Industrial Chain Correlation and Total Factor Productivity

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Abstract. As a matter of fact, the total factor productivity, as a crucial metric for measuring the speed and quality of output in enterprises, plays a vital role in optimizing resource allocation and fostering the synergistic development of industries especially in recent years. With this in mind, this paper studies and investigates how the degree of industrial chain correlation affects the total factor productivity. By using the methods of benchmark regression analysis, robustness test, heterogeneity analysis and quantile regression, the empirical findings indicate that the impact of industrial chain connectivity on enterprise total factor productivity follows a "U"-shaped distribution and remains robust. Furthermore, its influence varies among enterprises with different ownership structures as well as production factor intensities according to the analysis. At the same time, the panel quantile regression reveals that the effect of industrial chain connectivity on enterprise total factor productivity differs across firms with varying levels of total factor productivity.

Keywords: Industrial chain correlation; total factor productivity; quantile regression.

1. Introduction

With the ongoing technological advancements and industrial development in a new era, digital technologies continue to evolve, bringing about fundamental and systemic changes to the economy and society. This progression is driving China towards a digital and intelligent age, and it is closely linked to the relationships within industrial chains and total factor productivity. From the perspective of the development of industrial chain and industrial correlation, with the development of globalization, the global division of labor has been deepened and clarified, and has been continuously improved. At present, the research methods of industrial chain correlation measurement in China are mostly based on input and output, and the interaction between industries is analyzed from different angles when aiming at the degree of industrial correlation in a single region (or country) [1]. It also objectively shows the characteristics and laws of the correlation effect of digital transformation in the national economy from the aspect of economic production [2, 3]. Other scholars analyze the degree of industrial correlation between regions (or countries) horizontally, extend the input-output model, and study the multiplier and spillover effect between regions [4]. From the perspective of total factor productivity, it measures the output speed and quality of enterprises, and reflects the comprehensive output efficiency of enterprise production and operation capital, labor force, technological innovation, institutional environment, management skills and other factors [5]. At present, the relevant research mainly focuses on the analysis of its influencing factors. At the macro level, scholars have analyzed the influence of financial deepening, foreign direct investment, economic freedom and economic structure on total factor productivity [6]. At the micro level, numerous studies explore the factors affecting productivity based on aspects such as firm size, human capital, research and development investment, resource allocation, and industrial policies [7].

There has been relatively limited research on the relationship between industrial connectivity and total factor productivity, both domestically and internationally. Among existing studies, most scholars believe that industrial agglomeration and industrial integration can promote total factor productivity. Some research results suggest that the influence of industrial chain connectivity can lead to increased foreign direct investment in the service sector, which in turn can drive the development of manufacturing and stimulate improvements in total factor productivity [8].

Industrial synergy agglomeration can bring service and technology innovation through deepening division of labor and technology spillover, while innovation can improve production efficiency, and indirectly promote the growth of total factor productivity through optimizing resource allocation and expanding business scale [9, 10]. With the country's increasing emphasis on industrial digital transformation, the support for industrial digital transformation is increasing, and the technical and economic ties between different industries are getting closer and closer. Researching the relationship between industrial connectivity and total factor productivity can facilitate the optimization of resource allocation and the synergistic development of industries, furthering the process of China's modernization. The promotion of industrial chain correlation is an important achievement after the progress of digital technology and professional division of labor have reached a certain level. Total factor productivity, as a new engine for China's economic development, relies on enhanced industrial chain connectivity to achieve stable growth [11]. Therefore, this paper analyzes the impact of industrial chain connectivity on enterprise total factor productivity at the firm level. It constructs univariate and bivariate regression models, conducts robustness tests, and explores heterogeneity based on differences in ownership nature and factor intensity. Finally, with the help of quantile regression, this paper makes a concrete analysis on whether industrial correlation has different effects on the location of the horizontal distribution of total factor productivity at different levels.

2. Variable Selection and Model Construction

The dependent variable in this study is total factor productivity (TFP), which is calculated using the Levinsohn and Petrin (LP) method as proposed by Levinsohn and Petrin [12]. The LP method addresses issues of sample loss and endogeneity by replacing proxy variables, building upon the Olley-Pakes (OP) approach [13]. In this paper, TFP for enterprises is computed using data from publicly traded companies, and it is estimated using the following model:

$$\ln Y_{it} = \beta_{0i} + \beta_{1i}\ln L_{it} + \beta_{2i}\ln K_{it} + \beta_{3i}\ln M_{it} + \varepsilon_{it} \quad (1)$$

where Y_{it} is enterprise income, L_{it} measuring labor input using the number of employees, K_{it} measuring capital input using the net value of fixed assets. M_{it} denotes intermediate inputs, measured using cash expenditures on purchased goods and services.

Taking the degree of industrial chain correlation (as an explanatory variable, using the input-output tables of 2007, 2012 and 2017, the number of industrial production stages at the national industry level is calculated, and the degree of division of labor among enterprises is measured by calculating the value added by using the research methods of Yuan Chun for reference [14]. Because the industrial chain is connected with the upper, middle and lower reaches on the basis of input and output, and it is divided into enterprise and industry levels, the product of production stages and value added is used to measure the correlation degree of the industrial chain. Referring to the research of scholars such as Huang Dayu and combing relevant literature, the control group selects the following control variables: enterprise scale, enterprise age, current asset ratio, return on assets, asset-liability ratio, cash flow intensity, equity concentration ratio and book-to-market ratio [15].

Because the promotion of industrial correlation has various and superimposed effects on total factor productivity, this paper compares the linear and quadratic nonlinear regression models to judge and analyze the relationship between the two variables. Build the following models respectively:

$$TFP_{it} = \alpha_0 + \alpha_1 Linkage_{it} + \Sigma_j \lambda_j Controls_{ijt} + \Sigma_j Province + \Sigma_j Ind + \Sigma_j Year + \varepsilon_{it} \quad (2)$$

$$TFP_{it} = \alpha_0 + \alpha_1 Linkage_{it} + \alpha_2 Linkage_{it}^2 + \Sigma_j \lambda_j Controls_{ijt} + \Sigma_j Province + \Sigma_j Ind + \Sigma_j Year + \varepsilon_{it} \quad (3)$$

The paper focuses on Chinese A-share listed companies from 2007 to 2020 as the research subjects and collects microdata related to company annual reports, return on assets, debt ratios, and firm size. Prior to data analysis, the following preprocessing steps were undertaken to ensure data validity. Companies categorized as ST, PT , and those from the financial industry within the sample period were removed. Only companies with a continuous and uninterrupted data record of at least 5 years were retained. This step helps ensure a robust dataset for analysis. All continuous variables were subjected to trimming at the 1st and 99th percentiles. This process eliminates extreme values that could skew the analysis. The dataset comprises a total of 3,042 listed companies, and the data used in this study is sourced from the Guotai An database (CSMAR).

Table 1. Benchmark Regression and Robust Test

Variables	(1)	(2)	(3)	(4)	(5)
Linkage	0.0773*** (0.0115)	-1.0901*** (-15.2520)	-0.3629** (-2.3017)	0.0572 (1.5476)	-0.3629** (-2.3017)
Linkage2		0.1960*** (16.5504)	0.0645*** (2.8726)	0.0645*** (2.8726)	0.0645*** (2.8726)
lnsize			0.5506*** (38.9441)	0.5506*** (38.9441)	0.5506*** (38.9441)
lnage			0.1220** (2.4036)	0.1220** (2.4036)	0.1220** (2.4036)
liquid			1.1877*** (18.2102)	1.1877*** (18.2102)	1.1877*** (18.2102)
roa			0.3835*** (3.9685)	0.3835*** (3.9685)	0.3835*** (3.9685)
leverage			-0.0536** (-2.3317)	-0.0536** (-2.3317)	-0.0536** (-2.3317)
share			0.1186* (1.7436)	0.1186* (1.7436)	0.1186* (1.7436)
cash			-0.3701*** (-5.6084)	-0.3701*** (-5.6084)	-0.3701*** (-5.6084)
bm			-0.2874*** (-6.5058)	-0.2874*** (-6.5058)	-0.2874*** (-6.5058)
Constant	14.6690*** (0.0428)	16.2916*** (152.2838)	2.3867*** (5.2194)	1.8892*** (4.7526)	2.3867*** (5.2194)
Other Variables	NO	NO	YES	YES	YES
Observations	23,135	23,135	23,135	23,135	23,135

Note: ***p＜0.01，**p＜0.05，*p＜0.1，Robust standard error values are in brackets.

3. Results and Discussion

3.1. Benchmark Regression and Robustness Test

Firstly, this paper establishes linear regression model and quadratic nonlinear regression model to analyze the influence of industrial chain correlation on the total factor productivity of enterprises. The results are shown in Table 1. Column (1) and column (2) are linear and quadratic nonlinear regression models without any control variables. It is observed that the impact of industrial chain linkage on enterprise total factor productivity follows a "U"-shaped distribution. In column (2), when control variables and fixed effects for provinces, years, and industries are added, it further confirms the "U"-shaped distribution of the impact of industrial chain linkage on enterprise total factor productivity. When the degree of industrial chain linkage is low, increasing it tends to inhibit the improvement of total factor productivity. However, when industrial chain linkage reaches a certain level, further increasing it promotes an increase in total factor productivity. The reason for the inhibition of total factor productivity in industries with low linkage may be due to the relatively limited flow of funds, information dissemination, and talent training between industries during periods of low cooperation levels. This results in weaker collaborative capabilities between industries, leading to increased operating costs for enterprises and subsequently lowering total factor productivity.

In quadratic nonlinear regression, the linear term and quadratic term are prone to multicollinearity problems. To test for multicollinearity in the model presented in Table 1, column (3), the VIF value is found to be 16.42, indicating a significant multicollinearity issue. Therefore, the core explanatory variable "linkage" and its quadratic term are centralized, and the regression is conducted on the centralized variables. The results in column (4) show that the VIF value decreases to 3.71, indicating the absence of multicollinearity issues. Furthermore, the coefficient of the quadratic term for industrial chain linkage remains significantly positive. This suggests that as industrial chain linkage strengthens, enterprise total factor productivity first continuously decreases to a minimum before gradually rising.Upon examining the fixed-effects model in column (3), it is found that there is heteroscedasticity present. To address this, robust standard errors are used for the regression, as shown in column (5). The study finds that the conclusions from this regression remain consistent with the previous findings, thus enhancing the robustness of the conclusions.

3.2. Analysis of the Heterogeneity

Based on differences in enterprise ownership, companies can be classified into state-owned enterprises and non-state-owned enterprises. To explore the variations in the impact of industrial chain linkage on total factor productivity (TFP) for different ownership types, two separate quadratic non-linear regression analyses were conducted for these two categories. The results are presented in Table 2, columns (1) and (2). It is found that the improvement of industrial chain correlation still has a "U" shape on the total factor productivity of state-owned enterprises, while the impact on non-state-owned enterprises is not significant. The reason is that state-owned enterprises, as the core enterprises in the industrial chain, are the main force to reshape the industrial pattern and promote industrial synergy. The premise of promoting the modernization of industrial chain is the improvement of industrial basic capacity. Currently, the incomplete configuration of industrial infrastructure inhibits the effectiveness of industrial chain linkage, resulting in an initial reduction in TFP for state-owned enterprises. As industrial chain linkage intensifies, state-owned enterprises' ability to connect supply and demand information among themselves improves, reducing transaction costs and thereby enhancing their TFP. In contrast, non-state-owned enterprises are often in a more passive position within the industrial chain, with weaker influence in terms of scale and market power. Their role in collaborative development is less defined, often limited to short-term cooperative arrangements. Consequently, the increased industrial chain linkage does not significantly boost the TFP of non-state-owned enterprises.

Table 2. Heterogeneity Test Results

Variables	(1) State-owned Enterprise	(2) Non-state-owned enterprises	(3) Labor-intensive enterprises	(4) Technology-intensive enterprises	(5) Capital-intensive enterprises
Linkage	-0.384***	-0.119	-0.293***	0.365***	-0.460***
	(0.072)	(-0.482)	(0.107)	(0.091)	(0.074)
$Linkage^2$	0.063***	0.025	0.056***	-0.063***	0.068***
	(0.012)	(0.724)	(0.019)	(0.014)	(0.012)
Year	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes
Ind	Yes	Yes	Yes	Yes	Yes
Observations	10,853	11,959	5,552	8,150	13,449
R^2	0.5773	0.5954	0.5339	0.6221	0.6247
Intergroup Regression Coefficient Difference Test	$chi^2(1)=13.76$			$chi^2(2)=33.20$	
	$Prob>chi^2=0.0002$			$Prob>chi^2=0.0000$	

Note: ***p＜0.01，**p＜0.05，*p＜0.1，Robust standard error values are in brackets.

Additionally, the study explores the impact of industrial chain linkage on TFP under different levels of factor intensity. Enterprises are grouped based on their factor intensity, including labor-intensive, technology-intensive, and capital-intensive categories. The results are presented in Table 2, columns (3) to (5). It can be seen that the improvement of industrial chain correlation still has a "U" shape on the total factor productivity of labor-intensive and capital-intensive enterprises, and an inverted "U" shape on the total factor productivity of technology-intensive enterprises. For labor-intensive enterprises, in the early stage of the low level of industrial chain coordination, promoting inter-industry integration will weaken their original advantages, and the competitive pressure and production costs will continue to increase, thus inhibiting the improvement of total factor productivity. In the period of high level of industrial chain correlation, labor-intensive enterprises gradually adapt, which has strong convenience and synergy in supply chain, which can effectively reduce procurement costs and coordination costs and improve total factor productivity. Technology-intensive enterprises, on the other hand, can leverage their technical advantages and improve resource integration capabilities during the continuous integration of the industrial chain, boosting innovation and TFP. However, when industrial chain collaboration reaches a certain threshold, increased competition and resource competition among enterprises can lead to increased capital investment, suppressing TFP for technology-intensive enterprises. Capital-intensive enterprises have many inputs, high technical complexity, obvious economies of scale, no complete standardization and centralized production. With the improvement of industrial chain correlation, the industrial structure has gradually changed, resulting in a large number of cross-organizational production connection costs, thus reducing the total factor productivity of capital-intensive enterprises. When the industrial chain integration matures, reduced trade costs, significant market scale effects, and more standardized structural division of labor facilitate TFP improvement for capital-intensive enterprises.

3.3. Quantile Regression

Building on panel data analysis, this study employs quantile regression to investigate the relationship between enterprise total factor productivity (TFP) and industrial linkage. In order to gain a more detailed understanding of enterprises with different levels of TFP and to determine whether the impact of industrial linkage varies among them, the study conducts quantile regression. The objective is to identify distinct characteristics and differences in how industrial linkage affects TFP for enterprises with varying levels of TFP.

For the analysis conducted in this study, the initial approach is to construct a model that examines the overall effect of industrial linkage on enterprise TFP, considering the entire sample of enterprises. The model is formulated as follows:

$$Q_{\tau}(TFP_{it}|Linkage_{it}, x_{it}) = \alpha + \beta_{1\tau}Linkage + c_{ijt}\gamma_{\tau} \tag{4}$$

The empirical results reveal significant variations in the coefficients of industrial linkage concerning different levels of total factor productivity (TFP). These differences are evident across various percentiles and differ notably from the estimates obtained through ordinary least squares (OLS) regression. Specifically, the core explanatory variable, industrial linkage, exhibits negative coefficients at percentiles ranging from 10% to 40%, whereas it becomes positive at percentiles ranging from 50% to 90%. Furthermore, the coefficients for industrial linkage are statistically significant at the 5% confidence level across all percentiles except for the 50% percentile, where it is not significant. The results are summarized in Table 3 and Table 4.

Table 3. Quantile regression empirical results 0-40%.

	(1) 0LS	(2) 10%	(3) 20%	(4) 30%	(5) 40%
Linkage	-0.024***	-0.239***	-0.189***	-0.124***	-0.057***
	(-4.25)	(-25.03)	(-23.56)	(-18.81)	(-8.92)
lnSize	0.608***	0.602***	0.604***	0.596***	0.593***
	(191.28)	(111.06)	(132.29)	(159.42)	(163.92)
lnAge	0.049***	0.132***	0.090***	0.108***	0.088***
	(4.66)	(7.31)	(5.92)	(8.67)	(7.30)
Liquid	1.415***	1.706***	1.524***	1.420***	1.351***
	(69.63)	(49.20)	(52.17)	(59.38)	(58.39)
ROA	0.510***	0.386***	0.579***	0.950***	1.176***
	(13.63)	(6.04)	(10.76)	(21.56)	(27.57)
Leverage	0.146***	0.418***	0.443***	0.460***	0.465***
	(10.97)	(18.40)	(23.12)	(29.31)	(30.67)
Share	0.143***	0.094**	0.109***	0.110***	0.090***
	(5.20)	(2.00)	(2.76)	(3.40)	(2.87)
Cash	-0.223***	-0.437***	-0.308***	-0.261***	-0.264***
	(-6.19)	(-7.10)	(-5.93)	(-6.15)	(-6.43)
BM	-0.218***	-0.013	-0.036	-0.056*	-0.052*
	(-7.95)	(-0.27)	(-0.91)	(-1.73)	(-1.67)
Cons	0.609***	1.620***	1.335***	1.107***	0.900***
	(8.19)	(12.76)	(12.48)	(12.64)	(10.62)

Note: ***p＜0.01，**p＜0.05，*p＜0.1，Robust standard error values are in brackets.

As a result, when enterprises have high TFP levels (positioned in higher percentiles), an increase in industrial linkage is advantageous for their development. Conversely, for enterprises with low TFP levels (positioned in lower percentiles), an increase in industrial linkage may have adverse effects. This can be attributed to intensified market competition and internal/external conflicts that arise during the process of industrial integration. Enterprises face higher costs associated with managing these frictions, and those with lower TFP struggle to enhance critical development factors such as scale efficiency and technological innovation. This impedes their ability to expand operations and creates substantial challenges for their business.In contrast, enterprises with higher TFP levels have greater capabilities to address coordination issues and absorb sunk costs effectively. In the long term, increased industrial linkage strengthens inter-enterprise connections, enabling them to engage in continuous research and development of new technologies, expand their business reach, extend services up and down the supply chain, and produce products that closely align with customer demands. This approach allows them to acquire market information more effectively and enhance their responsiveness to market changes.

Table 4. Quantile regression empirical results 50-90%.

	(6)	(7)	(8)	(9)	(10)
	50%	60%	70%	80%	90%
Linkage	0.002	0.035***	0.065***	0.104***	0.146***
	(0.33)	(5.96)	(10.21)	(14.19)	(15.97)
lnSize	0.596***	0.598***	0.602***	0.611***	0.629***
	(167.26)	(177.40)	(166.68)	(146.11)	(120.93)
lnAge	0.070***	0.046***	0.027**	0.017	-0.025
	(5.89)	(4.12)	(2.28)	(1.19)	(-1.44)
Liquid	1.345***	1.322***	1.353***	1.363***	1.414***
	(59.02)	(61.33)	(58.49)	(50.95)	(42.49)
ROA	1.358***	1.598***	1.738***	1.805***	1.699***
	(32.34)	(40.23)	(40.78)	(36.63)	(27.70)
Leverage	0.391***	0.356***	0.275***	0.213***	0.108***
	(26.16)	(25.18)	(18.16)	(12.13)	(4.96)
Share	0.063**	0.062**	0.107***	0.090**	0.093**
	(2.03)	(2.12)	(3.41)	(2.48)	(2.07)
Cash	-0.302***	-0.339***	-0.412***	-0.422***	-0.394***
	(-7.45)	(-8.86)	(-10.02)	(-8.89)	(-6.66)
BM	-0.075**	-0.093***	-0.137***	-0.147***	-0.259***
	(-2.42)	(-3.18)	(-4.39)	(-4.05)	(-5.75)
Cons	0.619***	0.439***	0.175**	-0.236**	-0.846***
	(7.41)	(5.56)	(2.07)	(-2.41)	(-6.94)

Note: ***p＜0.01，**p＜0.05，*p＜0.1，Robust standard error values are in brackets.

4. Conclusion

To sum up, this study has explored the specific impact of industrial linkage on enterprise total factor productivity (TFP) using various methods, including benchmark regression, robustness tests, heterogeneity analysis, and quantile regression. Several conclusions have been drawn: the influence of industrial linkage on enterprise TFP follows a "U"-shaped distribution, as evidenced by regression results that considered control variables and fixed effects. Addressing issues like multicollinearity and heteroscedasticity, the findings remained consistent with those from the benchmark regression, enhancing the robustness of the conclusions; Differentiating enterprises based on ownership nature and factor intensity, it was observed that the impact of increased industrial linkage is more significant for state-owned enterprises. For labor-intensive and capital-intensive enterprises, industrial linkage still exhibits a "U"-shaped effect on TFP, while for technology-intensive enterprises, it takes an inverse "U"-shaped form; Panel quantile regression analysis indicates that when enterprise TFP is positioned in higher percentiles, an increase in industrial linkage is favorable for its development. Conversely, when TFP is positioned in lower percentiles, increased industrial linkage may have adverse effects. In the course of conducting this research, certain limitations and challenges were encountered. The measurement of industrial linkage was based on input-output tables released by the National Bureau of Statistics. These tables are not published every year, which may lead to data gaps. Although efforts were made to address this issue by utilizing existing research, there is still a possibility of deviations from actual conditions. Future research can focus on developing more precise measurement methods. Additionally, the study analyzed the impact of industrial linkage between manufacturing and service sectors on TFP without delving deeply into the underlying mechanisms. It is possible that there are related transmission mechanisms at play, which should be explored in future research to better understand how industrial linkage influences TFP. Despite these limitations, this study contributes valuable insights into the complex relationship between industrial linkage and enterprise TFP, with implications for different ownership structures and factor intensities. Further research can build upon these findings and explore the potential transmission mechanisms driving the impact of industrial linkage on TFP.

References

[1] Yu D, Zhang Y. Manufacturing-driven or service-driven? -empirical research based on the industrial correlation effect in China. Financial Research, 2015, 6: 19-31.

[2] Deng Z, Zhang K. Why does the spatial differentiation of China's economic growth exist? -An explanation of spatial economics. Economic Research, 2020, 4: 20-36.

[3] Han J, Gao Y. Calculation of industrial correlation effect of digital economy development in China province. Quantitative economy, technical and economic research, 2022, 4: 45-66.

[4] Wen W, Wang Q. Identification of Key Sectors and Key Provinces at the View of CO2 Reduction and Economic Growth in China: Linkage Analyses Based on the MRIO Model. Ecological Indicators, 2019, 96: 1-15.

[5] Qi Y, Zhang R. An empirical study on the impact of financial asset allocation on enterprise value. Finance and Trade Economy, 2018, 39(05): 38-52.

[6] Liu Z, Ling Y. Structural transformation, total factor productivity and high-quality development. Management World, 2020, 36(07): 15-29.

[7] Sun X, Wang Y. The impact of enterprise scale on productivity and its differences-an empirical study from the micro-data of industrial enterprises. China Industrial Economy, 2014, 5: 57-69.

[8] Fernandes A M, Paunov C. Foreign direct investment in services and manufacturing productivity growth: evidence for Chile. Journal of Development Economics, 2008, 97(2): 321.

[9] Chen J, Liu Y, Zou M. The improvement of urban production efficiency under industrial synergy-based on the background of integrating innovation and development power transformation. Journal of Zhejiang University (Humanities and Social Sciences Edition), 2016, 46(03): 150-163.

[10] Feng Y, Ma J, Hu Q. Empirical study on the impact of industrial integration development on agricultural total factor productivity. Statistics and decision, 2020, 36(10): 87-91.

[11] Liu Q, Ma Y, Xu S. Does the development of digital economy improve the efficiency of China's green economy. China population resources and environment, 2022, 32(03): 72-85.

[12] Levinsohn J, Petrin A. Estimating Production Functions Using Inputs to Control for Unobservable. Review of Economic Studies, 2003, 70(2): 317-341.

[13] Lu X, Lian Y. Total factor productivity estimation of industrial enterprises in China: 1999-2007. Economics (Quarterly), 2012, 11(02): 541-558.

[14] Yuan C, Xiao T, Geng C. Digital transformation and enterprise division of labor: specialization or vertical integration. China Industrial Economy, 2021, 9: 137-155.

[15] Huang D, Xie H, Meng X, et al. Digital transformation and enterprise value-empirical evidence based on text analysis method. Economist, 2021, 12: 41-51.