domain. This proposition expands the theoretical and empirical understanding of manufacturing employment, providing insights into the ramifications of technological advancements on employment within the spheres of the digital economy and labor market. Secondly, by assimilating the bilateral effects paradigm, we adopt a bilateral stochastic frontier model to precisely evaluate the substitution, creation, and overall effects of the digital economy on the manufacturing workforce. This approach enables us to holistically examine the cumulative influence of the digital economy on manufacturing roles, rectify possible inaccuracies in prior studies, and scrutinize the geospatial and chronological trends as well as the fluctuation dynamics of the bilateral impacts. In doing so, it addresses and bridges certain gaps in the existing studies. Lastly, diverging from prior research which predominantly emphasizes a national perspective, this research investigates the impact of the digital economy on manufacturing employment across diverse scales of digital advancement and varying labor skill tiers, incorporating a broader spectrum of research dimensions. By examining the differential changes in the net effect of the digital economy on manufacturing employment, this study sheds light on the ongoing debate surrounding the relationship between the digital economy and manufacturing employment. It facilitates a comprehensive understanding of the overarching patterns and the governing principles shaping the interaction of the digital economy with manufacturing employment, providing empirical references and policy insights on effectively managing the inherent conflict between smart manufacturing and labor employment within the digital economy context. At the micro level, this study will help enterprises to better grasp the law of the "pain period" of digital development and make full use of it. The remaining parts of the paper are organized as follows: Section 2 establishes theoretical foundation and analytical framework. Section 3 describes the methodologies and resources employed. Section 4 focuses on the empirical evaluations and results interpretation, encompassing benchmark analyses, regional disparities, and robustness tests. Section 5 presents conclusions and policy recommendations.

2. Theoretical Foundation and Analytical Framework

The application of new technologies facilitates the transformation and upgrading of manufacturing industries, which is a widely adopted approach for achieving sustainable economic growth globally. Based on Austrian law, industrial upgrading contributes to economic growth and typically leads to a decrease in the unemployment rate. In recent years, China's digital economy has experienced unprecedented growth in terms of scale, scope, and depth. As a result, it raises the question of how the technological upgrade driven by the digital economy will affect the job market.

2.1. Digital Economy Development and Manufacturing Employment: A Theoretical Model

Building upon the research conducted by Acemoglu and Restrepo (2017) [31], this paper introduces a static task model to uncover the potential influence of digital economy development on manufacturing employment and establish a theoretical foundation for the present study. The key components of the model are outlined as follows: producers utilize both capital and labor to complete individual tasks, with workers falling into two categories: low-skilled and high-skilled. The total output Y comprises a set of tasks X within the range of $[N, N + 1]$:

$$Y = \left(\int_N^{N+1} y(x)^{\frac{\mu-1}{\mu}} dx \right)^{\frac{\mu}{\mu-1}} \tag{1}$$

In Formula (1), μ is the elasticity of substitution between different tasks. Let M be the demarcation point between simple tasks and complex tasks, $M \in [N, N + 1]$; when simple tasks and complex tasks can be automated, capital is produced with productivity $e_k = 1$ and $e_k > 1$, respectively. $e_l(x)$ and $e_h(x)$ are the labor productivity of low-skilled workers and high-skilled workers, respectively. W_l and W_h are the wages of low-skilled workers and high-skilled workers, respectively, and W_k is the capital price; $W_l/e_l(x)$ and $W_h/e_h(x)$ are the costs of low-skilled workers and high-skilled workers, respectively. W_k and W_k/e_k are the costs of capital in different ranges.

As shown in Figure 1, assuming that highly skilled workers have an advantage in performing high-index tasks, then $e_h(x)/e_l(x)$ is a strictly increasing function of x. When simple tasks and complex tasks are automated, there are $W_l/e_l(x) > W_k$, $W_h/e_h(x) > W_k/e_k$. Under the condition of supply and demand balance, the task will be assigned to the lowest cost factor; B is the point where the cost of low-skilled workers and high-skilled workers is equal, and $W_l/e_l(B) = W_h/e_h(B)$.

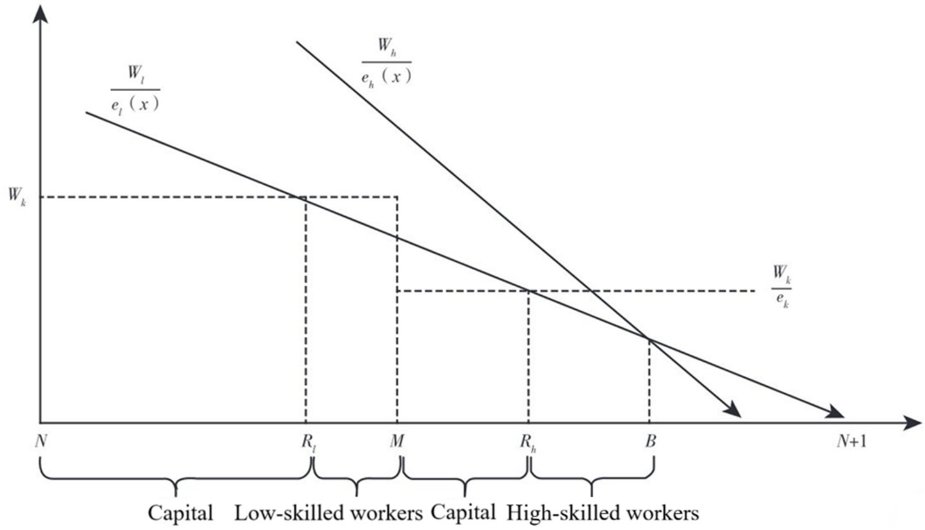

Figure 1. The manifestation of the digital economy driving manufacturing automation in different stages.

Based on the cost-minimization goal, the equilibrium number of tasks is determined to be $y(x) = p(x)^{-\mu}Y$, and the factor market clearing condition is that demand is equal to supply. The share of high-skilled workers, low-skilled workers, and capital is defined as:

$$S_l = \int_{R_l}^{\{M,B\}} e_l(x)^{\mu-1}dx \qquad S_h = \int_{\{M,B\}}^{M} e_h(x)^{\mu-1}dx + \int_{R_h}^{N+1} e_h(x)^{\mu-1}dx \qquad S_k = \int_N^{R_l} 1dx + \int_M^{R_h} e_k^{\mu-1}dx \\ = (R_l - N) + e_k^{\mu-1}(R_h - M) \tag{2}$$

The total output function is set to be in the form of CES, and the output under equilibrium conditions:

$$Y = \left(S_l^{1/\mu} l^{(\mu-1)/\mu} + S_h^{1/\mu} h^{(\mu-1)/\mu} + S_k^{1/\mu} k^{(\mu-1)/\mu}\right)^{\mu/(\mu-1)} \tag{3}$$

Let θ be the comparative advantage elasticity, then $\theta = e_h'(B)/e_h(B) - e_l'(B)/e_l(B) \geqslant 0$.

When the scope of low-skilled automation tasks is expanded, the share of impact factors $\frac{dS_l}{dR_l} = 1$.

$$\begin{gathered} \frac{dS_l}{dR_l} = \left\{ -e_l(R_l)^{\mu-1} < 0,\ B > M - e_l(R_l)^{\mu-1} \frac{\mu\theta + e_h\left(B\right)^{\mu-1}/S_h}{\mu\theta + e_h\left(B\right)^{\mu-1}/S_h + e_l\left(B\right)^{\mu-1}/S_l} < 0\ \ , B \leqslant M\ \ \frac{dS_h}{dR_l} = \{0\ , B \right. \\ > M - e_l(R_l)^{\mu-1} \frac{e_h\left(B\right)^{\mu-1}/S_l}{\mu\theta + e_h\left(B\right)^{\mu-1}/S_h + e_l\left(B\right)^{\mu-1}/S_l} < 0\ \ , B \leqslant M \end{gathered} \tag{4}$$

When the task scope of high-skill automation is expanded, the share of influencing factors is $\frac{dS_h}{dR_h} = e_k^{\mu}$.

$$\begin{gathered} \frac{dS_h}{dR_h} = \left\{ -e_h(R_h)^{\mu-1} < 0\ \ when\ B > M - e_h(R_h)^{\prime r-1} \frac{\mu\theta + e_l\left(B\right)^{\mu-1}/S_l}{\mu\theta + e_h\left(B\right)^{\mu-1}/S_h + e_l\left(B\right)^{\mu-1}/S_l} < 0\ \ when\ B \leqslant M\ \ \frac{dS_h}{dR_l} \right. \\ = \left\{ 0\ \ when\ B > M - e_h(R_h)^{\mu-1} \frac{e_l\left(B\right)^{\iota-1}/S_h}{\mu\theta + e_h\left(B\right)^{\mu-1}/S_h + e_l\left(B\right)^{\mu-1}/S_l} < 0\ \ when\ B \leqslant M \right. \end{gathered} \tag{5}$$

By analyzing Equations (4) and (5), we can infer that both low-skill automation and high-skill automation result in the substitution of a specific amount of labor and a decrease in the number of tasks carried out by workers. Specifically, low-skill automation diminishes the proportion of tasks executed by low-skill labor, whereas high-skill automation diminishes the proportion of tasks executed by high-skill labor.

2.2. The Substitution and Creation Effects of the Digital Economy on Manufacturing Employment

Drawing from the long-term historical perspective, it becomes evident that consecutive technological changes and upgrades exhibit a dual impact on employment, often described as a "double-edged sword" phenomenon [32]. Digitalization, as a novel general-purpose technology driving technological advancement, manifests two distinct effects on employment: employment substitution and employment creation. Furthermore, these dual effects exhibit notable disparities in various dimensions, as illustrated in Figure 2, while highlighting their significant structural variations.

2.2.1. Analysis of the Substitution Effect of the Digital Economy on Manufacturing Employment

The digital economy induces an employment-substitution effect through enhanced productivity, the application of digital technology innovations, and changes in the industrial structure. Firstly, productivity improvements result in a decrease in the demand for labor in the manufacturing sector. The adoption of digital technology in traditional manufacturing enables the digitalization and intelligent evolution of the industry. Information technology and intelligence facilitate the efficient circulation, integration, and optimal allocation of conventional factors, thereby driving changes in traditional production methods. As a result, the productivity of manufacturing enterprises is enhanced, leading to the displacement of human labor through reduced transaction costs, minimized resource mismatches, and stimulated innovation [33]. Moreover, the demand for labor in routine task areas is reduced [34], ultimately contributing to increased unemployment rates. Secondly, the introduction of digital technology innovations results in the displacement of human workers by machines. As digital technology enhances productivity, repetitive and low-skilled laborers become vulnerable to automation and intelligent technologies [35]. This dynamic creates a "zero-sum game" between industrial robots and low-skilled laborers, ultimately leading to the displacement of human workers by machines [36]. Unlike past automation technologies that primarily replaced manual labor, the utilization of big data, artificial intelligence, and other digital technologies enables the gradual automation of nonroutine tasks, gradually replacing traditional manufacturing blue-collar workers with intelligent systems. Thirdly, the digital economy drives changes in the industrial structure, resulting in technological unemployment. Digital technology can be integrated into traditional manufacturing and also facilitate the emergence of new industries, specifically, through the dual paths of digital industrialization and industrial digitalization. Notably, digital industrialization is expected to give rise to a customer-centric business model, rapidly replicating and promoting the development of new service industries. This transformation, from product manufacturing to service provision, contributes to the advancement of the industrial structure [37]. Consequently, this shift leads to the direct elimination of certain job roles and may result in technological unemployment.

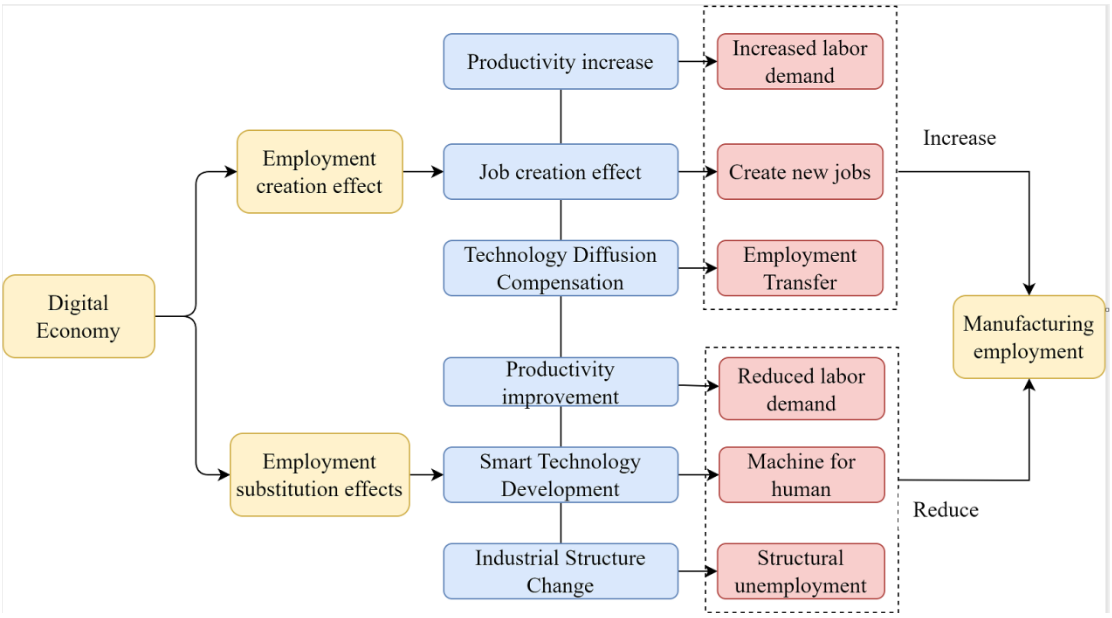

Figure 2. Theoretical analytical framework of the bilateral effects of the digital economy on manufacturing employment.

2.2.2. Analysis of the Job-Creation Effect of the Digital Economy on Manufacturing

In spite of the employment-substitution effect resulting from the technological revolution, the number of employed individuals has consistently exhibited an upward trend over the past few decades due to the continuous advancement of information and communication technologies [38]. This suggests that technological change also engenders a concurrent employment-creation effect, leading to an increase in job opportunities [39]. Based on existing studies, the digital economy can generate job-creation effects through compensatory mechanisms, such as increased productivity, the creation of new jobs, and the diffusion of digital technology. Firstly, an increase in productivity results in a rise in the demand for manufacturing labor. The synergistic nature of digital technology enhances factor flow and improves input–output efficiency. Moreover, its innovative attributes foster technological progress through knowledge production, consequently boosting manufacturing productivity. This productivity enhancement leads to reduced production costs, expansion of industrial scale, and heightened demand for digital and intelligent manufacturing products [40]. Ultimately, these factors stimulate manufacturing enterprises to continually increase labor input. Secondly, the digital economy fosters the emergence of novel occupations and jobs, thereby driving an increased demand for manufacturing labor. Digital technology possesses the inherent capacity to generate new job roles and job categories. As the conventional manufacturing production paradigm progressively gives way to intelligent production methods, a multitude of knowledge-intensive and skill-demanding tasks, such as programming, data analysis, sensing technology, associated research, and design activities, come to fruition [41]. The execution of these tasks necessitates substantial input from highly skilled laborers, particularly considering the augmented demand for such labor resulting from technologies such as artificial intelligence [26]. This, in turn, leads to the creation of numerous employment opportunities. Thirdly, the compensatory mechanism of digital technology diffusion contributes to a rise in the demand for manufacturing labor. With the integration of the digital economy and traditional manufacturing, the emergence of new industries and models has facilitated the creation of a significant number of employment opportunities [42]. This development has stimulated fresh job prospects in domains such as smart logistics and smart storage.

From a comprehensive perspective, the digital economy has both an employment-substitution effect and an employment-creation effect on manufacturing employment. The ultimate outcome of the impact on manufacturing employment depends on the interplay between these two forces; namely, the overall effect of the digital economy on manufacturing employment.

3. Model Settings and Data Description

3.1. Model Settings

Based on the previous analysis, the digital economy has both positive and negative effects on manufacturing employment. To investigate this, the present study adopts the approach proposed by Kumbhakar et al. (2009) [43] and constructs the following bilateral stochastic frontier model:

$$labor_{it} = i(x_{it}) + \omega_{it} - u_{it} + \varepsilon_{it} = i(x_{it}) + \xi_{it} = x_{it}\delta + \xi_{it} \tag{6}$$

In Equation (6), $labor_{it}$ represents manufacturing employment, while x_{it} denotes a series of control variables that affect manufacturing employment. These variables include the actual utilization of foreign capital, the number of granted patent applications, R&D expenditure of large-scale industrial enterprises, technology market turnover, government fiscal expenditure, import and export volume, average years of education, and GDP per capita. The parameter vector to be estimated is represented by δ. Furthermore, $i(x_{it})$ represents the frontier manufacturing employment, and ξ_{it} is the composite residual disturbance term, with $\xi_{it} = \omega_{it} - u_{it} + \varepsilon_{it}$. Here, ε_{it} is a random error term that reflects the deviation of manufacturing employment from the frontier level due to unobservable factors. Since the conditional expectation of the composite residual term ε_{it} may not be zero, it can lead to biased OLS estimation results. To address this, the method of maximum-likelihood estimation (MLE) is employed to obtain valid results. Through MLE estimation, Equation (6) is used to decompose ω_{it} and u_{it}, representing the upward and downward bias effects, respectively. Specifically, in Equation (6), $\omega_{it} \geqslant 0$ indicates the employment-creation effect of the digital economy on manufacturing employment, while $u_{it} \leqslant 0$ indicates the employment-substitution effect. When $u_{it} \leqslant 0$ and $\omega_{it} = 0$ or $\omega_{it} \geqslant 0$ and $u_{it} = 0$, the model becomes a one-sided stochastic frontier model, meaning there is only a single effect of the digital economy on manufacturing employment. When $\omega_{it} = u_{it} = 0$, the model becomes an ordinary least squares (OLS) model. If both ω_{it} and u_{it} are nonzero, it indicates a bilateral effect of the digital economy on manufacturing employment. Due to the potential nonzero value of ξ_{it}, the OLS model estimates can be biased.

According to Equation (6), it can be seen that the actual manufacturing employment level is the result of the bilateral combined effect of both the creation and substitution effects of the digital economy. The creation effect of the digital economy on manufacturing employment makes manufacturing employment higher than frontier manufacturing employment, while the substitution effect of the digital economy on manufacturing employment makes manufacturing employment lower than frontier manufacturing employment, and the deviation of real manufacturing employment is measured by calculating the net effect of the joint effect of the two. In addition, considering that the results obtained from the OLS estimation are biased, valid estimates can be obtained using the method of maximum-likelihood estimation (MLE). To this end, it is useful to make the following assumptions about the residual distribution: the random error term ε_{it} obeys a normal distribution with mean zero and variance σ_ε^2; $\varepsilon_{it} \sim iddN(0, \sigma_\varepsilon^2)$; ω_{it} and u_{it} both obey exponential distributions, i.e., $\omega_{it} \sim iddEXP(\sigma_\omega, \sigma_\omega^2)$ and $u_{it} \sim iddNEXP(\sigma_u, \sigma_u^2)$; the error terms satisfy the independence assumption condition between them and do not correlate with the interprovincial characteristic variables. Based on the distribution assumed as above, the probability density function of ξ_{it} is further derived as follows:

$$f(\xi_{it}) = \frac{exp\ exp\ (\alpha_{it})}{\sigma_u + \sigma_\omega} \Phi(\gamma_{it}) + \frac{exp\ exp\ (\beta_{it})}{\sigma_u + \sigma_\omega} \int_{-\eta_{it}}^{\infty} \varphi(x)dx = \frac{exp\ exp\ (\alpha_{it})}{\sigma_u + \sigma_\omega} \Phi(\gamma_{it}) + \frac{exp\ exp\ (\beta_{it})}{\sigma_u + \sigma_\omega} \varphi(\eta_{it}) \tag{7}$$

In Equation (7), $\varphi(\cdot)$ and $\varphi(\cdot)$ are the standard normal cumulative distribution function (CDF) and the standard normal distribution probability density function (PDF), respectively. Other parameters are set as follows:

$$\alpha_{it} = \frac{\sigma_v^2}{2\sigma_\omega^2} + \frac{\xi_i}{\sigma_\omega}\ \beta_{it} = \frac{\sigma_v^2}{2\sigma_u^2} - \frac{\xi_i}{\sigma_u}\ \gamma_{it} = -\frac{\xi_{it}}{\sigma_v} - \frac{\sigma_v}{\sigma_u}\ \eta_{it} = \frac{\xi_{it}}{\sigma_v} - \frac{\sigma_v}{\sigma_\omega} \tag{8}$$

Based on the parameter estimation of Equation (8), the maximum-likelihood function (MLE) expression is constructed as follows:

$$lL\ (X; \pi) = -nlnln\ (\sigma_\omega + \sigma_u) + \sum_{i=1}^{n} l\left[e^{\alpha_{it}} \Phi(\gamma_{it}) + e^{\beta_{it}} \Phi(\eta_{it})\right] \tag{9}$$

Here, $\pi = [\beta, \sigma_v, \sigma_\omega, \sigma_u]$. By further maximizing the likelihood function (9), all the parameter values of the maximum-likelihood estimation are finally obtained. In addition, ω_{it} and u_{it} need to be estimated. Therefore, the conditional density functions of the two are further derived:

$$f(\omega_{it} \mid \xi_{it}) = \frac{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right) exp\ exp\ \left[-\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)\omega_{it}\right] \Phi\left(\frac{\omega_{it}}{\sigma v} + \eta_{it}\right)}{exp\ exp\ (\beta_{it} - \alpha_i)\ [\Phi(\eta_{it}) + exp\ exp\ (\alpha_{it} - \beta_{it})\Phi(\gamma_{ii})\ ]} \tag{10}$$

$$f(u_{it} \mid \xi_{it}) = \frac{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right) exp\ exp\ \left[-\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)u_{it}\right] \Phi\left(\frac{u_{it}}{\sigma v} + \eta_{it}\right)}{\Phi(\eta_{it}) + exp\ exp\ (\alpha_{it} - \beta_{it})\Phi(\gamma_{it})} \tag{11}$$

Based on Equations (10) and (11), the conditional expectations of ω_{it} and u_{it} can be estimated:

$$E(\omega_{it} \mid \xi_{it}) = \frac{1}{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)} + \frac{\sigma_v[\Phi(-\eta_{it}) + \eta_{it}\Phi(\eta_{ii})]}{ex(\beta_{it} - \alpha_{it})\ [\Phi(\eta_{it}) + ex(\alpha_{it} - \beta_{it})\ \Phi(\gamma_{it})]} \tag{12}$$

$$E(u_{it} \mid \xi_{it}) = \frac{1}{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)} + \frac{ex(\alpha_{it} - \beta_{it})\ \sigma_v[\Phi(-\gamma_{it}) + \eta_{it}\Phi(\gamma_{ii})]}{\Phi(\eta_{it}) + ex(\alpha_{it} - \beta_{it})\ \Phi(\gamma_{it})} \tag{13}$$

Using Equations (12) and (13), we can estimate the absolute degree of manufacturing employment deviating from the frontier manufacturing employment in the face of the employment-creation effect and the employment-substitution effect. In order to facilitate the comparison, it is necessary to further convert the absolute value of the deviation degree of the digital economy affecting manufacturing employment into a percentage higher than or lower than the frontier level. The specific formula is as follows:

$$E\left(1 - e^{-\omega_{it}} \mid \xi_{it}\right) = 1 - \frac{\left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)\left[\Phi(\gamma_{it}) + ex(\beta_{it} - \alpha_{it})\ ex\left(\frac{\sigma_v^2}{2} - \sigma_v\eta_{it}\right)\ \Phi(\eta_{it} - \sigma_v)\right]}{\left[1 + \left(\frac{1}{\sigma_u} + \frac{1}{\sigma_\omega}\right)\right] ex(\beta_{it} - \alpha_{it})[\Phi(\eta_{it}) + ex(\alpha_{it} - \beta_{it})\ \Phi(\gamma_{it})]} \tag{14}$$

$$E\left(1-e^{-u_{it}} \mid \xi_{it}\right)=1-\frac{\left(\frac{1}{\sigma_u}+\frac{1}{\sigma_\omega}\right)\left[\Phi(\eta_{it})+ex(\alpha_{it}-\beta_{it})\,ex\left(\frac{\sigma_v^2}{2}-\sigma_v\gamma_{it}\right)\Phi(\gamma_{it}-\sigma_v)\right]}{\left[1+\left(\frac{1}{\sigma_u}+\frac{1}{\sigma_\omega}\right)\right][\Phi(\eta_{it})+ex(\alpha_{it}-\beta_{it})\,\Phi(\gamma_{it})]} \tag{15}$$

Based on Equations (14) and (15), the net effect of the digital economy on manufacturing employment is derived. The calculation formula is as follows:

$$NE=E\left(1-e^{-\omega_{it}} \mid \xi_{it}\right)-E\left(1-e^{-u_{it}} \mid \xi_{it}\right)=E\left(e^{-u_{it}}-e^{-\omega_{it}} \mid \xi_{it}\right) \tag{16}$$

Among them, NE represents the difference between the employment-creation effect and the employment-substitution effect. If $NE > 0$, it shows that the employment-creation effect is stronger than the substitution effect; that is, the employment-creation effect plays a leading role. If $NE < 0$, it indicates that the employment-substitution effect is stronger than the creation effect; that is, the employment-substitution effect plays a leading role.

3.2. Data Sources and Variable Description

Based on the above theoretical analysis and empirical model setting, and taking into account data availability, this study selects the provincial-level panel data of China from 2011 to 2020 to analyze the impact of the digital economy on manufacturing employment in each province, taking into account that some data are missing in Tibet and China, Hong Kong, Macao, and Taiwan, so they are excluded. The data of the variables selected for the study are obtained from the China Statistical Yearbook, the China Science and Technology Statistical Yearbook, the ESP Global Database, and the National Bureau of Statistics. The relevant involved variables are described specifically as follows:

3.2.1. Independent Variable

Level of digital economy development (sdig). Drawing on the idea of constructing the Internet development as the core of the measure by Liu Jun et al. (2020) [44], and adding the digital transaction index system, this study measures the comprehensive development index of the digital economy in two dimensions: Internet development and digital financial inclusion. The Internet is the carrier and reliance of the development of digital economy. To measure the level of Internet development at the provincial level, drawing on Huang Qunhui's approach [45], the four main aspects of Internet penetration, personnel employed in related industries, output of related industries, and cell phone penetration are used, respectively, as the number of Internet broadband access users per 100 people, the proportion of employees in the computer services and software industry to urban unit employees, the total amount of telecommunications business per capita, and the number of cell phone subscribers per 100 people. The measurement of digital financial inclusion is measured using the provincial digital financial inclusion index in China, compiled by Guo Feng et al. (2020) [6], which measures the breadth of digital financial coverage, depth of use, and degree of digitization. Thus, the entropy-weighting method is applied to measure the level of digital economy development.

3.2.2. Dependent Variable

The number of manufacturing employment (labor). Drawing on Han Minchun et al. (2020) [46] and Wang et al. (2022) [47], the number of manufacturing employment was selected as the dependent variable in this study, and it was logarithmically recorded as labor.

3.2.3. Control Variables

Refer to Wang et al. (2022) [47] and Acemoglu and Restrepo (2019) [48]. Among them, the level of economic development is expressed by using GDP per capita following Kwong et al. (2022) [49]; real utilized foreign capital is selected to observe the impact of foreign investment on employment; urbanization is expressed by using the percentage of the nonfarm population following Xu Weixiang et al. (2022) [50]; the number of patent applications granted is used to characterize the level of manufacturing innovation; R&D expenditure of above-regulated industrial enterprises is selected and the number of patent applications granted is used to characterize the level of innovation in the manufacturing industry; the R&D expenditure of above-scale industrial enterprises is chosen to characterize the level of R&D; the technology market turnover is used to illustrate the impact of technology introduction on employment; the amount of government fiscal expenditure is used to indicate the government's support for employment; the amount of import and export is chosen to observe the impact of regional foreign trade on employment; human capital is closely related to employment, and the average years of education is chosen here to indicate it; finally, the above variables are logarithmically processed. In addition, variables involving price factors are deflated in this study using 2011 as the base period. The results of descriptive statistics of the main variables are shown in Table 1.

Table 1. Descriptive statistics of variables.

Variable Category	Variable Name	Variable Code	Obs	Mean	SE	Min	Max
Dependent variable	Number of manufacturing employment	labor	300	4.488	1.080	1.974	6.928
Independent variable	Digital economy development level	sdig	300	0.327	0.142	0.125	0.937
Control variables	Per capita GDP	lnpgdp	300	1.631	0.436	0.495	2.803
	Actual utilization of foreign capital	fdi	300	14.539	1.949	6.702	17.602
	Urbanization	city	300	4.046	0.199	3.555	4.495
	Number of granted patent applications	pat	300	10.105	1.439	6.219	13.473
	R&D expenditure of industrial enterprises on the scale	rdd	300	10.618	1.373	7.054	13.459
	Technology Market Turnover	tem	300	4.730	1.790	−0.562	8.751
	Amount of government financial expenditure	govp	300	4.300	1.044	1.324	7.064
	Import and export value	ion	300	6.950	1.943	1.128	11.226
	Average years of education	edu	300	9.229	0.911	7.514	12.718

As shown in Table 1, the mean value of the number of manufacturing jobs (labor) is 4.488, and its maximum and minimum values are 6.928 and 1.974, respectively, with a standard deviation of 1.080, indicating a more significant gap in the number of manufacturing jobs between different regions of the country, similar to the findings of Han Minchun et al. (2020) [46]. The mean and standard error of the digital economy composite development index (sdig) are small. In terms of control variables, there are also significant differences among provinces in regional GDP per capita (lnpgdp), actual utilization of foreign capital (fdi), number of patent applications granted (pat), technology market turnover (tem), import and export volume (ion), and average years of schooling (edu).

4. Empirical Results and Analysis

4.1. Bilateral Stochastic Frontier Model Estimation

4.1.1. Baseline Regression Analysis

Based on the estimation by the method of the maximum-likelihood estimation (MLE), the bilateral effects of the digital economy on manufacturing employment are decomposed by combining the econometric model (1), and the estimation results are shown in Table 2, where the second column is the OLS estimation result of model (1) without considering the bias effect; model (2) is the estimation result without controlling for the time-fixed effect and the region-fixed effect; model (3) and model (4) are the estimation results of controlling for only model (3), and model (4) controls for area-only and time-only fixed effects, respectively; model (5) controls for both area- and time-fixed effects; model (6) considers the one-sided estimation results of the substitution effect of the digital economy on manufacturing employment only, i.e., the model residual term u_{it}; model (7) considers the one-sided estimation results of the creation effect of the digital economy on manufacturing employment only, i.e., the model residual term ω_{it}; model (8) considers the estimation results of both substitution and creation effects of the digital economy on manufacturing employment, i.e., the model residual terms ω_{it} and u_{it}. According to the likelihood ratio test (LR) of the model, after adding the deviation effect, model (8) is more reasonable than the OLS estimation and the residual model. After comprehensive comparison, it is finally determined that the later analysis is based on model (8) to analyze the bilateral effect decomposition measure of the subsequent digital economy.

Table 2. Basic estimation results of the bilateral stochastic frontier model for the digital economy.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Labor	Labor	Labor	Labor	Labor	Labor	Labor	Labor
fdi	0.000	−0.027 ***	−0.003 ***	−0.039 ***	0.001 ***	0.003 ***	0.003 ***	−0.001 ***
	(0.05)	(−129.01)	(−309.41)	(−781.58)	(76.25)	(170.58)	(57.35)	(−90.09)
city	0.449 *	−0.773 ***	−0.025 ***	−0.792 ***	0.481 ***	0.623 ***	0.618 ***	0.342 ***
	(1.83)	(−100.36)	(−15.67)	(−533.62)	(563.73)	(399.22)	(462.16)	(624.60)
pat	−0.054	−0.033 ***	−0.107 ***	0.066 ***	0.041 ***	0.021 ***	0.040 ***	0.036 ***
	(−1.48)	(−25.34)	(−473.96)	(151.42)	(314.60)	(84.48)	(289.53)	(276.44)
rdd	0.070 *	0.760 ***	0.162 ***	0.619 ***	0.069 ***	0.087 ***	0.069 ***	0.104 ***
	(1.81)	(408.51)	(1887.76)	(3607.93)	(246.17)	(386.05)	(376.79)	(1278.92)
govp	0.170 ***	0.004 **	0.040 ***	−0.022 ***	0.126 ***	0.076 ***	0.082 ***	0.062 ***
	(4.45)	(2.54)	(286.93)	(−94.66)	(633.88)	(674.22)	(445.56)	(309.15)
ion	0.008	0.076 ***	−0.043 ***	0.156 ***	0.014 ***	0.009 ***	0.011 ***	0.019 ***
	(0.63)	(131.57)	(−898.30)	(826.52)	(571.91)	(269.53)	(183.77)	(336.70)
edu	−0.029	0.004 ***	−0.095 ***	−0.057 ***	−0.059 ***	−0.006 ***	−0.028 ***	−0.048 ***
	(−0.94)	(2.71)	(−363.80)	(−268.43)	(−420.20)	(−75.70)	(−131.44)	(−966.50)
lnpgdp	−0.009	0.262 ***	0.015 ***	0.069 ***	−0.003 ***	−0.026 ***	−0.004 ***	0.005 ***
	(−0.41)	(199.33)	(119.05)	(176.77)	(−24.49)	(−235.51)	(−39.71)	(43.08)
_cons	2.020 *	−0.768 ***	6.523 ***	0.494 ***	1.407 ***	0.509 ***	0.674 ***	1.954 ***
	(1.93)	(−39.04)	(1874.15)	(82.72)	(243.15)	(122.53)	(140.88)	(973.45)
sigma_v								
_cons		−16.831	−18.334	−16.297	−21.575	−18.183	−30.377	−18.643
		(−0.01)	(−0.05)	(−0.04)	(−0.02)	(−0.05)	(−0.01)	(−0.04)
substitution effect								
sdig						−1.792 ***		−2.647 ***
						(−3.81)		(−5.08)
_cons			−1.950 ***	−1.728 ***	−2.454 ***	−2.007 ***	−2.517 ***	−1.650 ***
			(−32.45)	(−23.60)	(−37.68)	(−12.31)	(−38.01)	(−9.72)
Creation effect								
sdig							1.467 ***	2.948 ***
							(3.04)	(5.44)
_cons			−3.741 ***	−1.533 ***	−3.062 ***	−2.893 ***	−3.468 ***	−4.186 ***
			(−32.41)	(−22.35)	(−38.29)	(−38.66)	(−19.09)	(−19.04)
pro fixed	No	No	Yes	No	Yes	Yes	Yes	Yes
Year fixed	No	No	No	Yes	Yes	Yes	Yes	Yes
N	300	300	300	300	300	300	300	300

Note: *, **, and *** denote $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively, with estimates above parentheses and t-statistic values in parentheses, as below.

From the estimation results of model (8), it can be seen that the estimated coefficient of the employment-creation effect of the digital economy is significantly positive, indicating that the employment-creation effect of the digital economy increases the employment of the manufacturing industry. The estimated coefficient of the employment-substitution effect of the digital economy is significantly negative, indicating that the substitution effect of the digital economy significantly inhibits the increase in manufacturing employment. Accordingly, the hypothesis that the two effects of the digital economy on manufacturing employment exist simultaneously in the theoretical hypothesis of this paper has been tentatively verified in the estimation results of model (8).

4.1.2. Variance Decomposition: Measuring the Bilateral Effects of the Digital Economy on Manufacturing Employment

To comprehensively analyze the dominant effect of the digital economy on manufacturing employment, it is essential to decompose the creation effect and substitution effect of the digital economy on manufacturing employment using model (8), presented in Table 2. The decomposition results are provided in Table 3. The creation and substitution effects of the digital economy on manufacturing employment are quantified as 0.0441 and 0.0861, respectively, resulting in a net effect on manufacturing employment. The calculated degree of the effect is $E(\omega - u) = \sigma_\omega - \sigma_u = -0.0420$, indicating that the net effect of the digital economy on manufacturing employment hinders its growth. In conclusion, the digital economy has both employment-substitution and employment-creation effects; however, the dominance of the employment-substitution effect results in actual manufacturing employment in the province being lower than the optimal level. Hence, the digital economy plays a suppressive role in the growth of manufacturing employment.

Table 3. Variance decomposition: the creation and substitution effects of the digital economy on manufacturing employment.

	Meaning of Variables	**Symbol**	**Measurement Coefficient**
Digital Economy Impact	Variance decomposition	sigma_v	0.0000
	Substitution effects	sigma_u	0.0861
	Creation effect	sigma_w	0.0441
variance decomposition	Random total error term	Total sigma_sqs	0.0094
	Two effects accounted for	(sigu2 + sigw2)/Total	1.0000
	Proportion of substitution effect	sigu2/(sigu2 + sigw2)	0.7924
	Creation effect proportion	sigw2/(sigu2 + sigw2)	0.2076
		sig_u–sig_w	0.0420

Additionally, using the decomposition model, we can analyze the proportion of the substitution effect and the creation effect of the digital economy on manufacturing employment. According to Table 3, the substitution effect of the digital economy accounts for 68.52% of the impact on manufacturing employment, while the creation effect contributes to a 31.48% increase. These results highlight the dominance of the substitution effect, providing further support for the previous estimations. Consequently, the digital economy substantially restricts the growth of manufacturing employment through the employment-substitution effect. One possible explanation is that the Chinese manufacturing industry is currently heavily reliant on labor, with a significant portion of low-skilled workers in its workforce. Consequently, the introduction of digital technologies capable of performing repetitive tasks directly competes with this labor force, resulting in a decline in manufacturing jobs. As digital technology advances and economies of scale are realized through increased input quantity, the cost of its utilization will significantly decrease, thereby amplifying the employment-substitution effect.

4.1.3. Analysis of the Extent of the Dual Effect of the Digital Economy on Manufacturing Employment

Following an analysis of the impact of the digital economy on manufacturing employment, we proceed to calculate the deviation of regional manufacturing employment from the optimal level. This calculation utilizes a specific formula derived from Equations (13)–(15) in the model. The calculated result indicates the percentage by which actual employment deviates from the employment-frontier level, as well as the net effect weight of the digital economy on manufacturing employment. Additionally, the creation effect is compared to the substitution effect to determine the net effect size of each. This comprehensive analysis allows us to ascertain the true impact of the digital economy on manufacturing employment. Analysis of Table 4 reveals that the substitution effect of the digital economy leads to a 7.80% decrease in manufacturing employment compared to the frontier level. Conversely, the creation effect results in a 4.15% increase in manufacturing employment above the frontier level. Ultimately, the combined effect of these two factors causes manufacturing employment to be 3.66% lower than the frontier level. This finding suggests that the bilateral effect of the digital economy exhibits asymmetry, resulting in a predominant substitution effect on the level of manufacturing employment.

Table 4. Estimated net effect of the digital economy on manufacturing employment (%).

Type of Effect	Mean	SE	p25	p50	p75
Substitution effect	7.80	8.26	2.62	3.90	10.35
Creation effect	4.15	4.37	2.27	2.59	2.82
net effect	−3.66	10.31	−8.04	−1.32	0.37

Building upon this foundation, we conduct a more in-depth analysis of the distribution of the two effects of the digital economy on manufacturing employment. Table 4 illustrates the disparities in these effects at various percentile levels. More specifically, the substitution effect of the digital economy on manufacturing employment exhibits an upward trend, rising from 2.62% at the 25th percentile to 10.35% at the 75th percentile. On the other hand, the job-creation effect increases from 2.27% at the 25th percentile to 2.82% at the 75th percentile. Evidently, the disparity between these two effects is growing, with the employment-substitution effect consistently prevailing. This further confirms that the digital economy diminishes the overall quantity of manufacturing jobs, aligning with the previous findings.

Figure 3 presents the frequency distribution of the creation effect, substitution effect, and net effect of the digital economy on manufacturing employment. As depicted in Figure 3, the substitution effect of the digital economy on manufacturing employment exhibits a right-skewed distribution, with a substantial presence around 50%. This suggests that the manufacturing employment in certain provinces is highly responsive to variations in the digital economy and susceptible to its impact. Conversely, the creation effect of the digital economy on manufacturing employment diminishes around 25%, significantly lower than the substitution effect. This implies that the manufacturing employment in certain provinces experiences lesser influence from the creation effect of the digital economy. The distribution of the net effect reveals that the employment-substitution effect of the digital economy impacts the majority of provinces, while the employment-creation effect affects only a few provinces. These findings affirm that the digital economy diminishes manufacturing employment, aligning with the theoretical analysis conducted in the preceding section.

4.2. Regional Characterization of the Digital Economy Impact on Manufacturing Employment

Regarding regional distribution, the net effect of the digital economy on manufacturing employment is negative across all three regions: −2.38% in the central region, −4.97% in the west region, and −3.97% in the east region, as shown in Table 5. This suggests that the digital economy serves as a substitute for manufacturing employment in all three regions, with the magnitude of the substitution effect following the order: central > west > east. This can be attributed to the advanced level of digital economy development in the eastern region, which has attracted a considerable number of digital innovation talents and innovation capital. Consequently, the industrial and technological changes brought about by the digital economy may not significantly affect manufacturing employment in this region. However, the short-term impact of employment substitution remains significant, closely tied to the prevailing industrial structure and human capital level in China. The industries in the central and western regions primarily consist of labor-intensive sectors. Consequently, the development of the digital economy will inevitably affect the existing labor market in these regions, particularly with the extensive deployment of industrial robots, which will have a pronounced negative impact on manufacturing employment.

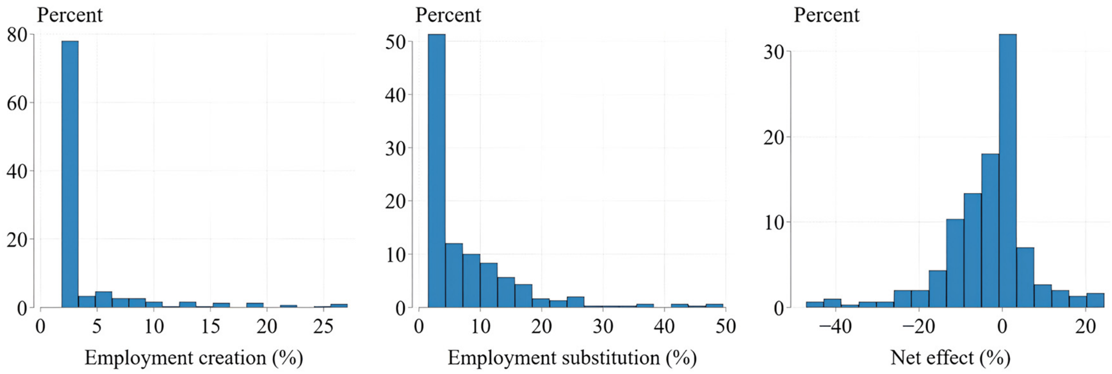

Figure 3. Distribution of the creation effect, substitution effect and net effect of the digital economy.

Table 5. Characteristics of the annual distribution of the net effect of the digital economy on manufacturing employment (%).

Province	Net Effect Mean	Province	Net Effect Mean	Province	Net Effect Mean
Hebei	−4.05	Heilongjiang	−4.89	Sichuan	−3.70
Liaoning	−1.77	Jilin	−5.63	Yunnan	−6.27
Fujian	3.05	Shanxi	−2.00	Inner Mongolia	−2.74
Shandong	−3.16	Hubei	−4.17	Ningxia	−4.38
Jiangsu	−7.90	Hunan	−3.11	Guangxi	−5.01
Zhejiang	−0.46	Anhui	−3.14	Xinjiang	−6.51
Guangdong	−5.70	Jiangxi	−6.25	Gansu	−0.08
Hainan	−3.18	Henan	−10.56	Guizhou	−3.18
Beijing	1.51			Chongqing	−2.36
Tianjin	−4.21			Shaanxi	−4.99
Shanghai	−0.36			Qinghai	−4.46
East region	−2.38	Central region	−4.97	West region	−3.97

4.3. Analysis of the Temporal Characteristics of the Digital Economy's Impact on Manufacturing Employment

In order to further examine the temporal trends in the impact of the digital economy on manufacturing employment, we analyze the variations in the effect of the digital economy on manufacturing employment over different years, taking time variables into account. The results are presented in Figure 4. In the majority of the years examined, the substitution effect of the digital economy prevails, with effect sizes ranging from −12.37% to 4.35%. Overall, as the time trend evolves, the substitution effect of the digital economy on manufacturing employment diminishes gradually. Particularly, starting from 2019, the net effect of the digital economy on manufacturing employment shifts from negative to positive, with the employment-creation effect gradually assuming a dominant role and displaying a continuous strengthening tendency. This outcome can be attributed to the deep integration of digital technologies, such as the Internet of Things, big data, and cloud computing, with the real economy. This integration has resulted in transformative changes in the real economy across production, distribution, circulation, and consumption, effectively driving the digital transformation and intelligent upgrading of the manufacturing industry (enterprises). Given that the digital transformation and intelligent upgrading of the industry will inevitably lead to the elimination of low-tech and repetitive labor, the digital economy will continue to exhibit substitution effects on manufacturing employment in the short term. However, intelligent manufacturing and the application of industrial robots do not entirely replace manual labor. Instead, they contribute to the emergence of a new industrial ecology capable of absorbing a significant amount of labor and generating numerous jobs associated with new technologies. Consequently, in the long term, the creation effect of the digital economy on manufacturing employment will persist.

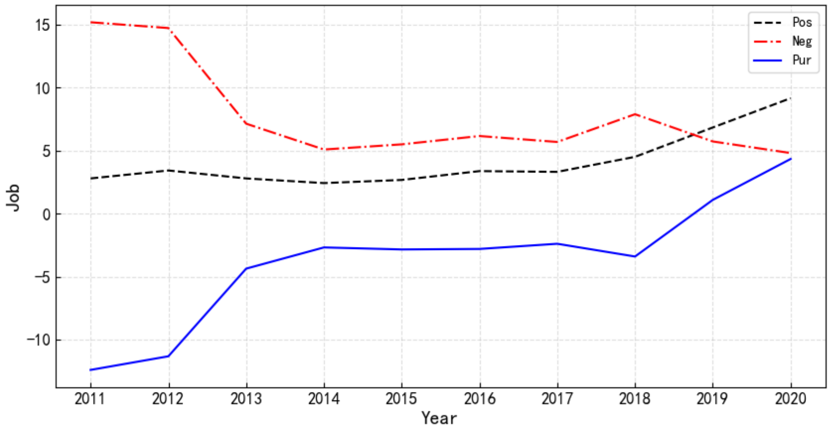

Figure 4. Characteristics of the annual distribution of the net effect of the digital economy on manufacturing employment (%). Note: Neg represents the employment-substitution effect, Pos represents the employment-creation effect, and Pur represents the net effect.

4.4. Analysis of Differences in Manufacturing Employment Affected by Different Levels of Digital Economy Development

Based on the previous analysis, it is evident that the digital economy exerts a predominant substitution effect on the level of manufacturing employment. Subsequently, the distribution of reciprocal effects at various levels of digital economy development is examined by dividing the levels into low, medium, and high categories based on the 25th, 50th, and 75th quartiles of digital economy development. The results are presented in Table 6. With the advancement of the digital economy's development level, the average substitution effect of the digital economy on manufacturing employment declines from 11.45% in the low-level group to 4.60% in the high-level group. The average creation effect rose from 2.68% in the low-level group to 7.13% in the high-level group, resulting in a shift of the mean net effect from negative to positive. The above analysis reveals that, while the substitution effect of the digital economy on manufacturing employment remains prevalent in the overall sample, there exists noteworthy heterogeneity in its impact across different levels of the digital economy. One possible explanation for this is that, in situations where the digital economy is at a low level, the integration between manufacturing and the digital economy is also limited. Consequently, this integration primarily affects low-skilled and highly repetitive jobs, such as assembly line work in the low-end manufacturing job market in China, leading to substantial replacement of employees in this category. As the digital economy progresses to higher levels, the manufacturing industry and the digital economy will achieve greater integration, necessitating a substantial number of skilled professionals to facilitate human–machine collaboration and generate a multitude of job opportunities. To summarize, the influence of the digital economy on manufacturing employment is a long-term cumulative process that necessitates a dynamic consideration of its comprehensive effect on manufacturing employment.

Table 6. Differences in the net effect of manufacturing employment at different levels of the digital economy (%).

Digital Economy	Decomposition of Effects	Mean	SE	p25	p50	p75
Low-level Group	Substitution effect	11.45	10.41	2.60	9.32	15.88
	Creation effect	2.68	2.50	2.00	2.13	2.20
	Net effect	−8.77	11.25	−13.82	−7.32	−0.40
Middle-level Group	Substitution effect	7.55	7.86	2.57	4.79	10.06
	Creation effect	3.39	3.23	2.37	2.56	2.74
	Net effect	−4.16	9.01	−7.55	−2.35	0.00
High-level Group	Substitution effect	4.60	4.29	2.70	2.80	3.56
	Creation effect	7.13	6.12	2.79	3.37	9.19
	Net effect	2.53	8.55	−0.83	1.01	6.60

4.5. Differential Analysis of the Impact of Digital Economy under Different Human Capital

The advancement of the digital economy increases the demand for human capital. Moreover, when a region possesses a significant amount of human capital, it leads to corresponding improvements in its industrial and demographic structures. Additionally, the agglomeration effect of human capital can partially mitigate the adverse effects of the digital economy, such as manufacturing unemployment. In order to examine this hypothesis, the present study employs average years of education as a measure of human capital [40]. The grouping methodology described in Section 4.4 is utilized, and the findings are presented in Table 7. The positive impact of the digital economy on manufacturing employment increases from 3.47% in the low-level group to 5.40% in the high-level group. Simultaneously, the negative substitution effect declines from 9.53% in the low-level group to 4.63% in the high-level group. As a result, the combined net effect shifts from negative to positive. These findings suggest that enhancing human capital skills can partially alleviate the substitution effect of the digital economy on manufacturing employment. This can be attributed to the fact that, as the digital economy advances, the employment prospects of low-skilled workers are increasingly influenced by digital technology. Furthermore, the digital economy generates numerous jobs that require knowledge and technological expertise, consequently leading to a growing demand for highly skilled individuals. This dynamic prompts the labor force to adapt to a more advanced employment skill structure, resulting in the creation of employment opportunities for high-skilled workers.

Table 7. Differences in the impact of the digital economy on manufacturing employment by labor skills (%).

Human Capital (EDU)	Decomposition of Effects	Mean	SE	p25	p50	p75
Low-skill Group	Creation effect	3.47	4.03	2.10	2.29	2.69
	Substitution effect	9.53	8.77	2.75	6.83	12.79
	Net effect	−6.06	10.53	−10.28	−4.48	0.00
Middle-skill Group	Creation effect	3.86	4.22	2.27	2.52	2.81
	Substitution effect	8.52	9.13	2.62	4.78	11.46
	Net effect	−4.66	10.92	−8.82	−2.34	0.00
High-skill Group	Creation effect	5.40	4.75	2.60	2.80	7.55
	Substitution effect	4.63	4.13	2.55	2.77	3.58
	Net effect	0.77	7.13	−1.16	0.00	4.77

Note: Years of education per capita = elementary school literate population × 6 + middle school literate population × 9 + high school literate population × 12 + college and above literate population × 16.

4.6. Robustness Analysis

To assess the robustness of the findings, this study incorporates the research conducted by Zhao Tao et al. (2020) [51]. Additionally, the level of digital economy development is recalculated through principal component analysis (PCA) and employed for robustness testing purposes. Building upon this foundation, the study reevaluates the creation effect, substitution effect, and net effect of the digital economy on manufacturing employment. The outcomes are presented in Table 8. The findings reveal that the substitution effect of the digital economy on regional manufacturing employment is 0.0835, while the creation effect is 0.0478. These figures align with the earlier findings. This suggests the presence of a two-way relationship between the digital economy and regional manufacturing employment. Regarding the net effect, the substitution effect of the digital economy represents 75.3%, while the creation effect accounts for 24.7%. This observation implies that the dominance of the digital economy's substitution effect in the context of manufacturing employment causes a relative deviation from the industry's frontier level. Consequently, this finding provides additional support for the robustness of the results.

Table 8. Impact effects and variance decomposition.

	Meaning of Variables	Symbol	Measurement Coefficient
Digital Economy Impact	Variance decomposition	sigma_v	0.0000
	Substitution effects	sigma_u	0.0835
	Creation effect	sigma_w	0.0478
Variance Decomposition	Random total error term	Total sigma_sqs	0.0092
	Two effects accounted for	(sigu2 + sigw2)/Total	1.0000
	Proportion of substitution effect	sigu2/(sigu2 + sigw2)	0.7533
	Creation effect proportion	sigw2/(sigu2 + sigw2)	0.2467
		sig_u − sig_w	0.0357

The study further estimates the substitution effect, creation effect, and net effect resulting from the interaction between the digital economy and manufacturing employment. The findings are presented in Table 9. The findings indicate that, with the advancement of digital economy development, the promotion effect increases regional manufacturing employment by 4.53%. However, the substitution effect decreases regional manufacturing employment by 7.53%. Consequently, the net effect results in actual regional manufacturing employment being 3.00% lower than the frontier level. These results align with the previous estimates.

Table 9. Degree of deviation from employment due to digital economy impact effects (%).

Type of Effect	Mean	SE	p25	p50	p75
Substitution effect	7.53	7.96	2.88	3.68	9.73
Creation effect	4.53	4.03	2.85	2.94	3.51
Net effect	−3.00	9.77	−6.82	−0.92	1.00

5. Conclusions and Policy Implications

5.1. Research Conclusions

This study examines the "creation effect" and "substitution effect" mechanisms of the digital economy on regional manufacturing employment, drawing from relevant literature. Additionally, it empirically tests the bilateral effects of the digital economy on manufacturing employment using a bilateral stochastic frontier model. The analysis is based on panel data from 30 provinces, regions, and cities in China spanning the period from 2011 to 2020. The aim of this investigation is to shed light on the potential employment shocks brought about by the digital economy. Drawing from panel data covering the period from 2011 to 2020 for 30 Chinese provinces (autonomous regions and municipalities), we employ a bilateral stochastic frontier model to empirically examine the bilateral effects of the digital economy on manufacturing employment. This analysis aims to address the prevailing concern surrounding potential employment shocks resulting from the digital economy. The primary findings are as follows:

(1) The digital economy generally exhibits a substitution effect on regional manufacturing employment. However, under the full sample, the creation effect of the digital economy on regional manufacturing employment outweighs the substitution effect. Specifically, the creation effect leads to manufacturing employment surpassing the frontier level by 4.15%, while the substitution effect results in manufacturing employment falling below the frontier level by 7.80%. Consequently, the combined effect of these two factors lowers manufacturing employment to a level 3.66% below the frontier level. Thus, the current stage of the digital economy has contributed to a reduction in the level of manufacturing employment to some extent;

(2) The digital economy impacts manufacturing employment with temporal and spatial variations. In terms of the temporal trend, the current stage is dominated by the substitution effect of the digital economy on manufacturing employment. However, in the medium and long term, this substitution effect will diminish, giving rise to a more prominent employment-creation effect. Regarding the geographical dimension, the employment-substitution effect of the digital economy exhibits a distribution pattern where the central region has the highest effect, followed by the west and the east;

(3) The impact of the digital economy on manufacturing employment varies in direction and magnitude across different levels of digital economy development and different levels of human capital. Specifically, regions with higher levels of digital economy and greater human capital exhibit a dominant short-term employment-substitution effect, although the negative influence of the digital economy on manufacturing employment tends to diminish over time. Conversely, regions with lower levels of digital economy and lower levels of human capital experience a stronger employment-substitution effect.

5.2. Policy Implications

This study aims to clarify the relationship between the digital economy and manufacturing employment. It seeks to provide a more systematic, profound, and thorough understanding of the short-term substitution and long-term creation of manufacturing employment induced by the digital economy. This insight can address concerns regarding the potential negative impact of intelligent upgrading on the manufacturing labor market. However, the bilateral stochastic frontier model has certain limitations, and the data are somewhat generalized, which means we cannot identify the spatial effects and industrial spillover effects of the digital economy on manufacturing employment. In the future, the digital economy's impact on employment will be examined in greater detail, incorporating data and exploring numerous dimensions, such as the regional, industrial, and enterprise levels. In particular, greater emphasis will be placed on analyzing its spatial impact and industrial spillover effects. In conclusion, the overall effect of the digital economy on employment relies on weighing the negative substitution effect against the positive creation effect. Investigating the nonlinear influence of the digital economy on employment represents a potential avenue for further research. Regarding these objectives, the paper presents the following policy implications:

First, governments at all levels should actively deepen the reform of vocational education to enhance the skill level and technological competence of the workforce. This includes identifying future employment trends in the digital economy; fostering collaboration between government, industry, academia, and research institutions; emphasizing skills enhancement and the application of new technologies in the manufacturing workforce [52]. To meet the demand for highly skilled labor in emerging roles within the manufacturing sector, targeted skills training programs should be implemented for currently underutilized personnel. For labor-intensive manufacturing areas facing heightened automation risks, the establishment of a lifelong vocational education system becomes necessary. It is worth noting that the substitution effect of the digital economy on manufacturing employment is more pronounced in the central and western regions than in the eastern regions. Accordingly, training approaches should be region-specific, the emphasis in the eastern regions should be on gaining high skills required for the adoption of digital economy, while the focus in the central and western regions should be on training low- and middle-skilled labor to meet the new requirements. Furthermore, considering the development status and demands of regional manufacturing industries, a rational allocation of digital technology and labor resources should be pursued. This includes actively fostering employment opportunities that involve human–machine collaboration and curbing the displacement impact of the digital economy on workers with low-to-mid-level skills in the manufacturing sector.

Second, the government should facilitate the alignment of labor market supply and demand to amplify the employment-creation effect of the digital economy. It could explore the establishment of a nationwide integrated employment monitoring and information services platform. Alongside this, a labor resource exchange and collaboration channels could be established at the provincial, city, district (county), and industry levels to promote the alignment of supply and demand in the manufacturing labor market. It is important for the government to pinpoint and extend support to those unemployed or at the brink of unemployment, especially those employed in traditional labor-intensive industries. The government should enhance guidance and investment in vocational skills education and training programs that enable workers to transition into a manageable entry point in the digital domain, such as data collection and content auditing roles. This approach ensures the availability of an ample labor pool for intelligent manufacturing while mitigating the employment repercussions of new technological advancements on traditional industries. Government departments should proactively offer enhanced policy initiatives and financial backing for educational endeavors in industrial intelligence, fortifying the reservoir of talents in this realm. Moreover, efforts should be made to amplify the employment-generating impact of the digital economy and foster the development of more high-skilled professionals to facilitate the digital and intelligent transformation of the manufacturing industry.

Third, it is important to establish specific industrial development plans and to facilitate the upgrading of manufacturing industries. Given the diverse effects of the digital economy on manufacturing employment, local administrative bodies should stay abreast of the evolving landscape of industrial intelligence, leverage their expertise in top-level industrial planning, and tailor gradient industrial upgrading plans and differentiated industry development strategies based on the specific characteristics of regions with varying levels of digital economy development and labor skill levels [38]. In areas where the digital economy and workforce skills are advanced, the focus should be on upscaling production with smart manufacturing to amplify the job-creation effect of the digital economy. Conversely, in regions where the digital economy and labor expertise are in nascent stages, the development of low-end manufacturing industries and the absorption of industrial transfers from other regions should be pursued gradually and strategically. Additionally, the utilization of digital technology to enhance the quality of products and services can help to alleviate the conflicts arising from the short-term employment-substitution effect of the digital economy.

Author Contributions: Conceptualization, C.D. and X.S.; methodology, C.D. and X.S.; writing—original draft preparation, X.S. and Y.X.; writing—review and editing, Y.X. and Y.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Hebei Social Science Fund Project (HB22GL051), and the project name is the internal mechanism, multi-dimensional effect and realization path of the digital transformation of specialized and special new enterprises in Hebei Province.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available from the corresponding author.

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

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