Qin, S., & Li, Y. (2023). Does Intelligence Improve the Total Factor Productivity of China's Manufacturing Industry? *Asian Economics Letters*, *6*(Early View). https://doi.org/10.46557/001c.39801

Peer-reviewed research

Does Intelligence Improve the Total Factor Productivity of China's Manufacturing Industry?

Shuai Qin[1], Yaya Li[1a]

[1] Jiangsu University, China

Keywords: Intelligence, Total factor productivity, Manufacturing industry, Heterogeneity, JEL: O14 O32

https://doi.org/10.46557/001c.39801

Asian Economics Letters

Vol. 6, Issue Early View, 2025

This paper empirically tests the impact of intelligence on the total factor productivity of China's manufacturing industry through a double fixed-effect model. The results show that the current process of *intelligentization* can significantly improve total factor productivity in China's manufacturing industry. Specifically, intelligence significantly promotes total factor productivity in the eastern region, but does not significantly impact total factor productivity in central and western regions.

I. Introduction

Over the past 40 years of reform and opening up, China's manufacturing industry has achieved considerable development in scale and quality by relying on its comparative advantage in labor. However, with the advancement of science and technology and social changes, China's demographic dividend has gradually disappeared, and labor prices no longer have a comparative advantage, and faced with practical problems, such as an aging population and overcapacity, factor input has a diminishing output. Therefore, facing bottlenecks in internal development and a turbulent external environment, China's manufacturing industry is in urgent need of intelligent transformation to achieve a new round of high-speed and high-quality growth.

At present, the research on the traditional determinants of total factor productivity (*TFP*) is relatively mature and is mostly from the perspectives of R&D, foreign direct investment, and urbanization (Ashraf et al., 2016; Kumar & Kober, 2012; Tsamadias et al., 2019). Some studies have investigated the impact of technological innovation on *TFP* from the perspectives of Internet technology, information and communications technology (ICT), and industrial robots (Brynjolfsson & Hitt, 1996; Cette et al., 2021; Kallal et al., 2021) but their conclusions are not uniform. Some scholars believe that technological innovation has improved *TFP* (Venturini, 2022), while others have concluded the opposite (Jorgenson et al., 2008). With the advent of Industry 4.0, intelligent manufacturing continues to penetrate all aspects of production, and intelligence is bound to have a huge impact on production practices. The existing literature has confirmed that intelligence has an important role in the labor force, especially in terms of labor substitution and polarization (Acemoglu & Autor, 2011; Autor et al., 2006; Autor & Salomons, 2018). Intelligence also has a positive role in energy saving, at the same time (Hao & Wu, 2021; Lan & Wen, 2021). Nevertheless, only a few studies have explored the impact of intelligence on *TFP*. Therefore, this paper explores the effect of intelligence on *TFP*. We construct and measure intelligence from a systematic perspective to avoid the subjectivity caused by the use of a single indicator in previous studies. Finally, we obtain more objective estimation results, which enrich the literature on *TFP* determinants.

The contribution of this paper is to select multiple indicators and combine the entropy method to comprehensively measure the level of intelligence in China, and to empirically test the actual impact of intelligence on the *TFP* of the manufacturing industry, expand related research on intelligence, and provide evidence for the planning and development of China's manufacturing industry.

II. Data and Method

A. Model

To test the impact of intelligence on the *TFP* of China's manufacturing industry, the following model is constructed:

$$TFP_{\mathrm{it}} = \alpha + \beta ID_{\mathrm{it}} + \beta_1 X_{it} + \mu_i + v_t + \varepsilon_{it} \qquad (1.1)$$

Where i represents the province and t represents the year; TFP_{it} represents the total factor productivity, ID_{it} represents the level of intelligence, X_{it} is a vector of control variables; μ_i and v_t represent the individual and time fixed effects, respectively, to control other potential determinants of *TFP* and time trends, and ε_{it} represents the random error term.

a Corresponding author email: yizhi19881107@126.com

Table 1. Intelligent comprehensive indicators

First-level indicators	Specific indicators	Unit
Intelligent technical	Investment in fixed assets of intelligent facilities	Million (RMB)
Intelligent application	Number of patent applications in the electronics and communication equipment manufacturing industry	Item
Smart Benefit	Profits of Electronic and Communication Equipment Manufacturing	Billion (RMB)

Notes: This table reports the index system for measuring the degree of intelligence. The first column is the first-level index; the second column is the specific quantitative index; the third column is the unit of each variable.

B. Variables

The explained variable is the manufacturing *TFP* of each region. This paper follows Wang et al. (2021) and uses the Malmquist index, a non-parametric data envelopment method, to calculate *TFP*. Among them, based on the index, the specific input indicators select the net value of fixed assets and the average number of all employees in each region over the years, and the output indicator selects the total output value of the manufacturing industry in each region.

The core explanatory variable is the degree of intelligence (*ID*). We choose comprehensive indicators to describe the degree of regional intelligence. This paper takes the manufacturing industry as an example to explore the impact of intelligence on *TFP*. Therefore, the selection of indicators needs to integrate the characteristics and actual conditions of the manufacturing industry. Specifically, we investigate intelligence from three levels, namely intelligent technical indicators, intelligent application indicators, and intelligent benefit indicators. As shown in Table 1, the investment in fixed assets of intelligent facilities, the number of patent applications in the electronic communication equipment manufacturing industry, and the profit of the electronic and communication equipment manufacturing industry are selected as the characterization indicators, and the final intelligence score is calculated by using the entropy method, and used as an indicator of the level of intelligence.

Control variables. (1) Foreign direct investment (*FDI*): the development of China's early manufacturing industry was supported by *FDI*, and, at the same time, it relied on the two-way spillover effect of *FDI* to obtain technological progress. This affected the overall development of the manufacturing industry. This paper multiplies the *FDI* value in a given year by the average exchange rate of that year and divides the resulting value by the GDP of that year, to measure *FDI*. (2) Government fiscal expenditure (*GOV*): existing studies have shown that *GOV* plays an important role in industrial development, especially for emerging industries and industries in transition. This paper uses the ratio of government fiscal expenditure to GDP to measure *GOV*. (3) Human capital (*HC*): this is measured in this paper using the average years of education. (4) The level of economic development (*PGDP*): the higher the level of economic development, the more priority will be given to the promotion of related applications of intelligence. We measure the level of regional economic development by the regional GDP per capita. (5) Industrial structure (*IND*): the industrial structure will affect the development and transformation directions of the regional industry, especially the continuous improvement of the secondary and tertiary industries. We measure the industrial structure as the proportion of the secondary and tertiary industries.

C. Data Sources

The data used in this article are all from China Statistical Yearbook, China Labor Statistical Yearbook, and China High-tech Industry Statistical Yearbook. Our dataset is constructed by considering that the development of China's ICT industry is relatively lagging, and by considering the continuity and availability of data in the relevant statistical yearbooks. Our dataset is a panel of 30 provinces in China from 2000 to 2019.

III. Empirical Results

This paper uses a double fixed-effect model, which controls for region and time fixed effects, to test the impact of intelligence on China's manufacturing *TFP*. Table 2 reports the empirical test results. The results show that the coefficient of intelligence is 0.014 and is statistically significant at the 1% level, indicating that intelligence promotes *TFP* growth in China's manufacturing industry. In addition, the regression coefficient of intelligence on *TFP* does not change in direction and size (the coefficient does not significantly fluctuate), after adding control variables in sequence, indicating that our estimates are robust.

In fact, the continuous development of intelligent technology and technological progress, such as the continuous decline in the price of ICT products, will stimulate the continuous increase of social-related intelligent investment, which will in turn expand per capita capital, and ultimately increase the productivity of society. At the same time, intelligent technology has the attributes of general-purpose technology and, hence, has a spillover effect (Lipsey et al., 2005); its impact on the economy is not limited to a certain industry. Over time, intelligent technology has spread to the whole Chinese industry to varying degrees. In order to adapt to the new technological environment and to changes in production conditions, the relevant organizational structure and business processes of enterprises will have to be adjusted and changed. This kind of change is different from the application of intelligent equipment, which directly affects production efficiency, but indirectly improves production efficiency by changing the intangible characteristics of enterprises, such as product quality, product variety, and service response speed. While improving production efficiency, intelligence has also changed the organizational structure and business processes of enterprises. Different from mechanization, intelligence is not a simple replacement for programmed production tasks, but

Table 2. Benchmark regression results

Variables	*TFP*	*TFP*	*TFP*	*TFP*	*TFP*	*TFP*
ID	0.012***	0.012***	0.013***	0.014***	0.015***	0.014***
	(3.25)	(3.30)	(3.52)	(3.60)	(3.79)	(3.73)
FDI		-0.241	-0.219	-0.250	-0.093	-0.133
		(-0.71)	(-0.64)	(-0.73)	(-0.26)	(-0.37)
GOV			-0.195	-0.213*	-0.240*	-0.244*
			(-1.56)	(-1.69)	(-1.89)	(-1.93)
HC				-0.024	-0.018	-0.016
				(-1.22)	(-0.91)	(-0.79)
PGDP					-0.047	-0.075**
					(-1.60)	(-1.99)
IND						0.154
						(1.18)
Constant	1.073***	1.081***	1.111***	1.308***	1.692***	1.862***
	(74.63)	(59.34)	(42.16)	(8.04)	(5.84)	(5.76)
Prov FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
R-squared	0.115	0.116	0.120	0.123	0.128	0.131

Notes: This table reports the regression results of the effect of intelligence on TFP. In order to obtain robust estimation results, the regression results after gradually adding control variables are specifically reported in the table. Finally, "*", "**", and "***" represent 10%, 5%, and 1% significance levels, respectively.

improves the comprehensive management ability and efficiency of enterprises, and gives enterprises higher dynamic capabilities to optimize their own factor input and improve the marginal output of factors.

For the regional regression results (Table 3), only the eastern region results are statistically significant. Thus, intelligence promotes *TFP* growth in the eastern region, but does not impact *TFP* growth in the central and western regions. The results show that there are regional differences in the effect of intelligence on *TFP* in China. The reason for the regional heterogeneity may lie in the differences in the level of regional intelligence. Figure 1 shows the trend chart of different regions based on intelligence. It can be seen that the intelligence levels of the three regions are relatively similar in the early stage of the sample. Compared with other regions, the eastern region has better infrastructure, human capital, and economic conditions, which can rapidly promote intelligent equipment and realize intelligent industrial production. The central and western regions gradually lag behind the eastern region in terms of intelligence level, as the Chinese economy develops; the gap in intelligence level between the eastern and central/western regions has become larger over time, explaining why intelligence has no impact on *TFP* in the central and western regions.

IV. Conclusion

Intelligent transformation is an inevitable direction for the development of the manufacturing industry. At present, there is limited research on the impact of intelligence on *TFP* in the context of China. This paper empirically tests whether intelligence has improved the *TFP* of China's manufacturing industry, by constructing a provincial panel dataset. The regression results show that the continuous popularization and deepening of intelligence has improved the *TFP* of China's manufacturing industry. The results of the regional heterogeneity test show that intelligence only significantly promotes *TFP* in the more developed eastern region, while it has no impact on *TFP* in the central and western regions.

Submitted: January 17, 2022 AEST. Accepted: March 16, 2022 AEST. Published: January 31, 2023 AEST.

Table 3. Heterogeneous regression results

Variables	Nationwide	Eastern	Central	Western
ID	0.014***	0.024***	0.003	-0.001
	(3.73)	(2.94)	(0.76)	(-0.32)
FDI	-0.133	3.676*	-0.033	-0.486
	(-0.37)	(1.93)	(-0.15)	(-0.77)
GOV	-0.244*	0.408	-0.321**	-0.061
	(-1.93)	(1.05)	(-2.60)	(-0.19)
HC	-0.016	-0.066	0.008	0.028
	(-0.79)	(-1.19)	(0.57)	(1.41)
PGDP	-0.075**	0.127	-0.056*	-0.039
	(-1.99)	(0.95)	(-1.80)	(-0.71)
IND	0.154	0.410	0.090	0.021
	(1.18)	(1.02)	(0.99)	(0.16)
Constant	1.862***	0.282	1.519***	1.123**
	(5.76)	(0.23)	(5.39)	(2.17)
Prov FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R-squared	0.131	0.229	0.234	0.438

Notes: This table reports the regression results of the impact of intelligence on TFP in different regions. Specifically, referring to the regional division standards of the National Bureau of Statistics of China, the research samples are divided into eastern, central and western regions. Finally, "*", "**", and "***" represent 10%, 5%, and 1% significance levels, respectively.

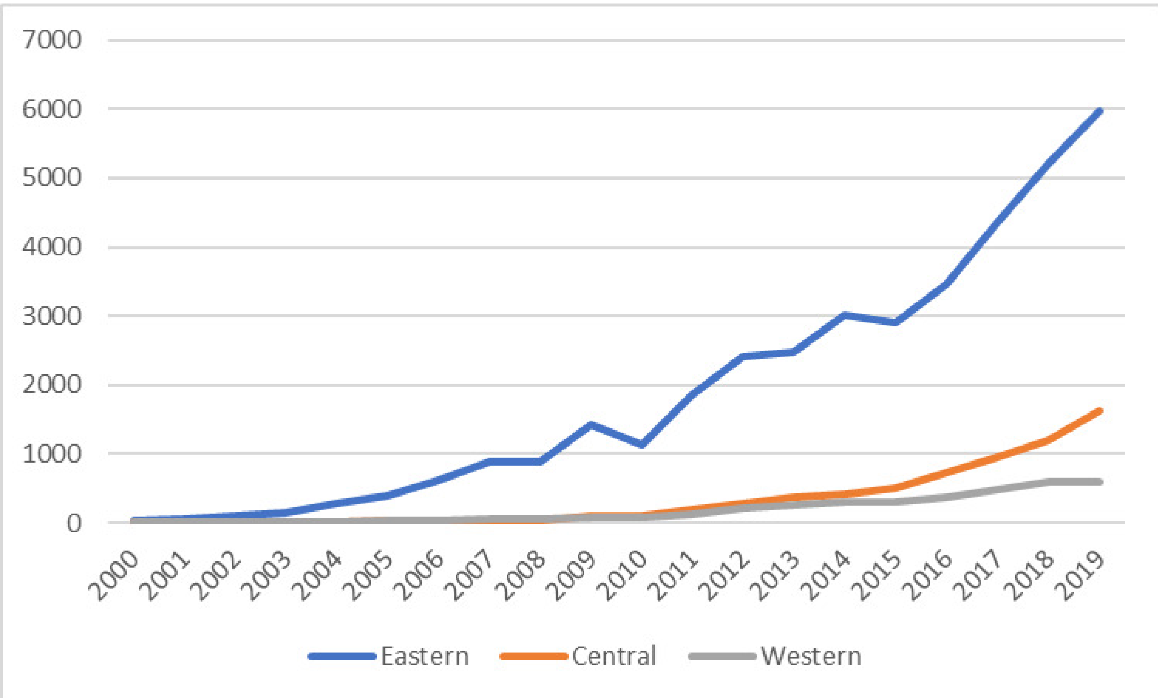

Figure 1. Trends on the intelligence degree (*ID*) in different regions.

Source: Calculated from the data shown in Table 1 above.

References

Acemoglu, D., & Autor, D. H. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics* (Vol. 4, pp. 1043–1171). Elsevier. https://doi.org/10.1016/s0169-7218(11)02410-5

Ashraf, A., Herzer, D., & Nunnenkamp, P. (2016). The effects of Greenfield FDI and cross-border M&As on total factor productivity. *The World Economy*, *39*(11), 1728–1755. https://doi.org/10.1111/twec.12321

Autor, D. H., Katz, L. F., & Kearney, M. S. (2006). The Polarization of the U.S. Labor Market. *American Economic Review*, *96*(2), 189–194. https://doi.org/10.1257/000282806777212620

Autor, D. H., & Salomons, A. (2018). *Is automation labor-displacing? Productivity growth, employment, and the labor share* (No. w24871). National Bureau of Economic Research. https://doi.org/10.3386/w24871

Brynjolfsson, E., & Hitt, L. (1996). Paradox lost? Firm-level evidence on the returns to information systems spending. *Management Science*, *42*(4), 541–558. https://doi.org/10.1287/mnsc.42.4.541

Cette, G., Devillard, A., & Spiezia, V. (2021). The contribution of robots to productivity growth in 30 OECD countries over 1975–2019. *Economics Letters*, *200*, 109762. https://doi.org/10.1016/j.econlet.2021.109762

Hao, Y., & Wu, H. (2021). The Role of Internet Development on Energy Intensity in China-Evidence From a Spatial Econometric Analysis. *Asian Economics Letters*, *1*(1), 1–6.

Jorgenson, D. W., Ho, M. S., & Stiroh, K. J. (2008). A retrospective look at the US productivity growth resurgence. *Journal of Economic Perspectives*, *22*(1), 3–24. https://doi.org/10.1257/jep.22.1.3

Kallal, R., Haddaji, A., & Ftiti, Z. (2021). ICT diffusion and economic growth: Evidence from the sectorial analysis of a periphery country. *Technological Forecasting and Social Change*, *162*, 120403. https://doi.org/10.1016/j.techfore.2020.120403

Kumar, A., & Kober, B. (2012). Urbanization, human capital, and cross-country productivity differences. *Economics Letters*, *117*(1), 14–17. https://doi.org/10.1016/j.econlet.2012.04.072

Lan, J., & Wen, H. (2021). Industrial Digitalization and Energy Intensity: Evidence from China's Manufacturing Sector. *Energy Research Letters*, *2*(2), 25733. https://doi.org/10.46557/001c.25733

Lipsey, R. G., Carlaw, K. I., & Bekar, C. T. (2005). *Economic transformations: General purpose technologies and long-term economic growth*. OUP Oxford.

Tsamadias, C., Pegkas, P., Mamatzakis, E., & Staikouras, C. (2019). Does R&D, human capital and FDI matter for TFP in OECD countries? *Economics of Innovation and New Technology*, *28*(4), 386–406. https://doi.org/10.1080/10438599.2018.1502394

Venturini, F. (2022). Intelligent technologies and productivity spillovers: Evidence from the Fourth Industrial Revolution. *Journal of Economic Behavior & Organization*, *194*, 220–243. https://doi.org/10.1016/j.jebo.2021.12.018

Wang, X., Wang, Y., & Lan, Y. (2021). Measuring the bias of technical change of industrial energy and environment productivity in China: A global DEA-Malmquist productivity approach. *Environmental Science and Pollution Research*, *28*(31), 1–16. https://doi.org/10.1007/s11356-021-13128-w