land

Article

The Financial Density and Improvement of Urban Technological Efficiency: An Estimation Based on the Stochastic Frontier Approach

Jing Guo [1], Ying Wang [2], Haidong Xu [3], Bo Li [4] and Yang Wang [5,*]

1 School of Government, Shenzhen University, Shenzhen 518060, China; derek.jguo@szu.edu.cn
2 Stevens Institute of Technology, Hoboken, NJ 07030, USA
3 National Academy of Economic Strategy, Chinese Academy of Social Sciences, Beijing 100732, China
4 School of Management, Tianjin University of Technology, Tianjin 300384, China
5 School of Management, Shenzhen University, Shenzhen 518060, China
* Correspondence: wangyang@szu.edu.cn

Abstract: Exploring the relationship between finance and economic growth is a key direction of financial economics. However, most of the literature starts from the aggregate perspective and uses the GDP or per capita GDP as the explained variable to study the role of finance. Such a perspective ignores the heterogeneity of financial activities with respect to geographical distribution and makes it difficult to distinguish the roles of factor input and efficiency improvement. Because of this, this article introduces a "density" perspective on new economic geography and the measurement of the efficiency of the transition of development economics into financial economics. This article uses the stochastic frontier analysis (SFA) method to measure the technical efficiency (TE) of 272 cities in China from 2005 to 2018 and then, based on "forward-looking" and "backward-looking" methods, measures the impact of financial density on urban technical efficiency. This study found that overall, before the financial crisis in 2008, the contribution of financial density to technical efficiency showed a downward trend, and in the regional and provincial dimensions, the distribution of financial density's contribution to technical efficiency was generally in line with that of backward regions, with less regularity in developed regions. In the urban dimension, the contribution rate of financial density to resource-based cities with slow technological progress or advanced cities with rich financial resources is not very prominent and may even play a negative role; however, cities that are at a medium level of development, rich in population resources, have convenient transportation, and have a certain industrial foundation can greatly promote the improvement of technical efficiency. Therefore, it may be possible to optimize the marginal contribution of urban financial density to the technical efficiency of Chinese cities by encouraging the flow of financial resources and activities from cities with small marginal effects to those with large marginal effects.

Keywords: financial density; technical efficiency; stochastic frontier; backward-looking; forward-looking; cities of the PR of China

check for updates

Citation: Guo, J.; Wang, Y.; Xu, H.; Li, B.; Wang, Y. The Financial Density and Improvement of Urban Technological Efficiency: An Estimation Based on the Stochastic Frontier Approach. *Land* **2023**, *12*, 1592. https://doi.org/10.3390/land12081592

Academic Editor: Hossein Azadi

Received: 21 July 2023
Revised: 6 August 2023
Accepted: 10 August 2023
Published: 12 August 2023

1. Introduction

As the core of the modern economy, the importance of the financial sector is self-evident. Exploring the relationship between finance and economic growth is also a key direction of financial economics. Generally speaking, the role of finance can be roughly divided into two categories. One is to promote the accumulation of capital, that is, to boost economic growth by assisting with the transformation of savings into investment; the other is to boost efficiency, that is, to optimize resources. The configuration brings about an increase in output under the same technical conditions and factor inputs. In the literature on the role of finance, most of the literature starts from the aggregate perspective and uses the GDP or per capita GDP as the explained variable to study the role of finance.

However, as this perspective ignores the heterogeneity of the geographical distribution of financial activities, it is also difficult to distinguish the roles of factor input and efficiency improvement. Among the few studies that explore the role of finance from the perspective of technical efficiency, most start at the national or provincial level [1], and few studies focus on cities. With the continuous advancement of urbanization, cities have become the most important spatial form for economic and social development. A question derived from this is how does financial density affect technical efficiency at the city level?

Because of this, this article introduces a "density" perspective on new economic geography and the measurement of the efficiency of the transition of development economics into financial economics. This article uses the stochastic frontier analysis (SFA) method to calculate the technical efficiency (TE) of 272 cities in China that are above the prefecture level from 2005 to 2018. Then based on the "forward-looking" and "backward-looking" methods, this article measures the impact of financial density on urban technical efficiency. The main contributions of this paper are as follows: (1) this article takes the city as the research subject, and the spatial scale is more subtle; (2) focusing on the relationship between financial density and urban technical efficiency fills gaps in the existing literature; and (3) in terms of the research methods and the comprehensive use of the "forward-looking" and "backward-looking" methods to measure the effect of financial density on urban technical efficiency, the robustness of the conclusion is stronger.

2. Literature Review

The issue of growth lies at the core of economic research. Classical economics considered labor and capital as the primary sources of growth, with corresponding measures mainly involving single-factor productivity, i.e., the output obtained per unit of input, such as labor productivity and capital productivity. Although such measures are straightforward and clear, they only reflect isolated and local production efficiency. For a more comprehensive measurement of social production efficiency, a comprehensive indicator needs to be constructed to measure the output efficiency of all factor inputs, i.e., the total factor productivity (TFP). Solow, R. M. (1957) [2] proposed a Hicks-neutral and constant-return-to-scale Cobb–Douglas production function in his representative paper, characterizing the total output as the result of the combined effect of capital, labor input, and the "Solow Residual" and established a growth-accounting equation that can separate the contribution of technological progress to economic growth. The "Solow Residual" can be understood as a generalized TFP.

The advantage of the Solow Residual method is its clarity and simplicity, which have led to its widespread adoption [3–6]. However, its underlying assumption of "no production inefficiency" is too stringent. To remedy this, Aigner, D. J. and Chu, S. F. (1968) [7] proposed the frontier analysis, which decomposes the source of TFP growth into the upward movement of the technological frontier, i.e., technical progress, and the closeness of the actual production face to the technological frontier, i.e., improvements in technical efficiency. The concept of technical efficiency can be traced back to Koopmans, T. C. (1951) [8]. Koopmans proposed that an input–output vector is considered technically efficient if it is technically impossible to increase any output without increasing other inputs. Building on Koopmans' research, different scholars have defined the connotation of technical efficiency. Farell, P. (1957) [9] believed that "technical efficiency refers to the ratio of the minimum cost required to produce a certain quantity of products to the actual cost, given a certain factor input ratio, with unchanged output scale and market prices". Uri, N. D. (2003) [10] suggested that "technical efficiency refers to the proportion of actual input saved relative to the optimal production frontier at the same output level". Wu, Y. and Zhang, L. (2004) [11] posited that "technical efficiency refers to the extent to which a producer's production activities approach the production frontier under the existing technology level". By integrating these scholars' views, it is not difficult to see that although there are differences in expression, the core idea of technical efficiency is the ratio of the actual economic output to the maximum possible output.

As shown in Figure 1, $f_{t+1}(x)$ and $f_t(x)$ represent the production frontier at times $t+1$ and t, i.e., the maximum possible output. Due to the influence of various controllable or uncontrollable factors, production on the production frontier is often an overly ideal situation (points D or B). Most of the time, activities occur off the production frontier (for example, points A and C). Therefore, given the level of technology, closeness to the production frontier implies an improvement in technical efficiency (movement from point A to B or from point C to D). Empirical research has found that most developing countries produce at positions off the production frontier, far from achieving possible technical efficiency [12].

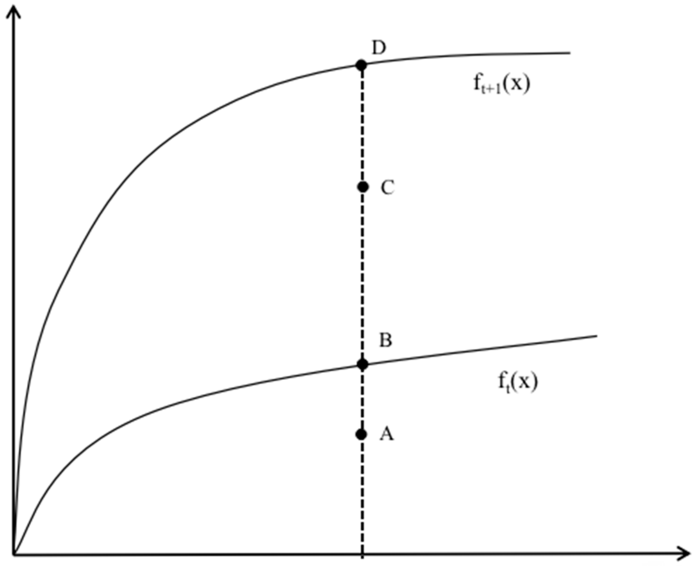

Figure 1. Representation of technical efficiency progress.

Given this, Aigner, D. et al. (1977) [13] and Meeusen, W. and Van Den Broeck, J. (1977) [14] pioneered the path of using the frontier production function method for the calculation of growth. A frontier analysis, depending on the setting of the frontier surface, can be divided into deterministic frontier and stochastic frontier methods. The deterministic frontier analysis implies that each production unit shares a fixed production frontier surface, and all factors influencing the output are included as reflections of technical inefficiency. Its advantage lies in simple calculations, but the main disadvantage is the absence of random factors, and it is thus unable to further separate inefficiency values from the error term.

A stochastic frontier analysis (SFA), on the other hand, assumes a random setting for the frontier production function. Each production unit does not need to share a frontier surface, allowing the inefficient term in the error term to be distinguished from the random error term, thus providing a more accurate calculation of the level of technical efficiency [15]. Several studies have used the SFA method for the calculation of China's economic growth [16–20]. These studies focused on the decomposition of the sources of China's economic growth efficiency and the measurement of efficiency losses and not specifically on the role of the financial sector.

In a research study performed from the financial perspective, Nourzad, F. (2002) [21] argued that financial development could promote economic growth by reducing technical inefficiency. He, F. et al. (2003) [22], based on the Cobb–Douglas production function setting, concluded that financial development had promoted the improvement of technical efficiency. Gu, N. (2010) [23], based on city panel data, analyzed and measured the channels and effects of the productive service industry on industrial spillover effects from a micro-perspective. Sheng, W. (2017) [1] used provincial panel data to study the relationship between financial development and China's technical efficiency of production, focusing on the role of the scale and structure of the credit sector on the technical efficiency of production.

Additionally, many scholars have used non-parametric methods for calculating growth, the most typical of which is the Manquist index method, which is based on a data envelopment analysis (DEA). This method began with Sten Malmquist and became widely used after being optimized by Fare, R. et al. (1994) [24], with representative studies including those by Xiaogang, C. et al. (2005), Guillaumont Jeanneney, S. et al. (2006), Bian, Y. and Yang, F. (2010), Shuai, S. and Fan, Z. (2021), and Chang, K. et al. (2023) [25–29]. The DEA method does not require the specification of the production function's form nor distribution assumption, thus avoiding potential setting errors. However, due to the lack of a production function setting, any deviation from the production boundary is measured as an inefficient component, which makes its decomposition and analytical capabilities inferior to the SFA method. Fu, X. and Wu, L. (2007) [30] compared the applicability of the DEA and SFA in the calculation of the TFP in China. They found that the DEA's estimation results are very sensitive to outliers, while the SFA's results have good robustness and are thus more suitable for China.

Upon conducting a review of the aforementioned literature, the current research reveals several shortcomings.

First, from a research perspective, most of the literature on developmental economics focuses on the decomposition of the sources of economic growth efficiency and the measurement of efficiency loss rather than the role of the financial sector. Financial economics often starts with financial development, lacking a geographical perspective in terms of density. Therefore, this paper attempts to integrate the perspectives of developmental economics on growth and economic geography on space, focusing on the impact of financial density on technological efficiency.

Second, in terms of the research subject, most previous studies were limited to the national or provincial dimensions, with a dearth of quantitative research based on the city level.

Third, in terms of research methodology, most past studies used the setting of an inefficiency function to measure the overall impact of finance on economic development, without the ability to discuss the differential effects of finance in different cities. This paper attempts to address these shortcomings in the existing literature.

3. Theoretical Analysis

Theoretically, equilibrium production in a perfectly competitive market should be on an optimal production curve. However, due to "market defects" under the neoclassical framework, such as market failures, public goods, externalities, asymmetric information, transaction costs, price rigidity, irrational behavior, etc., actual production often deviates from the optimal production curve. The progress of technical efficiency manifests as an approach to the optimal production curve. Therefore, the promotional effect of finance on technical efficiency should theoretically originate from overcoming "market defects". Referring to the analyses of financial functions by Merton, R. C. and Bodie, Z. (1995) and Allen, F and Gale, D. (2001) [31,32], this article argues that the improvement of financial density can correct "market defects" in terms of information failure and transaction costs by exerting its functions of resource allocation and information transmission.

From the perspective of information failure, information economics summarizes the issue of information failure as incomplete information [33]. In terms of manifestation, incomplete information can be divided into two types: information distortion and information asymmetry. Information distortion refers to the fact that due to human cognitive limitations and the costs of obtaining information, the information grasped by each market participant is incomplete and insufficient. Information asymmetry refers to the disparity in the information possessed by different market participants, with some having more information and some less. The problem caused by information distortion is making the premise of a complete market untenable, thus hindering the achievement of an optimal equilibrium. The main problem with information asymmetry is that it causes adverse selection and moral hazard issues. The information transmission function of finance can effectively alleviate the problem of incomplete information [34,35].

From the perspective of transaction costs, transaction costs broadly refer to the costs that need to be expended to achieve a transaction. Common forms include search costs, information costs, bargaining costs, decision-making costs, and supervision costs. Their specific forms will change with the specific transaction. The main mechanism through which financial development reduces transaction costs is by pooling scattered individual transactions and small transactions, leveraging economies of scale and scope to spread transaction inputs such as venue rent, machinery and equipment, and labor costs, thereby significantly reducing the costs of individual transactions [36].

In addition, the improvement of financial density will directly affect the technical efficiencies of cities through external economies of scale. The idea of external economies of scale originated from Marshall, A. (2009) [37]. He once pointed out that larger professional labor markets, the sharing of intermediate inputs, and knowledge spillovers are the sources of external economies of scale, as well as the reasons for agglomeration and high density. And Duranton, G and Puga, D. (2004) [38] further refined it into three micro-mechanisms of "sharing", "matching", and "learning". Subsequent studies have demonstrated that the impact of density is greatest among knowledge-based industries in which the sharing of ideas is central to the production process [39]. In reality, there is indeed a significant spatial agglomeration phenomenon in the financial industry which is specifically reflected in the widespread existence of financial center cities and financial functional areas. As the financial sector is an important economic component of a city, an increase in financial density means that the degree of agglomeration has increased. On one hand, this will lead to the improvement of the efficiency of the financial sector (through sharing, matching, and learning mechanisms), which will directly affect the improvement of the city's technical efficiency; on the other hand, it will also indirectly affect the technical efficiency of other sectors due to the improvement of the efficiency of the financial sector and the enhancement of financial function.

In general, an increase in financial density will bring externalities and promote the improvement of the technical efficiency of the local financial sector through sharing, matching, and learning mechanisms. Moreover, it will also enhance financial functions, thus optimizing issues of information failure and transaction costs, and provide support for the actual production curve to approach the production possible curve, promoting the improvement of technical efficiency.

4. Measurement of Financial Density and the Rate of Change in Urban Technical Efficiency

This section focuses on the measurement of urban financial density and changes in technical efficiency.

4.1. Setting beyond the Logarithmic Production Function

Referring to the approach of Aigner, D. et al. (1977) [13], the basic setting form for the frontier production function in this section is as follows:

$$Y_{it} = X_{it}\beta \cdot \exp(v_{it} - u_{it}) \tag{1}$$

Here, i represents the city, and t represents time; Y is the actual output level; X is the combination of production factor inputs, and β is its coefficient. The error term consists of two parts: the random error term v_{it} and the technical inefficiency term u_{it}. The two are independent of each other. v_{it} follows a standard normal distribution with a mean of 0 and a variance of σ_v^2, and u_{it} follows a truncated normal distribution with a mean of 0 and a variance of σ_u^2. By restricting the value of u_{it} to be non-negative, the mean of the technical inefficiency can be represented as a linear combination of a set of variables, as follows:

$$u_{it} = Z_{it}\delta = \delta_0 + \sum_{m=1}^{M} \delta_m z_m \tag{2}$$

where $Z = [Z_1, \cdots, Z_M]$ is a combination of M factors causing technical inefficiency. On this basis, Kumbhakar, S.C. (1991) [40] proposed using a one-stage maximum likelihood estimation method to simultaneously estimate Equations (1) and (2), a method known as the "one-step estimation method". Battese, G.E. and Coelli, T.J. (1995) [41] further extended this method to use panel data and defined technical efficiency (TE) as the ratio of the actual output to the potential maximized output. The calculation formula is as follows:

$$\text{TE} = E[\exp(-u_{it}) \mid v_{it} - u_{it}] \tag{3}$$

According to the specification, the TE value should range between 0 and 1, with values closer to 1 indicating proximity to the optimal production frontier, while values closer to 0 indicate a deviation from the optimal production frontier. Following the approach of Kumbhakar, S. C. and Wang, H-J. (2005) [42] in the specification of the production function, we transform the production function in Equation (1) into a transcendental logarithmic (trans-log) function form. The trans-log function was introduced by Christensen, L.R. et al. (1973) [43] as a flexible production function that relaxes the assumption of constant substitution elasticities among multiple inputs in the traditional C-D function. It allows for the study of output elasticities, substitution elasticities, interaction effects, and technological differences within the production function. The effectiveness of using this function was demonstrated in previous research [44]. The linearized form of the transcendental logarithmic production function can be expressed as follows:

$$\begin{aligned} \ln Y_{it} = \beta_0 + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \tfrac{1}{2}\beta_{KK}(\ln K_{it})^2 + \tfrac{1}{2}\beta_{LL}(\ln L_{it})^2 \\ +\beta_{KL}(\ln K_{it} \times \ln L_{it}) + \beta_{KT}(\ln K_{it} \times T) + \beta_{LT}(\ln L_{it} \times T) \\ +\beta_T T + \tfrac{1}{2}\beta_{TS} T^2 + (v_{it} - u_{it}) \end{aligned} \tag{4}$$

In the above, i represents the city, and t represents time, Y denotes the actual output level, and β represents the coefficient of production factors, in which L represents labor, K represents capital, and T represents the time trend variable. Considering the non-monotonic transformation of technology, the function also introduces quadratic terms. Additionally, considering the non-neutral aspect of technological progress, interaction terms between the time trend and input factors are included.

4.2. Setting the Technological Inefficiency Function

Referring to the existing literature [1,6], we select financial density, infrastructure, government expenditure, scientific research patents, and business environment as explanatory variables for the inefficiency function. Therefore, the estimation equation for technological inefficiency is as follows:

$$u_{it} = \delta_0 + \delta_1 FD_{it} + \delta_2 INFRA_{it} + \delta_3 \text{GOV}_{it} + \delta_4 \text{PAT}_{it} + \delta_5 \text{BSENV}_{it} \tag{5}$$

4.3. Data Source and Statistical Description

Firstly, we introduce the sources and processing methods of the output, labor, and fixed capital stock data used for the estimation of the production function. In terms of output, many researchers use the GDP to measure output levels [16,45]. This article continues with this approach, using the actual gross domestic product of each city at constant prices from 2005 as the measure of output level. For the calculation of labor, considering the impact of education level on the quality of labor, we refer to Han, F. and Yang, L. (2020) [46] and measure the effective labor quantity obtained by multiplying the average years of education by the actual number of employed personnel.

For data regarding the fixed capital stock, this article refers to the processing method of Zhang, Z. (2019) [45] and uses the following formula: $K_{it} = K_{i(t-1)}(1-\delta) + I_{it}$ in which K_{it} represents the fixed capital stock of a city i in the t-th year, δ is the depreciation rate, and I_{it} represents the actual newly added fixed asset investment of the city i in the t-th year. During the calculation, due to the lack of base period capital stock data, we need to estimate a base period stock. Referring to Liu, C. et al. (2017) and Yu, Y. et al. (2019) and [47,48], taking 1991 as the base year, the base year capital stock is determined as $K_0 = I_0/(g+\delta)$, in which I_0 is the base year investment amount, g is the annual average growth rate of a real investment during the sample period, and δ is the depreciation rate (which is 9.6%, referring to [49]).

In the inefficiency equation, the variables include financial density, infrastructure, government expenditure, research patents, and business environment. Financial density is represented in this study by the average scale of financial activity per square kilometer (in billions of CNY/km^2). The choice of this measure is due to the inclusion of the "density" concept, making it more appropriate for reflecting the supply of financial services. Financial activities can be divided into direct and indirect finance.

In terms of direct finance, this study, referencing existing research [50], categorizes it into equity financing and debt financing. Equity financing includes IPOs, rights issues, additional issues, and preferred shares. For debt financing, this study primarily measures the scale of funds entering the real economy, hence selecting eight types of debts: corporate bonds, company bonds, medium-term notes, short-term financing bonds, targeted tools, asset-backed securities, convertible bonds, and exchangeable bonds. The data come from the Wind database.

Indirect finance is measured using the end-of-year balances of various loans of financial institutions in the urban district, with data sourced from the *China Urban Statistical Yearbook*. After obtaining data for the scales of the direct and indirect financial activities for the year, the sum of these two gives the scale of the city's financial activity for that year. Dividing this by the area of the district gives the financial density (FD) variable.

Variables such as government expenditure, infrastructure, and research patents are calculated, respectively, as the logarithm of the current year's fiscal expenditure as a percentage of the GDP, the logarithm of the actual road area at year end, and the logarithm of the number of new patents in the city each year. The data are sourced, respectively, from the China Economic Database (CEIC), the *Urban Statistical Yearbook of China*, referring to versions published in various years, and the China Research Data Services Platform. The city business environment variable [1] is derived by collating data from the annual *China Provincial Marketization Index Report* to obtain provincial-level data, which are then assigned to cities under the province's jurisdiction and extended to the entire research period using the trend extrapolation method. Finally, this forms a panel data set covering 272 cities at the prefecture level and above, spanning from the year 2005 to 2018. A description of the data is provided in Table 1.

4.4. Estimation Results

Before estimating the model parameters, it is necessary to test the validity of the specified frontier production function model. To do this, we need to construct the test statistic $\lambda = -2[L(H_0) - L(H_1)]$, where $L(H_0)$ and $L(H_1)$ represent the log-likelihood function values under the null hypothesis and the alternative hypothesis, respectively. The alternative hypothesis H_1 corresponds to the original model. If H_0 holds, the test statistic λ follows an asymptotic χ^2 distribution with degrees of freedom equal to the number of constrained variables. The first test is to examine the presence of inefficiency. The null hypothesis, in this case, is that there is no inefficiency, which means the model can be reduced to ordinary least squares (OLSs), implying that the coefficients of all variables in the inefficiency function, as well as $\gamma = \delta_\mu^2 / \left(\delta_\mu^2 + \delta_v^2\right)$, are zero, i.e., $\gamma = \delta_0 = \delta_1 = \ldots = \delta_r = 0$. The second test aims to determine if the Cobb–Douglas production function is superior to the transcendental logarithmic production function. The null hypothesis here is that all quadratic term coefficients in the production function are zero, while the first-order terms of capital, labor, and the technological progress term T are retained. The third test investigates the existence of technological progress. The null hypothesis in this case is there is no technological progress but there exists interaction, meaning that all parameter coefficients associated with T are zero. The fourth test examines whether technological progress is Hick-neutral. The null hypothesis states that $\beta_{KT} = \beta_{LT} = 0$. The fifth test assesses if technological efficiency is a fixed effect. If technological efficiency is a fixed effect, a non-time-varying model should be selected; otherwise, a time-varying model is appropriate.

Table 1. Data sed for the measurement of city-level total factor productivity.

Variable Code	Variable Content	Data	Obs	Mean	Std	Min	Max
GDP	Output	Log of the actual GDP of the current year (in billions)	3808	6.80	0.97	3.80	10.15
lnK	Capital	Log of the fixed capital stock of the current year (in billions)	3808	7.92	1.08	1.79	11.19
lnL	Effective Labor Force	Log of the number of employees' average years of education (in tens of thousands)	3808	6.13	1.12	4.01	9.75
FD	Financial Density	Financial activity scale per square kilometer (in billions/km^2)	3808	0.30	1.08	0.00	30.41
INFRA	Infrastructure	Log of the area of existing roads at the end of the year (in tens of thousands of square meters)	3808	6.90	1.01	0.69	10.32
GOV	Government Expenditure	The proportion of government fiscal expenditure to the GDP (%)	3808	0.15	0.07	0.04	0.71
PAT	Research Patents	Log of the number of new patents in the city each year	3808	6.53	1.80	1.61	11.85
BSENV	Business Environment	Log of the business environment index	3808	4.14	0.22	2.16	4.55

Note: dates are collected from CEIC, WIND, *Urban Statistical Yearbook of China*, *China Provincial Marketization Index Report*, and the National Bureau of Statistics.

The test results, as shown in Table 2, indicate that at a significance level of 1%, we should reject the five null hypotheses mentioned above. This suggests that the specified transcendental logarithmic production model and the maximum likelihood estimation method employed in this study are reasonable, and the model does not exhibit any degeneracy. Subsequently, utilizing the compiled data from 272 cities at or above the prefecture level for the years 2005–2018, the transcendental logarithmic production function and production inefficiency function were estimated using the Frontier 4.1 software through maximum likelihood estimation. The estimation results are presented in Table 3.

From the estimation results in Table 3, the γ of the model is 0.892, and it is significant at the 1% level. This indicates that the model effectively captures the factors that cause production inefficiency. Approximately 89.2% of the inefficiency can be explained by the model variables, while the impact of random error terms is minimal. Secondly, based on the results of the inefficiency production function, the regression coefficient of the financial density is negative, suggesting that an increase in the local financial density helps alleviate technical inefficiency and positively contributes to improving technical efficiency. On the other hand, government expenditure has a significant negative effect, indicating that government intervention often exhibits inefficiency, which is consistent with the conclusions of Wang, Z. et al. (2006) [16] and Li, Q. et al. (2013) [51]. Furthermore, it is observed that scientific patents, business environment, and infrastructure play significant roles in improving the state of production inefficiency, which aligns with empirical expectations.

Table 2. Testing the applicability of the transcendental logarithmic production function specifications.

Testing	H0	H1	LR	Degrees of Freedom	1% Critical Value	Test Conclusion
T1: Test for the presence of inefficiency	−2040.83	1390.35	6862.35	3	10.501	Rejected
T2: Test for the form of the production function	1142.37	1390.35	495.97	3	10.501	Rejected
T3: Test for the existence of technological progress	1235.91	1390.35	308.87	3	10.501	Rejected
T4: Test for the Hicks neutrality of technological progress	1255.70	1390.35	269.31	3	10.501	Rejected
T5: Test for the fixed effects of technological efficiency	1064.27	1390.35	652.17	2	8.273	Rejected

Table 3. Estimation results for transcendental logarithmic production function and production inefficiency function.

Variable	Coefficient	Standard Error	T-Value
constant	8.504 ***	0.180	47.12
lnK	0.666 ***	0.042	16.00
lnL	−0.410 ***	0.045	−9.14
t	0.183 ***	0.012	15.78
lnk2	−0.015 ***	0.003	−4.65
lnl2	0.081 ***	0.008	10.58
t2	−0.003 ***	0.001	−7.14
tlnk	−0.008 ***	0.002	−5.30
tlnl	−0.004 *	0.002	−1.78
lnklnl	−0.051 ***	0.011	−4.79
constant	1.631 ***	0.100	16.33
FS	−0.570 ***	0.011	−53.01
INFRA	−0.078 ***	0.011	−6.89
GOV	2.667 ***	0.089	29.88
PAT	−0.079 ***	0.005	−16.035
BSENV	−0.098 ***	0.026	−3.722
σ2	0.109 ***	0.003	38.00
γ	0.892 ***	0.034	32.69
Log Likelihood		−1045.5417	
LR		1983.7106	

Note: *** and * represent significance at the 1% and 10% levels, respectively.

5. Analysis of Estimation Results

5.1. National and Regional Dimensions

From Figure 2, it can be observed that the technical efficiency of Chinese cities exhibited a fluctuating trend from 2005 to 2018. The first significant trough occurred in 2009, which was influenced by the global financial crisis in 2008. The average technical efficiency of Chinese cities experienced a substantial impact but began to rebound in 2010. The second cycle within the sample period started around 2014, and the average technical efficiency continued to decline for three years [52]. Finally, in the second half of 2015, stimulated by a series of demand-stimulating policies, the average technical efficiency bottomed out and rebounded in 2016.

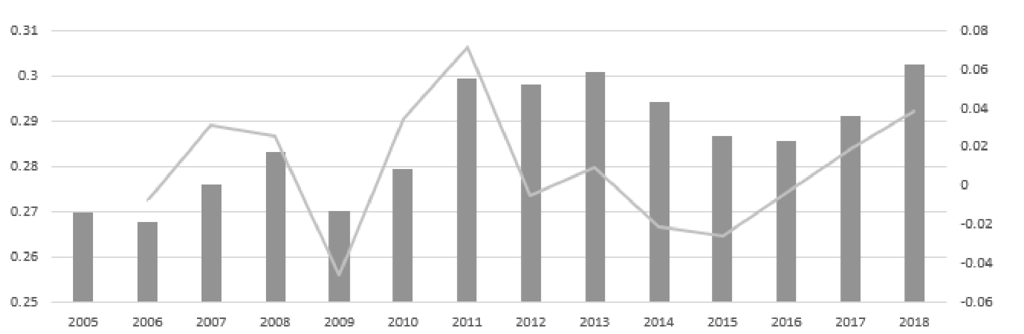

Figure 2. Evolution of the average technical efficiency of Chinese cities over time.

Of the six major regions in China, the Southeast region and the Bohai Bay region exhibit superior technical efficiency compared to the national average, with the Southeast region's lead continuously expanding (Figure 3). The Northeast region initially outperformed the national average in the early stage of the study period; however, it started to decline after 2011 and was gradually surpassed by other areas. Since 2016, its technical efficiency level has been the lowest among the six major regions, indicating a significant gap between its actual production curve and the production frontier. The Southwest region had the poorest initial foundation but has shown significant improvement over the years. The Central and Northwest regions had similar initial conditions, and their changes were relatively synchronous from 2005 to 2013. However, after 2013, as the technical efficiency of the Northwest region declined, it was gradually overtaken by the Central region.

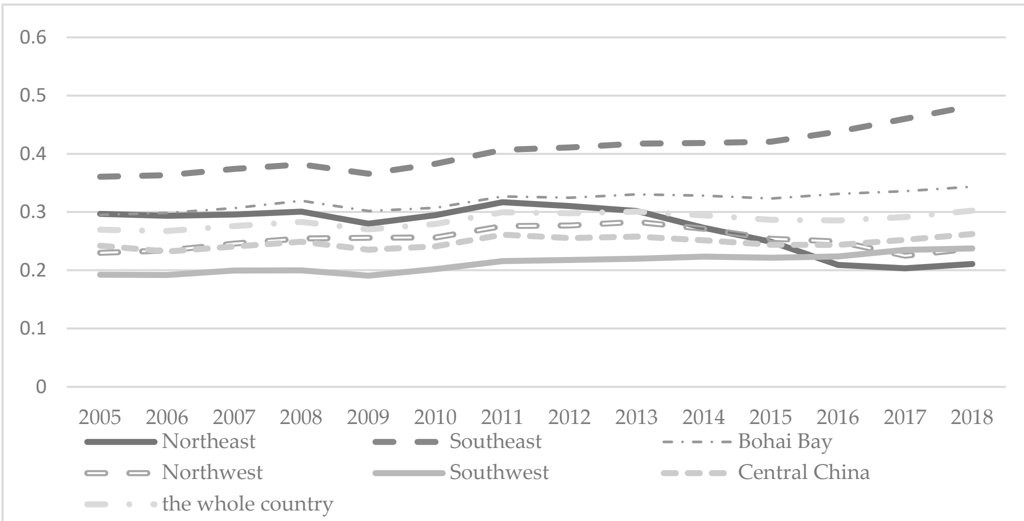

Figure 3. Evolution of national urban technical efficiency over time.

5.2. Provincial Level Dimensions

Looking at the situation across the provinces (Table 4), during the research period, on average, Jiangsu, Zhejiang, Beijing, Tianjin, and Shanghai were among the top in terms of overall technological efficiency. This aligns well with the stage characteristics of each province in China. Among them, Zhejiang, Tianjin, and Guangdong started the research period as the top three among all provincial administrative regions, while at the end of the research period, the top three provinces (cities) in terms of technological efficiency changed to Beijing, Shanghai, and Jiangsu. These three provinces (cities) have also made the most absolute progress in catching up with the production frontier, improving by 0.319, 0.290, and 0.249, respectively. Moreover, Chongqing and Zhejiang have seen relatively rapid improvements in technological efficiency. Chongqing has seen the most improvement in rankings; in 2005, Chongqing's technological efficiency was at the bottom among all provinces (cities) with an absolute level of only 0.103. However, after 14 years of catching up, Chongqing's technological efficiency reached 0.253 in 2018, rising to fourth place. Meanwhile, provinces such as Hebei, Jilin, Shanxi, Inner Mongolia, Gansu, Liaoning, and Heilongjiang saw a decline in technological efficiency during the research period, indicating a deviation from the production frontier.

Table 4. Performances of provinces in terms of technical efficiency.

Rank	Province	Average	Province	2005	Province	2018	Province	Change
1	Jiangsu	0.448	Zhejiang	0.390	Beijing	0.654	Beijing	0.319
2	Zhejiang	0.443	Tianjin	0.374	Shanghai	0.629	Shanghai	0.290
3	Beijing	0.441	Guangdong	0.374	Jiangsu	0.592	Jiangsu	0.249
4	Tianjin	0.434	Hainan	0.356	Zhejiang	0.524	Chongqing	0.151
5	Shanghai	0.432	Jiangsu	0.343	Tianjin	0.504	Zhejiang	0.134
6	Neimenggu	0.391	Shanghai	0.339	Fujian	0.440	Tianjin	0.129
7	Guangdong	0.380	Neimenggu	0.337	Guangdong	0.404	Fujian	0.117
8	Hai Nan	0.378	Beijing	0.335	Shandong	0.394	Guizhou	0.116
9	Shandong	0.363	Liaoning	0.330	Hainan	0.390	Shanxi	0.074
10	Fujian	0.357	Shandong	0.324	Yunnan	0.365	Shandong	0.070
11	Yunnan	0.321	Fujian	0.323	Hubei	0.326	Yunnan	0.066
12	Liao Ning	0.306	Heilong Jiang	0.305	Neimenggu	0.305	Hubei	0.062
13	Hu Bei	0.273	Yunnan	0.300	Guizhou	0.282	Hubei	0.050
14	Shan Xi	0.262	Shanxi	0.288	Shanxi	0.268	Jiangxi	0.041
15	Hei Long Jiang	0.253	Hubei	0.264	Jiangxi	0.265	Sichuan	0.040
16	He Nan	0.249	Hebei	0.243	Henan	0.263	Hainan	0.034
17	Ji Lin	0.249	Henan	0.241	Hunan	0.262	Guangdong	0.031
18	Jiang Xi	0.243	Anhui	0.232	Chongqing	0.253	Guangxi	0.023
19	Ning Xia	0.239	Jilin	0.227	Ningxia	0.241	Henan	0.022
20	Hu Nan	0.238	Jiangxi	0.224	Anhui	0.235	Ningxia	0.019
21	He Bei	0.235	Ningxia	0.222	Shanxi	0.230	Anhui	0.003
22	Anhui	0.229	Hunan	0.212	Liaoning	0.229	Hebei	−0.015
23	Shanxi	0.228	Shanxi	0.194	Hebei	0.228	Jilin	−0.019
24	Guizhou	0.211	Guangxi	0.186	Sichuan	0.219	Gansu	−0.027
25	Guangxi	0.197	Sichuan	0.178	Guangxi	0.208	Neimenggu	−0.033
26	Sichuan	0.196	Gansu	0.172	Jilin	0.207	Shanxi	−0.059
27	Chongqing	0.164	Guizhou	0.166	Heilongjiang	0.193	Liaoning	−0.101
28	Gansu	0.162	Chongqing	0.103	Gansu	0.145	Heilongjiang	−0.112

5.3. City Dimension

From the city perspective, the technological efficiency performance and changes in cities vividly reflect the economic and social development of China in the recent period.

As shown in Figure 4, cities with higher levels of technological efficiency exhibit two characteristics. Firstly, they are distributed on two horizontal and two vertical axes. The two horizontal axes are primarily formed around road and bridge connections and the Yangtze River channel, while the two vertical axes consist of the eastern coastline and the Beijing–Kowloon Railway. Secondly, cities with high levels of technological efficiency tend to appear together, showing obvious aggregation characteristics. On the other hand, as observed from Figure 4, cities with decreased levels of technological efficiency are mainly concentrated in the northern region, forming a "V"-shaped distribution. The left wing of the "V" represents the northwestern region, mainly involving Gansu, Inner Mongolia, Shaanxi, Shanxi, and other provinces, while the right wing represents the northeastern region, including Heilongjiang, Jilin, and Liaoning. In addition, there is a tendency for the "V" shape to transform into a "Y" shape, extending from the north towards the central China region, all the way to the Yangtze River.

Furthermore, as seen from Table 5, cities such as Zhuhai, Shenzhen, Guangzhou, Foshan, Zhongshan, Dongguan, Suzhou, Changzhou, Zhenjiang, and Xiamen, which are first-tier and strong second-tier cities, consistently rank at the forefront of national technological efficiency. Additionally, cities like Dongying, Daqing, and Ordos also have relatively outstanding performances in technological efficiency due to their high per capita incomes, which benefit from local energy industries.

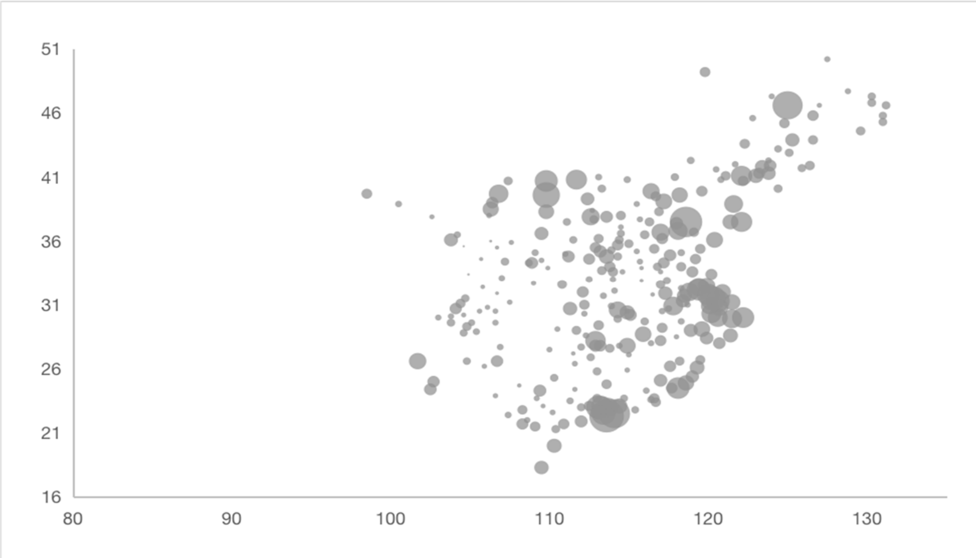

Figure 4. The average distribution of urban technological efficiency in China from 2005 to 2018. Note: The ordinate represents the north latitude, the abscissa represents the east longitude, and the bubble size represents the level of technological efficiency, with larger bubbles indicating higher technological levels.

Table 5. Performances of key cities.

Top 20 TE in 2005		Top 20 TE in 2018		Top 20 in Avg Value		Top 20 in Positive Change		Top 20 in a Negative Change	
Zhuhai	0.899	Shenzhen	0.959	Zhuhai	0.888	Nanjing	0.363	Daqing	−0.317
Daqing	0.864	Zhuhai	0.948	Dongying	0.835	Nantong	0.333	Benxi	−0.262
Dongying	0.864	Wuxi	0.856	Shenzhen	0.798	Changzhou	0.323	Anshan	−0.259
Panjin	0.657	Suzhou	0.809	Daqing	0.774	Beijing	0.319	Lvliang	−0.248
Shenzhen	0.651	Dongying	0.802	Eerduosi	0.702	Wuhan	0.318	Panjin	−0.243
Zhongshan	0.632	Changzhou	0.780	Wuxi	0.668	Suzhou	0.317	Wuhai	−0.232
Xiamen	0.617	Nanjing	0.742	Foshan	0.647	Yulin	0.313	Tongling	−0.208
Foshan	0.606	Hangzhou	0.696	Suzhou	0.613	Wuxi	0.311	Qitaihe	−0.180
Baotou	0.587	Xiamen	0.691	Zhenjiang	0.610	Shenzhen	0.308	Yichun	−0.176
Zhoushan	0.580	Foshan	0.689	Zhongshan	0.608	Changsha	0.296	Baotou	−0.172
Weihai	0.574	Zhenjiang	0.676	Baotou	0.593	Shanghai	0.290	Jixi	−0.168
Wuxi	0.545	Ningbo	0.671	Xiamen	0.592	Yangzhou	0.281	Hegang	−0.166
Wuhai	0.542	Changsha	0.669	Changzhou	0.586	Ningbo	0.272	Liaoyang	−0.154
Dongguan	0.531	Yangzhou	0.668	Zhoushan	0.569	Hangzhou	0.254	Fushun	−0.135
Zhenjiang	0.530	Eerduosi	0.657	Panjin	0.549	Yichang	0.247	Yangquan	−0.134
Tongling	0.530	Beijing	0.654	Weihai	0.548	Chengdu	0.236	Maanshan	−0.122
Eerduosi	0.506	Wuhan	0.653	Guangzhou	0.545	Taizhou	0.235	Jingmen	−0.117
Suzhou	0.492	Shanghai	0.629	Huhehaote	0.544	Huaian	0.213	Linfen	−0.114
Taiyuan	0.487	Nantong	0.624	Changsha	0.528	Xian	0.209	Dandong	−0.112
Maanshan	0.485	Guangzhou	0.619	Dongguan	0.516	Fuzhou	0.194	Huainan	−0.110

Moreover, in terms of changes (Figure 5), cities that have seen a faster increase in technological efficiency are mostly those in city clusters or regional center cities, such as Nanjing, Nantong, Changzhou, Beijing, Wuhan, Suzhou, Wuxi, Shenzhen, Changsha, Shanghai, Yangzhou, Ningbo, Hangzhou, Chengdu, Taizhou, and Xi'an. These are also cities in which industrial development has been particularly noticeable in the past. Among them, Yulin, Yichang, and Huai'an are all cities that have emerged as stars in the transition to development in recent years. Taking Yulin as an example, in recent years, under the influence of the national energy revolution innovation demonstration zone, it has transitioned to a modern, resource-leading city. Based on traditional industries in the chemical energy industry, it's the competitive advantage of its tertiary industry has gradually increased, and the results of its high-quality economic development are significant. Huai'an has accelerated the digital transformation of traditional manufacturing industries and promoted the deep integration of the digital economy and the real economy. As a national port-type logistics hub city, a regional central city in the middle and upper reaches of the Yangtze River, and a sub-central city in Hubei province, Yichang is accelerating its progress toward greener industries. Cities in which technological efficiency has declined are mostly resource-based cities that have struggled with their transformations, such as Daqing, Anshan, Benxi, Panjin, Hegang, Wuhai, and Qitaihe.

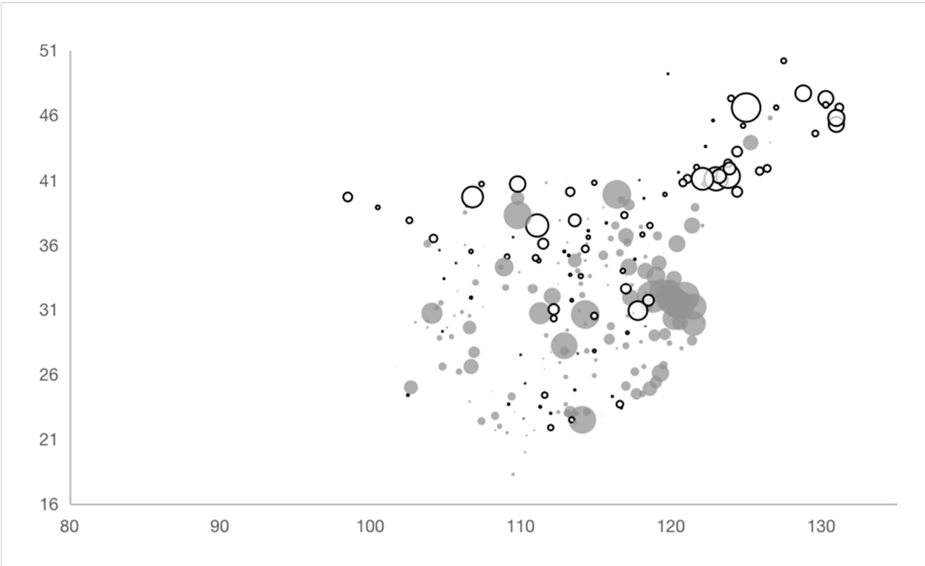

Figure 5. Changes in technological efficiency in Chinese cities: 2005 vs. 2015. Note: The ordinate represents the north latitude, and the abscissa represents the east longitude; a hollow bubble signifies a decrease, a solid bubble signifies an increase, and the size of the bubble indicates the degree of change, with larger bubbles denoting greater changes.

6. Measurement of the Contribution of Financial Agglomeration to Urban Production Technical Efficiency

To grasp the relationship between urban productivity and financial density more precisely, this paper continues to calculate the impact of financial density on the technical efficiencies of different cities. Coelli, T. et al. (1999) [53] and Henry, M. et al. (2009) [54] have, respectively, proposed methods to measure the contributions of influencing factors to technical efficiency in the context of a stochastic frontier model, based on the "forward-looking" and "backward-looking" principles. Firstly, based on Battese, G.E., Coelli, T.J. (1995) [41], and Coelli, T. et al. (1999) [53], technical efficiency (TE) can be calculated through the following formula:

$$TE_{it} = \left[\exp\left(-\mu_{it} + \frac{1}{2}\sigma_*^2\right)\right] \times \left\{\left[1 - \Phi\left(\sigma_* - \frac{\mu_{it}}{\sigma_*}\right)\right] / \left[1 - \Phi\left(-\frac{\mu_{it}}{\sigma_*}\right)\right]\right\} \tag{6}$$

$$\mu_{it} = (1-\gamma)\left(\delta_0 + \sum_{n=1}^{m} \delta_n Z_{n,it}\right) - \gamma\varepsilon_{it} \tag{7}$$

$$\sigma_*^2 = \gamma(1-\gamma)\sigma^2 \tag{8}$$

$$\gamma = \sigma_u^2 / \left(\sigma_u^2 + \sigma_v^2\right) \tag{9}$$

In Equation (6), Φ represents the cumulative distribution function of standard, normal-distribution variables; in Equation (7), $[Z_1, \ldots Z_m]$ is a combination of m factors that affect technical inefficiency. According to the "forward-looking" method, to judge the contribution rate of a certain influencing factor Z_n, it can be assumed that the situation of this influencing factor is completely the same for all individuals and is at the optimal level, that is, when $\delta_n Z_{n,it}$ in Equation (7) takes the minimum value $min\delta_n Z_{n,it}$, the calculated technical efficiency (TE_f) is the potential technical efficiency under optimal conditions. The higher the ratio of the potential technical efficiency to the actual technical efficiency (TE_f/TE-1) after conversion, the greater the contribution of this factor to the technical efficiency. The drawback of this method is that because the assumption of the optimal level of this influencing factor is based on the optimal situation of the existing observed individuals, it may underestimate the potential optimal level, resulting in an underestimation of the contribution rate.

The basic logic of the "backward-looking" calculation method can be described as judging the contribution rate of a certain influencing factor Z_n by excluding the effects of all other influencing factors; the obtained technical efficiency (TE_b) and the actual technical efficiency are compared, and the difference ($TE_b/TE - 1$) after conversion is the contribution rate of the influencing factor Z_n. For example, assuming that n = 1, i.e., $Z_n = Z_1$ when the promotion effect of other factors on technical efficiency is maximized, i.e., when $\delta_0 + \sum_{n=2}^{m} \delta_n Z_{n,it}$ in Equation (7) takes max($\delta_0 + \sum_{n=2}^{m} \delta_n Z_{n,it}$), the contribution of the influencing factor Z_1 is the smallest; on the contrary, when the promotion effect of the other factors on the technical efficiency is the smallest, i.e., when it takes min($\delta_0 + \sum_{n=2}^{m} \delta_n Z_{n,it}$), the contribution of Z_1 is the largest. The average of the minimum and maximum contributions is the average contribution rate of Z_1. The drawback of this method is that the combination of influencing factors in Equation (7) may not cover all the determinant variables of technical efficiency, which may result in overestimating the contribution rate.

In response to this, Wang, M. and Wong, M.S. (2012) [55] comprehensively used the "forward-looking" and "backward-looking" methods to analyze the evolutionary trend of international R&D activities and their contribution to a country's technical efficiency. The results show that the contribution rates calculated by the "forward-looking" and "backward-looking" methods have some differences, but the differences are systematic, and their results have consistency in time and regional dimensions and the fitting effect with the actual situation is good; overall, the robustness is strong. Therefore, this paper also comprehensively uses the "forward-looking" and "backward-looking" methods to calculate the contribution of financial agglomeration to the technical efficiency of Chinese cities.

6.1. Results and Comparison Based on "Forward-Looking" and "Backward-Looking" Calculations

The "forward-looking" and "backward-looking" methods have been used to measure the impact of financial density on technical efficiency, and the results are summarized in Figure 6.

Firstly, overall, financial density has a positive promoting effect on improving technical efficiency. The calculation results based on the "forward-looking" method show that the contribution rate of financial density is relatively small, and the fluctuation is gentle. The highest value is 28.15% for 2006, and the lowest value is 19.79% for 2018, mainly showing a slow downward trend during the sample period. The results calculated based on the "backward-looking" method are systematically higher than those of the "forward-looking" method, but its upper limit, lower limit, and average maintain a synchronized change trend. For example, the average contribution rate reached its highest at 154.18% in 2009 and its lowest at 129.65% in 2011, showing a fluctuating downward trend during the sample period.

In addition, based on their calculation logic, the results of the "forward-looking" and "backward-looking" methods may be affected by extreme values; under the "forward-looking" method, because it is assumed that the financial density (FD) is completely the same for all entities and is at the optimal level, the result is affected by the extreme values of the financial density (FD); similarly, the "backward-looking" method is affected by the extreme values of other factors. Therefore, to test the robustness of the results, this paper conducted a robustness test after a basic calculation. The specific approach for the "forward-looking" method is to take the smallest 10, 20, 30, 40, and 50 values and take the average, replacing extreme values with the average; for the "backward-looking" method, the approach is to take the maximum and minimum of 10, 20, 30, 40, 50 values of other influencing factors and take the average, replacing extreme values with the average. Table 6 compares the calculated results with the original results after updating the statistics.

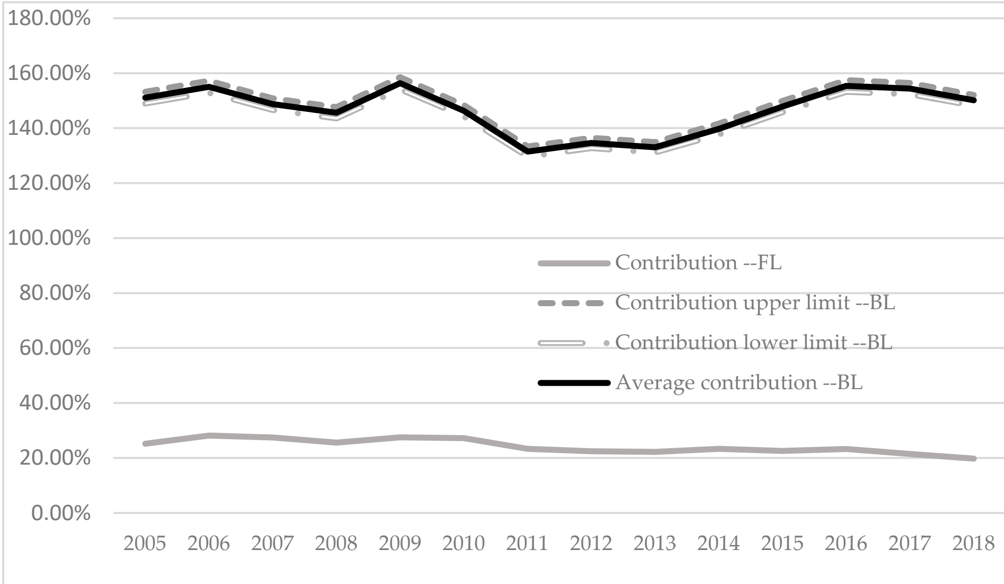

Figure 6. Contribution rate of FD to TE based on "forward-looking" and "backward-looking" methods.

Table 6. Robustness test.

	Variables	Observation	Mean	Std.Dev.	Min	Max
Backward-Looking	Backward-looking average contribution rate (baseline calculation)	3808	1.464	1.092	−0.279	8.046
	Backward-looking average contribution rate (10-item average)	3808	1.473	1.097	−0.278	8.091
	Backward-looking average contribution rate (20-item average)	3808	1.466	1.090	−0.276	8.036
	Backward-looking average contribution rate (30-item average)	3808	1.469	1.092	−0.275	8.045
	Backward-looking average contribution rate (40-item average)	3808	1.459	1.089	−0.280	8.023
	Backward-looking average contribution rate (50-item average)	3808	1.460	1.090	−0.280	8.030
Forward-Looking	Forward-looking contribution rate (baseline calculation)	3808	0.242	0.254	−0.519	1.208
	Forward-looking contribution rate (10-item average)	3808	0.01	0.154	−0.483	0.543
	Forward-looking contribution rate (20-item average)	3808	0.517	0.395	−0.562	2.232
	Forward-looking contribution rate (30-item average)	3808	0.504	0.385	−0.556	2.154
	Forward-looking contribution rate (40-item average)	3808	0.215	0.241	−0.514	1.122
	Forward-looking contribution rate (50-item average)	3808	0.23	0.248	−0.516	1.168

As can be seen from Table 6, within the research range of this study, the results calculated by the "backward-looking" method show better robustness (the average is relatively stable), while the results calculated by the "forward-looking" method are greatly influenced by extreme values. Therefore, the analysis in this article will mainly be based on the results calculated using the "backward-looking" method.

6.2. Results Based on the "Backward-Looking" Method

Overall, the contribution of financial density to technical efficiency had already shown a declining trend before the 2008 financial crisis (Figure 7). After 2008, due to the 4 trillion stimulus plan, the financial density in 2009 increased dramatically, which also led to a surge in its contribution to technical efficiency. However, excessive financial density caused distortion in the factor structure, so the contribution of financial density to technical efficiency rapidly declined after 2010 and gradually recovered after 2013. But by 2018, it only returned to its approximate level before the crisis.

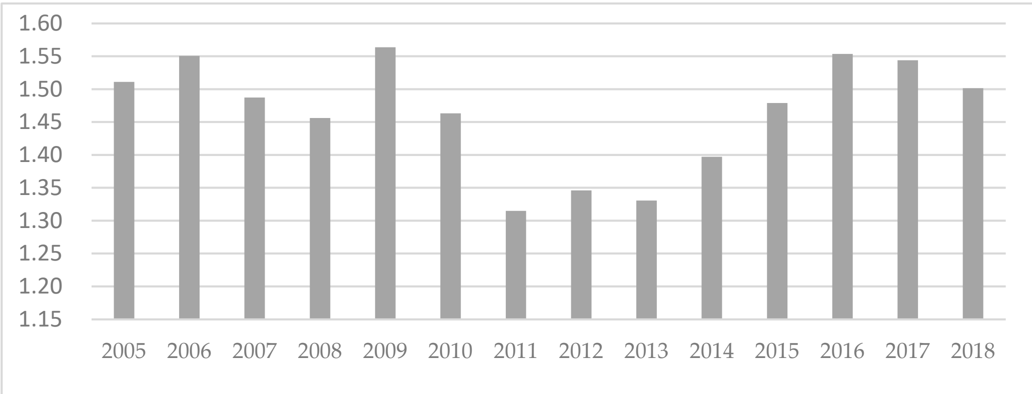

Figure 7. Contribution rate of FD to the TE values of national cities based on the "backward-looking" method.

6.3. Regional Dimension

From the regional perspective, the efficiency contribution of financial density in each region generally follows the rule that it is higher in less-developed areas and lower in developed areas, which is consistent with the results of Sheng, W. (2017) [1], which were calculated based on provincial data (Figure 8). Looking at the average annual contribution rate during the research period, it is higher in the northwest and southwest regions, followed by the central and northeast regions, with the Bohai Bay and Southeast regions being the lowest. In terms of changes, after experiencing shocks, most regions show a trend of declining and then rebounding with respect to the contribution rate of financial density; the decline in the northeast in the second stage is not obvious, which may mainly stem from the fact that the impact of the financial crisis and the four trillion stimuli mainly affected foreign trade, industry, real estate, local finance, and employment but had a smaller impact on fixed asset investment and consumer loans [56].

6.4. Provincial Dimension

As can be seen from Table 7, during the research period, the annual average contribution rate of financial density to urban production technical efficiency is lower in developed provinces such as Zhejiang, Tianjin, Jiangsu, and Beijing and higher in developing provinces like Gansu, Ningxia, Chongqing, Sichuan, Guangxi, and Guizhou. Over time, the positive role of financial density generally decreases, but the positive role is expanding in certain developing regions (Gansu, Heilongjiang, Hebei, Shanxi, Liaoning, etc.).

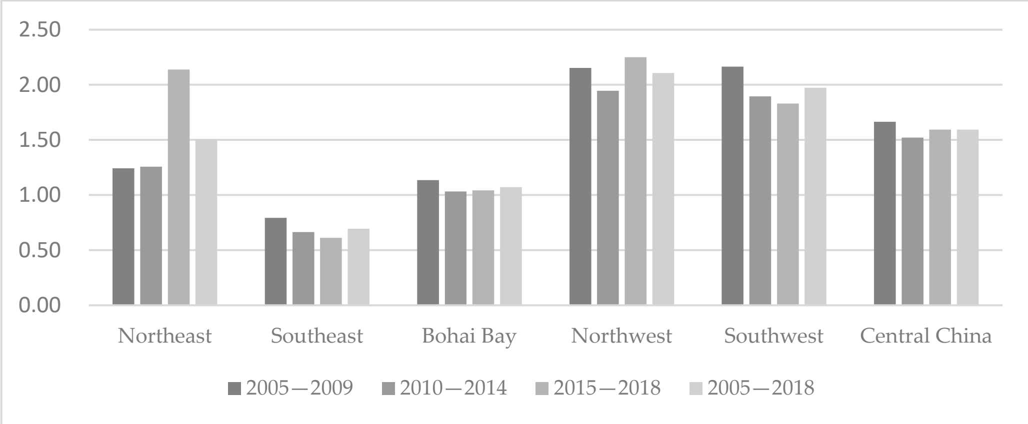

Figure 8. Contribution rate of FD to TE by region based on the "backward-looking" method.

Table 7. Contribution rate of FD to EF in provincial dimension based on the "forward-looking" method.

Province	2005–2009	2010–2014	2015–2018	2005–2018
Zhejiang	0.52	0.39	0.36	0.43
Tianjin	0.53	0.42	0.44	0.47
Jiangsu	0.77	0.44	0.28	0.51
Jiangsu	0.77	0.44	0.28	0.51
Beijing	0.70	0.58	0.46	0.59
Hainan	0.65	0.72	0.85	0.73
Fujian	0.95	0.74	0.63	0.78
Yunnan	0.96	0.81	0.76	0.85
Shandong	0.99	0.79	0.74	0.85
Guangdong	0.87	0.89	0.93	0.90
Neimenggu	0.93	0.66	1.15	0.90
Shanghai	1.08	1.05	0.73	0.97
Liaoning	1.05	0.92	1.89	1.24
Hubei	1.60	1.28	1.20	1.37
Henan	1.47	1.40	1.33	1.40
Jilin	1.44	1.14	1.71	1.41
Shanxi	1.19	1.32	2.06	1.49
Hebei	1.44	1.48	1.59	1.50
Jiangxi	1.85	1.58	1.43	1.64
Hunan	1.82	1.61	1.61	1.68
Shannxi	2.05	1.71	1.70	1.83
Heilongjiang	1.34	1.72	2.72	1.87
Anhui	2.00	1.85	1.95	1.93
Guizhou	2.49	1.88	1.34	1.94
Guangxi	2.20	2.00	2.02	2.08
Sichuan	2.31	2.07	2.05	2.15
Chongqing	3.17	2.01	1.29	2.22
Ningxia	2.71	2.32	2.34	2.47
Gansu	3.13	3.18	3.75	3.33

6.5. City Dimension

Summarizing the annual average contribution rate of financial density to technical efficiency by period and selecting the 10 cities with the highest and lowest contribution rates in each period, as can be seen from Table 8, it can be seen that cities in which the role of financial density in technical efficiency is relatively low can be divided into two categories. The first category is represented by resource-based cities such as Ordos, Dongying, Baotou, Daqing, and Panjin. Through research on resource-based cities in China, Sun, W. and Dong, G. (2010) [57] found that due to the slow progress of technology, the technical efficiency of resource-based cities in China is generally low and shows a downward trend. Combined with the findings of this article, the financial density in resource-based cities not only fails to contribute to the improvement of technical efficiency but may also distort resource allocation through distorted price signals, thereby affecting technical efficiency. The other category is represented by advanced cities such as Shenzhen, Zhuhai, Suzhou, Wuxi, Foshan, and Changzhou; a possible explanation for this categorization is that the financial resources and activities in these cities are relatively abundant, so the contribution rate is not particularly prominent. In contrast, the cities in which the role of financial density in technical efficiency is relatively high are represented by Longnan, Bazhong, Dingxi, Fuyang, Bozhou, Pingliang, Tianshui, Guyuan, and others, and the common feature of these cities is that they are at a medium level of development and are often characterized by abundant human resources, convenient transportation, and a certain industrial foundation. In these cities, financial activity is relatively scarce. Therefore, the increase in financial density can generate greater value in coordination with other resources, which manifests as a greater role for financial density in promoting the improvement of technical efficiency.

Table 8. Contribution rate of FD to EF in at the city level, based on the "forward-looking" method.

Year	2005–2009		2010–2014		2015–2018		2005–2018	
Content	City	Contribution Rate	City	Contribution Rate	City	Contribution Rate	City	Contribution Rate
Bottom 10	Dongying	−0.23	Daqing	−0.24	Dongying	−0.15	Dongying	−0.21
	Zhuhai	−0.21	Dongying	−0.23	Zhuhai	−0.12	Zhuhai	−0.17
	Daqing	−0.21	Zhuhai	−0.17	Eerduosi	−0.11	Daqing	−0.12
	Baotou	0.01	Eerduosi	−0.16	Wuxi	−0.01	Eerduosi	−0.08
	Zhongshan	0.02	Baotou	−0.04	Changzhou	0.00	Wuxi	0.04
	Eerduosi	0.02	Wuxi	0.02	Suzhou	0.05	Baotou	0.06
	Foshan	0.03	Zhenjiang	0.03	Zhenjiang	0.05	Zhenjiang	0.07
	Panjin	0.08	Panjin	0.08	Shenzhen	0.06	Foshan	0.08
	Zhoushan	0.10	Huhehaote	0.08	Yangzhou	0.06	Suzhou	0.12
	Wuxi	0.11	Foshan	0.10	Changsha	0.06	Zhongshan	0.13
Top 10	Dingxi	6.96	Dingxi	6.98	Dingxi	7.69	Dingxi	7.18
	Guyuan	6.62	Longnan	6.63	Longnan	6.66	Longnan	6.39
	Longnan	5.93	Guyuan	5.43	Guyuan	5.00	Guyuan	5.73
	Fuyang	4.16	Bazhong	4.37	Lvliang	4.85	Bazhong	4.20
	Anshun	3.85	Fuyang	3.59	Yichun	4.80	Pingliang	3.79
	Tianshui	3.74	Pingliang	3.57	Pingliang	4.61	Fuyang	3.79
	Bazhong	3.72	Tianshui	3.55	Bazhong	4.59	Tianshui	3.74
	Ankang	3.67	Haozhou	3.41	Tianshui	3.98	Hechi	3.45
	Shangluo	3.56	Hechi	3.33	Hegang	3.84	Haozhou	3.38
	Guangyuan	3.49	Shaoyang	3.32	Qitaihe	3.81	Guangyuan	3.34

7. Discussion

Although the research in this paper has obtained some early-stage results, due to the limitation of the data and research methods, there are still some questions that cannot be answered and some new thoughts to be explored.

7.1. Challenges Related to the Estimation of Urban Capital Stock and the Calculation of TE

Capital stock is an important variable in the process of calculating TE using the SFA method. In the calculation process, the estimation of the base period capital stock, the setting of the depreciation rate, and the selection of the price index will affect the settlement result. At the same time, from the perspective of demand, the level of capital utilization will also affect the authenticity of the estimation. Because even if the parameters from the supply side are correct, the difference in the capacity utilization rate will greatly compromise the authenticity of the calculated results. Since overcapacity is a common and differentiated problem in China, taking this factor into account can improve the authenticity of the calculated results. However, there is no mature method for evaluating the rate of utilization of urban fixed assets, which is a direction that can be promoted in the next stage of research.

7.2. Verification of the Mechanism though which Financial Density Acts on Technical Efficiency

After conducting a theoretical analysis, the authors of this article believe that financial density can optimize the problems of information asymmetry and transaction cost by providing resource allocation and information transfer functions to push the actual production curve closer to the production possibility curve and promote urban technical efficiency. The empirical study in this paper focuses more on the phenomenon level, namely, the impact of financial density on urban technical efficiency, but fails to verify it at the mechanism level. This is another direction for the work that can be continued in the future.

8. Conclusions and Implications

The enhancement of financial density can exert resource allocation and information transmission functions, optimize information asymmetry and transaction cost issues, and thus provide support to help the actual production curve approach the maximum possibility curve, promoting the improvement of technical efficiency. The research in this article finds that the technical efficiency of Chinese cities shows a fluctuating trend from 2005 to 2018, with two troughs appearing in 2009 and 2016, respectively. Cities with higher levels of technical efficiency are distributed on two horizontal and two vertical axes and often appear in clusters, exhibiting obvious aggregation characteristics. The Southeast region and the Bohai Bay area lead the country in technical efficiency, and the leading advantage of the Southeast region is constantly expanding. On the city level, first-tier and strong second-tier cities always rank at the forefront of national technical efficiency; in terms of changes, the cities with rapidly improved technical efficiency are mostly regional centers, cities within city clusters, or those that have undergone important changes in recent years, while cities with declining levels of technical efficiency are mostly resource-based cities facing challenging transformations.

As for the role of financial density, in general, before the 2008 financial crisis, the contribution of financial density to technical efficiency had already shown a downward trend. After 2008, due to the distortion of factor structure caused by the 4 trillion stimulus plan, a surge in 2009 and a rapid drop after 2010 occurred, gradually recovering only after 2013. From the regional and provincial perspectives, the efficiency contribution of financial density in various regions generally conforms to a pattern of being higher in backward areas and lower in developed areas. In the city dimension, the contribution of financial density to resource-based cities with slow technological progress or advanced cities with abundant financial density is not very prominent and may even have a negative effect. However, for cities at a medium level of development with abundant human resources, convenient transportation, and a certain industrial base, it can significantly promote the improvement of technical efficiency. Therefore, it may be possible to optimize the marginal contribution of urban financial density to the technical efficiency of Chinese cities by encouraging the flow of financial resources and activities from cities with small marginal effects to those with large marginal effects.

Author Contributions: Conceptualization, J.G.; Methodology, J.G. and H.X.; Software, J.G. and H.X.; Data curation, J.G., Y.W. (Ying Wang) and H.X.; Writing—original draft, J.G. and Y.W. (Ying Wang); Writing—review & editing, J.G., Y.W. (Ying Wang), B.L. and Y.W. (Yang Wang); Supervision, B.L.; Project administration, B.L. and Y.W. (Yang Wang); Funding acquisition, Y.W. (Yang Wang). All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Shenzhen Humanities and Social Sciences Key Research Bases.

Data Availability Statement: Not applicable.

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

Note

[1] Please refer to Guo, J. et al. (2023) for more a detailed calculation of city business environment variables.

References

1. Sheng, W. Does financial development favor the improvement of China's production technical efficiency?—Based on the test of the Stochastic Frontier Analysis method. *J. Cent. Univ. Financ. Econ.* **2017**, *12*, 15. (In Chinese with English Abstract)
2. Solow, R.M. Technical change and the aggregate production function. *Rev. Econ. Stat.* **1957**, *39*, 312–320. [CrossRef]
3. Zhang, J.; Jin, Y. Re-detection of the relationship between financial deepening and productivity in China: 1987–2001. *Econ. Res.* **2005**, *11*, 34–45. (In Chinese with English Abstract)
4. Xu, W.; Zhang, F. Financial development, industry characteristics, regional differences, and total factor productivity-based on the analysis of China's provincial industry data from 1999 to 2011. *Econ. Manag.* **2014**, *2*, 33–46. (In Chinese with English Abstract)
5. Chen, Q.; Wu, J. Financial development and technological progress: A study based on China's provincial data. *Econ. Rev.* **2013**, *6*, 98–107. (In Chinese with English Abstract)
6. Tao, F.; Hu, J.; Li, S.; Wei, J. How does the financial geographic structure affect corporate productivity?—Also discussing financial supply-side structural reform. *Econ. Res.* **2017**, *52*, 55–71. (In Chinese with English Abstract)
7. Aigner, D.J.; Chu, S.F. On Estimating the Industry Production Function. *Am. Econ. Rev.* **1968**, *58*, 826–839.
8. Koopmans, T.C. Efficient allocation of resources. *Econom. J. Econom. Soc.* **1951**, *19*, 455–465. [CrossRef]
9. Farell, P. DEA in production center: An input-output mode. *J. Econom.* **1957**, *3*, 23–49.
10. Uri, N.D. The adoption of incentive regulation and its effect on technical efficiency in telecommunications in the United States. *Int. J. Prod. Econ.* **2003**, *86*, 21–34. [CrossRef]
11. Wu, Y.; Zhang, L. Stochastic frontier model analysis of China's regional technical efficiency. *Stat. Inf. Forum* **2004**, *2*, 18–22. (In Chinese with English Abstract)
12. Jerzmanowski, M. Total factor productivity differences: Appropriate technology vs. efficiency. *Eur. Econ. Rev.* **2007**, *51*, 2080–2110. [CrossRef]
13. Aigner, D.; Lovell, C.K.; Schmidt, P. Formulation and estimation of stochastic frontier production function models. *J. Econom.* **1977**, *6*, 21–37. [CrossRef]
14. Meeusen, W.; Van Den Broeck, J. Efficiency estimation from Cobb-Douglas production functions with composed error. *Int. Econ. Rev.* **1977**, *18*, 435–444. [CrossRef]
15. Coelli, T.J.; Rao, D.S.P.; O'Donnell, C.J.; Battese, G.E. *An introduction to Efficiency and Productivity Analysis*; Springer: Berlin/Heidelberg, Germany, 2005.
16. Wang, Z.; Gong, L.; Chen, Y. Decomposition of regional production efficiency and total factor productivity growth rate (1978–2003). *Soc. Sci. China* **2006**, *2*, 55–66. (In Chinese with English Abstract)
17. Zhou, X.; Han, Z. Decomposition of production efficiency and total factor productivity growth rate in China's regions (1990–2006). *Nankai Econ. Stud.* **2009**, *5*, 26–48. (In Chinese with English Abstract)
18. Yao, Z. Productivity growth and factor re-allocation effects: A study of China's experience. *Econ. Res.* **2009**, *11*, 130–143. (In Chinese with English Abstract)
19. Zheng, R.; Gan, C.; Yu, D. Industrial structure and institutional effects on China's economic growth during the transition period—Based on a study of a stochastic frontier model. *China Ind. Econ.* **2010**, *2*, 58–67. (In Chinese with English Abstract)
20. Bai, J.; Bian, Y. Factor market distortion and efficiency loss of China's innovative production. *China Ind. Econ.* **2016**, *11*, 39–55. (In Chinese with English Abstract)
21. Nourzad, F. Financial development and productive efficiency: A panel study of developed and developing countries. *J. Econ. Financ.* **2002**, *26*, 138–148. [CrossRef]
22. He, F.; Chen, R.; He, L. The SFA model and its application in the estimation of China's technical efficiency. *Syst. Eng. Theory Pract.* **2003**, *24*, 46–50. (In Chinese with English Abstract)
23. Gu, N. The impact and channel of productive services on the profitability of industry. *China Ind. Econ.* **2010**, *5*, 48–58. (In Chinese with English Abstract)
24. Fare, R.; Grosskopf, S.; Lovell, C.K. *Production Frontiers*; Cambridge University Press: Cambridge, UK, 1994; pp. 24–61.
25. Xiaogang, C.; Skully, M.; Brown, K. Banking efficiency in China: Application of DEA to pre-and post-deregulation eras: 1993–2000. *China Econ. Rev.* **2005**, *16*, 229–245.
26. Guillaumont Jeanneney, S.; Hua, P.; Liang, Z. Financial development, economic efficiency, and productivity growth: Evidence from China. *Dev. Econ.* **2006**, *44*, 27–52. [CrossRef]
27. Bian, Y.; Yang, F. Resource and environment efficiency analysis of provinces in China: A DEA approach based on Shannon's entropy. *Energy Policy* **2010**, *38*, 1909–1917. [CrossRef]
28. Shuai, S.; Fan, Z. Modeling the role of environmental regulations in regional green economy efficiency of China: Empirical evidence from super efficiency DEA-Tobit model. *J. Environ. Manag.* **2020**, *261*, 110–227. [CrossRef]
29. Chang, K.; Cheng, X.; Wang, Y.; Liu, Q.; Hu, J. The impacts of ESG performance and digital finance on corporate financing efficiency in China. *Appl. Econ. Lett.* **2023**, *30*, 516–523. [CrossRef]
30. Fu, X.; Wu, L. The applicability of frontier analysis methods in China's economic growth accounting. *World Econ.* **2007**, *30*, 56–66. (In Chinese with English Abstract)

31. Merton, R.C.; Bodie, Z. A conceptual framework for analyzing the financial system. In *The Global Financial System: A Functional Perspective*; Harvard Business School Press: Boston, MA, USA, 1995; pp. 3–31.
32. Allen, F.; Gale, D. *Comparing Financial Systems*; MIT Press: Cambridge, MA, USA, 2001.
33. Stiglitz, J.E. The revolution of information economics: The past and the future (No. w23780). *Natl. Bur. Econ. Res.* 2017, working paper.
34. Merton, R.C. A functional perspective of financial intermediation. *Financ. Manag.* **1995**, *24*, 23–41. [CrossRef]
35. Scholtens, B.; Van Wensveen, D. A critique on the theory of financial intermediation. *J. Bank. Financ.* **2000**, *24*, 1243–1251. [CrossRef]
36. Allen, F.; Santomero, A.M. The theory of financial intermediation. *J. Bank. Financ.* **1997**, *21*, 1461–1485. [CrossRef]
37. Marshall, A. *Principles of Economics*, unabridged eighth ed.; Cosimo, Inc.: New York, NY, USA, 2009.
38. Duranton, G.; Puga, D. Micro-foundations of urban agglomeration economies. In *Handbook of Regional and Urban Economics*; Elsevier: Amsterdam, The Netherland, 2004; Volume 4, pp. 2063–2117.
39. Abel, J.R.; Dey, I.; Gabe, T.M. Productivity and the density of human capital. *J. Reg. Sci.* **2012**, *52*, 562–586. [CrossRef]
40. Kumbhakar, S.C. Estimation of technical inefficiency in panel data models with firm-and time-specific effects. *Econ. Lett.* **1991**, *36*, 43–48. [CrossRef]
41. Battese, G.E.; Coelli, T.J. A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empir. Econ.* **1995**, *20*, 325–332. [CrossRef]
42. Kumbhakar, S.C.; Wang, H.-J. Estimation of growth convergence using a stochastic production frontier approach. *Econ. Lett.* **2005**, *88*, 300–305. [CrossRef]
43. Christensen, L.R.; Jorgenson, D.W.; Lau, L.J. Transcendental logarithmic production frontiers. *Rev. Econ. Stat.* **1973**, *55*, 28–45. [CrossRef]
44. Altunbaş, Y.; Chakravarty, S.P. Frontier cost functions and bank efficiency. *Econ. Lett.* **2001**, *72*, 233–240. [CrossRef]
45. Zhang, Z. China's city TFP growth and potential growth rate. *J. Hunan Univ. Soc. Sci. Ed.* **2019**, *33*, 34–42. (In Chinese with English Abstract)
46. Han, F.; Yang, L. How does the agglomeration of productive services affect the upgrade of the manufacturing structure?—An integrated framework of agglomeration economy and Schumpeterian endogenous growth theory. *Manag. World* **2020**, *36*, 72–94. (In Chinese with English Abstract)
47. Liu, C.; Li, L.; Wei, P. Measurement of capital stock in Chinese cities at or above the prefecture level. *Urban Probl.* **2017**, *10*, 67–72. (In Chinese with English Abstract)
48. Yu, Y.; Liu, D.; Gong, Y. "Excess is not enough, things are slow and round": Local economic growth target constraints and total factor productivity. *Manag. World* **2019**, *35*, 18. (In Chinese with English Abstract)
49. Zhang, J.; Wu, G.; Zhang, J. Estimation of China's interprovincial material capital stock: 1952—2000. *Econ. Res.* **2004**, *10*, 35–44. (In Chinese with English Abstract)
50. Huang, X.; Huang, T. On China's "financial super-development". *Financ. Res.* **2017**, *440*, 26–41. (In Chinese with English Abstract)
51. Li, Q.; Li, J.; Jiang, C. Financial development and regional real economic capital allocation efficiency—evidence from provincial industrial data. *Econ. Q.* **2013**, *1*, 527–548. (In Chinese with English Abstract)
52. Wang, Y.; Lu, T.; Jia, S.; Guan, T.; Yin, J.; Xu, G.; Yu, Y.; Zhang, B.; Zhang, D.; Yu, M.; et al. The potential of China's economic growth, policy choices, and the outlook for the global macroeconomic situation in 2020. *Int. Econ. Rev.* **2020**, *9*, 124–160. (In Chinese with English Abstract)
53. Coelli, T.; Perelman, S.; Romano, E. Accounting for environmental influences in stochastic frontier models: With application to international airlines. *J. Product. Anal.* **1999**, *11*, 251–273. [CrossRef]
54. Henry, M.; Kneller, R.; Milner, C. Trade, technology transfer and national efficiency in developing countries. *Eur. Econ. Rev.* **2009**, *53*, 237–254. [CrossRef]
55. Wang, M.; Wong, M.S. International R&D transfer and technical efficiency: Evidence from panel study using stochastic frontier analysis. *World Dev.* **2012**, *40*, 1982–1998.
56. Wei, H. Analysis of the impact of the financial crisis on China's regional economy. *West. Financ.* **2009**, *5*, 3. (In Chinese with English Abstract)
57. Sun, W.; Dong, G. Analysis of the efficiency change of China's resource-based cities based on the DEA model. *Geogr. Res.* **2010**, *12*, 29. (In Chinese with English Abstract)