How Does Undertaking Industrial Transfer Demonstration Zone Affect Firm-Level Total Factor Productivity? Evidence from China

Zixuan Liu[1] and Che Su[2,*]

[1]School of Economics, Xinjiang University of Finance and Economics, Xinjiang 830012, China
[2]School of International Law, Shanghai University of Political Science and Law, Shanghai 201701, China
Email: irenelzx@163.com(Z.X.L); chesu076@gmail.com (C.S.)
*Corresponding author
Manuscript received March 5, 2025; accepted June 2, 2025; published September 19, 2025.

***Abstract*—A two-way fixed effects model with the approach of multi-period Difference-in-Differences (DID) is applied to the annual panel data of the Chinese listed firms from 2003 to 2020 to study the effect of the undertaking industrial transfer demonstration zone on firm-level Total Factor Productivity (TFP). It is founded that firm-level TFP increases for the treated firms during policy intervention years in comparison to firms in the control group. Before proceeding to estimating the result, a parallel trends test is conducted and it is passed. The dynamic effect test show that the treatment effect becomes significant and shows a trend of strengthening over time after the policy intervention. The placebo test suggests that the estimated results are robust and it is almost impossible for the non-observed area characteristics to affect the estimated results. Four conducted robustness tests, including changing dependent variable, elimination of outliers' effects, changing level of clustering in standard errors and changing policy intervention year, has proved the robustness of the result.**

***Keywords*—industrial transfer demonstration zonefirst term, total factor productivity, robustness tests, two-way fixed effects model, difference-in-differences**

I. Introduction

Following China's economic reform, eastern and southern coastal regions gained competitive advantages in attracting industrial transfers through strategic locational advantages, demographic dividends, and policy support. This facilitated sustained economic expansion in eastern regions, though accompanied by urban overcrowding contrasted with sparser populations in central/western cities (Xiang *et al.*, 2020). Responding to rising factor costs, resource competition, and declining competitiveness of traditional industries in eastern regions, the government redirected policy focus to central/western areas featuring lower production costs, abundant natural resources, improving infrastructure, and untapped market potential.

To stimulate industrial upgrading and regional rebalancing, China established Undertaking Industrial Transfer Demonstration Zones (UITDZ) in central and western regions since 2010. By 2019, 11 zones spanned 13 provinces and 36 cities, offering land use incentives and tax concessions to relocating firms. These measures aimed to catalyze factor reallocation and regional development.

Enterprise relocation under UITDZ contributed to substantial GDP growth: China's 285 cities saw real GDP expand from ¥32.5 trillion to ¥51.4 trillion (2010–2015), averaging 11.64% annual growth, while 28 UITDZ cities outperformed with 13.8% growth (He *et al.*, 2019). This indicates the policy's effectiveness in accelerating regional economic convergence.

The policy seeks to leverage agglomeration externalities by enhancing industrial scale and sophistication. However, persistent gaps in innovation capacity, technology, and human capital between eastern and central/western regions warrant investigation.

Despite UITDZ's macroeconomic impacts, firm-level productivity effects remain underexplored. This study addresses this gap by employing multi-period Difference-in-Differences (DID) analysis on 2003-2020 panel data of listed firms, departing from prior province-level TFP studies.

II. Literature Review

Yuan *et al.* (2017) examined three agglomeration externalities—Marshall-Arrow-Romer (MAR), Jacobs, and Porter—on scale and technical efficiency. MAR externalities enhance technical efficiency through technological acceleration and pure technical efficiency gains, whereas Jacobs externalities improve technical processes and scale efficiency but reduce pure technical efficiency. Conversely, Porter externalities reduce scale efficiency while negatively affecting technical processes and efficiency. Liu and Wang (2010) identified strong MAR and Jacobs spillover effects in high-tech industrial agglomeration. These divergent impacts have generated mixed conclusions on agglomeration economies' effects across firm-, industry-, and city-level productivity, with three debated dimensions: effect significance, directionality, and contextual boundaries.

Empirical evidence confirms agglomeration's notable productivity impacts. Ke and Yu (2014) attribute 50% of intercity TFP variation in China to agglomeration differentials. Zhang *et al.* (2020) document construction sector productivity disparities driven by agglomeration intensity, suggesting smaller cities may exceed critical industrial mass while larger cities require industrial decentralization (Wang, 2021). Sectoral heterogeneity further emerges: technology-intensive industries exhibit larger optimal agglomeration scales than labor-intensive sectors, producing an inverted U-shaped firm size-agglomeration relationship and a U-shaped firm age-agglomeration linkage.

Proponents highlight positive agglomeration-productivity correlations. Urban agglomeration enhances firm-level TFP irrespective of administrative boundaries (Wang, 2021). Ke's

(2010) spatial analysis of 600+ Chinese cities links industrial concentration to higher productivity in large cities, with reciprocal TFP-agglomeration reinforcement. Hierarchical advantages amplify this effect: cities with higher administrative status or larger special economic zones show stronger agglomeration due to resource advantages improving low-productivity firms' survival (Wang, 2021). Sectorally, He and Zhu (2009) identify positive labor productivity-industrial agglomeration ties, prominent in globalized industries post-1990s. For creative industries, clustering smaller firms boosts efficiency contingent on firm type and cluster composition. Mechanistically, localized knowledge spillovers exceed non-agglomerative spillovers (Jianhua, 2011), while industrial agglomeration drives TFP via technical efficiency and frontier technology (Ke and Yu, 2014). Methodologically, Huang *et al.* (2002) employ data envelopment analysis to quantify agglomeration's role in optimizing rural-urban land conversion efficiency through production technology innovation and factor reallocation. Spatially, Wang (2021) finds development zones generate 9% TFP premium within 1,000-meter radii, with knowledge spillovers dominant for high-tech and mature manufacturing firms exhibiting Marshallian cluster externalities.

Critics emphasize agglomeration's negative externalities. Liu (2019) observes TFP declines in Guangdong's industrial inflow zones versus gains in outflow zones. Ke and Yu (2014) note urban employment density suppresses technical efficiency and TFP growth. Analyzing Beijing-Tianjin-Hebei urban clusters, Huang *et al.* (2020) report fluctuating TFP declines (2008–2017) attributable to deteriorating technological, scale, and technical efficiencies. Wei *et al.* (2020) warn of congestion effects outweighing agglomeration benefits in central/western regions, where excessive clustering lowers cost-benefit ratios below national averages (Xu *et al.*, 2012).

Beyond agglomeration, TFP is shaped by multifactorial dynamics. Technological progress dominates intercity TFP variation (Zhang, 2018; Shi, 2009), though its marginal returns diminish for domestic firms (Liu *et al.*, 2014). Innovation complements this: R&D investments strengthen productivity (He *et al.,* 2018; Liu *et al.,* 2016), while innovation transfer offsets declining technological impacts (Liu *et al.*, 2014). Labor market factors yield contested outcomes: employment density boosts firm productivity (He *et al.*, 2018) but reduces sectoral efficiency in creative industries (Yu, 2018) and urban productivity post-industrial scaling (Ke, 2010).

III. Materials and Methods

We sourced annual panel data (2003–2020) for 1,277 Chinese public companies from the China Stock Market, Accounting Research Database and corporate annual reports. The final sample covers listed firms operating across 168 cities in 20 provinces within northeastern, central, and western regions, geographic units subject to distinct regional policies: Western Development, Rise of Central China, and Northeast Revitalization. Compared to aggregated county/city/province-level data, firm-level microdata mitigate information loss while enabling granular analysis of individual-level variable interactions and robust regression testing.

A. Dependent Variable

The study's dependent variable, Total Factor Productivity (TFP), measures output growth unexplained by factor inputs (Zhang, 2018). In China's UITDZ context, TFP captures industrial clusters' capacity to convert inputs into outputs efficiently (Lu *et al.*, 2016), reflecting resource allocation quality, scale economies, and technological advancement. We estimate TFP using both Olley-Pakes (OP) and Levinsohn-Petrin (LP) semi-parametric estimators to address OLS limitations in simultaneity bias and selection issues.

The OP estimator employs investment to proxy productivity shocks correlated with variable inputs in a reduced production function, while the LP method substitutes intermediate inputs to circumvent OP's zero-investment constraint (Levinsohn and Petrin, 2003). Both approaches derive TFP from deviations between predicted and observed output in a Cobb-Douglas framework, with OP estimating labor/capital coefficients through two-stage Solow residual calculation. Key divergence lies in LP's intermediate input proxy eliminating truncation bias from OP's nonzero investment requirement and labor endogeneity.

Our main specifications use OP estimated TFP.

B. Main Independent Variable

The main independent variable of the study is did_{it}, which is also a dummy variable. It represents the interaction term of treatment dummy variable and time dummy variable $Treated_i \times Period_t$, in general DID approach. When $Treated_i$ as the time variable turns 1, it indicates the period of policy intervention, which starts from one of the six policy intervention years until 2020 (the last recorded year of sample data), and it is 0 otherwise. $Treated_i$ as the treatment variable turns 1 when a firm is located in the UITDZ in central and western regions so it is treated by the policy intervention, and it is 0 otherwise. A firm turns 1 under did_{it} if and only if it is located in the UITDZ in central and western regions of China ($Treated_i$=1) after one of the six policy implementation years as presented in Table 1 ($Period_t$=1), and the firm maintains as 1 from then on. It is 0 otherwise.

C. Control Variables

Nine firm-level control variables are added to the regression model, which include roa_{it} tl_{it} $assetgrowth_{it}$ $mgnt_{it}$ $lemployee_{it}$ $budget_{it}$ $revenue_{it}$ $cash_{it}$ *and* $wage_{it}$. roa_{it} refers to return on assets, which measures the amount of money made by a firm from using its assets. tl_{it} refer to debt to asset ratio, in which is a leverage ratio implying total amount of debt owned by a firm relative to the total amount of its assets. $assetgrowth_{it}$ refers to total assets growth rate, which is defined as the year-over-year percentage change in a firm's total assets and it shows how quickly the firm is in growing its assets. $mgnt_{it}$ is the number of executives and $lemployee_{it}$ is the number of employees in a firm. $budget_{it}$ refers to the working capital, which is the difference between a firm's current assets and current liabilities. $revenue_{it}$ refers to the total operating income, which is the gross profit of a firm subtracting its regular and recurring expenses and costs. $cash_{it}$ refers to a listed company's cash payments for interest expenses and distribution of dividends or profits. $wage_{it}$ refers to the sum total of the salary of the top three chairmen of the board, members of the board of supervisors or the executives.

D. Descriptive Summary

Table 1 shows the descriptive summary of all dependent variables, the main independent variable and all control variables. As compared to the LP approach estimated TFP, OP's has a larger standard deviation (2.194) and both a larger minimum (−7.51) and maximum values (16.89). The larger deviation and distance between maximum and minimum values create more room for research to understand the main causes behind.

Table 1. Descriptive statistics of variables

Variables	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
did	14,048	0.0918	0.289	0	1
OP0	14,048	6.425	2.194	−7.510	16.89
LP0	14,048	6.426	2.191	−7.023	16.51
roa	14,048	1.741	198.5	−51.95	23,510
tl	14,048	0.557	2.179	−0.549	142.7
assetgrowth	14,004	0.188	1.183	−1.061	107.1
mgnt	14,048	6.476	2.396	2	27
lemployee	14,043	7.623	1.315	0	11.63
budget	14,048	4.692	53.68	−1,451	1,501
revenue	14,048	49.65	124.2	237.3	3,186
cash	14,048	2.362	6.962	−5.288	240.9
wage	14,048	1.646	2.535	2.400	92.69

E. Methodology

To examine the effect of UITDZ on the firm-level TFP in central and western regions in China, a multi-period DID approach with a quasi-experimental design is utilised in the study. The standard DID estimator with two groups and two time periods is expanded to a general DID estimator with two groups and multiple time periods. The reason behind the DID estimator extension is that the UITDZ policy was introduced to different cities in central and western regions at different times. As a result, the policy intervention year varies across different cities in these regions as presented in Table 1. Out of 168 cities in the sample data, 27 cities are approved as the UITDZ. Therefore, the firms located in these demonstration zones after one of the 6 policy implementation years belongs to the treatment group, other firms in the sample data are under control group.

After a city becomes a UITDZ under the policy, there will be mainly three causes that lead to the firm-level TFP change in the treatment group: (1) the policy shock from the UITDZ policy; (2) individual effects which differ across firms but are constant over time; and (3) time effects which are constant across firms but vary over time. After controlling time fixed effects and individual fixed effects using two-way fixed effects model and deducting the firm-level TFP change of control group from that of treatment group using the DID method, the net effect of policy could be obtained.

Since firms in the treatment group are treated in different periods, the two-way fixed effects regression model applying multi-period DID technique is presented as follows:

$$TFP_{it} = \beta_0 + \beta_1 did_{it} + \beta_2 Control_{it} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In the equation, TFP_{it} refers to the TFP of firm *i* in period *t*, namely the OP approach estimated TFP. β_0 is the constant term or the default TFP values which does not vary across firms and periods. did_{it} is the policy variable which is also the interaction term. The DID estimator, β_1 is critical as it measures the difference between the TFP changes of treatment group and control group over time with the intervention of the policy. $Control_{it}$ are the group of control variables as introduced in Section III, and β_2 measures the effects of these control variables on firm-level TFP. α_i represents the firm fixed effects on TFP which does not vary across time. λ_t represents the year fixed effects on TFP which does not vary across firms. Since the individual fixed effects and time fixed effects are controlled in the regression, the treatment and time variables of the DID method, $Treated_i$ and $Period_t$ are excluded from the equation to avoid the collinearity issue. ε_{it} is the residual term.

IV. Result and Discussion

A. Parallel Trends Test and Dynamic Effect Test

Parallel trends test is the prerequisite of the use of DID approach, which identifies if there exists significant differences between treatment and control groups before and after the policy is implemented. If there is no significant difference before the policy implementation, then the parallel trends test is passed. If there is a significant difference after the policy implementation, it indicates a dynamic effect under dynamic effect test.

The left-side section of the graph from "-5-" to "0" on the x axis presents the results of the parallel trends test. The right-side section of the graph from "0" to "5+" presents the results of the dynamic effect test. The study uses the policy implementation years: 2010, 2011, 2012, 2013, 2014, 2018, as the benchmark year ("0" on the x axis) for the two tests as shown in the Fig. 1.

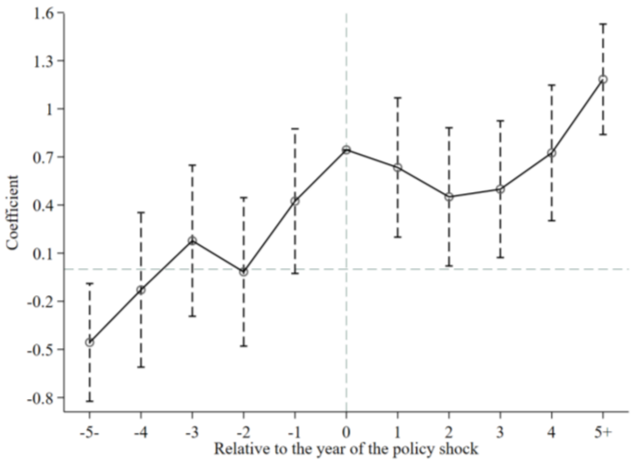

Fig. 1. Results of parallel trends test and dynamic effect test.

Before the implementation of the policy, the coefficient of the policy variable fluctuates around 0 on the y axis, indicating that there is no significant difference between the treatment and control groups. Therefore, the parallel trends test is passed and it implies the proceeding of the treatment.

After the policy intervention, the treatment effect becomes significant and positive above 0 on the y axis, and it shows a trend of strengthening over time. It also indicates a certain time lag from the policy implementation before the policy effect becomes significant, and the policy has always had a significant effect on firm-level TFP over time.

B. Placebo Test

In the placebo test, treatment and control groups in the baseline regression are combined together. The treatment is distributed randomly on some of these firms. To ensure the randomness of the policy shocks to certain firms, coefficient of this random treatment is calculated and generated by Stata and this procedure is repeated 1000 times. The random processing could ensure the policy would not impose any effect on firm-level TFP.

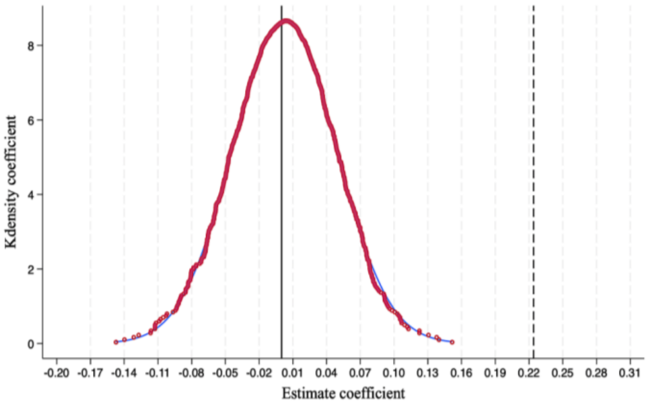

Fig. 2. Results of placebo test.

C. Fixed Effects Regression Analysis

The firm-level TFP at 1% level with a policy effect of 0.224. The result suggests that with the execution of the policy, TFP increases for the firms located in central and western regions' demonstration zones during policy intervention years in comparison to firms in the control group.

Table 2. Summary of results of fixed effects regression

Variables	*TFP*
did	0.224***
	(0.080)
Control	YES
Firm FE	YES
Year FE	YES
N	13,999
adj.R^2	0.157

D. Robustness Tests

Our two-way fixed effects regression analysis reveals a significant positive effect of the policy (did_{it}) on firm-level Total Factor Productivity (TFP) in western and central regions. We conduct four robustness checks reported in columns (1)–(4) of Table 3:

(1) Alternative TFP Measure: To address potential model misspecification, we replace the OP method with the LP approach for TFP estimation. The coefficient on did_{it} remains positive (0.172) and significant at 5%, consistent with baseline results.

(2) Outlier Treatment: We winsorize variables below the 1st and above the 99th percentiles. The did_{it} coefficient maintains its magnitude and significance (1% level), confirming minimal outlier influence.

(3) Clustering Adjustment: Changing standard error clustering from firm-year to province-year level preserves did_{it}'s significance (5% level), demonstrating estimator stability.

(4) Policy Timing Test: Using a two-year lagged did_{it} specification eliminates policy significance, confirming the baseline specification's temporal accuracy. Random temporal adjustments nullify the treatment effect, supporting result robustness.

Table 3. Robustness check results

Variable	*TFP*			
	(1)	(2)	(3)	(4)
did	0.172**	0.224***	0.224**	0.102
	(0.0794)	(0.0802)	(0.0995)	(0.0886)
Control	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	13,999	13,999	13,999	11,557
Adjuested R^2	0.159	0.157	0.157	0.132

This comprehensive testing framework establishes the reliability of our core findings regarding regional productivity effects.

E. Heterogeneity Analysis

The effect of the policy on firm-level TFP might vary among firms in different industries. After running the baseline regression by the categorical dummy variable, $industry_{it}$, which refers to the industry that a firm is categorized into, it is found that the policy effect is positive and significant at 5% level for the manufacturing, construction and electronics and water industry, and for the commercial industry. It requires R&D, innovation and certain technology to consistently develop the manufacturing, construction and electronics and water industry. With the policy intervention, these industries' firm level TFP might benefit more from technological spillover brought by the policy which promotes agglomeration economies. Because of the policy, more talents are attracted into the UITDZ which leads to more interaction with the commercial industry, a higher possibility of commercial industry upgrading. These possible results might generate a higher TFP for the commercial industry.

However, the policy effect becomes insignificant for the public utility, real estates, comprehensive and financial services industry. Especially in public utility industry, the insignificance of the policy effect might be due to the potential free rider problem. For real estate industry, properties as their products cannot be relocated to the UITDZ from other regions, so the industry is not largely affected by the policy.

Table 4. Heterogeneity by Industries

Variable	*Manufa-cturing*	*Public Utility*	*Commer-cial*	*Real Estate*	*Compre-hensive*
did	0.225*	−0.0740	0.578*	−0.155	−0.398
	(0.093)	(0.224)	(0.303)	(0.370)	(0.348)
Control	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
N	9915	1906	832	636	310
adj.R^2	0.144	0.264	0.446	0.429	0.270

V. Conclusion

The main findings of the study are as the followings. After conducting the two-way fixed effect regression model with the DID approach, it is founded that firm-level TFP increases for the treated firms during policy intervention years in comparison to firms in the control group. The parallel trends test is passed and dynamic effect test show that the treatment effect becomes significant and shows a trend of strengthening over time after the policy intervention. The placebo test suggests that the estimated results are robust and it is almost impossible for the non-observed area characteristics to affect the estimated results. Four conducted robustness tests, including changing dependent variable, elimination of outliers' effects, changing level of clustering in standard errors and changing policy intervention year, has proved the robustness of the result. The results heterogeneity analysis suggests with the policy effect is more significant at for the manufacturing, construction, electronics, water, and commercial industry; the treated firms shall avoid corporate defaults and invest into invention to be benefited from the policy to a larger extent.

Regarding the weaknesses of the study, it has not considered the spatial spillover effect of the policy, that is, UITDZ will not only affect the local TFP, but it might also affect the firm-level TFP of the surrounding areas. Without considering the spatial spillover effect, the estimated results of the policy effect in this research might be biased. Therefore, the follow-up improvement is to explore the technological improvement effect of the policy based on the spatial measurement model by constructing a spatial weights matrix.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Zixuan Liu contributed to data collection, data analysis, interpretation, manuscript preparation, and editing; Che Su contributed to the conceptualization and study design, as well as the introduction and conclusion sections of the manuscript; both authors had approved the final version.

Funding

This work was supported by the Project supported by the Shanghai Philosophy and Social Science Planning Youth Project (2024EGL008).

Acknowledgment

We thank the participants who made this research possible.

References

He, S. B., Liu, Y. J., Duan, C. M., 2019. Do national industrial relocation demonstration zones have higher total factor productivity? ***Journal of Finance and Economics***, 45: 127–140.

He, C. F., Zhu, S. J., 2009. Industrial agglomeration and labour productivity in transition: An empirical study of Chinese manufacturing industries. ***Post-Communist Economies***, 21: 103–115.

He, M., Chen, Y., Schramm, R., 2018., Technological spillovers in space and firm productivity: Evidence from China's electric apparatus industry. ***Urban Studies***, 55: 2522–2541.

Huang, K., Dallimer, M., Stringer, L. C., Zhang, A., Zhang, T. 2021. Does economic agglomeration lead to efficient rural to urban land conversion? An examination of China's metropolitan area development strategy. ***Sustainability***, 13: 2002.

Ke, S., 2010. Agglomeration, productivity, and spatial spillovers across Chinese cities. ***The Annals of Regional Science***, 45: 157–179.

Ke, S., Yu, Y., 2014. The pathways from industrial agglomeration to TFP growth-the experience of Chinese cities for 2001-2010. ***Journal of the Asia Pacific Economy***, 19: 310–332.

Liu, L., 2019. Research on the productivity effect of inter-regional industry transfer—Taking Guangdong province as an example. ***Modern Economy***, 10: 872–1896.

Liu, N., Ye, X., Yang, H., Li, Y., Leipnik, M., 2014. Manufacturing firm heterogeneity and regional economic growth difference in China. ***Regional Science Policy & Practice***, 6: 213–231.

Liu, S. A., Wang, J., 2010. Agglomeration externalities, industry growth and innovation effect: Based on panel data analysis of high-tech industry. ***Proceedings of 2010 2nd IEEE International Conference on Information Management and Engineering***.

Liu, W. S., Agbola, F. W., Dzator, J. A., 2016. The impact of FDI spillover effects on total factor productivity in the Chinese electronic industry: A panel data analysis. ***Journal of the Asia Pacific Economy***, 21: 217–234.

Lu, R., Ruan, M., Reve, T., 2016. Cluster and co-located cluster effects: An empirical study of six Chinese city regions. ***Research Policy***, 45: 1984–1995.

Shi, Y. J., 2009. Resource-based city's industry developing efficiency evaluation based on BE-DEA model. ***Proceedings of 2009 16th International Conference on Industrial Engineering and Engineering Management***.

Wang, Y., 2021. Development zone spillover effect: The externality of the gathering of manufacturing enterprises. ***Proceedings of E3S Web of Conferences***.

Wei, W., Zhang, W. L., Wen, J., Wang, J. S., 2020. TFP growth in Chinese cities: The role of factor-intensity and industrial agglomeration. ***Economic Modelling***, 91: 534–549.

Xiang, G., Xiong, Y., Liu, J., Zhong, S., Jiang, X., 2020. How far is the optimal intercity distance? Evidence from China. ***International Regional Science Review***, 43: 344–369.

Xu, Y. Q., Wang, C. J., Xu, W. X. 2012. Empirical study on the relationship between the spatial agglomeration index and agglomeration efficiency in the textile industry. ***Proceedings of 2012 International Conference on Management Science & Engineering 19th Annual Conference Proceedings***.

Yu, H., Liu, Y., Zhao, J., Li, G., 2019. Urban total factor productivity: Does urban spatial structure matter in China? ***Sustainability***, 12: 214.

Yuan, H., Zhang, J., Zhang, Y., Hong, Y., Zhao, H., 2017. Effects of agglomeration externalities on total factor productivity: Evidence from China's Textile Industry. ***Ind. Textila***, 68: 474–480.

Zhang, J., Zhang, Y., Philbin, S. P., Ballesteros-Pérez, P., Ouyang, Y., Cheng, J., 2020. Influence of agglomeration and selection effects on the Chinese construction industry. ***Proceedings of the Institution of Civil Engineers-engineering Sustainability***.

Zhang, M. 2018. The economic growth efficiency of the Beijing-Tianjin-Hebei urban agglomeration. ***Proceedings of 2018 5th International Conference on Industrial Economics System and Industrial Security Engineering***.

Zhang, J. H., 2011. Agglomeration within industry, vertical spillovers related industries and enterprises efficiency—Based on panel data of Guangdong Province manufacturing enterprises. ***Proceedings of 2011 International Conference on Business Management and Electronic Information***, 2: 389–393.