



Spatial spillover effects of manufacturing agglomeration on China's total factor carbon productivity: evidence from the regulatory role of fiscal decentralization

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Abstract

Based on the theory of new economic geography, this paper used panel data from 284 cities in China from 2006 to 2019 to determine the effects of spatial spillover and heterogeneity of manufacturing agglomeration (MA) on urban total factor carbon productivity (TFCP) and the regulatory effect of fiscal decentralization on the outcome. The results showed that (1) MA shifted from the eastern region of China to the central and western regions, with the center of gravity moving towards the south. The spatial pattern of urban TFCP displayed the solidifying characteristics of “low-level agglomeration and high-level dispersion,” with technological progress being the primary driver. (2) The MA had a significant U-shaped effect on the TFCP of local and nearby cities, promoting the improvement of urban TFCP through Jacobs' and Porter's externalities but not MAR externalities. (3) Regarding regional differences, MA had a significant U-shaped impact on urban TFCP in the eastern and central regions. At different levels of manufacturing development, there was an inverted U-shaped relationship in both manufacturing and non-manufacturing metropolitan areas. For varying degrees of manufacturing industry agglomeration, increasing the level of MA improved urban TFCP in low agglomeration areas, but inhibited it in high agglomeration areas. (4) The implementation of fiscal decentralization nationwide and in the eastern and central regions significantly weakened the impact of MA on TFCP. Furthermore, fiscal decentralization significantly enhanced the influence of MA on TFCP in cities exhibiting high levels of economic development, advanced industrial structure and strict environmental regulations. Therefore, based on the unique developmental characteristics of the manufacturing industry in various cities, fiscal policies ought to be tailored to local circumstances to support key areas. This strategy should facilitate the high-quality development of manufacturing industry and low-carbon development of cities.

Keywords Manufacturing agglomeration · Total factor carbon productivity · Spatial spillover effect · Fiscal decentralization · Spatial distribution · Regulation effect · Heterogeneity

Introduction

On August 9, 2021, the United Nations Intergovernmental Panel on Climate Change (IPCC) published the findings of the first working group in the Sixth Assessment Report: Climate Change 2021: the Physical Science Basis. The report revealed that atmospheric carbon dioxide concentrations reached their highest levels in the past 2 million years

in 2019, while methane and nitrous oxide concentrations reached peaks not seen for the past 800,000 years (IPCC 2021). Given the current global situation, nations worldwide have implemented proactive strategies to reduce carbon emissions. In 2021, China achieved a 50.8% reduction in its carbon dioxide emissions per unit GDP compared to 2005, with the successful launch of the world's largest carbon trading market for mitigating the rapid growth of carbon emissions. However, China's CO₂ emissions reached 11.89 billion tons in 2021, increasing by 1.991 billion tons from 2020. Thus, China still faces significant challenges in achieving the ambitious goal of carbon neutrality (Wang et al. 2022a).

In the long term, technological advancements are the primary driving forces for balancing economic growth with

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carbon emission reduction (Gu et al. 2019). Germany's successful launch of *Industry 4.0* served as a model for China's *Made in China 2025* and the white paper on industrial intelligence in 2015 and 2019, respectively. These initiatives aimed to improve manufacturing capabilities and address environmental pollution by reducing costs, enhancing efficiency, and restructuring organizations. China's manufacturing industry is its largest sector, the backbone of its economy, and the key driver of urban and regional development. The formation, aggregation, and diffusion of manufacturing clusters significantly influence operational efficiency and regional spatial patterns (Guo and Sun 2023). Currently, the focus on transitioning from manufacturing 2.0 (the electrification and automation production stage) to manufacturing 3.0 (the information production stage), with the promotion of manufacturing clusters has become a crucial element of China's development of a high-quality manufacturing industry (Yuan et al. 2020).

As of the end of 2019, the operating income of China's manufacturing industry accounted for 88.40% of the entire industrial sector and used over 50% of the country's energy. From 1990 to 2017, China's economic losses due to air pollution increased from 3.38 to 6.44%, significantly higher than the OECD's average of 3.396% for all countries. Thus, MA is a vital engine for China's economic growth, but also a significant source of energy consumption and carbon emissions (Lan et al. 2021). In light of these issues, this study attempted to answer the question, does MA affect China's TFCP, and if so, what are its features, governing principles, and the internal mechanisms driving this influence? Thus, in this study, we investigated the impact of MA on China's TFCP through the lens of the theory of economic externalities. This study deepens our understanding of the theoretical aspects of agglomeration economics and offers a novel perspective and approach to China's high-quality development and transformation to a green economy.

Since the implementation of fiscal decentralization, the percentage of local fiscal expenditures has increased to 86% in 2021, while central fiscal expenditures have decreased to 14%. This has resulted in an increase in financial control by local governments. Past assessments of GDP championships have caused local governments to overlook environmental pollution while blindly pursuing economic growth; however, now they are shifting towards green GDP competitions that prioritize environmental quality and promote green manufacturing practices and low-carbon development (Pan et al. 2023; Sun et al. 2022). However, there has been little academic research on whether fiscal decentralization moderates the impact of MA on TFCP. Therefore, this study focused on measuring and analyzing the spatial spillover effect of MA on urban TFCP while testing the regulatory effect of fiscal decentralization. It is hoped that local governments will use this data to establish effective and scientifically supported

low-carbon development policies for the manufacturing sector through rational financial control.

Several contributions were made by this study, compared with previous studies. First, we calculated TFCP on a city-wide level, whereas previous studies primarily measured carbon productivity as a single factor; however, carbon dioxide emission performance is influenced by a range of factors, including energy consumption and economic development. Thus, taking into account all relevant factors, TFCP may be a more appropriate metric (Li et al. 2018). Additionally, since most of the literature on MA and TFCP has focused on provinces (Han et al. 2022) and industries (Hu and Xiong 2021) with limited research on measuring TFCP at the city level, it was deemed necessary to broaden the scope in this investigation. Second, existing studies on MA primarily focused on examining its impact on green total factor productivity (Yang and Shen 2023), total factor energy efficiency (Zhang et al. 2023), pollution (Cheng 2016), and other economic and environmental variables. However, there have been few studies exploring the impact of MA on urban TFCP. Thus, we conducted an analysis of the spatial spillover and externality effects of MA on urban TFCP using the spatial Durbin model and externality theory. We also discussed the diversity arising from geographic location, as well as variations in manufacturing development levels and degree of agglomeration, addressing gaps in the current literature on spatial spillover effects and heterogeneity analysis. Third, we also penetrated more deeply into the mechanism of MA. There has been limited research on the regulatory impact of fiscal decentralization on MA and its effects on urban TFCP. This paper not only explores this aspect but also examines the varied regulatory impact of fiscal decentralization in different regional contexts, improves our perspective on the mechanism of MA that affects urban TFCP, and addresses gaps in the literature.

Literature review and research hypotheses

Literature review

Research on carbon productivity

Carbon productivity can be categorized into two types: single-factor carbon productivity and total-factor carbon productivity. Single-factor carbon productivity is the ratio of GDP to carbon dioxide emissions (Li et al. 2018; Xu et al. 2023), while carbon emission intensity is defined as the reciprocal of single-factor carbon productivity. However, due to the complexity of measuring carbon emissions, which involve both energy and non-energy inputs as well as positive and negative outputs, single-factor carbon productivity fails to capture the substitutability of carbon

emissions with energy, capital, and labor. Consequently, it cannot fully reflect the current stage of low-carbon development in China. Therefore, some studies proposed using the concept of TFCP within the framework of total-factor integrated production (Cui et al. 2022; Mo 2023). Utilizing TFCP allowed us to measure the contribution of improved production efficiency on economic growth and the impact of economic development on carbon emissions, providing key indicators for evaluating China's current low-carbon development status.

Impact of MA on urban TFCP

The relationship between MA and environmental performance has been extensively debated and researched, attracting considerable attention (Han et al. 2022); however, consensus on the impact of MA on environmental quality has yet to be achieved. TFCP is a crucial indicator for measuring input-output efficiency as it considers carbon emissions as an unexpected output (Li et al. 2018). MA is a significant factor influencing TFCP, and the question we attempted to answer was can MA enrich China's TFCP and environmental performance? In general, there are three lines of reasoning about this. The first argument suggests that agglomeration in manufacturing can enhance environmental performance by boosting TFCP. According to Han et al. (2022), clustering labor-intensive and technology-intensive manufacturing industries can enhance environmental efficiency, while clustering capital-intensive manufacturing can negatively impact it. Furthermore, He et al. (2023) found that co-agglomeration of manufacturing and production services greatly improved carbon productivity and green technology progress. The second point is that MA can lead to increased pollution, which is harmful to the environment. Wei et al. (2020) found a negative correlation between MA and TFCP, and the lack of transportation and pollution treatment technology increased environmental pollution, which transformed the agglomeration effect into a congestion effect. Ren (2020) also demonstrated the adverse impacts of manufacturing clusters on a city's innovation efficiency in the short and long term. The third point is that scholars commonly observe a nonlinear relationship between MA and environmental performance. Liu et al. (2022) found a significant U-shaped relationship between spatial agglomeration and enterprise energy efficiency. The internal mechanisms that affect enterprise energy efficiency in terms of agglomeration externality include the effects of scale, learning, competition, and policy. Xu et al. (2023) identified a U-shaped effect on carbon productivity for the co-agglomeration of manufacturing and producer services, with an inflection point of 3.63.

Based on a careful reading of the literature, we found that current research primarily focused on the correlation between MA, green total factor productivity, energy

efficiency, and single-factor carbon productivity. However, there has been limited research and analysis on the impact and mechanism of TFCP, and the effect of MA on urban low-carbon construction remains unclear.

The agglomeration externalities of the manufacturing industry also have an impact on TFCP, but there is currently no consensus on the relationship between them. Some studies indicated that agglomeration externalities were crucial for enhancing carbon productivity and achieving convergence in this area (Shen et al. 2021), while other scholars have found a nonlinear relationship between agglomeration externalities and carbon productivity (Liu et al. 2022). The relative impact of MAR, Porter's, and Jacobs' externalities in promoting carbon productivity growth is still uncertain, with some research indicating that industrial diversification and competitive agglomeration have both played a role in improving carbon productivity in the Yellow River Basin; but the latter has a "beggar-thy-neighbor" spillover effect (Guo et al. 2023). Other studies found that both specialized and diversified agglomeration in urban agglomeration economies could significantly promote carbon emission reduction in local and neighboring cities (Han et al. 2018). However, the impact of manufacturing externality agglomeration on the heterogeneity of urban TFCP remains unclear. This paper aimed to explore the impact of agglomeration externalities on manufacturing by using externality theory to address this gap in the literature.

Research hypotheses

Agglomeration effect and crowding effect of MA on TFCP

Regarding the investigation of agglomeration's effects and their positive impact on economic efficiency, some research has identified three main sources of agglomeration effects: the labor reservoir, intermediate input sharing, and knowledge spillover (Marshall 1890). It should be noted, however, that MA does not always lead to improved economic efficiency. The Williamson hypothesis holds that in the early stages of economic development, the spatial agglomeration of factors of production and economic activities should promote the improvement of economic efficiency (Williamson 1965). According to the new economic geography theory, the spatial agglomeration of economic activities results from the interaction of two opposing forces—centripetal force that promotes spatial agglomeration and centrifugal force that results in scattering. The centripetal force promotes the spatial diffusion of economic activities and factors. Driven by centripetal force, production factors and the labor market tend to be concentrated, which brings more input sharing and knowledge spillover, contributes to technology diffusion, strengthens input-output correlation and cooperation complementarity among enterprises, reduces transaction costs and risks among enterprises, and creates an agglomeration

effect to promote economic efficiency (Martinez-Galarraga et al. 2008). However, as agglomeration grows at an accelerating rate and production factors become excessively concentrated, firms within the agglomeration space confront not only market and geographic limitations, but also infrastructure shortages, escalating land rents, and environmental pollution. This results in fierce competition for limited resources and energy, inhibiting the access and development of new enterprises, and the entry of new technologies and new knowledge. The congestion effect negatively impacts the improvement of economic efficiency (Wu et al. 2022).

MA can enhance human capital and reduce production costs and carbon emissions through various channels such as the labor reservoir, intermediate product input sharing, and knowledge and technology spillovers, which ultimately improve TFCP. However, excessive MA may also lead to crowding effects, such as population surge, increased pollution from technological advancements, and resource wastage due to industrial competition.

MA's influence on TFCP also depends on the combined effects of agglomeration and crowding. In the initial phase of MA, the extensive economic development leads to environmental problems and increased carbon emissions. Within the realm of actual economic operations, once MA is established in a region, the precise location of the optimal scale remains uncertain in the short term, leading to continuous expansion (Zheng 2023). Resource congestion in the agglomeration area is salient, and increasing costs and environmental pollution impede the entry of new enterprises (Potter and Wattsy 2011). The lack of innovation and dissemination of green resources can further inhibit the progress of TFCP.

With the further expansion of MA, the optimization of resource allocation, and the application of better methods and technology for controlling carbon emissions, the benefits of increased agglomeration scale become apparent. Knowledge spillover and the diffusion of green production technology play an increasing role in environmental performance and the improvement of TFCP (Wang and Wang 2019). Furthermore, MA is a spatial phenomenon (Cheng 2016) with cities becoming increasingly interconnected during economic expansion. This indicates the necessity of considering spatial elements affecting MA's impact on TFCP in the process of capturing and identifying the dual impacts of MA on TFCP. Therefore, we proposed:

Hypothesis 1: The spatial spillover impact of MA on TFCP exhibits positive U-shaped non-linear effects, initially inhibiting growth and then promoting it.

Regulatory role of fiscal decentralization

Fiscal decentralization is one of the most important institutional factors affecting the overall planning of financial resources. The institutional arrangement of fiscal

decentralization has an important impact on MA by mobilizing the enthusiasm of local governments to action. MA is not only the result of market choice but also the result of government promotion (Yang et al. 2021). Among the many factors affecting MA, local government behavior has an especially important position.

China's fiscal decentralization system significantly influences government management and policy-making, encouraging local governments to prioritize economic progress within their jurisdictions. The resulting "fiscal decentralization" effect makes it feasible for local governments to play an active role in economic construction and environmental protection (Wang et al. 2023). It also suggests that the greater the financial endowment of a local government, the greater its financial autonomy, and the more robust and proactive its efforts to foster industrial growth and pollution control through land procurement, new development zones, investment attraction, production subsidies, and tax incentives. Therefore, it is critically necessary to analyze the regulatory role of fiscal decentralization in the impact of MA on TFCP.

Fiscal spending on manufacturing plays a vital role in structural transformation and resource allocation (Thanh and Canh 2020). As the concept of sustainable development has become more prominent, environmental protection factors have been incorporated into the evaluation system for local governments in China. Researchers have differing opinions on the impact of fiscal decentralization on environmental governance. Some argue that local governments have blindly pursued economic growth to the detriment of environmental protection, and thus fiscal decentralization did not improve environmental governance (Zang and Liu 2020). Others contend that local governments currently prioritize environmental governance, encouraging firms to invest in pollution control research, innovation in pollution control technologies, and the attraction of minimally polluting foreign direct investment through tax incentives (Xu 2022). The varying degrees of fiscal decentralization of individual regions have had distinct effects on carbon efficiency (Feng et al. 2022; Song et al. 2018). Thus, we proposed:

Hypothesis 2: Fiscal decentralization plays a moderating role between MA and urban TFCP.

Research design

Spatial correlation analysis

We used Moran's I to test spatial correlation. The formula for calculation of the Moran index of urban TFCP is as follows:

$$Moran's I_i = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (TFCP_i - \overline{TFCP}) (TFCP_j - \overline{TFCP})}{\left(\sum_{i=1}^n \sum_{j=1}^n W_{ij} \right) \sum_{i=1}^n (TFCP_i - \overline{TFCP})^2} \quad (1)$$

In the formula, \overline{TFCP} represents the average value of samples and W_{ij} refers to the corresponding element of the spatial weight matrix (i, j). The index value of Moran's I ranges from $[-1, 1]$. A positive correlation exists between the TFCP of adjacent regions when Moran's $I > 0$. The closer the index value is to 1, the stronger the positive correlation. Conversely, a Moran's $I < 0$ signifies a negative correlation between adjacent regions in TFCP. When the index value is close to 0, the TFCPs of neighboring regions are not correlated, and the distribution is random.

To improve the reliability of the findings, this study thoroughly examined the spatial correlations between urban TFCP and geography, economics, and geo-economics. It also created spatial weight matrices for geographic distance (W_1), economic distance (W_2), and combined geographic and economic distance (W_3). The weight matrix for economic distance is based on the reciprocal of per capita GDP difference, while the weight matrix for geographic distance employs the reciprocal of the squared geographic distance. A spatial weight matrix, which accounts for both geographic and economic distance was utilized to assess robustness.

Spatial econometric model

Model of MA's impact on urban TFCP

The movement of production resources and the dissemination of knowledge and technology foster stronger connections between regions. Hence, we employed a spatial econometric model to examine the spatial influence of MA on urban TFCP. As the impact of MA on urban TFCP may follow a nonlinear pattern, the model included the squared term for MA. Spatial measurement models commonly used are the spatial lag model (SAR), spatial error model (SEM), and spatial Durbin model (SDM). The formulas are as follows:

$$SAR : TFCP = \rho W \times TFCP + \beta_i (MA + MA^2 + X) + \mu \quad (2)$$

$$SEM : TFCP = \beta_i (MA + MA^2 + X) + \mu, \mu = \lambda W \mu + \varepsilon \quad (3)$$

$$SDM : TFCP = \rho W \times TFCP + \beta_i (MA + MA^2 + X) + \theta_i W \times (MA + MA^2 + X) + \mu \quad (4)$$

In this study, $TFCP$ stands for urban total factor carbon productivity, MA represents the degree of MA, X denotes a series of control variables, and W is the spatial weight matrix.

Model of the effect of MA externalities on urban TFCP

After conducting a thorough literature review and theoretical analysis, it was discovered that MA externalities have a significant impact on urban TFCP. These externalities can be categorized as specialization agglomeration (MAR externalities), diversification agglomeration (Jacobs' externalities), and competitive agglomeration (Porter's externalities) based on their distinct modes of agglomeration (Yuan et al. 2017). To determine the specific influence of these MA externalities on urban TFCP, the following model was developed:

$$SDM : TFCP = \rho W \times TFCP + \beta_i (EXT + X) + \theta_i W \times (EXT + X) + \mu \quad (5)$$

where EXT represents the MAR, Jacobs', and Porter's externalities in city i at year t . Other variables were defined as previously stated.

Drawing from relevant scholarly ideas (Cheng et al. 2023), this study utilized specialization, diversification, and the Porter index to measure MAR, Jacobs', and Porter's externalities of MA, respectively. The equations for the calculation are as follows:

$$MAR_i = \max_j \left(\frac{s_{ji}}{s_i} \right)$$

$$Jacobs_i = 1 / \sum_j |s_{ji} - s_i| \quad (6)$$

$$Porter_i = MA_i \times Com_i$$

where j denotes the industry and i represents the city, s_{ji} denotes the number of employees in industry j in city i , while s_i is the total number of employment units in city i at the end of the year. The degree of market competition for the manufacturing industry is denoted by Com_i , which is calculated as follows: $Com_i = (\text{number of large-scale industrial enterprises in region } i / \text{value added of large-scale industrial enterprises in region } i) / (\text{number of large-scale industrial enterprises in all regions} / \text{value added of large-scale industrial enterprises in all regions})$.

Adjustment model of fiscal decentralization

To explore the regulatory impact of fiscal decentralization (FD) on the correlation between MA and urban TFCP, models 7 to 9 were introduced that include MA, the square term of MA, the cross term of fiscal decentralization and MA, and the cross term of fiscal decentralization and the square term of MA. The formulas for the three models are as follows:

$$SAR : TFCP = \rho W \times TFCP + \beta_i (MA + MA^2 + MA \times FD + MA^2 \times FD + X) + \mu \quad (7)$$

Table 1 Method of assessing the fiscal decentralization function

Regression coefficient of MA^2	Curve shape of MA 's impact on $TFCP$	Regression coefficient of $MA^2 \times FD$	Function of FD
Positive	Positive U-shape	Positive	FD enhanced the effect of MA on $TFCP$
Positive	Positive U-shape	Negative	FD weakened the effect of MA on $TFCP$
Negative	Inverted U-shape	Positive	FD weakened the effect of MA on $TFCP$
Negative	Inverted U-shape	Negative	FD enhanced the effect of MA on $TFCP$

$$SEM : TFCP = \beta_i(MA + MA^2 + MA \times FD + MA^2 \times FD + X) + \mu, \mu = \lambda W\mu + \varepsilon \tag{8}$$

$$SDM : TFCP = \rho W \times TFCP + \beta_i(MA + MA^2 + MA \times FD + MA^2 \times FD + X) + \theta_i W \times (MA + MA^2 + MA \times FD + MA^2 \times FD + X) + \mu \tag{9}$$

According to Haans et al. (2016), the impact of fiscal decentralization can be evaluated by the direction of MA on the urban TFCP curve, as well as the positive and negative regression coefficients of $MA^2 \times FD$ (Table 1).

The methodological analysis was divided into four parts, as represented by the flow chart (Fig. 1). The first part delved into the evolutionary process of the temporal and spatial patterns of MA and urban TFCP. The second part employed the spatial Durbin model to analyze the benchmark regression and spillover effects. The third part involved a multi-perspective analysis of heterogeneity and a robustness test. The fourth part explored the regulatory role of fiscal decentralization.

Description of variables

The explained variable

Urban total factor carbon productivity (TFCP) is the explained variable. The slacks-based measure of the directional distance functions model (SBM-DDF) and the Luenberger index were used to calculate TFCP in China (Cui et al. 2022). Select capital, personnel, and energy were the input indicators. Capital investment was measured through fixed capital stock using the perpetual inventory method (Thampapillai 2022). The personnel input index reflected the total population of each locality, because residents were both consumers and producers and had a direct impact on carbon emissions. Energy input was measured by energy consumption in various areas. Output indicators were categorized according to whether they were expected or unexpected output types. Expected output indicators were measured by the GDP of different regions, adjusted for inflation using the 2006 base period. The calculations of unexpected output indicators were based on measurements of carbon dioxide emissions resulting from energy derived from consumption of coal, coke, petroleum, gasoline, kerosene, diesel oil, fuel

oil, liquefied petroleum gas, and natural gas, using the Intergovernmental Panel on Climate Change (IPCC) calculation method. Specific indicators are shown in Table 2.

Core explanatory variable

The location entropy index is widely used due to its advantageous calculation in measuring the degree of regional industrial specialization (Wu and Lin 2021). In this study, we used the location entropy to measure the agglomeration degree of urban manufacturing industry. The calculation method is shown in formula (10), where MA_{it} is the location entropy of the manufacturing industry in city i during year t . As output value data of prefecture-level cities is unavailable, we calculated the location entropy using the number of employees of the manufacturing industries in each city. Q_{itm} is the urban manufacturing employment in city i during year t , Q_{it} represents the number of employed people in all industries in the year t of city i , Q_{tm} denotes all urban manufacturing employment in year t , and Q_t gives the number of people employed in all industries in all cities in year t .

$$MA_{it} = \frac{Q_{itm}/Q_{it}}{Q_{tm}/Q_t} \tag{10}$$

Regulating variable

Under fixed fiscal revenue, fiscal decentralization redistributes expenditures between central and local governments. The ratio of prefecture-level city expenditures to the total national expenditure was used to measure fiscal expenditure decentralization (FD), as based on the method of Jia et al. (2014).

Control variables

Based on the literature reviewed, we identified the following variables as suitable for use as control variables. (1) Economic development (GDP) is commonly measured through per capita GDP; however, there may be a relationship between economic development and carbon productivity as demonstrated by the environmental Kuznets curve, thus the logarithmic square of per capita GDP was also

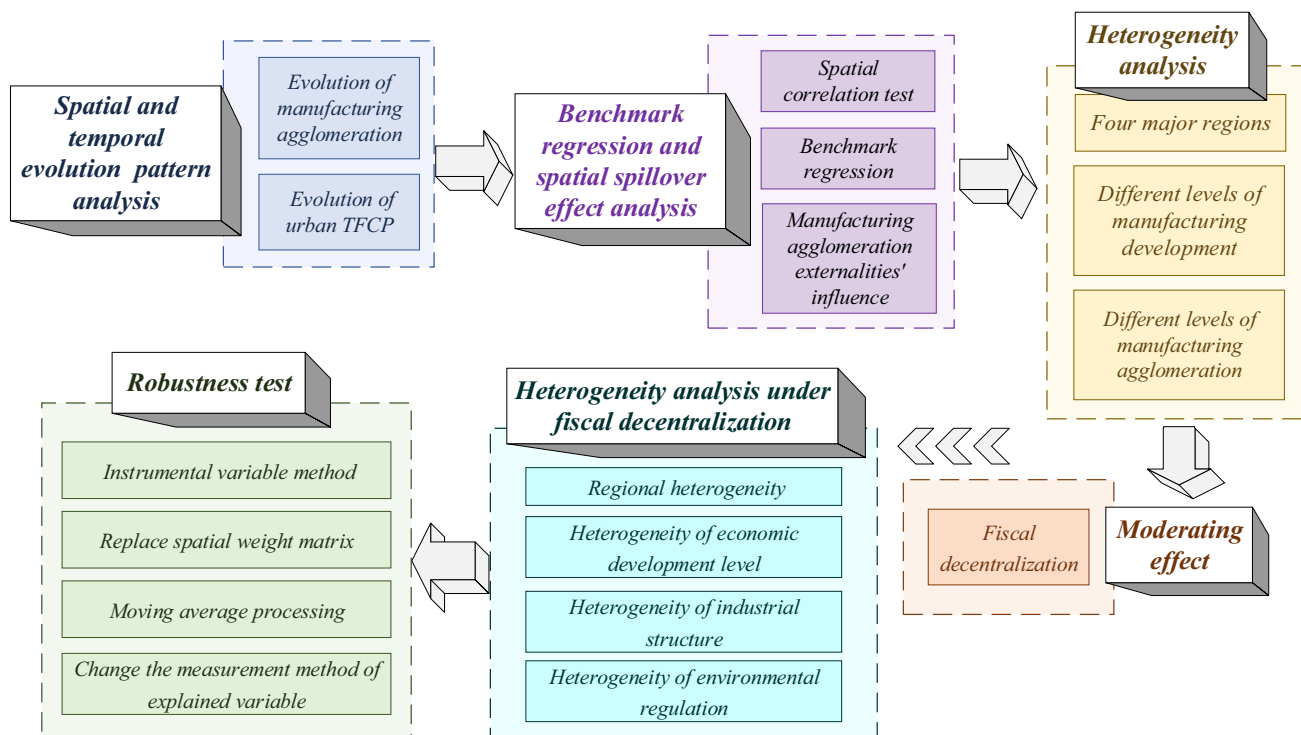


Fig. 1 Flow chart of research methodology

Table 2 Indicators and explanations for measuring TFCP

Primary indicators	Secondary indicators	Explanation	Unit
Input	Capital	Fixed assets investment	Ten thousand yuan
	People	Total population	Ten thousand people
	Energy	Energy consumption	Ten thousand tons of standard coal
Expected output	Economic output	GDP	100 million yuan
Unexpected output	Carbon dioxide emissions	The IPCC methodology was utilized to convert the energy consumption of coal, coke, petroleum, gasoline, kerosene, diesel fuel, fuel oil, liquefied petroleum gas, and natural gas to CO ₂ emission.	Million tons

incorporated into the model. (2) Industrial structure (Industry) was determined by the ratio of value added from tertiary and secondary industries. The industrial structure was linked not only to economic growth but also to the level of technological advancement (Dong et al. 2020). (3) Human capital (Human) was expressed as the number of college students per 100,000 population. College students are a key driving force in innovation, representing the future of cities (Liao and Li 2022). A population with a larger number of college students usually results in greater city vitality and benefits for enterprises carrying out carbon innovation activities, ultimately enhancing TFCP. (4) Foreign direct investment (FDI) is a key metric for measuring economic activity. There are two opposing views related to its environmental impact. The pollution sanctuary hypothesis

predicts an increase in pollution due to the transfer of polluting companies from developed countries, while the pollution halo hypothesis suggests that foreign investment can bring modern management and technology expertise (Kenh 2023), resulting in improved TFCP. (5) Environmental regulation (ENV) was computed as the weighted average of pollutant emissions, including wastewater, SO₂, smoke, and dust, divided by the region’s GDP. According to Jaffe and Palmer (1997), effective environmental regulations can boost growth and output, and improve efficiency. They can also stimulate innovation within enterprises and be considered a “no-cost lunch” that helps organizations achieve higher output. (6) Endowment structure (Endow) was indicated by the ratio of fixed capital stock to total employees (Wang and Li 2020). A higher endowment structure value

Table 3 Descriptive statistics

Variables	Index	Observations	Mean	Std. Dev.	Min	Max
Explained variable	TFCP	3976	1.0076	0.0943	0.3460	2.4850
Core explanatory variable	MA	3976	0.8561	0.4820	0.0211	3.0583
Moderator variable	FD	3976	0.0022	0.0034	0.0001	0.0444
Control variables	GDP	3976	10.4111	0.7250	4.5951	13.0556
	Industry	3976	1.5095	1.1413	0.1865	21.1601
	Human	3976	10.4101	1.3601	6.3421	13.9578
	FDI	3976	9.7566	1.9039	3.7376	14.9413
	ENV	3976	31.5388	2.3205	20.8630	38.7081
	Endow	3976	12.2000	0.7839	9.4190	14.2864
	Infor	3976	5.5546	0.8827	2.4239	8.3128
	INFRA	3976	4.4070	0.8665	2.0794	7.7952

corresponded to a higher proportion of capital investment, which may include investment in carbon innovation activities to improve TFCP. (7) Information level (Infor) was based on the number of mobile phone users at the end of the year. The development of information technology can facilitate the flow of production elements, speed up the dissemination of information and technology, and increase TFCP (Kan 2021). (8) Infrastructure level (INFRA) was expressed by the area of urban construction land (Wang et al. 2022b).

Data source

The study focused on 284 prefecture-level cities in China from 2006 to 2019, using data from the China Statistical Yearbook, the China Financial Yearbook, and the China Urban Statistical Yearbook. To eliminate the effect of price, all indices related to output value were deflated based on 2006. Additionally, in order to avoid the impact of outliers on empirical outcomes, a 1% tail reduction was performed on all variables. Descriptive statistics for related variables are shown in Table 3.

The terrain slope data originated from the DEM digital elevation data provided by the Geospatial Data Cloud of the Chinese Academy of Sciences, specifically the SRT-MSLOPE 90 m resolution. Each grid's slope was calculated using ArcGIS software, and the DEM data intersected with the administrative divisions of prefecture-level cities to determine the terrain slope for each city.

Evolution of MA and urban TFCP

Spatial and temporal evolution of MA

We utilized the natural break method in ArcGIS 10.2 to create a map displaying the spatial distribution of MA in urban China at the start and end of the study period (Fig. 2). The eastern region

had a significant advantage over the central and western regions in 2006. Cities with favorable manufacturing development were mainly concentrated in the east, in close proximity to the Bohai Rim, Yangtze River Delta, and Pearl River Delta regions. By 2019, MA had significantly increased throughout China, with a substantial rise in the number of cities with advantageous conditions. The western region and particularly the central region experienced a significant surge in manufacturing concentration. Many cities in Henan Province and Jiangxi Province showed a high-level of manufacturing concentration, covering large areas. The western region of China likewise saw a rise in the number of cities with advantageous high-level manufacturing concentrations emerging in Shaanxi, Inner Mongolia, Gansu, and Yunnan provinces. Although the degree of manufacturing concentration in the eastern region also increased during the sample period, the advantages of manufacturing concentration in the Bohai Rim, Yangtze River Delta, and Pearl River Delta gradually decreased compared to those in the central region. The number of high-level manufacturing concentration cities in the eastern region was significantly lower than in the central region, and the distribution changed from contiguous to sporadic.

Figure 3 depicts the spatial distribution characteristics and shift of the center of gravity in MA. From 2006 to 2019, the short half-axis was, on average, 1.5 times that of the long half-axis, with the azimuth angle decreasing from 18.11 to 15.54°. This indicates that China's MA was mainly oriented in a north-south direction, with little influence in the east-west direction. Second, China's MA displayed a spatial pattern of greater concentration in the south than in the north, and its center of gravity exhibited a noticeable trend of shifting towards the south.

Analysis of temporal and spatial evolution of urban TFCP

This study used the SBM-DDF method and the Luenberger index to measure the TFCP of 284 prefecture-level cities from 2006 to 2019. TFCP can be decomposed into

technological progress and efficiency, and the curve in Fig. 4 shows the changes in TFCP and its decomposition term during the sample period. There was a U-shaped change in TFCP from 2008 to 2010 and an inverted U-shaped change from 2017 to 2019, with two distinct extreme points. During other periods, the trend was towards a stable fluctuation around 1. The trend of technological progress aligns with TFCP, and there is an inverse relationship between technological efficiency and TFCP. These findings highlight technological progress as the primary driving force behind the promotion of TFCP.

To better comprehend the changes in TFCP at China's prefecture-level cities over time and space during the study period, we utilized ArcGIS 10.7 to visually represent the years 2006, 2011, 2015, and 2019. These results are presented in Fig. 5.

In general, the TFCP of urban areas in China followed a pattern of mainly medium and low-level distribution, with some high-level clustering. Specifically, from 2006 to 2019, over 50% of the cities in China had low or lower-level TFCP, and these were mainly located in industrial areas in the central and northeast regions. Approximately 40% of the cities in the sample had medium-level TFCP, and these were scattered in central and northern provinces such as Shaanxi, Shanxi, and Gansu, as well as in southeast coastal cities in Guangdong and Jiangsu provinces. High-level or higher-level samples accounted for around 10% and were mainly located in Shiyan and Jingzhou in Hubei province, Dingxi and Pingliang in Gansu province, and Shangqiu in Henan province. It should be noted that the spatial distribution pattern of “low-level clustering and high-level dispersion” remained largely unchanged for 14 years, indicating a stable spatial structure.

The impact of MA on urban TFCP

Spatial correlation test of urban TFCP

Before conducting spatial econometric analysis, we assessed the spatial correlation of urban TFCP by calculating Moran's *I*. The results of this test (Table 4) indicate a significant positive spatial autocorrelation of TFCP across different cities. This suggests that cities with high TFCP are adjacent to cities with high TFCP, while cities with low TFCP are adjacent to cities with low TFCP. Thus, it was appropriate in this paper to incorporate spatial correlations in examining the factors that affect urban TFCP.

Regression results of the spatial econometric model

Table 5 displays the regression outcomes of the relationship between MA and urban TFCP. Columns 1 and 2 reveal that

MA has a significant U-shaped impact on urban TFCP with no control variables considered. When the level of MA is low, urban TFCP declines as MA level improves. However, when the level of MA reaches the inflection point, urban TFCP increases congruent with the upsurge in MA. The indirect effect coefficient shows that the agglomeration of the manufacturing industry in this metropolis has a significant, positive, U-shaped spatial spillover effect on the TFCP of neighboring cities.

Columns 3 and 4 demonstrate that, even after controlling for other factors, the influence of MA on urban TFCP remains significantly positive and follows a U-shaped pattern. Furthermore, the coefficient of indirect effect reveals that MA in one city exerts a significant, positive, U-shaped spatial spillover impact on the TFCP of surrounding cities. This observation validates **Hypothesis 1**, confirming that the spatial spillover effect of MA on TFCP has a positive U-shaped nonlinear effect. Additionally, a comparison of geographic and economic matrices showed that this spatial spillover effect occurred predominantly through geographical channels. Lastly, our analysis suggested that urban TFCP was significantly positively influenced by economic growth and an increase in foreign direct investment. Conversely, the industrial structure, level of human capital, and environmental regulations were negatively associated with urban TFCP.

Analysis of the influence of MA externalities on urban TFCP

In this study, we examined MA from an externality perspective. Table 6 presents estimations of the influence of three different externalities on urban TFCP. Columns 1 to 3 indicate that specialized, diversified, and competitive agglomeration significantly enhances urban TFCP. In column 4, these three externalities are included in the same model. The regression coefficients for Jacobs' and Porter's externalities remained positive and statistically significant at 5%, whereas those for MAR externalities were not significant possibly due to high emissions resulting from specialized agglomeration of manufacturing industry, which impeded the improvement of urban TFCP. It should be noted that the positive impact of Jacobs' externality was greater than that of Porter's externality, illustrating that diversified agglomeration of the manufacturing industry is a key driver promoting urban TFCP.

Heterogeneity analysis

Heterogeneity analysis was performed in four major regions

The national sample was divided into east, central, west, and northeast regions to determine the effects of diversity on the

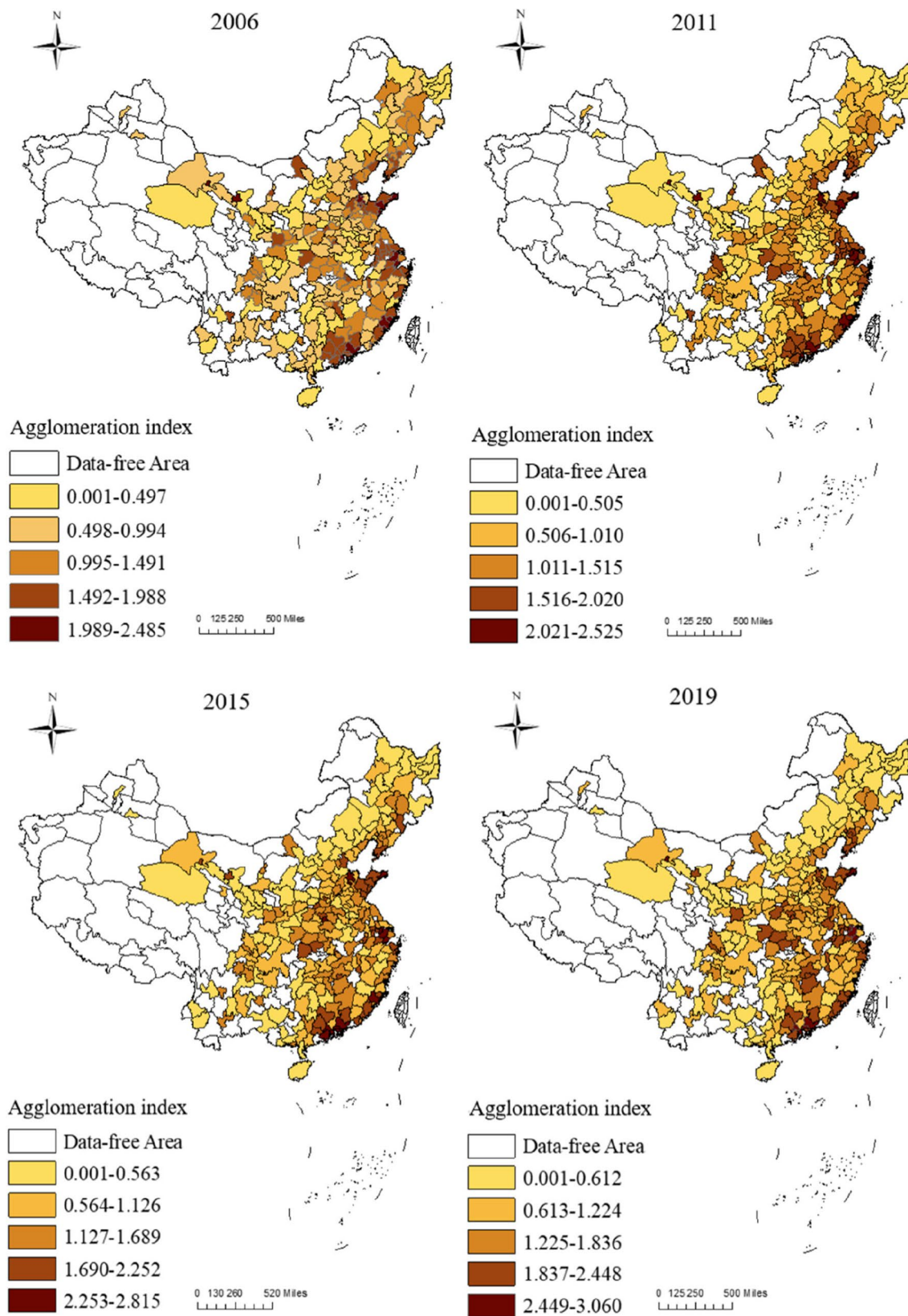


Fig. 2 Spatial distribution of MA in 2006 and 2019. Note: The figure is based on the standard map created by the National Bureau of Surveying. Mapping and geographical information is available at map review number GS (2016) 1592; the base map remained unaltered

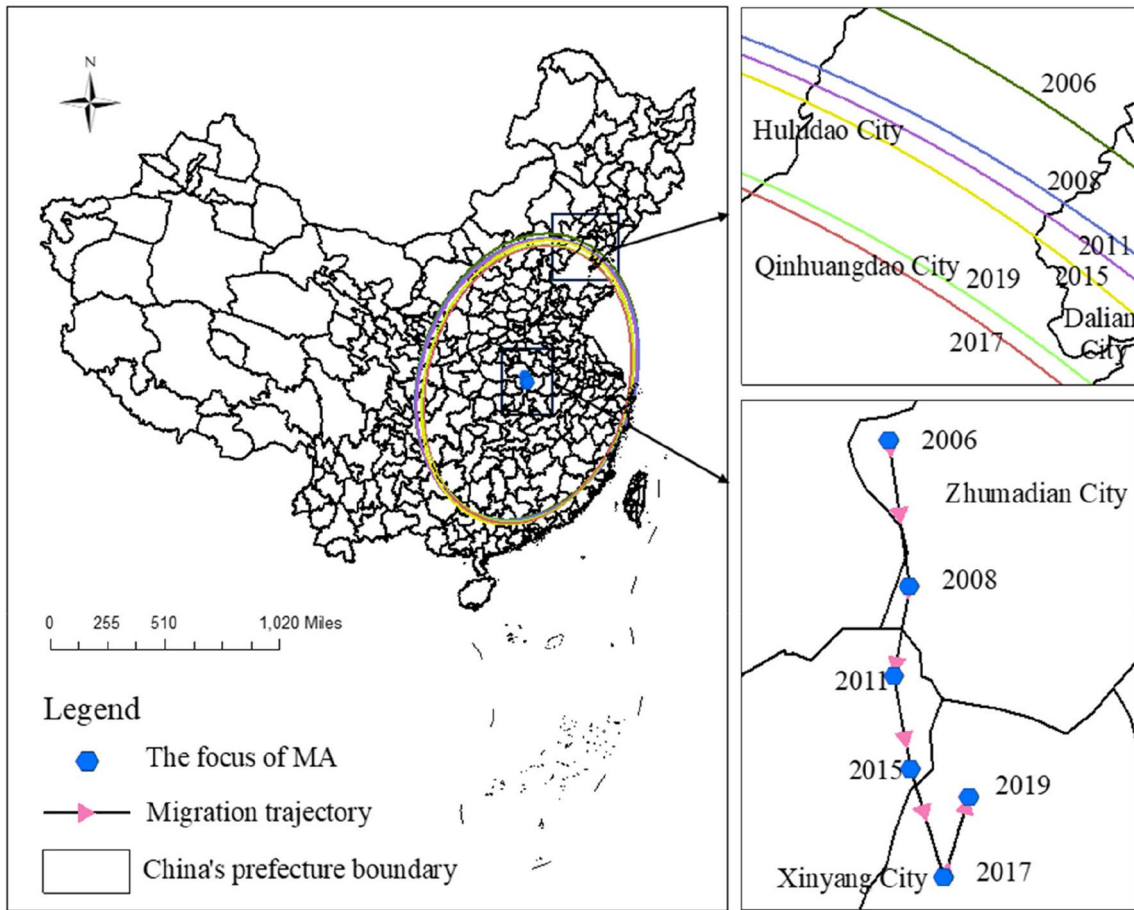
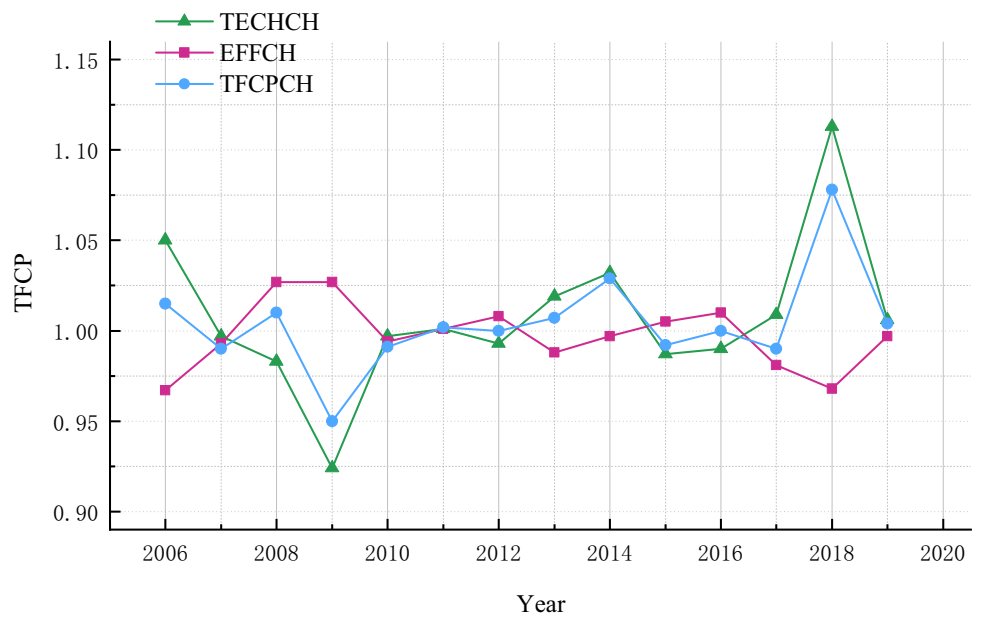


Fig. 3 Moving trajectory of elliptical center of gravity in MA. Note: The figure is based on the standard map created by the National Bureau of Surveying. Mapping and geographical information is available at map review number GS (2016) 1592; the base map remained unaltered

Fig. 4 Changing trends of TFCP and its component parts from 2006 to 2019



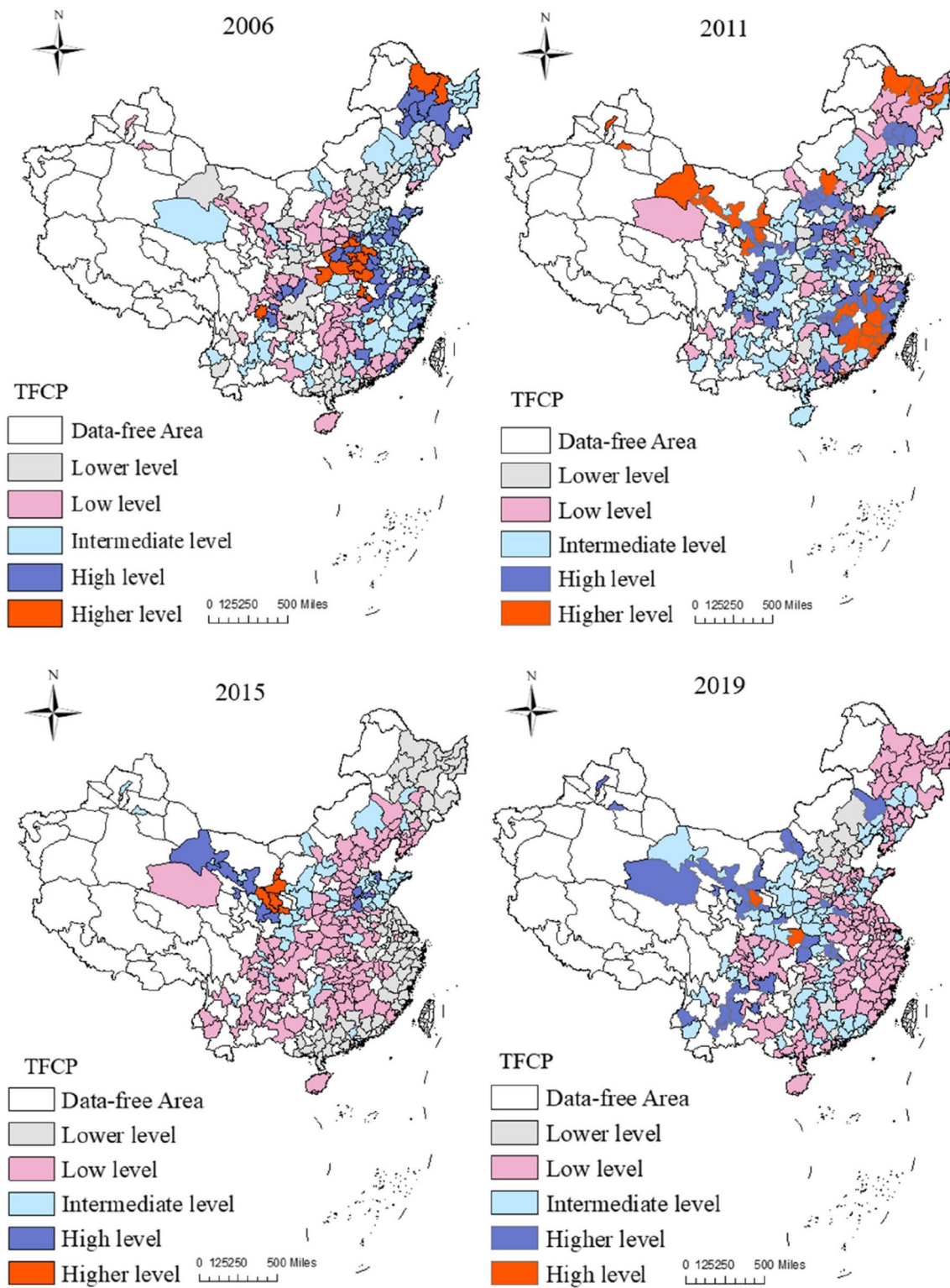


Fig. 5 Patterns of spatial evolution of TFCP from 2006 to 2019. Note: The figure is based on the standard map created by the National Bureau of Surveying. Mapping and geographical information is available at map review number GS (2016) 1592; the base map remained unaltered

Table 4 Moran's *I* test

Year	<i>I</i>	<i>E(I)</i>	sd(<i>I</i>)	<i>z</i>
2006	0.292***	−0.004	0.018	16.006
2007	0.268***	−0.004	0.018	14.691
2008	0.108***	−0.004	0.016	6.894
2009	0.288***	−0.004	0.018	16.022
2010	0.205***	−0.004	0.019	11.243
2011	0.167***	−0.004	0.018	9.210
2012	0.163***	−0.004	0.018	9.048
2013	0.211***	−0.004	0.018	11.873
2014	0.303***	−0.004	0.018	16.700
2015	0.419***	−0.004	0.018	23.624
2016	0.266***	−0.004	0.018	14.774
2017	0.108***	−0.004	0.018	6.284
2018	0.143***	−0.004	0.018	8.302
2019	0.289***	−0.004	0.018	15.878

****p* < 0.01, ***p* < 0.05, **p* < 0.1

impact of MA on TFCP in Chinese cities (Table 7). The findings revealed a significant U-shaped trend for MA's impact on urban TFCP in the eastern and central regions. By using the equation, $MA = -\frac{\beta_1}{2\beta_2}$, we determined the inflection point of the regression curve linking MA to urban TFCP. In the eastern region, the average MA level was 1.171, which falls to the left of the inflection point. In central China, the average MA level was 0.804, which falls to the right of the inflection point. Thus, increasing MA in the east may initially hinder the improvement of urban TFCP; however, once it reaches the inflection point, it will ultimately lead to an improvement in urban TFCP. On the other hand, boosting the MA level in central China could immediately enhance the TFCP of cities in that region. Although the impact of MA in the western and northeastern regions was not significant, cities in the northeast region could have a positive U-shaped spatial spillover effect on the TFCP of surrounding cities.

The results of regional heterogeneity analysis indicated that TFCP in the eastern region can only be improved when MA reaches the inflection point; the MA in the central region has passed the inflection point, which resulted in the continuous enhancement of TFCP. The spatial distribution map of MA and the migration map of MA's center of gravity (Figures 2 and 3) reveal that the number of cities with high MA in central China has increased significantly. The advantages of MA are shifting from the east to the central and western regions, and the center of gravity of MA is shifting from north to south. The TFCP distribution map in Fig. 5 indicates that cities with higher levels of TFCP are mainly located in central and southern regions such as Hubei and Henan provinces. This confirms that the results of the

regional heterogeneity analysis are consistent with the patterns on the spatio-temporal distribution map.

Heterogeneity analysis of major manufacturing cities compared with non-manufacturing cities

The investigated regions were categorized based on their number of manufacturing employees between 2006 and 2019. Regions above the average were considered significant manufacturing hubs, while those below the average were non-manufacturing areas. The impact of MA on urban TFCP was separately measured for these two regions, and the findings are presented in columns 1 and 2 of Table 8.

In large manufacturing cities, the impact of MA on urban TFCP followed an inverted U-shape; however, the quadratic term relating to MA did not display significance. Throughout the period of investigation, the average level of MA for these cities was 1.119, which was to the left side of the inflection point. In such regions, enhancing the level of MA can lead to an improvement in urban TFCP. For major non-manufacturing cities, the effect of MA on urban TFCP shows an inverted U-shaped curve, with significant results found in both primary and secondary terms of MA. The average urban TFCP for these cities during the study period was 0.593; thus, for cities on the left side of the inflection point, increasing MA can enhance urban TFCP, but enhancing MA in major manufacturing cities has a more substantial impact on urban TFCP.

Heterogeneity analysis of regions with different MA levels

To examine the disparities in the impact of MA on urban TFCP in regions with varying levels of agglomeration, the regions with above-average agglomeration levels during the sample period were classified as high MA areas, while those with below-average agglomeration levels were classified as low MA areas. The findings are shown in columns 3–4 of Table 8.

The influence of MA on urban TFCP in low agglomeration areas exhibits a U-shaped pattern. Throughout the observation period, the average degree of MA in these areas (0.510) was located to the right of the inflection point; therefore, increasing the level of MA boosted urban TFCP. The impact of MA on urban TFCP in high agglomeration regions also displayed a U-shaped pattern. However, the degree of MA in such regions (1.202) during the sample period was located to the left of the inflection point. Improving the degree of MA would hinder the urban TFCP in this area. One possible explanation for this outcome is that the excessive agglomeration of manufacturing industry leads

Table 5 Effects of MA on urban TFCP

Variable	SDM (W_1) (1)	SDM (W_2) (2)	SDM (W_1) (3)	SDM (W_2) (4)
<i>MA</i>	−0.0025** (0.0025)	−0.0051** (0.0027)	−0.0021** (0.0026)	−0.0021** (0.0028)
MA^2	0.0015** (0.0009)	0.0027*** (0.0011)	0.0002** (0.0011)	0.0006** (0.0010)
GDP			0.0021** (0.0012)	0.0004** (0.0018)
Industry			−0.0014*** (0.0003)	−0.0020*** (0.0003)
Human			−0.0026** (0.0011)	−0.0041*** (0.0011)
FDI			0.0018*** (0.0005)	0.0039*** (0.0005)
ENV			−0.0006** (0.0002)	−0.0005** (0.0002)
Endow			−0.0001 (0.0005)	−0.0002 (0.0005)
Infor			−0.0010 (0.0009)	−0.0026*** (0.0009)
INFRA			0.0021 (0.0013)	0.0019 (0.0014)
Rho	0.8389*** (0.0176)	0.5246*** (0.0197)	0.7830*** (0.0208)	0.4641*** (0.0214)
$W \times MA$	−0.0066** (0.0073)	−0.0152** (0.0077)	−0.0109*** (0.0087)	−0.0103** (0.0083)
$W \times MA^2$	0.0020** (0.0025)	0.0056** (0.0032)	0.0041*** (0.0030)	0.0042** (0.0034)
Direct (<i>MA</i>)	−0.0034** (0.0026)	−0.0068** (0.0029)	−0.0029** (0.0028)	−0.0029** (0.0030)
Direct (MA^2)	0.0018** (0.0010)	0.0034*** (0.0011)	0.0001** (0.0010)	−0.0003** (0.0012)
Indirect (<i>MA</i>)	−0.0587** (0.0422)	−0.0378** (0.015)	−0.0579** (0.0385)	−0.0209** (0.0147)
Indirect (MA^2)	0.0222** (0.0143)	0.0150** (0.0062)	0.0184** (0.0137)	0.0075** (0.0063)
City effect fixed	Yes	Yes	Yes	Yes
Year effect fixed	Yes	Yes	Yes	Yes
Adj'd R^2	0.128	0.083	0.648	0.510
Observations	3976	3976	3976	3976

Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

to a scarcity of infrastructures, escalating land rents, and environmental contamination, which give rise to crowding effects that obstruct urban TFCP.

Analysis of the regulatory role of fiscal decentralization

The spatial model incorporates fiscal decentralization as an adjustment variable, and the resulting measurements are shown in Table 9. Taking a national perspective and incorporating the crossed elements of fiscal decentralization and MA, a significant inverted U-shaped relationship between MA and TFCP in Chinese cities was found.

As shown in Table 1, when the primary effect produced an inverted U-shaped curve, the regression coefficient of $MA^2 \times FD$ was positive. This indicates that fiscal decentralization smooths the curve of the effect of MA on urban TFCP on both sides of the inflection point of and reduces its impact. This suggests that local governments tend to prioritize economic growth over environmental governance and reducing manufacturing carbon emissions, which is also linked to the current performance evaluation system of local governments. This finding also validates **Hypothesis 2**, confirming that fiscal decentralization plays a moderating role between MA and urban TFCP.

Table 6 Influence of MA externalities on urban TFCP

Variable	(1)	(2)	(3)	(4)
MAR	0.0049** (0.0113)			−0.0205 (0.0131)
Jacobs'		0.0700** (0.0309)		0.0305** (0.0094)
Porter's			0.0002* (0.0002)	0.0003** (0.0002)
Control	Yes	Yes	Yes	Yes
Rho	0.7861*** (0.0032)	0.7892*** (0.0206)	0.7843*** (0.0208)	0.7865*** (0.0209)
City effect fixed	Yes	Yes	Yes	Yes
Year effect fixed	Yes	Yes	Yes	Yes
Adj'd R^2	0.509	0.497	0.508	0.500
Observations	3976	3976	3976	3976

Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7 Effect of MA on urban TFCP in the four major regions of China

Variable	East	Central	West	Northeast
MA	−0.0024* (0.0041)	−0.0022* (0.0053)	−0.0011 (0.0070)	−0.0079 (0.0141)
MA ²	0.0008* (0.0013)	0.0024* (0.0025)	−0.0044 (0.0034)	0.0027 (0.0076)
W×MA	−0.0361*** (0.0122)	−0.0041* (0.0170)	−0.0262 (0.023)	−0.0767** (0.0430)
W×MA ²	0.0105*** (0.0038)	−0.0022* (0.0078)	0.0113 (0.0096)	0.0191* (0.0229)
Rho	0.5937*** (0.0382)	0.6624*** (0.0337)	0.525*** (0.0442)	0.6556*** (0.0464)
Model	SDM	SDM	SDM	SDM
Control	Yes	Yes	Yes	Yes
Adj'd R^2	0.933	0.731	0.269	0.222
Observations	1204	1246	1050	476
Inflection point	1.500	0.4583	0.1250	1.4629

Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Regional heterogeneity

From the perspective of the four major regions (Table 9), the effect of MA on urban TFCP in the eastern region exhibits an inverted U-shaped curve after accounting for fiscal decentralization, which is opposite to the situation without the inclusion of fiscal decentralization. In the central region, regardless of fiscal decentralization, the impact curve of MA on urban TFCP is U-shaped. According to Table 1, fiscal decentralization in areas with high levels of MA (eastern and central regions) diminishes the effect of MA on urban TFCP, indicating that the current pattern and intensity of fiscal decentralization in eastern and central areas is unfavorable to MA.

Heterogeneity of economic development level

Effective fiscal decentralization strategies reduce the nation's economic imbalance and accelerate growth (Liu 2020). Hence, this study assessed the heterogeneous influence of MA on TFCP across various economic contexts. The sample was divided according to the mean level of economic development into urban groups of high economic development and low economic development, and the results are shown in columns 1 and 2 of Table 10.

In terms of cities with high levels of economic development, the relationship between MA and TFCP exhibits a significantly inverted U-shape after considering the regulation of fiscal decentralization. With reference to Table 1, it can be seen that when the main effect was inverted U-shaped and the regression coefficient of $MA^2 \times FD$ was significantly negative, fiscal decentralization enhanced the impact of MA on TFCP in cities with high levels of economic development. However, for underdeveloped cities, the relationship between MA and TFCP exhibited a significantly positive U-shape. Combined with Table 1, it was evident that when the primary effect was positive U-shaped, and the regression coefficient of $MA^2 \times FD$ was significantly negative, fiscal decentralization decelerated the impact of MA on TFCP in underdeveloped cities.

Heterogeneity of industrial structure

Research has indicated that fiscal decentralization enhances regional industrial structure (Zhao et al. 2023). Utilizing the mean value of industrial structure level, we classified our sample into groups with high and low structure to investigate the heterogeneity of the influence of different industrial structure levels after considering fiscal decentralization. These findings are shown in columns 3 and 4 of Table 10.

For cities with high industrial structures, MA's impact on TFCP has a significant inverse U-shaped relationship after considering fiscal decentralization. With regard to Table 1, it was found that when the main effect was inverted U-shaped, and the regression coefficient of $MA^2 \times FD$ was significantly negative, fiscal decentralization enhanced MA's influence on TFCP in these cities. However, for cities with low industrial structures, the same relationship was not significant. The regression coefficient of $MA^2 \times FD$ was negative and also not significant, suggesting that fiscal decentralization had no significant regulatory effect on the impact of MA on TFCP in groups with low industrial structure.

Heterogeneity of environmental regulation

In light of fiscal decentralization and promotional championships, local governments may slightly relax environmental regulations and ignore the carbon emissions of some

Table 8 Effect of MA on urban TFCP in different regions

Variable	Large manufacturing city (1)	Non-manufacturing city (2)	High manufacturing agglomeration (3)	Low manufacturing agglomeration (4)
MA	0.0028** (0.0034)	0.0026** (0.0050)	-0.0036*** (0.0036)	-0.0067* (0.0086)
MA ²	-0.0011 (0.0011)	-0.0002* (0.0025)	0.0002*** (0.0011)	0.0050* (0.0065)
W × MA	-0.0217** (0.0097)	-0.0145* (0.0147)	-0.0117** (0.0100)	-0.0314** (0.0258)
W × MA ²	0.0036* (0.0030)	0.0095* (0.0074)	0.0034** (0.0032)	0.0227** (0.0201)
rho	0.7568*** (0.0255)	0.6286*** (0.0289)	0.7193*** (0.0264)	0.6604*** (0.0288)
Model	SDM	SDM	SDM	SDM
Control	Yes	Yes	Yes	Yes
Adj'd R ²	0.103	0.546	0.391	0.562
Observations	1988	1988	1988	1988
Inflection point	1.273	6.500	9.000	0.3895

Standard errors are in parentheses; ****p* < 0.01, ***p* < 0.05, **p* < 0.1

Table 9 Results of fiscal decentralization adjustment

Variable	National	East	Central	West	Northeast
MA	0.0002* (0.0030)	0.0004* (0.0044)	-0.0095** (0.0063)	-0.0001 (0.0075)	-0.0051 (0.0159)
MA ²	-0.0013* (0.0013)	-0.0002* (0.0016)	0.0081** (0.0035)	-0.0040 (0.0034)	0.0057 (0.0095)
MA × FD	-0.9625* (0.5911)	-0.7223** (0.5217)	5.9239** (2.7113)	3.6931 (3.1280)	-7.6074 (5.8712)
MA ² × FD	0.4138** (0.3373)	0.3425** (0.2970)	-4.3572** (1.9116)	-3.6700 (2.8917)	2.1773 (3.8124)
W × MA	-0.0001 (0.0122)	-0.0319** (0.0137)	0.0022 (0.0214)	-0.0220 (0.0252)	-0.0833* (0.0494)
W × MA ²	0.0006 (0.0054)	0.0083** (0.0052)	-0.0044 (0.0115)	0.0114 (0.0102)	0.0243 (0.0319)
Rho	0.7816*** (0.0209)	0.5948*** (0.0382)	0.6611*** (0.0339)	0.5237*** (0.0442)	0.6538*** (0.0463)
Model	SDM	SDM	SDM	SDM	SDM
Control	Yes	Yes	Yes	Yes	Yes
Adj'd R ²	0.636	0.706	0.765	0.230	0.146
Observations	3976	1204	1246	1050	476

Standard errors are in parentheses; ****p* < 0.01, ***p* < 0.05, **p* < 0.1

enterprises in order to attract foreign investment and safeguard local advantages; however, this could amplify the detrimental impact of energy mismatch on TFCP (Song et al. 2018). Consequently, this study divided the sample into two groups of cities: those with strict environmental regulation and those with weak environmental regulation (columns 5 and 6 of Table 10).

Cities with strong environmental regulations, under fiscal decentralization, exhibit a notable inverted U-shaped link between MA and TFCP. Combined with Table 1, the

inverted U-shaped main effect was associated with a negative regression coefficient of MA² × FD. This suggests that fiscal decentralization enhances the impact of MA on TFCP in these areas. Strict enforcement of environmental rules, despite fiscal decentralization, can lead MA to reduce carbon emissions, thereby enhancing TFCP. For cities with weak environmental regulations, under fiscal decentralization, a significant positive U-shaped relationship exists between MA and TFCP. Combined with Table 1, a main effect with a positive U-shape and negative regression coefficient of

Table 10 Heterogeneity analysis results based on fiscal decentralization

Variable	High level of economic development (1)	Low level of economic development (2)	High level industrial structure (3)	Low level industrial structure (4)	Strong environmental regulation (5)	Weak environmental regulation (6)
<i>MA</i>	0.0296** (0.0249)	-0.1020** (0.0538)	0.0102** (0.0345)	0.0243 (0.0307)	0.0082* (0.0316)	-0.0539** (0.0252)
<i>MA</i> ²	-0.0086** (0.0078)	0.0377* (0.0316)	-0.0059** (0.0190)	-0.0064 (0.0100)	-0.0049* (0.0103)	0.0185** (0.0092)
<i>MA</i> × <i>FD</i>	0.4738** (3.4333)	61.0254* (46.6856)	-0.1007 (6.7987)	0.1354 (7.1146)	7.2073** (4.8861)	27.8635** (18.0469)
<i>MA</i> ² × <i>FD</i>	-0.6180** (1.5220)	-23.0764* (27.7135)	-0.1771* (3.3714)	-0.2449 (2.5205)	-4.6586** (2.1528)	-9.0340** (5.4538)
<i>W</i> × <i>MA</i>	0.0845** (0.0625)	-0.3091** (0.1719)	-0.0682 (0.1018)	0.0835 (0.0753)	0.0024 (0.0840)	-0.0092* (0.1001)
<i>W</i> × <i>MA</i> ²	-0.0298** (0.0198)	0.1465** (0.0989)	0.0050 (0.0647)	-0.0086 (0.0251)	-0.0080 (0.0436)	-0.0058* (0.0340)
Rho	0.7708*** (0.0426)	0.8325*** (0.0483)	0.9214*** (0.0284)	0.7775*** (0.0325)	0.8114*** (0.0465)	0.7920*** (0.0471)
Model	SDM	SDM	SDM	SDM	SDM	SDM
Control	Yes	Yes	Yes	Yes	Yes	Yes
Adj'd <i>R</i> ²	0.1165	0.0503	0.0275	0.0190	0.0236	0.0510
Observations	1988	1988	1988	1988	1988	1988

Standard errors are in parentheses; ****p* < 0.01, ***p* < 0.05, **p* < 0.1

*MA*² × *FD* indicated that fiscal decentralization diminished the effect of *MA* on TFCP in cities with weak environmental regulations.

Robustness tests

Instrumental variable method

Because of the potential for endogenous problems within the model such as missing variables and errors that limit the effective identification of *MA*'s true impact on urban TFCP, the instrumental variable method was utilized to determine the robustness of benchmark regression outcomes.

Industrial agglomeration is a dynamic process of adapting industrial organization at geographical and spatial levels. When constructing instrumental variables, it is important to identify a variable that has a direct impact on changes in industrial organization, but does not directly affect urban TFCP. Following the suggestions of Wang et al. (2022c), the topographic slope value (TSV) of prefecture-level cities was chosen as the instrumental variable. The terrain slope of prefecture-level cities fulfills the correlation criterion for a tool variable. Low terrain slopes are typically flat and tend to have a dense population and greater concentration of industry, making them attractive for industrial agglomeration. In addition, manufacturing enterprises often opt for areas with a low terrain gradient as this can reduce transaction and transportation costs. Consequently, cities with

low terrain slopes tend to have a higher degree of industrial agglomeration. The terrain slope of prefecture-level cities is an objective natural geographical fact that has no impact on the urban TFCP and meets the requirement for an exogenous instrumental variable.

The outcomes are presented in column 1 of Table 11 and show a significant U-shaped correlation between *MA* and urban TFCP. The results of tests on weak instrumental variables demonstrate the effectiveness of the instrumental variable method, and the robustness of the benchmark conclusions remains intact.

Replacing the spatial weight matrix

In this study, we replaced the original spatial weight matrix with the nested distance matrix of economic geography (*W*₃) and re-estimated the benchmark model using the SDM method. We also included estimates for the spatial lag model (SAR) and spatial error model (SEM) to confirm the model's robustness. Columns 2 to 5 in Table 11 show that the U-shaped relationship between *MA* and urban TFCP remains unchanged despite changes in spatial weight, matrix, and model.

Moving average processing

To account for the potential influence of long-term trends on regression outcomes, the relevant variables were subjected to a three-time moving average. Examination of column 6

Table 11 Results of robustness tests

Variable	Instrumental variable (TSV) (1)	Variable	SDM (W_3) (2)	SDM (W_3) (3)	SAR (W_1) (4)	SEM (W_1) (5)	Moving average processing (6)	Change explained variable (7)
MA	-0.0459* (0.0425)	MA	-0.0024* (0.0024)	-0.0025** (0.0026)	-0.0019* (0.0025)	-0.0011* (0.0026)	-0.0033** (0.0031)	-0.0128* (0.0215)
MA ²	0.0178* (0.0158)	MA ²	0.0015* (0.0009)	0.0008* (0.0010)	0.0003* (0.0009)	0.0006 (0.0009)	0.0007* (0.0011)	0.0043* (0.0083)
Cons	4.6038*** (0.0176)	Rho	0.8521*** (0.0176)	0.7907*** (0.0212)	0.8185*** (0.0186)		0.7839*** (0.0231)	0.9402*** (0.0143)
Cragg-Donald Wald F statistic	13.630	W×MA	-0.0085* (0.0069)	-0.0160* (0.0082)			-0.0217** (0.0107)	-0.0895** (0.0738)
Cragg-Kleibergen-Paap Wald rk F statistic	17.011	W×MA ²	0.0020* (0.0022)	0.0062* (0.0027)			0.0077** (0.0036)	0.0271** (0.025)
Control	Yes	Control	No	Yes	Yes	Yes	Yes	Yes
City effect fixed	Yes	City effect fixed	Yes	Yes	Yes	Yes	Yes	Yes
Year effect fixed	Yes	Year effect fixed	Yes	Yes	Yes	Yes	Yes	Yes
Adj'd R ²	0.733	Adj R ²	0.021	0.770	0.301	0.015	0.862	0.532
Observations	3976	Observations	3976	3976	3976	3976	3124	3976

Standard errors are in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

in Table 11 shows that the U-shaped relationship between MA and urban TFCP remains consistent, indicating that the primary conclusions of this study were unaffected by annual data fluctuations.

Changes in the measurement method of the explained variable

Drawing on Xu et al.'s (2020) research on carbon productivity, the TFCP was measured as the industrial output value generated per unit of carbon emission in the manufacturing sector, using a benchmark model for regression analysis. As shown in column 7 of Table 11, the curve of TFCP for MA in Chinese cities was U-shaped. This result reinforces the core conclusions of the study and confirms its robustness to any changes in the methodology or variables under consideration.

Conclusions and policy implications

Enhancing TFCP is imperative for reducing carbon emissions and achieving sustainable development. This study employed panel data on 284 Chinese cities from 2006 to 2019 to investigate the effects of spatial spillover from MA

on urban TFCP, as well as the regulating effects of fiscal decentralization. The main findings are as follows:

- (1) The spatial and temporal distribution of MA shows that its advantages are shifting from eastern cities to central and western cities, and the focus of MA is shifting from north to south. The spatial mapping of urban TFCP displays the solidification characteristics of “low-level agglomeration and high-level dispersion.” In addition, technological progress, the decomposition of TFCP, is the main driving force for the improvement of TFCP.
- (2) Regardless of whether control variables were included, MA had a significant U-shaped effect on the TFCP of local cities. It also exhibited a U-shaped spatial spillover effect on the TFCP of surrounding cities. Economic development and increased FDI can significantly enhance urban TFCP; however, industrial structure, human capital, and environmental regulations negatively affected urban TFCP. Analysis of agglomeration externalities shows that MA can boost urban TFCP through Jacobs’ and Porter’s externalities. The positive impact of Jacobs’ externalities was considerably greater than Porter’s externalities, but MAR externalities did not contribute to the enhancement of urban TFCP.
- (3) Regional heterogeneity analysis indicated that MA had a significant effect on urban TFCP in the eastern and central regions, resulting in a U-shaped curve, but the

impact was not significant in the western and north-eastern regions. Regarding the heterogeneity analysis of manufacturing development levels, the impact of MA on urban TFCP followed an inverted U-shape for both manufacturing and non-manufacturing cities. The promotion of MA levels in big manufacturing cities had a greater impact on urban TFCP than in non-manufacturing cities. The heterogeneity analysis of agglomeration degree indicated that enhancing MA in low agglomeration regions could boost TFCP, while, such improvement in high agglomeration regions may hinder the progress of TFCP.

- (4) Nationally, fiscal decentralization weakens the impact of MA on TFCP. Regional heterogeneity indicates that fiscal decentralization in the eastern and central regions also weakens the effect of MA on TFCP. For heterogeneity of levels of economic development, fiscal decentralization enhances the impact of MA on TFCP in cities with high levels of economic growth, but weakens the impact of MA on TFCP in those with lower levels of economic development. For heterogeneity of industrial structure, fiscal decentralization amplifies the impact of MA on TFCP in urban clusters with superior industrial structure, while it has no significant impact on TFCP in urban areas with less developed industrial structure. Concerning the heterogeneity of environmental regulations, fiscal decentralization bolsters the impact of MA on TFCP in cities with strict environmental regulation, while reducing the impact of MA on TFCP in cities with weak environmental regulation.

Based on our research findings, the following policy recommendations are proposed:

First, the temporal and spatial differences and dynamic changes in urban TFCP must be fully considered. Under these conditions, a pattern of “low-level agglomeration and high-level dispersion” emerged during the research period, which meant that tailoring specific policies to promote the enhancement of TFCP was imperative to fully account for the vast disparities across China’s regions. In addition, as the advantages of MA shifted from eastern cities to central and western cities, its weighted center of gravity shifted southward, indicating a gradual shift towards central and southern regions during the sampling period. This migration pattern should be taken into account in future planning, with a greater focus on the development of MA in central and southern areas to foster regional harmonious growth.

Second, the findings indicate that both the direct and spatial spillover effects of MA on urban TFCP exhibit U-shaped patterns, particularly in eastern and central regions, major manufacturing cities, and cities with low MA. Therefore,

when utilizing MA to enhance TFCP, the need for devising region-specific policies supersedes the one-size-fits-all idea. For cities with low MA, efforts should be made to increase both the quantity and quality of MA, while avoiding over-concentration. Cities with low MA should prioritize quantitative and qualitative enhancements of MA, but also place restrictions on excessive concentration. High MA cities necessitate the execution of the “go out and bring in” strategy. Through market and government intervention, enterprises with outdated capabilities, rudimentary technology, and severe pollution can be phased out. At the same time, the synergies between economic growth and FDI in promoting low-carbon development should be prioritized.

Third, Jacobs’ externalities and Porter’s externalities facilitate China’s TFCP enhancement, while MAR externalities hinder this process. Consequently, we should urge the manufacturing industry to develop a diverse and competitive cluster strategy, fostering collaboration between associated industries and extending the industrial chain. In addition, comprehensive economic and administrative measures should be implemented to mitigate excessive specialized MA, reduce carbon emissions, and improve TFCP.

Fourth, a dynamic adjustment mechanism should be implemented between central and municipal fiscal revenue and expenditure, appropriately expanding fiscal spending on manufacturing industries. Concurrently, given the developmental characteristics of the manufacturing sector across a multitude of cities, especially those at a high stage of economic development, industrial structure, and strict environmental regulation, it is advisable to tailor fiscal strategies towards these cities to endorse green and low-carbon progress. In the context of optimizing the functionality of the market mechanism in the distribution of resources, financial instruments and devices are employed to facilitate the transformation of MA from “quantitative augmentation” to “qualitative enhancement,” and to leverage their role in fostering TFCP.

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Declarations

Ethics approval and consent to participate We declare that we have no human participants, human data, or human tissues.

Consent for publication We do not have any individual person’s data in any form.

Competing interests The authors declare no competing interests.

References

- Cheng Z (2016) The spatial correlation and interaction between manufacturing agglomeration and environmental pollution. *Ecol Indic* 61:1024–1032. <https://doi.org/10.1016/j.ecolind.2015.10.060>
- Cheng Z, Li X, Zhu Y, Wang M (2023) The effects of agglomeration externalities on urban green total-factor productivity in China. *Econ Syst* 47(2):101025. <https://doi.org/10.1016/j.ecosys.2022.101025>
- Cui S, Wang Y, Xu P, Zhu Z (2022) The evolutionary characteristics and influencing factors of total carbon productivity: evidence from China. *Environ Sci Pollut Res* 30(6):15951–15963. <https://doi.org/10.1007/s11356-022-23321-0>
- Dong B, Xu Y, Fan X (2020) How to achieve a win-win situation between economic growth and carbon emission reduction: empirical evidence from the perspective of industrial structure upgrading. *Environ Sci Pollut Res* 27(35):43829–43844. <https://doi.org/10.1007/s11356-020-09883-x>
- Feng G, Xue S, Sun R (2022) Does fiscal decentralization promote or inhibit the improvement of carbon productivity? Empirical analysis based on China's data. *Front Environ Sci* 10:903434. <https://doi.org/10.3389/fenvs.2022.903434>
- Gu W, Zhao X, Yan X, Wang C, Li Q (2019) Energy technological progress, energy consumption, and CO₂ emissions: empirical evidence from China. *J Clean Prod* 236:117666. <https://doi.org/10.1016/j.jclepro.2019.117666>
- Guo A, Yang C, Zhong F (2023) Influence mechanisms and spatial spillover effects of industrial agglomeration on carbon productivity in China's Yellow River Basin. *Environ Sci Pollut Res* 30(6):15861–15880. <https://doi.org/10.1007/s11356-022-23121-6>
- Guo J, Sun Z (2023) How does manufacturing agglomeration affect high-quality economic development in China? *Econ Anal Policy* 78:673–691. <https://doi.org/10.1016/j.eap.2023.04.007>
- Haans R, Pieters C, He Z (2016) Thinking about U: theorizing and testing U and inverted U-shaped relationships in strategy research. *Strateg Manag J* 37(7):1177–1195. <https://doi.org/10.1002/smj.2399>
- Han F, Xie R, Lu Y, Fang J, Liu Y (2018) The effects of urban agglomeration economies on carbon emissions: evidence from Chinese cities. *J Clean Prod* 172:1096–1110. <https://doi.org/10.1016/j.jclepro.2017.09.273>
- Han J, Li G, Shen Z, Song M, Zhao X (2022) Manufacturing transfer and environmental efficiency: evidence from the spatial agglomeration of manufacturing in China. *J Environ Manage* 314:115039. <https://doi.org/10.1016/j.jenvman.2022.115039>
- He W, Li Y, Meng X, Song M, Ramsey T, An M (2023) Will green technological progress help industrial collaborative agglomeration increase regional carbon productivity: evidence from Yangtze River Delta urban agglomerations. *Environ Dev Sustain*. <https://doi.org/10.1007/s10668-023-03716-w>
- Hu W, Xiong Z (2021) Do stringent environmental regulations help improve the total factor carbon productivity? Empirical evidence from China's industrial sectors. *Appl Econ* 53(55):6398–6411. <https://doi.org/10.1080/00036846.2021.1940083>
- Intergovernmental Panel on Climate Change Climate change (2021) the physical science basis. <https://www.ipcc.ch/>
- Jaffe A, Palmer K (1997) Environmental regulation and innovation: a panel data study. *Rev Econ Stat* 79(4):610–619
- Jia J, Guo Q, Zhang J (2014) Fiscal decentralization and local expenditure policy in China. *China Econ Rev* 28:107–122. <https://doi.org/10.1016/j.chieco.2014.01.002>
- Kan X (2021) Research on the application of informatization in eco-agricultural tourism. *Fresen Environ Bull* 30(68):7210–7216
- Kenh S (2023) The impact of development strategy choice on capital mobility and economic growth. *J Int Dev*. <https://doi.org/10.1002/jid.3754>
- Lan F, Sun L, Pu W (2021) Research on the influence of manufacturing agglomeration modes on regional carbon emission and spatial effect in China. *Economic Modelling* 96:346–352. <https://doi.org/10.1016/j.econmod.2020.03.016>
- Li W, Wang W, Wang Y, Ali M (2018) Historical growth in total factor carbon productivity of the Chinese industry - a comprehensive analysis. *J Clean Prod* 170:471–485. <https://doi.org/10.1016/j.jclepro.2017.09.145>
- Liao B, Li L (2022) Spatial division of labor, specialization of green technology innovation process and urban coordinated green development: evidence from China. *Sustain Cities Soc* 80:103778. <https://doi.org/10.1016/j.scs.2022.103778>
- Liu K, Liu X, Long H, Wang D, Zhang G (2022) Spatial agglomeration and energy efficiency: evidence from China's manufacturing enterprises. *J Clean Prod* 380(2):135109. <https://doi.org/10.1016/j.jclepro.2022.135109>
- Liu L (2020) Fiscal decentralization and the imbalance between consumption and investment in China. *Ann Reg Sci* 66(1):1–17. <https://doi.org/10.1007/s00168-020-01006-1>
- Marshall A (1890) *Principle of Economics*. Macmillan, London
- Martinez-Galarraga J, Paluzie E, Pons J, Tirado-Fabregat D (2008) Agglomeration and labour productivity in Spain over the long term. *Clometrica* 2(3):195–212. <https://doi.org/10.1007/s11698-007-0017-1>
- Mo J (2023) Do environmental policy and innovation improve carbon productivity? Evidence from the Korean Emission Trading Scheme. *Energy Environ* 34(3):445–462. <https://doi.org/10.1177/0958305X211064575>
- Pan H, Ren J, Zhang Q, Du S (2023) Effect of “green technology-institution” collaborative innovation on ecological efficiency-the moderating role of fiscal decentralization. *Environ Sci Pollut Res* 30(7):19132–19148. <https://doi.org/10.1007/s11356-022-23472-0>
- Potter A, Watsy H (2011) Evolutionary agglomeration theory: increasing returns, diminishing returns, and the industry life cycle. *J Econ Geogr* 11(3):417–455. <https://doi.org/10.1093/jeg/lbq004>
- Ren Y (2020) Intelligent statistical analysis on the influence of industrial agglomeration on innovation efficiency by spatial econometric model. *J Intell Fuzzy Syst* 39(4):4881–4890. <https://doi.org/10.3233/JIFS-179974>
- Shen N, Peng H, Wang Q (2021) Spatial dependence, agglomeration externalities and the convergence of carbon productivity. *Socioecon Plann Sci* 78:101060. <https://doi.org/10.1016/j.seps.2021.101060>
- Song M, Du J, Tan K (2018) Impact of fiscal decentralization on green total factor productivity. *Int J Prod Econ* 205:359–367. <https://doi.org/10.1016/j.ijpe.2018.09.019>
- Sun Y, Guan W, Razzaq A, Shahzad M, An N (2022) Transition towards ecological sustainability through fiscal decentralization, renewable energy and green investment in OECD countries. *Renew Energy* 190:385–395. <https://doi.org/10.1016/j.renene.2022.03.099>
- Thampapillai D (2022) The size of an air shed: a macroeconomic stock estimate. *Singap Econ Rev* 67(04):1447–1455. <https://doi.org/10.1142/S0217590818500200>
- Thanh S, Canh N (2020) Fiscal decentralization and economic growth of Vietnamese provinces: the role of local public governance. *Ann Public Coop Econ* 91(1):119–149. <https://doi.org/10.1111/apce.12255>
- Wang J, Li Y (2020) Does factor endowment allocation improve technological innovation performance? An empirical study on the Yangtze River Delta region. *Sci Total Environ* 716:137107. <https://doi.org/10.1016/j.scitotenv.2020.137107>

- Wang J, Wu W, Ren J (2022a) Suitability evaluation of urban green landscape infrastructure based on entity interaction model. *Fresen Environ Bull* 31(3A):3167–3174
- Wang L, Wang H, Cao Z, He Y, Dong Z, Wang S (2022b) Can industrial intellectualization reduce carbon emissions? Empirical evidence from the perspective of carbon total factor productivity in China. *Technol Forecast Soc Change* 184:121969. <https://doi.org/10.1016/j.techfore.2022.121969>
- Wang M, Zhang H, Dang D, Guan J, He Y, Chen Y (2023) Fiscal decentralization, local government environmental protection preference, and regional green innovation efficiency: evidence from China. *Environ Sci Pollut Res* 30(36):85466–85481. <https://doi.org/10.1007/s11356-023-28391-2>
- Wang X, Zhang Q, Chang W (2022c) Does economic agglomeration affect haze pollution? Evidence from China's Yellow River basin. *J Clean Prod* 335:130271. <https://doi.org/10.1016/j.jclepro.2021.130271>
- Wang Y, Wang J (2019) Does industrial agglomeration facilitate environmental performance: new evidence from urban China? *J Environ Manage* 248:109244. <https://doi.org/10.1016/j.jenvman.2019.07.015>
- Wei W, Zhang W, Wen J, Wang J (2020) TFP growth in Chinese cities: the role of factor-intensity and industrial agglomeration. *Econ Model* 91:534–549. <https://doi.org/10.1016/j.econmod.2019.12.022>
- Williamson J (1965) Regional inequality and the process of national development: a description of the patterns. *Econ Dev Cult Change* 4:3–45
- Wu K, You K, Ren H, Gan L (2022) The impact of industrial agglomeration on ecological efficiency: an empirical analysis based on 244 Chinese cities. *Environ Impact Assess Rev* 96. <https://doi.org/10.1016/j.eiar.2022.106841>
- Wu R, Lin B (2021) Does industrial agglomeration improve effective energy service: an empirical study of China's iron and steel industry. *Appl Energy* 295. <https://doi.org/10.1016/j.apenergy.2021.117066>
- Xu H, Liu W, Zhang D (2023) Exploring the role of co-agglomeration of manufacturing and producer services on carbon productivity: an empirical study of 282 cities in China. *J Clean Prod* 399:136674. <https://doi.org/10.1016/j.jclepro.2023.136674>
- Xu M (2022) Research on the relationship between fiscal decentralization and environmental management efficiency under competitive pressure: evidence from China. *Environ Sci Pollut Res* 29(16):23392–23406. <https://doi.org/10.1007/s11356-021-17426-1>
- Xu R, Wu Y, Huang Y (2020) Measurement and convergence of carbon productivity across Shanghai's manufacturing sectors. *Int J Clim Change Strat Manag* 12(3):369–387. <https://doi.org/10.1108/IJCCSM-11-2019-0065>
- Yang H, Zhang F, He Y (2021) Exploring the effect of producer services and manufacturing industrial co-agglomeration on the ecological environment pollution control in China. *Environ Dev Sustain* 23(11):16119–16144. <https://doi.org/10.1007/s10668-021-01339-7>
- Yang Z, Shen Y (2023) The impact of intelligent manufacturing on industrial green total factor productivity and its multiple mechanisms. *Front Environ Sci* 10:1058664. <https://doi.org/10.3389/fenvs.2022.1058664>
- Yuan H, Feng Y, Lee C, Cen Y (2020) How does manufacturing agglomeration affect green economic efficiency? *Energy Econ* 92:104944. <https://doi.org/10.1016/j.eneco.2020.104944>
- 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. *Industria Textila* 68(6):474–480
- Zang J, Liu L (2020) Fiscal decentralization, government environmental preference, and regional environmental governance efficiency: evidence from China. *Ann Reg Sci* 65(2):439–457. <https://doi.org/10.1007/s00168-020-00989-1>
- Zhang W, Cheng J, Liu X, Zhu Z (2023) Heterogeneous industrial agglomeration, its coordinated development and total factor energy efficiency. *Environ Dev Sustain* 25(6):5511–5537. <https://doi.org/10.1007/s10668-022-02277-8>
- Zhao B, Wang K, Xu R (2023) Fiscal decentralization, industrial structure upgrading, and carbon emissions: evidence from China. *Environ Sci Pollut Res* 30(13):39210–39222. <https://doi.org/10.1007/s11356-022-24971-w>
- Zheng W (2023) Land supply and industrial agglomeration: extension of the new economic geography model with land elements incorporated. *Land Use Policy* 132:106757. <https://doi.org/10.1016/j.landusepol.2023.106757>

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