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Digitalization as a Factor of Production in China and the Impact on Total Factor Productivity (TFP)

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Abstract: In the digital transformation era, digitalization integrates deeply into production, bolstering output efficiency and economic value. Through stochastic frontier analysis (SFA), this research positions digitalization as an input in the production function, dissecting its elasticity impact on capital, labor, and output. The effect of digitalization on total factor productivity change (TFPC) is explained by comparing TFPC with and without digitalization. Findings reveal that digitalization's integration into economic growth displays a U-shaped trajectory, with initial productivity setbacks transitioning to long-term benefits as industries adapt. The periodic complementarity and substitution between digitalization and labor, along with a weak substitution relationship with capital, illustrate that, as a production factor, digitalization dynamically interacts with other factors, both complementing and substituting them. This dynamic interplay highlights the intricate role that digitalization plays within the production function. Furthermore, digitalization has played a crucial role in China's TFP growth, which also highlights the lack of other technological progress. Meanwhile, the pace of digital transformation presents scalability challenges, evident in the fluctuating scale efficiency change (SEC). Policymakers are advised to address these early stage challenges through supportive measures, ensuring smoother digital transitions. Concurrently, industries should embrace this non-linear transformation, emphasizing adaptability to maximize digitalization's long-term advantages.

Keywords: digitalization; production function; total factor productivity (TFP); stochastic frontier analysis (SFA)

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Citation: Li, P.; Liu, J.; Lu, X.; Xie, Y.; Wang, Z. Digitalization as a Factor of Production in China and the Impact on Total Factor Productivity (TFP). *Systems* **2024**, *12*, 164. https://doi.org/10.3390/systems12050164

Academic Editor: William T. Scherer

Received: 22 March 2024
Revised: 19 April 2024
Accepted: 30 April 2024
Published: 5 May 2024

1. Introduction

In the era of digital transformation, data has transitioned from being a mere byproduct of economic activities to a core asset with significant intrinsic value. Traditionally, the economic value of data was often overlooked due to limited computational capabilities and inadequate analytical techniques [1,2]. However, with the advent of advanced analytics and substantial increases in computational power, the role of data in enhancing economic analysis and decision-making processes has become increasingly recognized [3,4].

Digitalization has fundamentally reshaped industrial operations by integrating deep analytics into economic activities, thus becoming standard in industries, leading to labor savings and improved production efficiency [5,6]. Data analytics now underpins various quantitative studies, facilitating complex modeling and effective problem-solving that optimize outputs and refine resource allocation [7,8]. These advancements have substantiated digitalization's role in boosting economic throughput [9].

Despite the strategic emphasis on digitalization by several countries, including the United States, Germany, and China, and its acknowledgment as a pivotal economic force, digitalization has not been independently characterized as a production factor in economic modeling [10]. Typically subsumed under broader categories such as technological progress or capital investments, digitalization's direct impacts and interactions with traditional factors like labor and capital have been somewhat obscured.

This study addresses this gap by focusing on 281 Chinese prefecture-level cities over the period from 2011 to 2019, using a dataset that captures comprehensive economic activities influenced by digitalization. By explicitly incorporating digitalization as a standalone factor within the Cobb–Douglas production function model, this research aims to elucidate the nuanced impacts of digital technologies on economic productivity. By treating digitalization as an independent factor, this research not only provides a novel perspective on its economic contributions but also offers valuable insights that could help policymakers and business leaders optimize the use of digital technologies for economic growth and productivity enhancement.

The primary contributions of this study are as follows: First, it systematically incorporates digitalization as an independent production factor within the Cobb–Douglas production function, a novel approach that allows for an explicit examination of how digitalization impacts economic output alongside traditional factors like capital and labor. Second, the periodic complementarity and substitution between digitalization and labor, along with a weak substitution relationship with capital, illustrate that, as a production factor, digitalization dynamically interacts with other factors, both complementing and substituting them. This dynamic interplay highlights the intricate role that digitalization plays within the production function. This integration provides a clearer understanding of digitalization's unique contribution and elasticity's impact on these traditional factors. Third, by employing a comparative analysis of total factor productivity change (TFPC) with and without the inclusion of digitalization, this study highlights the significant role of digital inputs in enhancing productivity. The decomposition of TFPC reveals that digitalization contributes positively to technological efficiency changes and scale efficiency changes, providing robust empirical evidence that supports the reevaluation of productivity metrics in the digital age. This detailed comparison not only quantifies the impact of digitalization but also showcases its pivotal role in fostering economic growth and productivity improvements.

The remainder of the paper proceeds as follows: Section 2 briefly reviews the relevant literature. Section 3 describes the methodology. Section 4 provides the data and variables. Results and discussions are presented in Sections 5 and 6. Section 7 concludes.

2. Literature Review

2.1. Digitalization as an Input in Production Systems

Amidst the rapid pace of technological advancements, data and digitalization have emerged as cornerstones of modern society, with the digital economy gaining increasing prominence. Often referred to as "the new oil," data's critical role in decision-making, innovation, and strategic foresight across various sectors is undeniable [11]. Despite its importance, the role of data transcends mere usage; it involves the transformation of these data into tangible economic value through effective digitalization practices [12–14], which formed the concept of the digital economy [15,16]. For instance, data analytics has revolutionized finance through enhanced quantitative trading, while real-time data from IoT devices has significantly improved predictive maintenance in manufacturing [17–19].

Digitalization, distinguished from mere data utilization, involves integrating and refining data as a core production factor, akin to labor and capital. This transformative process not only optimizes operations within sectors but also drives innovation and value creation [20,21]. Studies have consistently shown that digitalization's impact on economic development is profound, enhancing productivity and efficiency at multiple levels [22,23]. For example, the deployment of electronic health records (EHRs) significantly improves patient care by predicting needs and enhancing diagnostic accuracy [24]. Unlike the broader digital economy, which includes all digital activities, digitalization specifically refers to the operational application of data, making it a more precise and impactful factor in production processes. This crucial distinction underscores digitalization's role not just in supporting, but actively driving economic activities, validating its position as a fundamental element in the economic discourse [25].

It is widely acknowledged that digitalization is a form of technological progress [26]. Therefore, it is valuable to review studies that incorporate technology as an independent production factor within production functions. For instance, Crespi and Zuniga (2012), Edeh and Acedo (2021), Gaglio et al. (2022), etc. examined the determinants of technological innovation and its impact on productivity based on Crepon–Duguet–Mairesse (1998), which is often known as the CDM model [27–30]. The CDM model provides a comprehensive analytical framework that spans the entire chain from technological R&D inputs to outputs and then to efficiency. However, the CDM model essentially treats technological inputs as tools or an "environment" that enhance the productivity of capital and labor. This perspective is also accepted in the digital realm, where digitization is viewed as a driving force behind the productivity enhancements of capital and labor, thereby identifying the indirect effects of digitization on increasing productivity. For instance, based on the two-stage process, Wang et al. (2023) first measured the total factor productivity by using capital and labor, then took it as the explained variable and found the positive effect of ICT on GTFP [31]. Similarly, Gërguri-Rashit et al. (2017), Chedrawi et al. (2019), Nakatani (2021), and Le et al. (2022) also adopted similar two-stage methodologies to analyze the relationship between digital technology and productivity [32–35].

The aforementioned studies primarily focus on the positive effects of digitization on the productivity of capital and labor, revealing the indirect impact of digitization on productivity. However, we emphasize that digitization itself is already forming an independent industry, based on "data" and associated capital investments, which has a direct effect on productivity. Therefore, it is necessary to segregate digitization from the broader concept of technological progress and view it as a separate factor of production to analyze its economic effects. This involves measuring digitization and explaining its relationships with other factors of production.

2.2. The Measurement of Digitalization

The task of quantifying and deciphering the socioeconomic dividends of digitalization has emerged as a pivotal topic in contemporary academic discourse. Given digitalization's multifarious nature, its measurement demands a comprehensive analytical framework.

In the early stages, efforts to gauge the extent of digitalization were anchored in singular metrics such as internet coverage or internet access per capita [36]. However, the academic milieu swiftly highlighted the inadequacies of such metrics. The predominant contention was that these metrics, being overly simplistic, could not capture the multifaceted essence and transformative potential of digitalization [37,38]. In response to these limitations, international bodies have fashioned more intricate indices. For instance, the European Union developed the Digital Economy and Society Index (DESI). It evaluates nations based on criteria like the assimilation of digital technology and the degree of internet adoption [39]. Concurrently, the World Economic Forum (WEF) introduced the Network Readiness Index (NRI) to assess how primed a nation is to harness information technology for socioeconomic gains. Such composite metrics have come to be revered by scholars for their ability to provide a nuanced perspective on a country's digitalization journey [40,41].

In response to the burgeoning digital landscape in China, the Digitalization Research Center of Peking University has proactively introduced a tailored digital index. This index, meticulously designed with China's unique socio-economic fabric in mind, offers insights that are both profound and pertinent to the nation's rapidly evolving digital milieu. While the DESI and NRI capture global trends and technological readiness, Peking University's index is astutely sensitive to China's distinct digital trajectory [42]. Notably, its strength lies in its precision and depth, addressing the unique contours of China's digital landscape. It fathoms the intricacies of China's vast digital payment ecosystem, the sprawling e-commerce platforms, and the symbiotic relationship between burgeoning digital infrastructures and traditional sectors. For instance, Li et al. (2020) applied the digital index to the panel regression model, revealing the positive impact of the digitalization process in China on residents' consumption, which accords with the reality in China and proves the effectiveness of the index [43]. Chen and Zhang (2021) exploited the causal effect of digitalization on manufacturing servitization in China based on this index, which showed that digitalization has a significant positive impact on the servitization of the manufacturing industry; moreover, the impact on sub-sectors is heterogeneous [44]. Yan et al. (2023) explored the dynamic spatial-temporal correlation effects of digitalization and environmental regulation on manufacturing carbon emissions by applying the Peking University digitalization index, which found that digitalization has effectively strengthened the emission reduction effect of environmental regulation [45]. These examples show that the digitalization index from Peking University effectively depicts the digitalization process in China and also highlight its application value in quantitative analysis.

In essence, while global indices like DESI and NRI offer a panoramic view of digital readiness, the digital index from the Digitalization Research Center of Peking University provides a telescopic perspective, capturing the nuances and vibrancy of China's digital metamorphosis. To sum up, as digitalization permeates deeper into the global fabric, our assessment methodologies must evolve in tandem. It's imperative to adopt a holistic lens to truly fathom its profound socioeconomic implications.

2.3. The Socioeconomic Dividends of Digitalization

The transformative power of digitalization on the socioeconomic landscape is a topic of paramount importance in contemporary economic literature. One of the foremost arenas witnessing the influence of digitalization is economic growth [46]. The proliferation of digital technologies has catalyzed innovations, paved avenues for new business models [47], and expanded market reach to transcend geographical boundaries [48]. Industries have metamorphosed, with sectors such as fintech, e-commerce, and digital health redefining traditional business paradigms [17–19]. Furthermore, labor markets have been reshaped by digitalization [49]. While there's a tangible concern about technology-induced job displacements, there's also an acknowledgment of job creation in new digital domains, necessitating a workforce equipped with digital literacy [50]. Trade, another critical dimension, has also been revolutionized [51]. Digital platforms have democratized access to global markets, enabling even micro-entrepreneurs to engage in cross-border trade, thus fostering inclusivity in the global economy [52].

Besides that, the crux of the discourse gravitates towards the impact of digitalization on total factor productivity (TFP). TFP, a measure that captures the residual growth in total output of a production process that cannot be attributed to the accumulation of utilized traditional inputs, stands as a testament to the efficiency gains from digitalization [53,54]. Recent studies have underscored how digital technologies, by optimizing resource allocations, streamlining processes, and fostering innovations, have bolstered TFP [48,55]. The seamless integration of artificial intelligence, IoT, and big data analytics, among others, has been instrumental in this TFP augmentation, offering insights and efficiencies previously deemed unattainable [18,19].

Notably, a significant portion of the prevailing literature on digitalization and TFP adopts a somewhat siloed perspective, examining the causal relationship between the two while often sidelining digitalization's intrinsic role as a production factor. This oversight tends to obscure the direct influence of digitalization on TFP. Recognizing and integrating digitalization as a fundamental constituent within the TFP framework, rather than an external influencer, is crucial for a more holistic understanding of contemporary economic productivity.

Therefore, this paper uses 281 cities in China as the basic unit, introduces digitalization as an input factor into the production function, combines labor and capital factors, and explores the elasticity of substitution between digitalization and other factors. Then, a new total factor productivity that takes digitalization into account and its decomposition is adopted. Lastly, the new TFP is compared with the previous TFP, and the difference between them is explained.

3. Methodology

3.1. Stochastic Frontier Analysis (SFA) with Transcendental Logarithmic Production Function Model

The stochastic frontier analysis (SFA) model proposed by Aigner et al. (1977) is a parameter method that analyzes the production activities of an economic entity by constructing a specific production function [56]. The SFA method takes into account the influence of random factors and is applicable to the panel data used in this study. Its basic form is as follows:

$$y_{it} = f(x_{it}, \beta) \cdot e^{v_{it} - u_{it}} \tag{1}$$

Subscript I (i = 1, 2, 3, . . .) represents 281 different prefecture-level cities, t represents the time year, x_{it} represents the indicator input quantity of the i-th city in the t-th year, β is the parameter to be estimated, v_{it} represents the inefficiency random error term of the i-th city in the t-th year, and uit represents the inefficiency technological loss error term, with $v_{it} \geq 0$. v_{it} and u_{it} are mutually independent.

Where *f(•)* represents the frontier production function, and the Cobb–Douglas production function is one of its forms. In this study, we employ the stochastic frontier analysis (SFA) model, specifically the Transcendental Logarithmic Production Function Model, which is easy to estimate and has strong inclusiveness. The model uses a logarithmic form of a linear equation for estimation, which facilitates the investigation of the input elasticity of different factors and the elasticity of substitution between factors. This approach allows for a better understanding of the interdependence among inputs in the production function.

The current study is based on the Cobb–Douglas production function and incorporates the introduction of digital factors using this model. In order to investigate the effects of digital, capital, and labor on economic growth, as well as the potential positive interactions between these three factors in promoting output and whether they are influenced by time, the model includes respective squared terms, interaction terms between them, and a time trend term (t). The specific functional expression is as follows:

$$\begin{aligned} \ln gdp_{it} &= \beta_0 + \beta_1 \ln D_{it} + \beta_2 \ln L_{it} + \beta_3 \ln K_{it} + \beta_4 t \\ &+ \tfrac{1}{2}\beta_5 t^2 + \tfrac{1}{2}\beta_6 (\ln D_{it})^2 + \tfrac{1}{2}\beta_7 (\ln L_{it})^2 + \tfrac{1}{2}\beta_8 (\ln K_{it})^2 \\ &+ \beta_9 \ln D_{it} \ln L_{it} + \beta_{10} \ln D_{it} \ln K_{it} + \beta_{11} \ln K_{it} \ln L_{it} + \beta_{12} \ln D_{it} t + \beta_{13} \ln L_{it} t + \beta_{14} \ln K_{it} t \\ &+ (v_{it} - u_{it}) \end{aligned} \tag{2}$$

Among them, gdp_{it}, D_{it}, L_{it}, and K_{it} represent output, digital, labor, and capital factors, respectively. The inefficiency term, u_{it}, is defined as follows:

$$u_{it} = u_i e^{-\eta(t-T)} \tag{3}$$

$$\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2} \tag{4}$$

When η is an estimated parameter, if $\eta < 0$, the technical inefficiency term $e^{-\eta(t - T)}$ increases at an increasing rate, indicating that the technical efficiency decreases at an increasing rate. On the other hand, if $\eta > 0$, the technical inefficiency term $e^{-\eta(t - T)}$ decreases at a decreasing rate, indicating that the technical efficiency increases at a decreasing rate. γ represents the proportion of the inefficiency term in the random disturbance term. If γ is close to 1, it suggests that the model error primarily comes from the inefficiency term u_{it}.

3.2. Calculation of Elasticity

Based on the aforementioned transcendental logarithmic production function formula, the partial derivatives of the digitalization, labor, and capital inputs can be calculated to obtain their respective input elasticities, which indicate the percentage change in output resulting from a one percent change in the respective input, holding all other factors constant. That is, the elasticities reflect the responsiveness of output to changes in each type of input within the production process [57].

The input elasticity of digitalization is:

$$\delta_{D_{it}} = \frac{d \ln y}{d \ln D} = \beta_1 + \beta_6 \ln D_{it} + \beta_9 \ln L_{it} + \beta_{10} \ln K_{it} + \beta_{12} t \tag{5}$$

The input elasticity of labor is:

$$\delta_{L_{it}} = \frac{d \ln y}{d \ln L} = \beta_2 + \beta_7 \ln L_{it} + \beta_9 \ln D_{it} + \beta_{11} \ln K_{it} + \beta_{13} t \tag{6}$$

The input elasticity of capital is:

$$\delta_{K_{it}} = \frac{d \ln y}{d \ln K} = \beta_3 + \beta_8 \ln K_{it} + \beta_{10} \ln D_{it} + \beta_{11} \ln L_{it} + \beta_{14} t \tag{7}$$

These input elasticities are calculated as point elasticities for each year in the prefecture-level cities, and they vary with time, deviating from the fixed input elasticities in the Cobb–Douglas production function, which is more in line with the actual situation. Based on these input elasticities, the elasticities of substitution between the pairs of inputs can be calculated to reflect the substitution relationships between the different factors, which measure the degree to which one production factor can replace another under the condition of constant cost or other technical conditions without affecting the total output. When the elasticity of substitution is greater than 0, it indicates that the two factors are substitutable. When it is less than 0, it indicates that the factors are complementary.

The elasticity of substitution between digital and labor inputs is:

$$\xi_{DL_{it}} = \left[1 + \frac{(\delta_{D_{it}} / \delta_{L_{it}})\beta_7 - \beta_9}{\delta_{L_{it}} - \delta_{D_{it}}}\right]^{-1} \tag{8}$$

The elasticity of substitution between digital and output inputs is:

$$\xi_{DK_{it}} = \left[1 + \frac{(\delta_{D_{it}} / \delta_{K_{it}})\beta_8 - \beta_{10}}{\delta_{K_{it}} - \delta_{D_{it}}}\right]^{-1} \tag{9}$$

The elasticity of substitution between labor and output inputs is:

$$\xi_{KL_{it}} = \left[1 + \frac{(\delta_{K_{it}} / \delta_{L_{it}})\beta_7 - \beta_{11}}{\delta_{L_{it}} - \delta_{K_{it}}}\right]^{-1} \tag{10}$$

3.3. Decomposition of TFP Change (TFPC)

In this study, we adopt the method proposed by Kumbhakar et al. (2000) to calculate the growth rate of total factor productivity (TFP) and its decomposition efficiency [58]. Based on the parameter estimation of the stochastic frontier transcendental logarithmic production function model, the growth rate of TFP is decomposed as follows:

$$TFPC_{it} = TEC_{it} + TC_{it} + SEC_{it} \tag{11}$$

where $TFPC_{it}$ represents the growth rate of total factor productivity, TEC_{it} represents the technological efficiency change, TC_{it} represents the technological change, and SEC_{it} represents the scale efficiency change. Since we are calculating growth rates, the final calculated data does not include the data for the first year, 2011.

(1) Technological Efficiency Change (*TEC*)

Based on the production function used in this study, the technological efficiency is obtained as follows:

$$TE_{it} = e^{-u_{it}} \tag{12}$$

The technological efficiency change (*TEC*) is calculated as follows:

$$TEC_{it} = \frac{TE_{it} - TE_{it-1}}{TE_{it-1}} \tag{13}$$

TEC represents the change in the gap between the actual output and the maximum possible output at a given level of technology and factor inputs.

(2) Technological Change (*TC*)

Technological change is mainly related to time and represents the efficiency change caused by time. It can be viewed as the partial derivative of the function with respect to time. The specific formula is as follows:

$$TC = \delta_t = \frac{d \ln y}{dt} = \beta_4 + \beta_5 t + \beta_{12} \ln D_{it} + \beta_{13} \ln L_{it} + \beta_{14} \ln K_{it} \tag{14}$$

TC refers to the change rate of output over time when the input factors are fixed; that is, the output growth brought about by technological progress.

(3) scale efficiency change (SEC)

$$SEC_{it} = (\delta_{D_{it}} + \delta_{L_{it}} + \delta_{K_{it}} - 1)(\lambda_{D_{it}} x_{D_{it}} + \lambda_{L_{it}} x_{L_{it}} + \lambda_{K_{it}} x_{K_{it}}) \tag{15}$$

$$\lambda_j = \frac{\delta_j}{\delta_{D_{it}} + \delta_{L_{it}} + \delta_{K_{it}}} \tag{16}$$

where δ_{Dit} + δ_{Lit} + δ_{Kit} represents the sum of the input elasticities of each input factor, indicating the scale economy effect. Δ_j represents the elasticity of factor *j*, and λ_j represents the proportion of the input elasticity of factor *j* on the production frontier to the overall scale elasticity of returns. x_{Dit}, x_{Lit}, and x_{Kit} represent the input growth rates of the digital, labor, and capital factors, respectively. *SEC* refers to the productivity changes caused by economies of scale or diseconomies of scale.

4. Data Source and Variable Selection

4.1. Data Source

The output data used in this study is the regional gross domestic product (GDP) of 281 prefecture-level cities, measured in billions of yuan. The input variables include labor force and capital stock from 2011 to 2019. The input and output indicators data are obtained in China's City Statistical Yearbooks from 2012 to 2020, and the relevant yearbooks for Chinese provinces. The digitalization index is derived from the Digitalization Research Center of Peking University, covering the years 2011 to 2019.

4.2. Variable Selection

The output variable used in this study is the regional gross domestic product (GDP), measured in billions of yuan. Intuitively, the idea of incorporating data into the production function is to treat the total amount of data as a factor in production. However, this implies that the amount of data measured in GB or MB is an input, overlooking the fact that most data results from production activities rather than serving as an input to them. Therefore, identifying the data that enters the production system is crucial and aligns more closely with the concepts of digitalization or the digital economy. Numerous studies have discussed the positive effects of digitalization and the digital economy on improving economic efficiency. This suggests that the level of digitalization or the advancement of the digital economy is an input-driven factor that needs to be considered in the production system or in the production function. Therefore, the digital factor is represented by the digitalization index, which is constructed based on the breadth of coverage, depth of usage, and digital support services of digitalization [43–45]. The specific indicators of the digitalization index are shown in Table 1:

Table 1. Digitalization index system.

Primary Dimension	Secondary Dimension	Specific Indicators
Breadth of coverage	Account coverage	Number of Alipay accounts per 10,000 people Percentage of Alipay-tied card users Average number of bank cards tied to each Alipay account
Depth of use	Payment business	Number of payments per capita Amount paid per capita The number of active users with a high amount (50 or more annual activities) as a percentage of annual activities 1 or more times
	Credit business to individual users	Number of Internet consumer loans per 10,000 adult Alipay users Number of loans per capita Loan amount per capita
	Credit business for micro and small operators	Number of Internet micro and small business loans per million adult Alipay users Average number of loans per household for micro and small operators Average loan amount for small and micro operators
	Insurance business	Number of insured users per 10,000 Alipay users Number of insurance strokes per capita Amount of insurance per capita
	Investment business	Number of Alipay users per 10,000 people involved in Internet investment and wealth management Number of investments per capita Investment amount per capita
	Credit business	Number of people using credit-based lifestyle services (including finance, accommodation, travel, social, etc.) per 10,000 Alipay users Number of calls per capita for natural person credit
Degree of digital support services	Convenience	Percentage of mobile payment transactions Percentage of mobile payment amount
	Financial services costs	Average loan interest rate for small and micro operators Average personal loan interest rate

For the above-mentioned comprehensive system containing 33 indexes, we refer to Li (2022) [42], and adopt the efficacy function to realize dimensionless. Further, for the weights, we refer to the weights given by the Digitalization Research Center of Peking University, Li (2022), and Li et al. (2020) [42,43]. Their weight selection combines subjective evaluation (expert scoring) and objective evaluation (data mining), which has been recognized by other studies. Finally, the digital index is obtained by the weighted summation of dimensionless indexes.

The input of the labor force is represented by the number of employed people at the end of the year, measured in ten thousand individuals. The capital input is measured by the fixed capital stock, following the calculation method of inter-provincial material capital stock in Zhang's (2008) perpetual inventory method [59]. The capital stock for prefecture-level cities is calculated using the following formula:

$$K_{it} = K_{it-1}(1 - v_{it}) + I_{it} \tag{17}$$

where V_{it} represents the capital depreciation rate for city I in year t, which is derived from the economic depreciation rate of the total fixed capital formation calculated by Zhang

(2008) at 9.6% [59]. I_{it} represents capital investment, measured in billions of yuan, using the actual total fixed capital formation.

4.3. Descriptive Statistics of the Data

4.3.1. Descriptive Statistics of Input-Output Variables

Descriptive statistical analysis was conducted on the input-output variables of 281 cities from 2011 to 2019. The results are presented in Table 2.

Table 2. Descriptive statistics of input-output variables.

	Mean	**Std.Dev**	**Min**	**Max**
GDP	2414.766	3502.174	34.953	38,156.010
D	165.261	65.429	17.020	321.646
L	60.104	90.076	5.691	986.872
K	6092.681	6867.597	289.685	72,423.381
$\ln gdp$	7.280	0.972	3.554	10.549
$\ln D$	5.003	0.513	2.834	5.774
$\ln L$	3.647	0.849	1.739	6.895
$\ln K$	8.301	0.887	5.669	11.190

In Table 2, it can be observed that there are significant differences in output and the input of digital, capital, and labor factors among the various prefecture-level cities, which is consistent with the current uneven regional development situation in China. The natural logarithm of input-output factors was used to reduce the impact of large numerical differences among different factors and to ensure that their standard errors fall within the range of 0–1.

The correlation coefficients between the various factors and between the factors and output are obtained in Table 3, as shown in the following table. It can be seen that there is a significant positive correlation between the input factors and output, as well as significant positive correlations among the different factors. Moreover, the correlations between $\ln D$, $\ln L$, and $\ln K$ are all below 0.4, which indicates that there is no significant collinearity between variables.

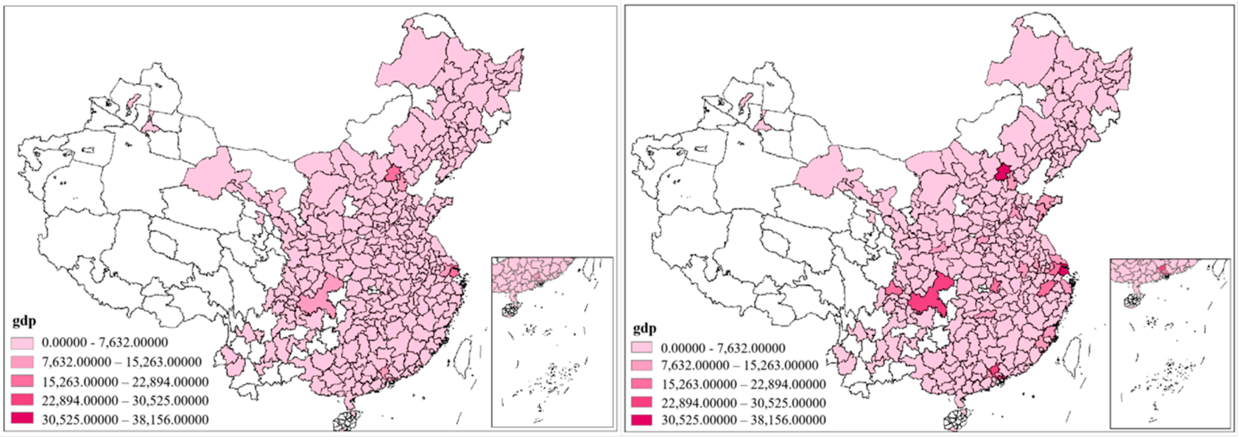
Table 3. Correlation coefficients between variables.

	$\ln gdp$	$\ln D$	$\ln L$	$\ln K$
$\ln gdp$	1			
$\ln d$	0.548	1		
$\ln l$	0.872	0.209	1	
$\ln k$	0.793	0.389	0.266	1

4.3.2. Comparison of Input-Output Elements between 2011 and 2019

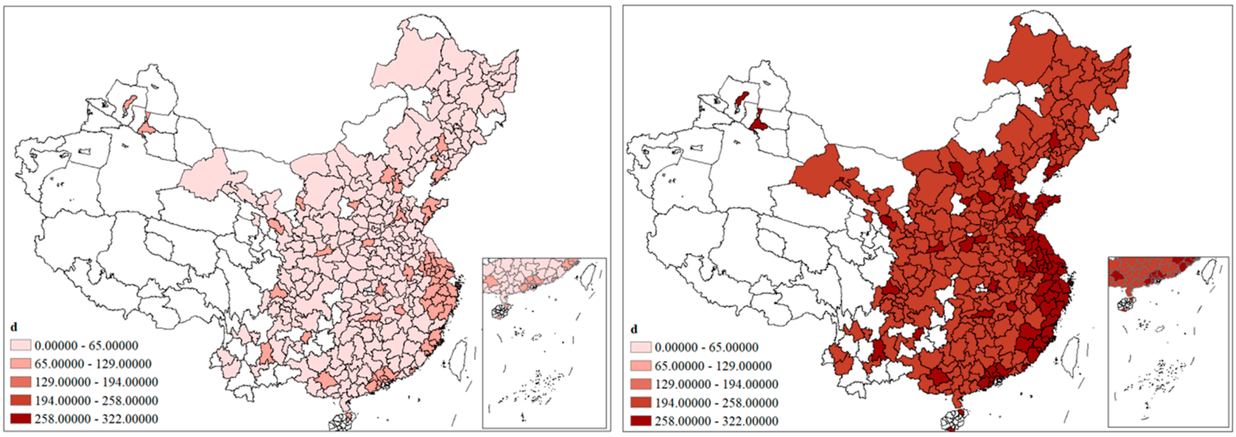
Using ArcGIS 10.8 software, spatial distributions of input-output elements were created to illustrate the regional differences between 2011 and 2019 (as shown in Figures 1–4).

From the above graphs, it can be observed that there are significant regional differences in both output and input variables between 2011 and 2019, indicating the persistent issue of regional development imbalance. The regional disparities between 2011 and 2019 remain relatively stable. In particular, as shown in Figure 2, it is evident that the digital economy was mainly concentrated in coastal areas and provincial capital cities in the central and western regions in 2011. However, by 2019, there had been a significant improvement in the digitalization index for all 281 prefecture-level cities, resulting in a reduction in regional disparities. In terms of the labor force, there was not much variation among regions in 2011. However, by 2019, there was a significant increase in labor force input in the southeastern and central regions compared to other areas. This can be attributed to the influx of a large number of laborers to economically developed regions such as the Beijing-Tianjin-Hebei region and the Yangtze River Delta, which provide substantial labor input.



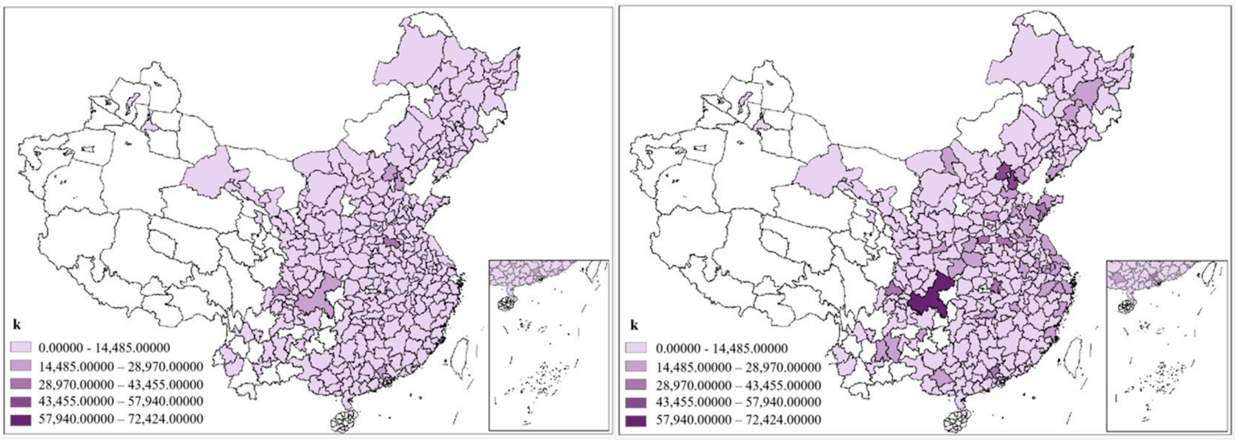
(**a**) 2011 (**b**) 2019

Figure 1. GDP of cities.



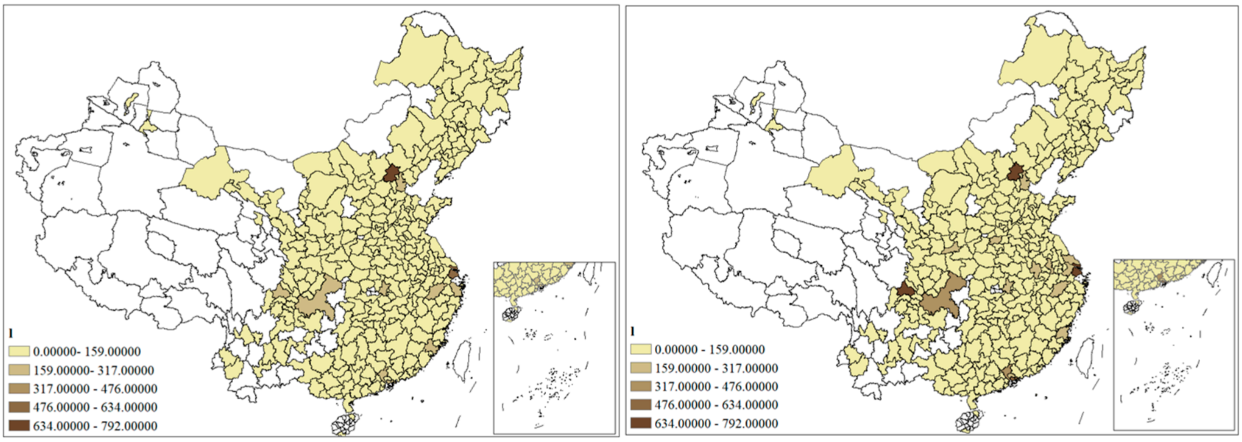
(**a**) 2011 (**b**) 2019

Figure 2. Digitalization (*D*) of cities.



(**a**) 2011 (**b**) 2019

Figure 3. Capital stock (*K*) of cities.



(**a**) 2011 (**b**) 2019

Figure 4. Labor (*L*) of cities.

On the whole, the spatial distribution of labor force and GDP is partially similar, while other indicators are spatially differentiated, which indicates that the driving mechanism of various production factors for GDP is complex and probably non-independent. Therefore, it is necessary to integrate all the elements through the SFA method to measure TFP. This also reflects the advantages of SFA, which describes the complementary or substitution relationship between elements by transcending logarithmic functions [60].

5. Estimation of Parameters and Elasticity

5.1. Results of the SFA

The specification of the stochastic frontier production function is crucial for the specific analysis. Therefore, it is essential to correctly specify the production function based on the data. In this study, different models were used to test the parameters of the stochastic frontier production function. The final, suitable production function model was selected for subsequent estimation and analysis. The specific parameter estimation results are presented in Table 4:

Table 4. Model estimation results.

	(1)	**(2)**	**(3)**	**(4)**
ln*D*	−1.382 * (0.661)		4.847 *** (0.450)	3.041 *** (0.491)
ln*L*	0.602 (0.371)	0.470 (0.259)	-0.791 * (0.376)	0.065 (0.214)
ln*K*	0.876 * (0.442)	0.687 (0.364)	1.399 ** (0.458)	0.500 (0.265)
t	2.161 *** (0.227)	−0.191 *** (0.055)	0.0875 (0.165)	
t^2	0.122 *** (0.010)	0.029 *** (0.003)		0.0371 *** (0.006)
$\ln D^2$	0.273 ** (0.090)		−0.540 *** (0.064)	−0.389 *** (0.066)
$\ln L^2$	−0.031 (0.028)	−0.018 (0.025)	−0.055 (0.029)	−0.021 (0.023)
$\ln K^2$	−0.019 (0.031)	−0.017 (0.031)	−0.0204 (0.033)	0.007 (0.027)
ln*D**ln*L*	−0.081 (0.138)		0.537 *** (0.135)	0.280 *** (0.073)

Table 4. *Cont.*

	(1)	(2)	(3)	(4)
$\ln D^*\ln K$	−0.075 (0.129)		−0.420 ** (0.132)	−0.045 (0.080)
$\ln K^*\ln L$	0.061 (0.097)	0.044 (0.094)	0.152 (0.104)	−0.007 (0.083)
$\ln D^*t$	−0.544 *** (0.049)		−0.0271	
$\ln L^*t$	0.027 (0.014)	0.014 (0.007)	−0.042 ** (0.013)	
$\ln K^*t$	0.0221 (0.014)	−0.004 (0.009)	0.051 *** (0.015)	
_cons	2.992 (1.861)	2.598 (11.341)	−7.668 *** (1.693)	1.418 (3.926)
μ	2.446 *** (0.458)	1.589 (11.566)	2.008 *** (0.352)	6.809 (3.571)
η	−0.060 *** (0.008)	−0.003 (0.010)	−0.027 *** (0.007)	−0.024 ** (0.009)
σ^2	0.320 *** (0.034)	0.187 ** (0.010)	0.258 * (0.226)	0.209 ** (0.012)
γ	0.700 *** (0.035)	0.396 * (0.034)	0.596 ** (0.039)	0.486 ** (0.039)
$\sigma^2{}_u$	0.224 *** (0.035)	0.074 *** (0.010)	0.154 ** (0.023)	0.101 ** (0.015)
$\sigma^2{}_v$	0.096 *** (0.003)	0.113 *** (0.003)	0.104 *** (0.003)	0.107 *** (0.003)
Breusch–Pagan/Cook–Weisberg test for heteroskedasticity				
chi2	0.371	4.120	0.611	6.852
Prob > chi2	0.541	0.042	0.436	0.009

Notes: Whit's robust standard errors are in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

In Table 4, column 1 presents the regression results of the transcendental logarithmic production function including the time trend terms t and t^2, column 2 omits the digitalization variable, and columns 3 and 4, in comparison to column 1, exclude the time trend terms t and t^2, respectively. This regression strategy benefits from allowing comparisons between the results in columns 2–4 and column 1, which facilitate the assessment of which model configuration yields the optimal fit for the transcendental logarithmic function through the size of the signal-to-noise ratio. Furthermore, by comparing the coefficients of the remaining variables after excluding certain variables, we can observe if there is significant multicollinearity, that is, interference between variables, thereby evaluating the robustness of the model.

The comparison reveals that the regression results of column 1, including digitalization, time trends t and t^2 possess the highest signal-to-noise ratio γ, surpassing 0.7 (a signal-to-noise ratio closer to 1 indicates a better model fit [56]). Additionally, the inefficiency standard deviation σ^2 is significant across all results, indicating clear variations in technical efficiency among the samples, which highlights the applicability of the stochastic frontier analysis method. Lastly, the results of the heteroscedasticity tests indicate that models with all four parameter settings do not exhibit significant heteroscedasticity. Nevertheless, to ensure the reliability of the coefficients and their significance levels, we continue to use Whit's robust standard errors.

In column 1, the coefficients pertaining to digitalization suggest a U-shaped relationship with economic growth. The negative linear term $\ln D$ indicates an initial decline in productivity with increased digitalization, while the positive squared term $\ln D^2$ points to a subsequent rebound. This U-shaped curve is consistent with the study of Xiang et al. (2022) [61]. This is also consistent with many studies on science and technology investment and economic growth [62], which aligns with the industry life cycle theory, where new technological adoptions or industry disruptions often lead to initial inefficiencies or challenges, represented by the downturn. As industries mature, adapt, and optimize the new technologies, there is a phase of recovery and growth, leading to the upward curve of the. In this context, the early stages of digital integration might have brought about challenges such as the need for skill upgrades, infrastructure revamps, and alignment with existing processes. However, as firms navigate these challenges, learn from their experiences, and fully harness the potential of digital tools, the benefits start to materialize, reflected in the eventual upturn in productivity. Therefore, further analysis will be conducted on the elasticity of factors to output, the elasticity of substitution between factors, total factor productivity, and its decomposition.

5.2. Elasticity of Factors

Based on the final results obtained, Table 5 presents a systematic evolution of the elasticity coefficients for digitalization, labor, and capital in terms of output and the substitution interplay between digitalization and other factors over the period 2011–2019.

Table 5. Input elasticity and elasticity of substitution.

Year	Input Elasticity			Elasticity of Substitution		
	Digitalization	Labor	Capital	Digitalization and Labor	Digitalization and Capital	Labor and Capital
2011	0.4301	0.5678	0.4104	0.1399	1.2987	0.1779
2012	0.5646	0.5454	0.4518	−0.4762	1.6381	0.0299
2013	0.6290	0.5722	0.4342	−2.4564	0.9826	0.1546
2014	0.6522	0.5882	0.4234	0.8302	1.0550	0.1922
2015	0.6887	0.5995	0.4199	−1.1001	1.2114	0.2099
2016	0.7128	0.6151	0.4120	−0.6615	1.0561	0.2552
2017	0.7334	0.6385	0.3983	3.0075	0.5801	0.3065
2018	0.7342	0.6700	0.3755	−0.0552	1.1150	0.3846
2019	0.7322	0.7095	0.3451	−0.9825	1.2260	0.4675
mean	0.6530	0.6118	0.4079	−0.1949	1.1292	0.2420

Over the span from 2011 to 2019, the input elasticity of digitalization, labor, and capital has generally shown an upward trend, indicating that all three inputs are increasingly effective in contributing to economic output. Specifically, digitalization's elasticity increased from 0.4301 to 0.7322, labor's from 0.5678 to 0.7095, and capital's from 0.4104 to 0.3451. This trend can be attributed to technological advancements that enhance the productivity of digital technologies and improvements in workforce skills and capital equipment efficiency. The growing integration of digital tools has likely made labor and capital not only more productive individually but has also enhanced their interdependencies and collective output potential.

The elasticity of substitution between digitalization and labor exhibits clear periodicity, alternating between positive and negative values, which aligns with practical observations. Digitalization development itself relies on substantial human capital investment and simultaneously creates numerous new job positions, leading to a negative substitution elasticity. However, once digital technologies are established, their integration into production tends to replace some labor, especially in the industrial sector. The phenomenon in China is particularly interesting; for example, after the central government launched the "Internet Plu" action plan in 2015, digital technology development accelerated, creating many related jobs and showing a complementary relationship with labor. By 2017, various e-commerce platforms, industrial digital platforms, and other artificial intelligence technologies were extensively integrated into the real economy, resulting in significant labor substitution (with coefficients reaching 3.0075). According to this pattern, complementarity and substitution between labor and digitalization will continue, but the complementary relationship may weaken as the scale of technical staff reaches its limit, whereas the substitution relationship may strengthen.

The substitution relationship between digitalization and capital shows a growing trend. Over the past period, China has invested heavily in capital to build the infrastructure necessary for the internet and other digital platforms, resulting in a weak substitution relationship between the two. However, as these infrastructures are completed and gradually put into operation, the vitality of digital technologies has increased, replacing a large amount of industrial production capital and even leading to "stranded asset" phenomena. Nonetheless, compared to labor, digitalization still depends somewhat on capital; therefore, overall, the substitution elasticity between the two is not high (average only 0.2420), and the positive elasticity is more likely due to China's industrially oriented economic structure.

In summary, the data underscores the growing prominence of digitalization in influencing output and its interplay with traditional factors like labor and capital. The consistently rising input elasticity for digitalization accentuates its pivotal role in the production process. Concurrently, the evolving elasticities of substitution highlight the shifting dynamics and adaptations in integrating digital processes within the traditional production framework.

6. Decomposition of TFPC and Comparative Analysis

6.1. TFPC and Decomposition

Based on the fitting of the random frontier transcendental logarithmic production function model and the calculation of input elasticity mentioned above, the mean value of TFP change (TFPC) is calculated annually. The average values are provided in Table 6.

Table 6. TFPC and decomposition.

Year	*TFPC*	*TEC*	*TC*	*SEC*
2011	-	-	-	-
2012	−0.0993	−0.1112	−0.0258	0.0377
2013	−0.2981	−0.2603	−0.0709	0.0331
2014	0.0799	0.1333	−0.0641	0.0107
2015	−0.1388	−0.0889	−0.0636	0.0137
2016	−0.1013	−0.0398	−0.0703	0.0088
2017	−3.1595	−3.0825	−0.0858	0.0088
2018	0.5074	0.5972	−0.0918	0.0020
2019	−0.4120	−0.2816	−0.1337	0.0033
mean	−0.4527	−0.3917	−0.0757	0.0148

Table 6 offers a comprehensive account of the total factor productivity change (TFPC) and its constituent elements spanning from 2011 to 2019. The following observations and interpretations can be drawn: The TFPC values, representing the amalgamated effect of technological efficiency, technological change, and scale efficiency, predominantly exhibit a negative trend. Averaging across the years, the mean TFPC stands at −0.4092, signifying a general decline in productivity over the observed period. Noteworthy is the sharp decline in 2017, with a value of −3.1136, marking the most significant dip in productivity. The TEC values fluctuate over the years but lean towards the negative, with an average of −0.3917. This suggests that the efficiency of utilizing available technologies has, on average, been declining. The year 2017 again stands out with a pronounced decrease of −3.0825. TC values, which highlight shifts in frontier technology, are consistently negative across the years, averaging at −0.0347. This indicates that frontier technology might not have progressed favorably over the period, possibly suggesting that innovations in the sector may not have been adequately transformative. Although the SEC (scale efficiency change) is positive, its mean value is only 0.0172, indicating that its contribution to the total factor productivity change (TFPC) is minimal.

In summation, the data underscores a pressing need for interventions aimed at bolstering technological efficiency, fostering impactful innovations, and refining scaling strategies. According to the TFPC studied previously, the change in TFP in China is attributed to generalized technological progress. After considering digitalization, the negative TFPC reflects the important role of digitalization in TFP growth in China. That is to say, besides the role of digitalization, other remaining technological innovations may not have a significant positive effect on TFP in China. This further highlights the leading role of digitalization in China's economic growth.

6.2. Comparison with TFPC without Digitalization

In order to further clarify the role of digitalization in economic growth, TFPC with digitalization (the new TFPC) and TFPC without digitalization are thought to be compared. Going back to our methodology, a series of previous equations (Equations (1)–(11)) have included digitalization as a production factor in the production function. In order to calculate TFPC without digitization, the variable D (or ln$D$) in Equations (1)–(11) is eliminated, and then TFPC with only labor (L) and capital (K) is calculated. Since the difference between the two TFPCs is only whether digitalization is included, the detailed equation need not be repeated. The results are shown in Figure 5.

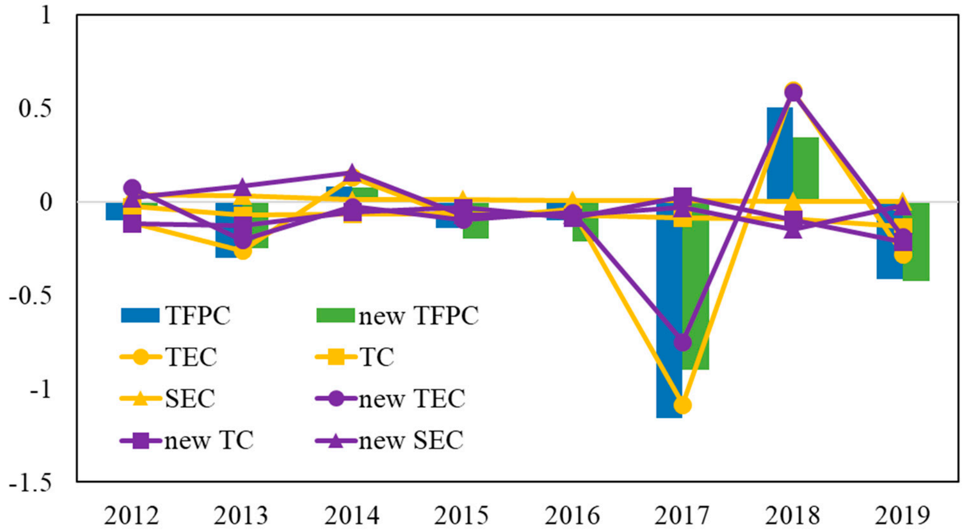


Figure 5. Comparison of TFPC with and without digitization.

Figure 5 distinctly juxtaposes the trajectories of TFPC values, distinguishing between scenarios with and without the incorporation of digital elements. The TFPC curve associated with digitalization is discernibly subdued in comparison to its non-digitalized counterpart for a majority of the observed years, which is consistent with research results on TFPC in China of Xia and Fu (2020), Chen et al. (2022), Ren et al. (2023), and others [63–65]. Furthermore, the digitalized curve even delves into negative terrain, indicating potential declines in productivity.

When accounting for digitalization, there is a discernible accentuation in the declining trend of TFPC. This pronounced decline, post-consideration of digitalization, can be attributed to the now-recognized role of digitalization in economic growth. Essentially, by factoring in digitalization, we are isolating its effects on productivity. As a result, the residual TFPC (after considering digitalization) exhibits a more pronounced decline or, in certain contexts, a smaller value compared to when digitalization is not taken into account. This nuanced perspective suggests that as we account for the transformative effects of digitalization on productivity, the remaining factors influencing TFPC become more apparent. It underscores the transformative impact of digitalization and emphasizes the importance of understanding its intricacies to get a clearer picture of the overall productivity dynamics.

Incorporating digitalization reveals pronounced negative shifts in TEC values, especially in 2017. This suggests that, as we factor in the efficiency contributions of digitalization, traditional technological paradigms might seem less efficient in comparison. This could be indicative of a transitional phase where industries and firms grapple with the integration of digital tools and technologies, leading to temporary efficiency lags. When considering digitalization, technological change appears to be less progressive. The predominantly negative values, especially in the 'new T', emphasize that as we recognize the advancements brought about by digitalization, traditional technological innovations might appear less impactful. Factoring in digitalization brings about significant variations in scale efficiency. The sharp negative dip in the new SEC in 2015 is particularly telling. This might point towards challenges in scaling operations in the face of rapid digital transformations, possibly due to the need for new infrastructure, skill sets, or organizational changes.

In essence, while the transformative potential of digitalization remains undisputed, the graph underscores the importance of a calibrated and informed approach to its adoption. The challenges highlighted by the TFPC trends emphasize the need for strategic planning, continuous learning, and iterative adaptation in the journey of digital integration.

7. Conclusions and Implications

This research has embarked on an intricate exploration into the nexus between digitalization and the TFP, with a focal lens on China's dynamic landscape. Utilizing robust stochastic frontier analysis (SFA), we have unraveled several salient insights. The main conclusions are as follows:

1. The study identified a U-shaped trajectory in the impact of digitalization on economic growth. Initially, the integration of digital technologies might lead to productivity setbacks due to adaptation challenges and investment costs. However, over time, as firms adjust and synergies begin to materialize, digitalization significantly enhances productivity, resulting in long-term economic benefits. This U-shaped impact underscores the transformative role of digitalization in reshaping economic outputs.
2. This analysis reveals the complex interplay of substitution and complementarity among digitalization, labor, and capital within the production function. Digitalization not only substitutes for labor and capital in certain cases but also exhibits dependency on both. These relationships underscore that digitalization is no longer just an adjunct to traditional production factors; rather, it highlights its role as a production factor in its own right, dynamically interacting with other factors in both complementary and substitutive manners.
3. By recalculating total factor productivity (TFP) to include digitalization, the study demonstrated that TFP assessments that fail to consider digital inputs underestimate economic outputs. The comparison between TFP calculations with and without digitalization inputs revealed that ignoring digital inputs could lead to a significant underestimation of productivity levels and potential economic growth.

The above conclusions have the following implications:

1. Policymakers and business leaders should anticipate initial productivity dips following digital investments. Supportive measures, such as training programs for workforce adaptation and phased implementation strategies, can mitigate these early stage challenges. Recognizing the long-term benefits, continued investments in digital infrastructure and technologies are crucial, even if immediate gains appear modest.
2. The dual substitutive and complementary roles of digitalization necessitate a balanced approach in policy and business strategy formulation. Firms should leverage digital technologies to optimize labor and capital use, potentially reducing costs and enhancing output quality. Economic policies should facilitate this integration by supporting digital skills development and encouraging R&D in digital technologies.
3. Economic analysts and policymakers should include digital inputs in productivity analyses to avoid underestimations of economic potential. The significant difference in TFP with and without digital inputs underscores the need for modernizing existing economic models to reflect the reality of digital impacts. This includes revising economic indicators and growth forecasts to integrate digitalization's effects accurately.

While this study offers valuable insights into the relationship between digitalization and TFP/TFPC in China, it also presents avenues for further exploration. A potential limitation arises from the macro-level data employed, which may introduce aggregation bias; future research could delve into micro-level, firm-specific data to tease out more nuanced effects. The generalized metric for digitalization used in this research emphasizes the tangible capital associated with digitization as a production factor. Additionally, the measurement of intangible capital, especially with the advancement of technologies like AI, also needs to be refined to accurately reflect the evolving nature of digital assets. Extending the temporal scope or focusing on periods of rapid technological shifts might provide a richer context, while integrating external factors such as global trade dynamics or international technological spillovers can offer a more holistic understanding. Therefore, a significant future research direction is how to measure the level of digitization from the perspective of production factors appropriately, possibly by focusing more specifically on technologies like AI, blockchain, or cloud computing. Complementing the quantitative findings with qualitative insights from industry stakeholders could bridge interpretative gaps and present a more comprehensive narrative of the digital transformation journey in the service sector. This approach will enhance the robustness of digitalization metrics and deepen insights into its economic impacts, highlighting areas for policy intervention to maximize the benefits of technological advancements.

Author Contributions: Conceptualization, P.L., J.L. and X.L.; methodology, P.L., J.L., X.L., Y.X. and Z.W.; software, J.L. and X.L.; validation, P.L., Y.X. and Z.W.; formal analysis, P.L., J.L., X.L. and Z.W.; investigation, P.L., J.L. and Y.X.; data curation, X.L. and Y.X.; writing—original draft preparation, P.L., J.L., X.L. and Y.X.; writing—review and editing, P.L., J.L., X.L. and Z.W.; visualization, Y.X.; supervision, P.L. and X.L.; project administration, P.L. and Z.W.; funding acquisition, P.L., X.L. and Z.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Technology development research project of China National Administration of Coal Geology, grant number ZMKJ-2023-JBGS06 and China Scholarship Council, grant number 202306410135.

Data Availability Statement: All the original data in this paper are publicly available. China's City Statistical Yearbooks and China's Provincial Statistical Yearbooks can be obtained on EPS Database, https://www.epsnet.com.cn/index.html (accessed on 28 March 2024). The digital financial index is derived from the Digital Finance Research Center of Peking University, covering the years 2011 to 2019, https://en.idf.pku.edu.cn/achievements/seriesofdigitafinanceindexes/index.htm (accessed on 5 March 2024).

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

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