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Does manufacturing agglomeration promote green productivity growth in China? Fresh evidence from partially linear functional-coefficient models

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ABSTRACT

The influence of manufacturing agglomeration on economic efficiency is substantial, yet its effects on Green Total Factor Productivity (GTFP) are still subject to debate. It is vital to comprehend the relationship between these two factors to craft effective sustainable development policies. Employing the newly developed partially linear functional-coefficient panel data approach, this study examines the nonlinear relationship between manufacturing agglomeration and GTFP, with a comprehensive consideration of the heterogeneity inherent to city geographical attributes and urban scale. Our results reveal that manufacturing agglomeration, on average, fosters GTFP, while the positive effect consists of two opposite components. Agglomeration promotes the diffusion of technology at any stage of urban development, but it can lead to congestion effects in well-developed economies, thereby diminishing efficiency. Our nonlinear approach indicates the turning points of the negative impact. Additionally, the heterogeneity of the relationship between agglomeration and GTFP across cities with varied locations and scales suggested that strategies for manufacturing agglomeration and green development should be tailor-made for individual city types.

1. Introduction

Over the past few decades, China's manufacturing industry's degree of agglomeration and specialization has increased significantly (Ge, 2009). Although manufacturing agglomeration (MA) has created effective external economic growth through technological progress and resource allocation, it has also rapidly aggravated China's environmental pollution (Cheng, 2016). Recently, the Chinese government declared that China would reach its carbon emissions peak by 2030 and achieve carbon neutrality by 2060 at the seventy-fifth United Nations General Assembly (Shi et al., 2021). Therefore, the coordination of MA and sustainable development has become essential in China.

Marshall's external economic theory proposes that industrial economic growth benefits from external economies generated by agglomeration, including the creation of skilled labor markets, professional service intermediate industries, and technology spillovers (Marshall and Guillebaud, 1961). Subsequently, the new economic geography theory represented by Krugman (1991) supplemented the externality brought by industrial agglomeration, including the externality of economic growth theory (Romer, 1986; Lucas Jr, 1988) and three factors of Marshall industry (Baldwin et al., 2010). Both theories believe MA can significantly increase Total Factor Productivity (TFP) through knowledge information spillover and human capital flow. And TFP is the key to economic growth (Easterly and Levine, 2001). Many scholars have also proved the significant positive correlation between MA and TFP (Sveikauskas, 1975; Segal, 1976; Moomaw, 1981; Beeson, 1987; Ciccone, 2002; Lu et al., 2021; He et al., 2022). However, some scholars have found no positive correlation between MA and TFP, and even MA inhibits TFP based on the same model (Carlino, 1979; Combes, 2000). Williamson's hypothesis explains the controversy about the difference in

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regression effect. The hypothesis points out that the growth of industrial agglomeration will bring economic marginal promotion benefits. In contrast, the excessive increase of MA will get an industrial congestion effect, reducing the marginal benefit or even producing negative effects in TFP. And with the enhancement of openness, the impact of industrial agglomeration on production efficiency is also weakening (Bernard et al., 2003; Melitz and Ottaviano, 2008). Some scholars have also verified that the agglomeration degree is significantly negatively correlated with the crowding effect from the perspective of city size (Henderson, 1986). Scholars have many controversies over the relationship between MA and GTFP. Therefore, studying the relationship between MA and GTFP is vital.

However, the three questions about whether MA can improve GTFP in China make the answer uncertain. The description of the questions is as follows: (1) The mechanism of influence of MA and GTFP is complex. How to construct the complex nonlinear relationship between MA and GTFP? (2) The effect of MA on GTFP changes gradually due to the impact of economic and other factors. How can financial and other parametric factors be added to the quantitative relationship between MA and GTFP as the main variables? (3) The degree of MA is distributed unevenly among cities (Cheng, 2016; Feng et al., 2020). How to verify the impact of the robustness test and heterogeneity analysis on the model?

To solve the above problems, we give the solutions in detail. For the first question, some scholars describe the nonlinear relationship between MA and GTFP based on the inverted 'U' function and differential equations (Futagami and Ohkusa, 2003; Yang et al., 2022). The inverted 'U' function model can describe the relationship between MA and GTFP, which grows first and then declines. In contrast, this model is difficult to describe other types of nonlinear relationships, such as continuous rise and continuous decline. The differential equations model can simulate the mathematical change characteristics of MA and GTFP in detail under different sensitivity analysis scenarios. But this model cannot effectively deal with the influence of multiple variables. And the relationship between MA and GTFP is significantly influenced by labor intensity, resource abundance, and Foreign Direct Investment (FDI) (Ezcurra et al., 2006; Wei, 2007; He et al., 2008; Liu, 2008). We mainly construct the panel model with threshold variables and the partially linear functional-coefficient panel data model in this study. Specifically, the two models we consider are progressive relationships. The threshold regression model divides the regression effect into different stages by setting the number of thresholds to explain the nonlinear difference problem (Wu et al., 2020). The discontinuous nonlinear result can be obtained through threshold regression. According to the change of the threshold variable, the influence of MA on GFTP will also change. But the number of thresholds needs to be put in advance. In other words, the threshold number set has a priori defect. And the limited threshold value makes the nonlinear relationship discontinuous. So we built the partially linear functional-coefficient model (PLFC) to solve the limitations of the threshold model. We can get continuous nonlinear results using the non-parametric method to estimate the local linear model (Du et al., 2020). Meanwhile, the PLFC model can consider the impact of PGDP changes as a non-parametric function of MA (Lin and Ma, 2022). So we could solve problem 2 (increasing the dimension of core variables) through this model.

Finally, this study chooses population and regional development as influencing factors for the heterogeneity analysis. There are some reasons for us to select these factors. On the one hand, different regions have unequal labor productivity, technology, and resource endowments, which will affect the development of MA (Fujita and Hu, 2001). For example, manufacturing will gather in regions with abundant raw materials and labor relatively cheap. On the other hand, the expansion of China's urbanization has reduced the search cost of professional labor and enhanced the industrial infrastructure of cities. Cities with large populations are more likely to accommodate research institutions and promote GTFP (Isard, 1949). But the excessive expansion of urbanization also brings about cost squeeze and competition from the same type of enterprises, which will inhibit the development of MA. And China's manufacturing industry has formed a production pattern with the core cities of the urban agglomeration as the manufacturing center and the peripheral cities as the supply chain. These studies have shown that regional and people differences will affect the quantitative relationship between MA and GTFP. Therefore, this study discusses heterogeneity and robustness in Section 4.

This study mainly has the following potential contributions through the above work: (1) Controversy among scholars proves the importance of studying the nonlinear relationship between MA and GTFP. We construct the panel model with threshold variables and the partially linear functional-coefficient panel data model. Specifically, the two models we consider are progressive relationships. (2) The effect of MA on GTFP changes gradually due to the impact of economic and other factors. Our PLFC model incorporates PGDP (we use electricity consumption per capita as a proxy variable) as a core explanatory variable into the relationship between MA and GTFP, providing a synergy analysis framework. (3) We investigate the nonlinear relationship between GTFP decomposition effects and MA. This work could analyze whether the nonlinear influence of MA on GTFP comes from a technical change component (MLTECH) and an efficiency change component (MLEFFCH). And we can get their contribution to GTFP with the change in economic level. (4) The differences in demographics, population, and income level will affect MA and GTFP regression results. This study chooses population and regional development as influencing factors for the robustness test and heterogeneity analysis. Then we can provide more insightful and detailed implications to policymakers.

The structure of this article is as follows. Firstly, we collected the MA and GTFP data of 260 cities from 2003 to 2019. Secondly, we use the Malmquist-Luenberger productivity index (MLPI) and Luenberger productivity indicator (LPI) to measure GTFP. It refers to studies that constrain unneeded output while keeping goods output and inputs constant (Du and Li, 2019). Following Wang et al. (2019), we decompose GTFP into MLTECH and MLEFFCH. Thirdly, we use the linear panel model, linear panel model with interaction terms, threshold panel data model, and PLFC model to construct the relationships between MA and GTFP. Especially the four models we consider are a progressive relationship. Finally, we explore the heterogeneity from the spatial area and population size dimensions. We choose eastern, central, and western cities for the spatial dimension. And large cities (over 6.2 million), medium-sized cities (2.55 million-6.2 million), and small cities (<2.55 million) are used to distinguish population heterogeneity.

2. Methods and data

2.1. Measurement of manufacturing agglomeration

MA is the concentrated distribution of the manufacturing industry in a specific region, which reflects the distribution relationship between the manufacturing industry and space (Florida, 1994). Some studies cluster enterprises in the spatial range to evaluate agglomeration degree, which effectively shows the distribution range of enterprises, such as kernel density estimation (Alfaro and Chen, 2014). However, the limitation of the clustering scale is uncertain, and the data after clustering is challenging to match with administrative data. To solve this problem, some scholars divide the overall unit into different administrative area units to calculate MA. For example, some scholars use the location entropy method based on information theory to measure MA (Hoen and Oosterhaven, 2006; Crawley et al., 2013). This method can effectively measure the relative agglomeration degree of a single city and the whole city.

Specifically, we define the core variable MA as follows:

$$MA_{it} = \frac{N_{it}}{N_t} \tag{1}$$

where N_{it} denotes the share of manufacturing employment in the city i in year t over the employment of all kinds of industries i year t or across all years in the sample, while N_t means the percentage of manufacturing employees from all the cities over that of all employees in the society in year t. Therefore, when MA_{it} is larger, the degree of manufacturing agglomeration is higher.

2.2. Measurement of green total factor productivity

Data envelopment analysis (DEA) has received much attention because of its ability to produce multiple output techniques without requiring a priori information in the form of production functions (Färe et al., 1994). However, social development has a lousy output (Mahlberg and Sahoo, 2011). The Malmquist-Luenberger productivity index (MLPI) was developed to address the problem of undesirable outputs (Chung et al., 1997). This method inherits the advantages of the original Malmquist index and has good economic explanatory implications. For example, when MLPI is 1.1, it represents a 10% increase compared to the base year, and MLPI has been widely used by scholars in the calculation and decomposition of GTFP (Zhou et al., 2012; Lin and Du, 2015). However, the directional distance function used by MLPI has a low-resolution ability. Therefore, some scholars have proposed the Luenberger productivity indicator (LPI) based on the non-radial directional distance function. LPI does not have a perfect economic explanation. Therefore, we use MLPI and LPI in Chapters 3 and 4 to combine both methods' advantages and robustness tests.

In the MLPI calculation, we first represent the inputs, desirable outputs, and undesirable outputs as $x \in R_+^N, y \in R_+^M$ and $b \in R_+^H$, then the production technology can be defined as follows:

$$T = \{(x, y, b) : x \text{ can produce } (y, b)\} \tag{2}$$

Following Chung et al. (1997), the radial directional distance function (DDF) is defined as follows:

$$D(x, y, b; g) = sup\{\mathbf{w}^T\boldsymbol{\beta} : ((x, y, b) + \beta \cdot g) \in T\} \tag{3}$$

Where $g = \left(g_x, g_y, g_b\right) \in R_+^N \times R_+^M \times R_+^H$ is a preassigned nonzero vector used to specify the distance between (x, y, b).

To estimate the DDF, researchers have proposed different types of production frontier estimation methods. The production technology set at time t in this study is defined as follows:

$$T(t) = \left\{(x, y, b) : \sum_{\tau \in \Gamma_t}\sum_{j=1}^{J}\lambda_{j\tau}x_{j\tau} \le x, \sum_{\tau \in \Gamma_t}\sum_{j=1}^{J}\lambda_{j\tau}y_{j\tau} \ge y, \sum_{\tau \in \Gamma_t}\sum_{j=1}^{J}\lambda_{j\tau}b_{j\tau} = b, \lambda \ge 0\right\} \tag{4}$$

Where $\tau \in \Gamma_t$ is expressed as $\tau < t_{\max}$, $t_{\max}$ represents the last period in the sample.

Then we can solve the DDF function by linear programming. The method is defined as follows:

$$\begin{aligned} & D_r(x, y, b; g) = \max_{\beta,\lambda}\beta \\ & s.t. \sum_{\tau \in \Gamma_t}\sum_{j=1}^{J}\lambda_{j\tau}x_{j\tau} \le x + \beta g_x \\ & \sum_{\tau \in \Gamma_t}\sum_{j=1}^{J}\lambda_{j\tau}y_{j\tau} \ge y + \beta g_y \\ & \sum_{\tau \in \Gamma_t}\sum_{j=1}^{J}\lambda_{j\tau}b_{j\tau} = b + \beta g_b \\ & \lambda_{j\tau} \ge 0, j = 1, \dots, J \end{aligned} \tag{5}$$

Specifically, in this study, there exist three types of inputs x, i.e., CT (capital stock), EM (employment), and EC (electricity consumption), and two types of outputs, namely desirable one, RGDP (real gross regional product), and undesirable three, emissions of industrial wastewater, industrial sulfur dioxide, and industrial dust. Then, if we select direction as $g = (0, y, -b)$, the GTFP can be calculated based on the radial DDF:

$$ML = \left\{\frac{1 + D_r^t(x^s, y^s, b^s; g)}{1 + D_r^t(x^t, y^t, b^t; g)} \times \frac{1 + D_r^s(x^s, y^s, b^s; g)}{1 + D_r^s(x^s, y^s, b^s; g)}\right\}^{1/2} \tag{6}$$

GTFP, which ranges from zero to unity, indicates the potential to decrease pollution intensity. When GTFP equals 1, the decision-making unit (DMU) is considered to have the best performance in green manufacturing.

Then, the MLPI can be decomposed into efficiency change (MLEFFCH) and technology change (MLTECH), which could be defined as follows:

$$MLEFFCH = \frac{1 + D_r^s(x^s, y^s, b^s; g)}{1 + D_r^t(x^t, y^t, b^t; g)} \tag{7}$$

$$MLTECH = \left\{\frac{1 + D_r^t(x^s, y^s, b^s; g)}{1 + D_r^s(x^t, y^t, b^t; g)} \times \frac{1 + D_r^t(x^s, y^s, b^s; g)}{1 + D_r^s(x^s, y^s, b^s; g)}\right\}^{1/2} \tag{8}$$

In LPI calculation, we first define the production technology in Eq. (2). Then following Zhou et al. (2012), the non-radial DDF is defined as follows:

$$D_{nr}(x, y, b; g) = sup\{w^{'}\beta : ((x, y, b) + diag(\beta) \cdot g) \in T\} \tag{9}$$

Where w is the input and output weight vector and $\beta = \left(\beta_x, \beta_y, \beta_c\right)$ denotes the vector of the scaling factors, the advantage of the non-radial DDF measure is that it can adjust the weight non-proportionally.

Then the production technology set at time t can be defined by Eq. (4). We solve the DDF function through linear programming, and the method is described as follows:

$$\begin{aligned} & D_{nr}(x, y, b; g) = \max_{\beta,\lambda} w^{'}\beta \\ & s.t. \sum_{\tau \in \Gamma_t}\sum_{j=1}^{J}\lambda_{j\tau}x_{j\tau} \le x + diag(\beta_x) \times g_x \\ & \sum_{\tau \in \Gamma_t}\sum_{j=1}^{J}\lambda_{j\tau}y_{j\tau} \ge y + diag(\beta_y) \times g_y \\ & \sum_{\tau \in \Gamma_t}\sum_{j=1}^{J}\lambda_{j\tau}b_{j\tau} = b + diag(\beta_b) \times g_b \\ & \beta \ge 0; \lambda_{j\tau} \ge 0, j = 1, \dots, J \end{aligned} \tag{10}$$

The LPI based on nonradial DDFs is defined as:

$$\begin{aligned} NL = & \left\{D_{nr}^t(x^s, y^s, b^s; g) - D_{nr}^t(x^t, y^t, b^t; g)\right\} \times \frac{1}{2} \\ & + \left\{D_{nr}^s(x^s, y^s, b^s; g) - D_{nr}^s(x^t, y^t, b^t; g)\right\} \times \frac{1}{2} \end{aligned} \tag{11}$$

The LPI can be decomposed into efficiency change (NLEFFCH) and technology change (NLTECH), which could be defined as follows:

$$NLEFFCH = D_{nr}^s(x^s, y^s, b^s; g) - D_{nr}^t(x^t, y^t, b^t; g) \tag{12}$$

$$\begin{aligned} NLTECH = & \left\{D_{nr}^t(x^t, y^t, b^t; g) - D_{nr}^s(x^t, y^t, b^t; g)\right\} \times \frac{1}{2} \\ & + \left\{D_{nr}^t(x^s, y^s, b^s; g) - D_{nr}^s(x^s, y^s, b^s; g)\right\} \times \frac{1}{2} \end{aligned} \tag{13}$$

2.3. Econometric models

GTFP growth benefits from external economies generated by MA, including the creation of skilled labor markets, professional service intermediate industries, and technology spillovers. But many manufacturing industries have the disadvantages of low threshold and challenging transformation. And there will be vicious competition among manufacturing (congestion effect) with the growth of MA.

Therefore, the marginal benefit of MA to GTFP will gradually decrease with the development of MA. Meanwhile, cities have different resource endowments and economic levels, which lead to different marginal benefit results of MA on GTFP. The marginal benefit of MA to GTFP varies with the different regions and economic level. Therefore, we argue that the impact of manufacturing agglomeration on green total factor productivity satisfies the two characteristics of nonlinearity and heterogeneity, and this nonlinear relationship is affected by the economic level. So we use PGDP as the threshold variable in the threshold model and the function coefficient in the PLFC model. Our model could explore how changes in economic levels would affect the nonlinear relationship between MA and GTFP.

In this study, we consider four models. We mainly construct the basic and panel models with interaction terms in the linear model. The nonlinear models include the panel model with threshold variables and the partially linear functional-coefficient panel data model. Especially the four models we consider are a progressive relationship from linear to nonlinear. The panel model is to discuss the linear relationship between MA and GFTP, and the regression coefficient is an average effect. The panel model with interaction variables explores whether MA impact on GFTP is asymmetric, caused by different regions and income factors. Based on the results of Model II, we consider group regression to discuss the regional heterogeneity of MA and GTFP. And the significance of the coefficient can also prove that the relationship between MA and GTFP needs to consider the factor of the economic level. To further explore the nonlinear relationship between MA and GTFP caused by this asymmetric difference, the variables that cause MA to produce asymmetric characteristics are considered threshold variables. And the discontinuous nonlinear result can be obtained through threshold regression. According to the change of the threshold variable, the influence of MA on GFTP will also change, which is impossible for the Baseline model. However, the limited threshold value makes the obtained nonlinear relationship discontinuous. And the number of thresholds needs to be put in advance. In other words, the threshold number set has a priori defect. Finally, we can get continuous nonlinear results using the non-parametric method to estimate the local linear model. In addition, we added the dimension of PGDP to consider how the economic level affects the relationship between MA and GTFP. Compared with the nonlinear models of other papers, our model has a better economic interpretation. The details of the models are as follows:

Model I: Linear panel data model

The model formula is defined as follows:

$$lnGTFP_{i,t} = \alpha lnMA_{i,t-1} + \beta Z_{i,t-1} + \lambda_i + \varepsilon_{i,t} \tag{14}$$

where $lnGTFP_{i,t}$ is the log term of green total factor productivity in the city i and year t, while $lnMA_{i,t-1}$ is the log term of MA in the city i and year $t-1$. And $Z_{i,t}$ are control variables. To avoid the heteroskedasticity effect, we take the form of a logarithm of all the variables. λ_i denotes unobservable individual effects, and $\varepsilon_{i,t}$ is the regression error.

Model II: Linear panel data model with interaction terms

The model formulae are defined as follows:

$$\begin{gathered} lnGTFP_{i,t} = \alpha_1 lnMA_{i,t-1} + \alpha_2 \left(lnMA_{i,t-1} \times Area_i\right) + \beta Z_{i,t-1} + \lambda_i + \varepsilon_{i,t} \\ lnGTFP_{i,t} = \alpha_1 lnMA_{i,t-1} + \alpha_2 \left(lnMA_{i,t-1} \times Develpopment_i\right) + \beta Z_{i,t-1} + \lambda_i + \varepsilon_{i,t} \\ lnGTFP_{i,t} = \alpha_1 lnMA_{i,t-1} + \alpha_2 \left(lnMA_{i,t-1} \times Population_i\right) + \beta Z_{i,t-1} + \lambda_i + \varepsilon_{i,t} \\ lnGTFP_{i,t} = \alpha_1 lnMA_{i,t-1} + \alpha_2 \left(lnMA_{i,t-1} \times lnPGDP_{i,t-1}\right) + \beta Z_{i,t-1} + \lambda_i + \varepsilon_{i,t} \end{gathered} \tag{15}$$

where the variables $Area_i$,$Development_i$,$Population_i$ are dummy variables. Considering different cities have individual effects, we divide the 243 cities into three types of groups. First, according to the location factor, we divide the respective data into eastern, central, and western cities, and the grouping results are referred to as A1. Here we mainly focus on the impact of eastern cities, so we define the dummy variable $Area_i = 1$ when the individual is in the eastern city, otherwise $Area_i = 0$; Second, according to the demographic factor, we divide the cities into large, medium, and small cities and refer to A2 for the grouping results. We focus on large cities and set the dummy variable $Population_i = 1$, otherwise $Population_i = 0$. Finally, according to different economic development factors of other cities, we set dummy variables about the economic level of different cities, according to the division of the GDP of each city in 2015, with the GDP of each city in 2015 $>$ 288 billion yuan set as economically developed regions, set dummy variables $Development_i$ as 1 and the rest of the cities as 0. Similarly, we consider a continuous variable about the economic level of $lnPGDP_{it}$.

Model III: Threshold panel data model

The model formula is defined as follows:

$$\begin{gathered} lnGTFP_{i,t} = \alpha_1 lnMA_{i,t-1} I\left(lnPGDP_{i,t-1} \le \gamma\right) + \alpha_2 lnMA_{i,t-1} I\left(lnPGDP_{i,t-1} > \gamma\right) \\ + \beta Z_{i,t-1} + \lambda_i + \varepsilon_{i,t} \end{gathered} \tag{16}$$

Here we set $lnPGDP_{it-1}$ as threshold variables, then the core variable $lnMA_{it-1}$ exists regime switch. Since this paper further discusses the nonlinear effects of manufacturing agglomeration on green total factor productivity, we consider the existence of threshold effects for the core explanatory variables. Considering that there are differences in MA between cities of different economic levels, which leads to differences in the impact on green total factor productivity in that city, the threshold effect may exist.

Model IV: Partially linear functional-coefficient panel data model

The above three models tend to have some shortcomings in some specific situations. Model I explores the effect of manufacturing agglomeration on total factor productivity when the remaining variables are controlled, and this effect is a fixed coefficient. Model II considers the interaction between the core explanatory variables and other variables. But it only adds the interaction term for regression, and this effect changes from α_1 to $\alpha_1 + \alpha_2$. Model III considers the threshold variables, but the threshold value is often limited. For example, the core explanatory variables have three coefficients in the double threshold model. And it can only explain three kinds of effects on the dependent variable. Then we may make the coefficients of the core explanatory variables set to a functional form, i.e., consider the partially linear functional-coefficient panel data model. This model will give the result of its continuous influence on the explanatory variables, which is more suitable in the current complex economic environment, and the model formula is defined as follows:

$$lnGTFP_{it} = g(u_{it-1}) lnMA_{it-1} + \beta Z_{it-1} + \lambda_i + \varepsilon_{it} \tag{17}$$

The coefficient of $lnMA_{it-1}$ is $g\left(u_{i,t-1}\right)$, which is a nonlinear function of u_{it-1}, defined as follows:

$$u_{it-1} = \frac{lnPGDP_{i,t-1} - min\left(lnPGDP_{i,t-1}\right)}{max\left(lnPGDP_{i,t-1}\right) - min\left(lnPGDP_{i,t-1}\right)} \tag{18}$$

where u_{it-1} is within the interval [0,1].

To facilitate the comparison with threshold panel regression results, we define u_{it} as a function of the threshold variable according to the estimation method in Du et al. (2020).

The standard partially linear functional-coefficient panel data model is as follows:

$$Y_{it} = g(u_{it}) X_{it} + \beta Z_{it} + \varepsilon_{it} \tag{19}$$

where Y_{it} is the dependent variable, and X_{it} are the explanatory variables we care about, and Z_{it} are control variables. And $g(u_{it})$ are the coefficients of the core explanatory variables, which are the nonlinear function of u_{it}, and β are the coefficients of the linear part.

Through the spline sieve method, we make a linear combination of a known form of function $h(u_{it}) = \left(h_1(u_{it}), h_2(u_{it}), \ldots, h_p(u_{it})\right)$, and unknown parameters $\gamma = \left(\gamma_1, \ldots \gamma_p\right)$ to obtain the form of $g(u) = h(u)' \gamma$. At this point, the original model can be written as:

$$Y_{it} = H'_{it}\gamma + \beta Z_{it} + \nu_{it} \tag{20}$$

where $H_{it} = x_{it}h(u_{it})$ and $\nu_{it} = \epsilon_{it} + g(u)X_{it} - \gamma X_{it}h(u)$ when the sample size is large, i.e. $T\rightarrow\infty$, $N\rightarrow\infty$, $g(u)X_{it} - \gamma X_{it}h(u)\rightarrow 0$.

Differentiating Eq. (20) on two sides, we can obtain the following:

$$\Delta Y_{it} = \Delta H'_{it}\gamma + \beta\Delta Z_{it} + \Delta\nu_{it} \tag{21}$$

It can be expressed in the matrix form as follows:

$$\Delta Y = \Delta\widetilde{Z}\Gamma + \Delta\nu \tag{22}$$

where $\Delta\widetilde{Z} = (\Delta H_{it}, \Delta Z_{it})$, $\Gamma = (\gamma, \beta)^{'}$.

Finally, through the least square method, we can obtain the following:

$$(\widetilde{\gamma}, \widetilde{\beta})^{'} = (\Delta\widetilde{Z}^{'}\Delta\widetilde{Z})^{'}(\Delta\widetilde{Z}^{'}\Delta Y) \tag{23}$$

2.4. Data

The data are obtained from the China Statistical Yearbook, China Urban Statistical Yearbook, and urban statistical yearbooks of 243 major prefecture-level cities in China during 2003–2019. As the COVID-19 disaster in 2020 has significantly affected the MA and GTFP data, our panel data is up to 2019. Meanwhile, a small amount of missing data is supplemented by cubic spline interpolation.

First, MA adopts the measurement method defined in Subsection 2.1 to measure and calculate. Fig. 1 describes the trend of MA variables in China's core cities from 2003 to 2019. We selected six major cities in China's urban agglomerations as sample descriptions. According to the statistical results, we find the following conclusions. First, the declining trend of MA in the core cities of most urban agglomerations is evident under the time trend. Specifically, the proportions of significant urban changes are: BeiJing (−44.13%), TianJin (−22.92%), ShenZhen (12.30%), GuangZhou (−32.92%), ShangHai (−25.07%), NanJing (−31.86%), ChengDu (−25.23%), Chongqing (−13.47%), Wuhan (−26.66%), Zhengzhou (37.66%). Second, the manufacturing industry of urban agglomerations has shifted from the core city manufacturing to the surrounding cities. For example, Suzhou's MA rose by 22.59% from 2.13 in 2003 to 2.61 in 2019. It also proves the speculation that the core city's manufacturing supply chain moves out in urban development. The same evidence was verified in the adjacent cities of FoShan (61.34%), DongGuan (125.28%), and SuZhou (22.59%). Third, the manufacturing centers are concentrated in the Yangtze River Delta urban agglomeration and the Pearl River Delta urban agglomeration. Although the central urban agglomeration has the effect of MA increasing yearly, the main manufacturing centers are still around the eastern cities.

Secondly, the calculation method of GTFP is shown in Subsection 2.2. According to the existing research on energy efficiency (Zhang et al., 2018; Wang et al., 2019), this study selects employees of the whole society to represent labor input and electricity consumption of the entire society as the energy input. Moreover, the capital stock is calculated by the permanent inventory method (Zhang et al., 2004). In addition, due to regional economic and technological development differences (Liu et al., 2017a, 2017b; Li et al., 2020), we divide the cities into groups for the heterogeneity analysis. Table A1 shows the results of city classification based on regional factors. Existing research also shows that the difference in population will also significantly affect the results of GTFP (Liu et al., 2021). Therefore, we divide cities into large cities (over 6.2 million), medium cities (2.55 to 6.2 million), and small cities (below 2.55 million). Table A2 shows detailed classification results.

Finally, the control variables are selected and defined as follows:

(1) Industrial structure (IS).

In upgrading the industrial structure, the leading industry transforms from primary to secondary and tertiary industries. Increasing capital and technology agglomeration density will affect production efficiency and pollution emissions, leading to GTFP changes (Xiaoli et al., 2014). We follow Ding et al. (2022) use the ratio of the tertiary and secondary industries to measure industrial structure variables.

(2) Government control (GC).

The government is vital in allocating resources for the energy economy. Appropriate government measures can significantly improve industry efficiency, while excessive intervention will reduce GTFP (Liu et al., 2017a, 2017b; Han et al., 2018). In this study, we choose government public expenditure as a measure of government control variables.

(3) Human capital (HC).

Agglomeration of the labor force can promote technology exchange and form a stable labor market (Marshall and Guillebaud, 1961). And the relationship model between population and technology proposed by Ehrlich and Holdren (1971) proves that the labor force can promote total factor productivity. Therefore, we choose the ratio of the number of college students and the total urban population to measure Human Capital variables.

(4) Science and technology inputs (STI).

Science and technology inputs are the most critical factors for developing innovation activities. Large-scale investment in science and technology is conducive to efficient energy use and reduces pollution (Xu et al., 2022; Sun et al., 2015). In this study, we choose the expenditure on science and technology in public fiscal expenditure to measure science and technology input variables.

(5) Structure of endowment (SE).

In studying new economic theory, the deepening of capital structure promotes technical efficiency (Krugman, 1991). In addition, according to the theory of pollutant shelters, capital structure is an essential factor affecting pollutants (Feng et al., 2020; Pan et al., 2023). In this study, we use the per capita capital stock index to measure the system of endowment variables.

Table 1 and Table 2 show the results of descriptive statistics. The panel dataset contains 3888 samples of 243 cities in China from 2003 to 2019. Table 1 describes the data needed to calculate GTFP, including input variables, desired output, and undesirable outputs. Table 2 describes the data required by the model in Chapter 2.3. MA is the core explanatory variable. PGDP indicates the degree of economic development as the threshold and interaction variable. HC, SE, IS, STI, and GC are control variables. The variables are uniformly taking logarithms. To ensure the accuracy of GTFP, we divide the input and output data by the mean of variables as the model data to estimate the value of GTFP (Färe et al., 2005).

3. Nonlinear effects of manufacturing agglomeration on GTFP

3.1. Results of GTFP estimation and decomposition

According to the method in Section 2.2, we calculated GTFP and its two decomposition parts, including a technical change component (MLTECH) and an efficiency change component (MLEFFCH). MLEFFCH is the comprehensive management efficiency of the GTFP system, reflecting whether a city can promote the system. MLTECH is the ability of the city GTFP system to continuously innovate, improve the technical level, and achieve continuous progress. Table 3 shows the results of the statistics. GTFP and MLEFFCH increased steadily, while MLTECH showed little change.

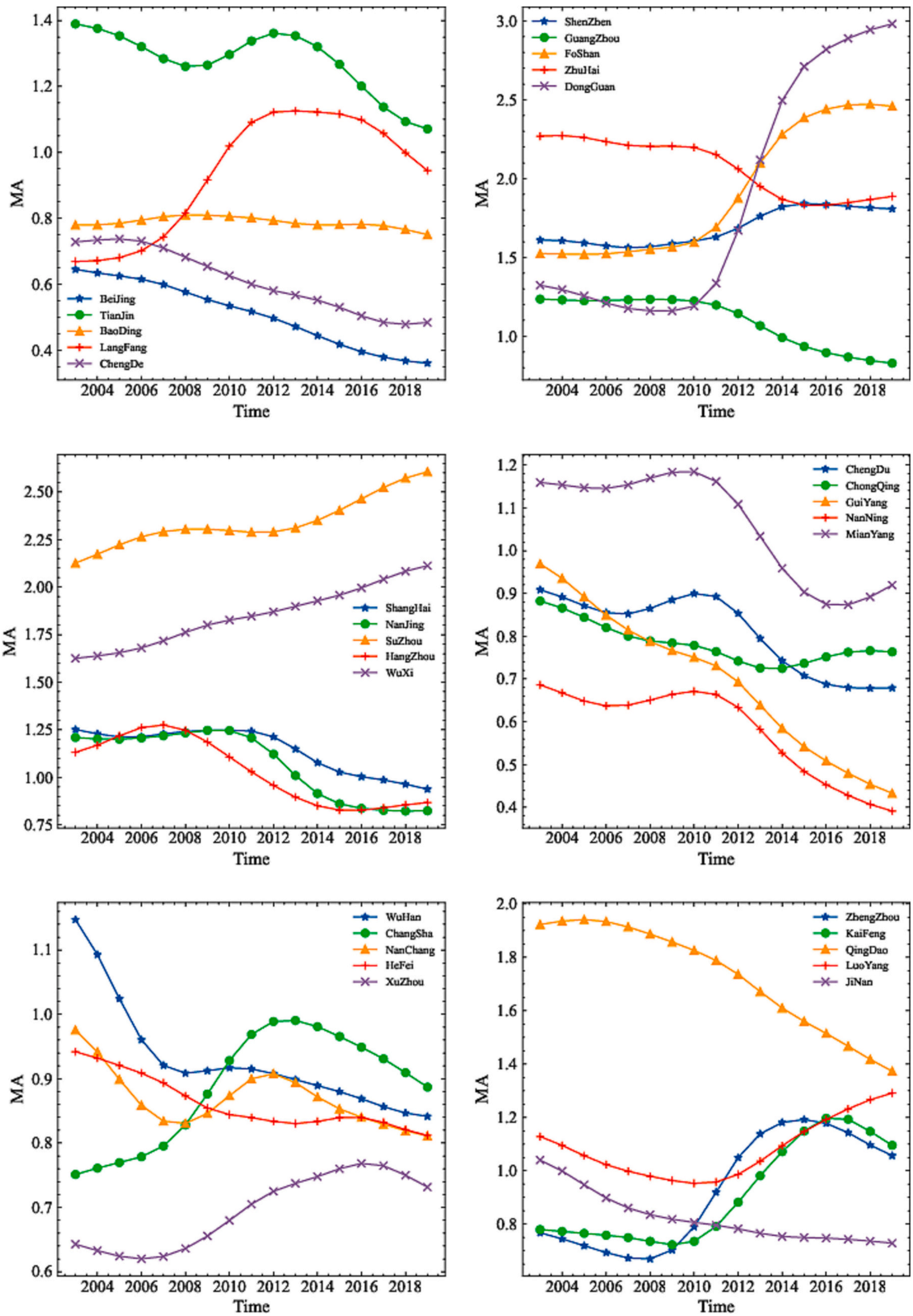

Fig. 1. Changes of MA in core cities.

Table 1
Descriptive statistics of estimated GTFP.

		input variables			desired output	undesirable output		
Year		Employment	electricity consumption	capital stock	real GDP	industrial wastewater	industrial SO2	industrial dust
Unit		thousand people	million kWh	–	billion RMB	million tons	tons	tons
2003	Ave.	389.2	3998.84	57,696.43	51.17	75.76	56,649.53	28,331.46
	S.D.	546.4	7214.47	109,342.15	69.28	103.44	62,061.45	30,712.46
	Min.	44.9	103.11	5067.44	2.49	1.79	279	51
	Max.	7032.8	74,597	1,179,419	665.22	819.73	599,664	250,308
2007	Ave.	422.2	6438.07	146,901.47	88.52	89.80	70,056.57	25,296.51
	S.D.	514.1	10,957.89	206,295.15	119.03	124.50	67,032.09	21,705.44
	Min.	43.7	199.05	15,313.84	4.60	0.22	140	130
	Max.	5443.8	107,238	1,905,007	1101.66	912.60	682,922	130,350
2011	Ave.	510.3	9003.40	321,854.94	143.60	82.79	174,528.09	53,747.24
	S.D.	675.5	14,139.16	369,802.15	183.02	96.56	226,059.50	218,478.07
	Min.	57.3	292.76	25,443.49	7.60	0.78	32	239
	Max.	6859	133,962	2,625,353	1563.49	868.04	1,526,334	32,572,610
2015	Ave.	684.7	10,772.80	589,950.86	205.28	70.38	50,289.98	51,007.59
	S.D.	1054.9	16,536.69	608,060	257.28	74.49	42,340.02	145,582.44
	Min.	72.9	225.15	42,998.40	12.06	0.53	208	854
	Max.	9868.7	140,555	4,266,741	2078.25	605.06	426,800	1,859,866
2019	Ave.	630.9	24,136.46	884,688.77	268.47	47.42	10,670.44	14,655.30
	S.D.	950.6	24,245.07	834,465.74	336.78	78.53	13,845.34	21,696.49
	Min.	58.6	2495.81	55,134.35	15.35	0.96	75	79.00
	Max.	7913	156,857.75	6,894,404	2681.08	965.01	115,089	213,693
Total	Ave.	527.5	10,869.91	400,218.50	151.41	73.23	72,438.92	34,607.62
	S.D.	786.4	17,181.76	585,176.85	228.94	98.12	123,480.90	119,795.11
	Min.	43.7	103.11	5067.44	2.49	0.22	32	51
	Max.	9868.7	156,857.75	6,894,404	2681.08	965.01	1,526,334	3,257,261

Table 2
Descriptive statistics of the data for econometric model.

		explanatory variable		control variable				
Year		MA	PGDP	IS	GC	HC	STI	SE
Unit		–	RMB	–	million RMB	–	million RMB	–
2003	Ave.	0.91	12,786.86	0.85	4702.91	0.01	22.77	146.94
	S.D.	0.43	17,292.17	0.34	9214.07	0.01	99.20	235.11
	Min.	0.14	2433.69	0.14	330.50	0	0	20.59
	Max.	2.65	228,661.95	2.23	110,264.24	0.06	1134.39	2724.46
2007	Ave.	0.87	21,065.20	0.79	10,903.88	0.01	2005.62	351.04
	S.D.	0.46	25,019.75	0.37	19,056.02	0.02	2714.28	351.05
	Min.	0.09	3556.12	0.11	785.49	0	111.97	52.53
	Max.	2.37	294,439.40	2.69	218,167.80	0.11	28,333.35	2997.04
2011	Ave.	0.87	32,630.86	0.72	25,846.67	0.02	4527.39	761.93
	S.D.	0.47	29,878.79	0.38	38,692.26	0.03	5651.64	611.43
	Min.	0.04	509.41	0.11	1678.39	0	200.48	9.31
	Max.	2.46	189,718.11	3.29	391,488.20	0.35	54,923.93	4674.37
2015	Ave.	0.90	45,501.93	0.95	43,393.66	0.02	7286.16	1353.37
	S.D.	0.47	41,994.14	0.48	64,647.49	0.03	8924.36	848.33
	Min.	0.11	7789.43	0.35	2509.95	0	359.25	236.44
	Max.	2.78	392,416.61	4.03	619,156.01	0.13	85,566.54	4828.91
2019	Ave.	0.88	56,347.43	1.38	34,577.72	0.02	1577.79	1929.68
	S.D.	0.51	45,550.12	0.71	82,238.96	0.03	5512.16	1044.49
	Min.	0.07	10,693.56	0.44	1151.64	0	0.86	516.61
	Max.	3.03	344,542.05	5.17	817,928.42	0.13	54,842.49	5739.90
Total	Ave.	0.89	33,666.04	0.94	23,884.97	0.02	3083.95	908.59
	S.D.	0.47	37,120.86	0.53	52,695.37	0.02	6024.21	949.77
	Min.	0.04	509.41	0.11	330.50	0	0	9.31
	Max.	3.03	392,416.61	5.17	817,928.42	0.35	85,566.54	5739.90

Fig. 2 shows the time variation trend of the average GTFP and its decomposition according to the regional classification. We can learn from the figure that GTFP and MLEFFCH in different regions of China showed a steady upward trend from 2003 to 2018, while MLTECH kept the trend steady. In the regional comparative analysis, the rising rank of GTFP and MLEFFCH is central cities > eastern cities > western Cities. Fig. 3 shows the time trend of the average GTFP and its decomposition according to the population classification. GTFP and MLEFFCH also show a significant and stable upward trend, while MLTECH shows an overall oscillation trend. In the comparative analysis among regions, the order of GTFP is big cities > small cities > meddle cities, and the order of MLEFFCH is small cities > big cities > meddle cities.

3.2. *Results from baseline models*

We run regressions according to the setup of Model I. Based on the Hausman test, we choose the fixed effects panel model. As shown in Table 4, the MA degree significantly positively affects green total factor productivity. For a 1% increase in MA, GTFP will increase by 0.0455%. We add the control variables to the model sequentially to ensure that the

Table 3
Descriptive statistics of econometric models.

		2003	2006	2009	2012	2015	2018	total
ML	Ave.	0.9427	1.0030	1.0068	0.9725	1.0590	1.0261	1.0017
	S.D.	0.1876	0.0751	0.1325	0.2321	0.2655	0.1903	0.1943
	Min.	0.7293	0.4914	0.6215	0.3825	0.7120	0.2083	0.2083
	Max.	3.5674	1.4730	2.5235	3.3948	4.3874	2.7036	4.3874
MLTECH	Ave.	1.0546	1.0337	1.0077	0.9385	1.0579	1.0317	1.0207
	S.D.	0.1531	0.1803	0.1607	0.1884	0.2010	0.2588	0.1974
	Min.	0.6501	0.4632	0.5555	0.3235	0.6128	0.3332	0.3235
	Max.	2.3191	2.3891	2.1824	1.5414	2.3314	2.6934	2.6934
MLEFFCH	Ave.	0.8984	0.9890	1.0142	1.0691	1.0264	1.0287	1.0043
	S.D.	0.1064	0.1295	0.1601	0.2968	0.2988	0.2473	0.2266
	Min.	0.5554	0.4932	0.4880	0.5328	0.5442	0.3092	0.3092
	Max.	1.5383	1.4730	2.5235	3.3948	4.3874	3.1596	4.3874

model results are robust. With adding control variables, the increase in MA on GTFP diminishes but still maintains a significant positive effect. It does not change the significance of other parameters and the sign of the coefficients. And the industrial structure positively affects GTFP. The secondary industry's system has also adjusted with the increase of the tertiary industry's proportion. The transition of the manufacturing industry from inefficient and pollution-free electricity production to environmentally friendly and efficient industrial production has significantly increased GTFP. Therefore, the regression results are more in line with expectations, and the increase in the proportion of the tertiary industry is conducive to the improvement of green total factor productivity.

According to column (3) of Table 4, science and technology inputs (STI) significantly impact GTFP. STI is the main expenditure of the enterprise R&D department, and some enterprises with higher science and technology content will use this part to invest in more efficient and energy-saving products to increase the added value of their product. Therefore, high STI helps improve GTFP. For the neoclassical model, increasing the capital-labor ratio increases productive efficiency (Marshall and Guillebaud, 1961). The capital-labor ratio is called capital deepening, contributing to the enterprise's R&D to achieve technological progress. According to the regression results on the data, the results are as expected. The coefficient of the capital-labor ratio is significantly positive. Under normal circumstances, greater government fiscal spending is conducive to increasing GTFP. However, if the government intervenes excessively in the enterprises, it may distort GTFP and achieve the opposite effect. The empirical results of this paper find that excessive government fiscal spending reduces GTFP. After adding the human capital variable, we find that human capital positively contributes to GTFP. We choose the number of university students over the total urban population in different regions as the human capital variable. And the regression results indicate that adding human capital will promote enterprise R&D and technological progress.

Table 5 shows the regression results of model II. Since location, economic, and demographic factors affect the GTFP of cities, we consider panel models that include interaction terms between these factors. Here we mainly focus on the cities located in the eastern region, which is more economically developed or with a larger population. We consider the following interaction terms AA, AI, AP, and AG. AA indicates whether it is an interaction variable between the developed eastern region and manufacturing agglomeration. AI means whether it is an interaction variable between the higher-income region and manufacturing agglomeration. AP shows whether it is an interaction variable between the more populated area and manufacturing agglomeration. Continuous interaction terms are also considered in this study. AG is the interaction variable between real GDP per capita and manufacturing agglomeration. Based on the regression results in Table 5, the results for the other control variables remain significant. The sign of the coefficients of the variables does not change, further certifying that the previous results are robust. In the four models, the core explanatory variables continue to have an overall positive effect on GTFP. The coefficients of AA, AI, and AG are negative, indicating that with the constant development of the urban economy, MA has gradually weakened the growth of GTFP. In fact, with the rapid development of the eastern region of China, some overcapacity or technologically backward enterprises are gradually eliminated or relocated. And urban areas are steadily deindustrialized in favor of vigorous development of light industries, service industries, etc. Therefore, MA has weakened the improvement of GTFP in these regions. The results of column (3) of Table 5 contain the interaction term with more populated areas, and a positive coefficient does not affect the above conclusion that a more significant population benefits GTFP.

3.3. *Results from panel threshold models*

Following the conclusion of Lu et al. (2021), We suspect a nonlinear link between GTFP and MA. According to the regression results of the interaction model above, a region's economic development degree has a specific negative effect on the increase of GTFP. Therefore, We include economic indicators to examine how the impact of MA on GTFP changes as the economic level changes. To further discuss this nonlinear characteristic, we first consider the panel regression model with threshold effects, where the threshold variable is chosen as GDP per capita, denoted as variable u_{it}. We argue that the region with higher real GDP per capita will also have a higher level of economic development. At the beginning of regression, we test the number of thresholds. Table 6 shows the test results.

We use an approximate likelihood ratio to test the null and alternative hypotheses. So, the null hypothesis of F_1 statistics has no threshold effect, and the alternative hypothesis is that there is a single threshold. Similarly, the F_2 statistic test only a single threshold versus there exists two thresholds. Then F_3 is to test whether there are triple thresholds values. As the results of Table 6, The first two statistics reject the null hypothesis at the confidence level of 5% and 10%. Respectively, we accept the null hypothesis in the third test. We confirm that there exist two threshold effects.

Fig. 4 shows the estimation of the thresholds, the curve represents the LR statistic, and the red dashed part is for the critical value. The threshold estimates are the likelihood ratio value that hits the zero axis. We can find the 95% confidence interval for the double thresholds, the values in which the likelihood ratio lies beneath the dotted line. And two values arrive at zero, so there are two threshold values.

According to the results of the threshold test, we can find that the influence of MA on GTFP has a double threshold effect. And the regression results verify that there is a nonlinear relationship between MA and GTFP, and the threshold variable economic level restricts it. Table 7 shows the regression results of the threshold panel model. The results of columns (1) (2) (3) of Table 5 represent regression results based on the model, which is a single, double, and triple threshold panel model. According to the regression results, the two-threshold panel model performs better, and the double thresholds are 0.5409 (PGDP = 11,877.64) and 0.7075 (PGDP =32,593.92). Respectively, with

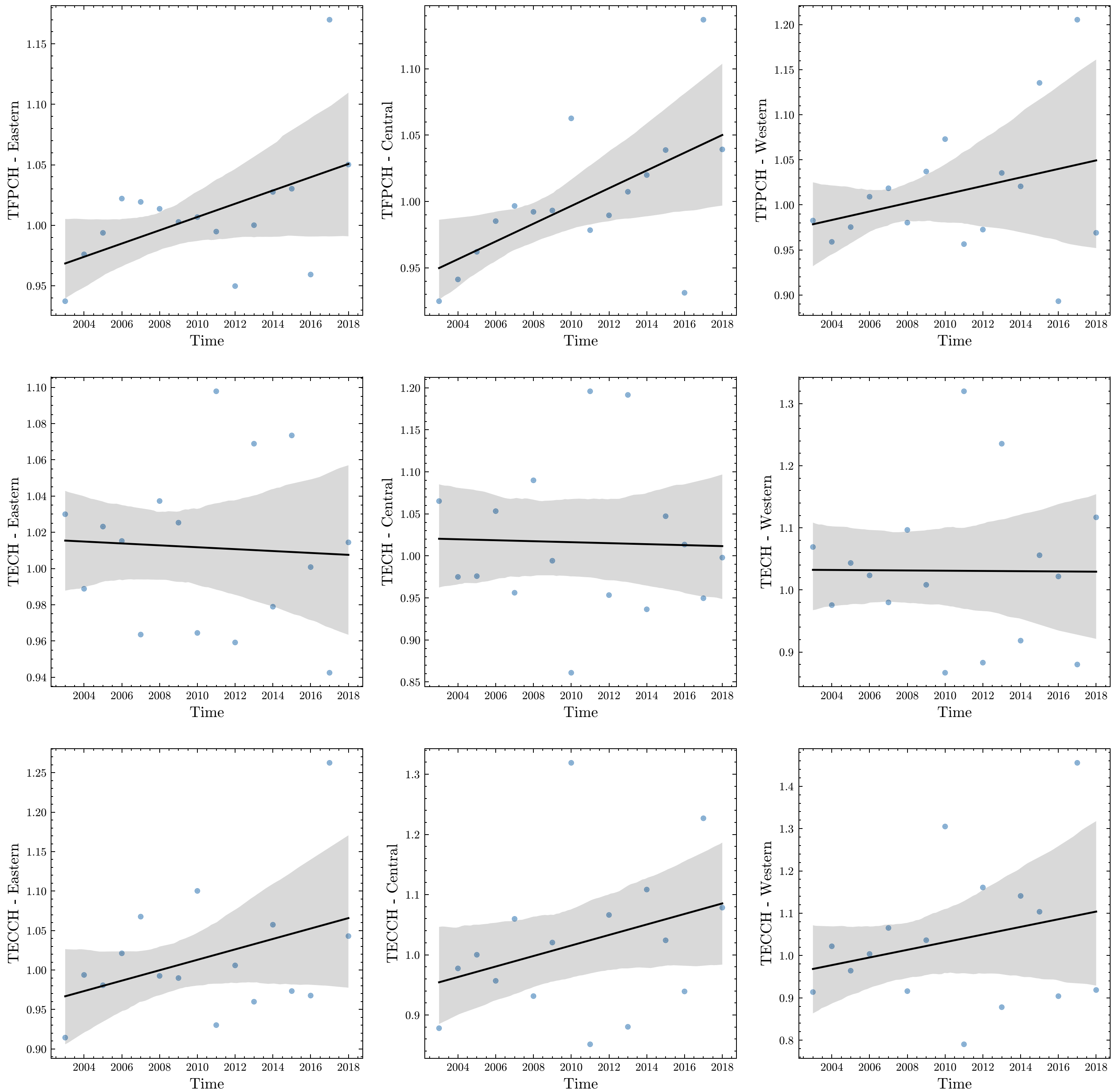

Fig. 2. Average ML and its decomposition of different groups by region.
Notes: MLE stands for MLEFFCH, and MLT stands for MLTECH. The black line represents the trend line, and the gray shading represents the confidence interval (95%).

significant results at a 5% confidence level. The third threshold value of 0.2437 is insignificant for the triple threshold panel model. And the significance of other control variables is reduced. According to the regression results with the inclusion of the threshold effect, the increase in GTFP by the degree of MA gradually diminishes with the increase in real GDP per capita, whether a single, double, or triple threshold. It is consistent with the analysis of the regression results of the model in the presence of interaction variables. As for the other control variables, the results are still significant. And the coefficients are entirely consistent with the regression results of the primary panel model and the panel model with interaction variables, further verifying that the model is robust.

3.4. Results from partially linear functional-coefficient models

Finally, we regress model IV. This model can more flexibly describe the nonlinear characteristics between the core and dependent variables. The linear panel model only yields an average effect. At the same time, the regression with interaction variables and the regression with threshold variables can only find that the regression coefficients are asymmetric or vary within different threshold intervals. These results are still discrete in the strict sense. The advantage of the PLFC model is that the coefficient functions of the core explanatory variables are estimated (Du et al., 2020), allowing a more intuitive portrayal of the impact of the degree of MA on GTFP. Unlike the other studies that have obtained non-linear results, we have added a new dimension. The

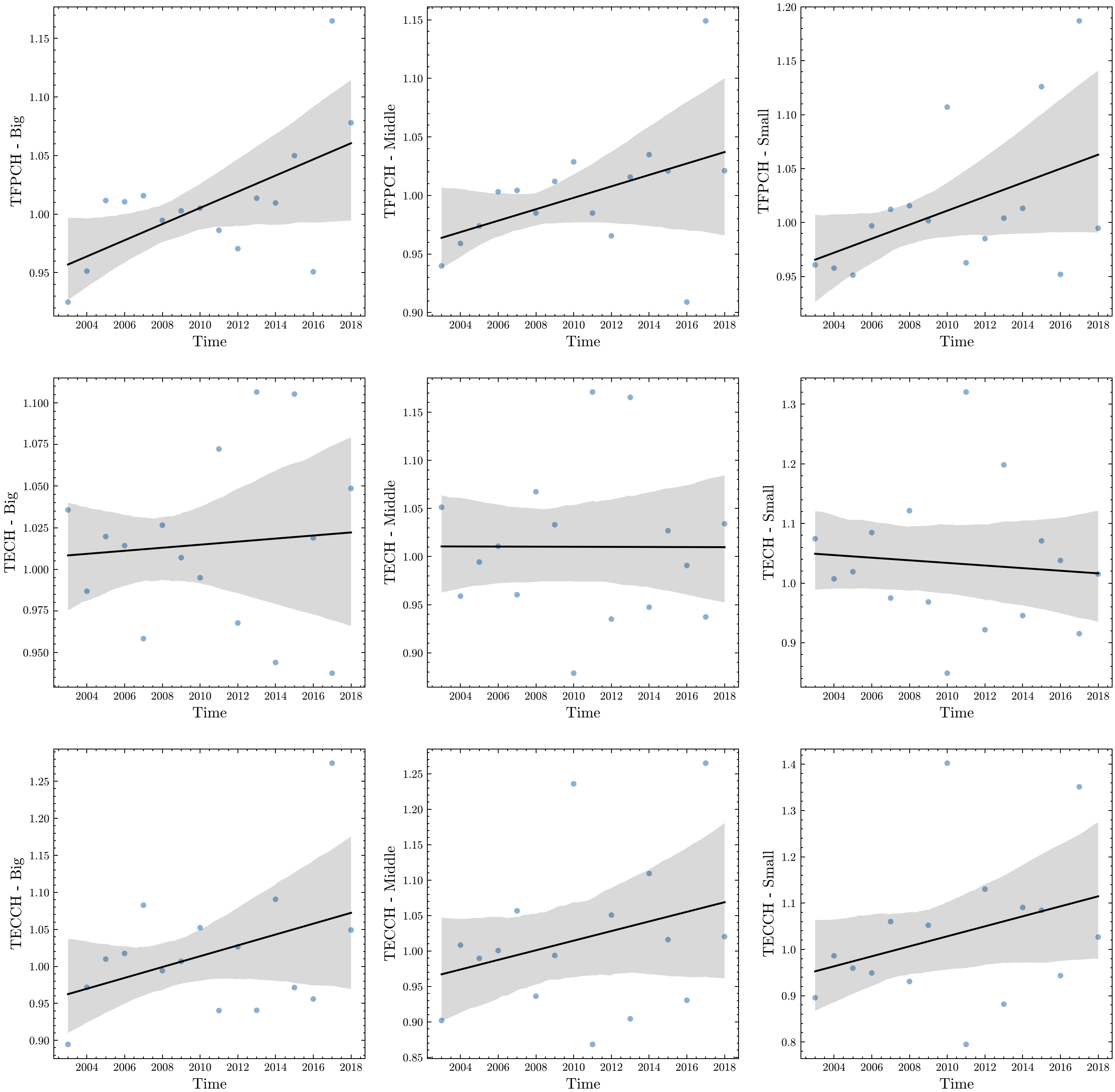

Fig. 3. Average ML and its decomposition of different groups by size.
Notes: MLE stands for MLEFFCH, and MLT stands for MLTECH. The black line represents the trend line, and the gray shading represents the confidence interval (95%).

economic level restricts MA, so PGDP is considered a function coefficient. We can examine the change in the effect of MA on GTFP as the status of the economy changes. Fig. 5a shows the non-linear results of the non-parametric estimation.

We present the estimation results of nonlinear coefficients. The abscissa in Fig. 5a is $lnPGDP_{it}$, and the ordinate is the marginal effect of MA on GTFP. Fig. 5a shows MA promotes the growth of GTFP, which is consistent with the results of the linear and threshold models. And the results from our nonlinear models reveal more details. As $lnPGDP_{it}$ increases, the coefficient of the nonlinear part gradually decreases from 0.4 to about 0. It means that as the level of regional economic development rises, the positive effect of MA on GTFP in the region gradually decreases. In other words, the impact of MA on the GTFP of the area is significantly higher than that of the developed region (in-line with the results from threshold regressions).

Following Wang et al. (2019), we decompose GTFP into MLTECH and MLEFFCH. We regress the nonlinear relationship between the MA and the decomposition variables based on the PLFC model. From the results in Fig. 5b and Fig. 5c, we can find that MA did not significantly promote management efficiency and even had a negative effect in well-developed areas. One potential explanation is the congestion effect, which means that regions with higher levels of development already have well-developed public infrastructure and industrial systems. Excessive MA may reduce the matching degree of their various resources, creating the congestion effect and reducing efficiency. Fig. 5c shows that MA has a significant contribution to technological progress.

Table 4
Regression results of linear models.

	(1)	(2)	(3)	(4)	(5)
Variable	lnGTFP	lnGTFP	lnGTFP	lnGTFP	lnGTFP
lnMA	0.0455***	0.0327***	0.0239***	0.0281***	0.0290***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
lnIS	0.0410***	0.0474***	0.0361***	0.0356***	0.0356***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
lnSTI		0.0100***	0.0066***	0.0117***	0.0115***
		(0.001)	(0.002)	(0.002)	(0.002)
lnSE			0.0122***	0.0350***	0.0328***
			(0.004)	(0.006)	(0.007)
lnGC				−0.0353***	−0.0348***
				(0.008)	(0.008)
lnHC					0.0041
					(0.003)
Constant	0.1430***	−0.0130	−0.0776**	0.2311***	0.2252***
	(0.020)	(0.029)	(0.035)	(0.079)	(0.079)
Observations	3888	3888	3888	3888	3888
Number of the cities	243	243	243	243	243
City FE	Yes	Yes	Yes	Yes	Yes
Hausman Test	23.43	24.37	13.49	20.99	22.86
	(0.0000)	(0.0000)	(0.0091)	(0.0008)	(0.0008)

Notes: (1) Standard errors in parentheses; (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5
Regression results of linear models with the interaction term.

	(1)	(2)	(3)	(4)
Variable	lnGTFP	lnGTFP	lnGTFP	lnGTFP
lnMA	0.0317***	0.0308***	0.0248***	0.0964***
	(0.008)	(0.008)	(0.008)	(0.014)
AA	−0.0088			
	(0.014)			
AI		−0.0087		
		(0.016)		
AP			0.0159	
			(0.014)	
AG				−0.0105***
				(0.002)
lnIS	0.0362***	0.0362***	0.0356***	0.0298***
	(0.010)	(0.010)	(0.010)	(0.010)
lnHC	0.0041	0.0040	0.0042	0.0024
	(0.003)	(0.003)	(0.003)	(0.003)
lnSTI	0.0115***	0.0115***	0.0115***	0.0126***
	(0.002)	(0.002)	(0.002)	(0.002)
lnSE	0.0326***	0.0326***	0.0326***	0.0083
	(0.007)	(0.007)	(0.007)	(0.008)
lnGC	−0.0345***	−0.0345***	−0.0350***	−0.0264***
	(0.008)	(0.008)	(0.008)	(0.008)
Constant	0.2211***	0.2215***	0.2274***	0.2311***
	(0.079)	(0.079)	(0.079)	(0.078)
Observations	3888	3888	3888	3888
Number of the cities	243	243	243	243
City FE	Yes	Yes	Yes	Yes

Notes: (1) Standard errors in parentheses; (2) *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 6
Results of threshold tests.

	F	P-value	(10%, 5%, and 1% critical values based on bootstrap samples)
Single threshold	26.32	0.03	(22.41, 25.08, 30.60)
Double thresholds	16.05	0.03	(13.66, 14.94, 19.46)
Triple thresholds	11.84	0.91	(31.65, 35.24, 42.20)

Notes: F statistic, P-value, and critical values in different runs are similar but not identical, because of the randomness of bootstrap sampling. The present value is the result of random seed 42.

Technology spillover is the most important reason (Du and Li, 2019). MA can promote technical exchange between enterprises. This effect varies across regions. With the development of the economy, the technological progress effect of MA decreases. An important reason is that areas with poor economies also have low technical levels. The technology spillover effect of MA plays a more significant role in the interaction between enterprises, and the marginal effect is more pronounced.

In this section, we investigate the impact of MA on GTFP using a nonlinear approach and examine the mechanism of its effect. And we analyze how MA affects GTFP by influencing technology spillovers and managerial efficiency. Results from our proposed functional-coefficient model help us to reveal the impact of MA on GTFP and its mechanism more clearly. The policy implications of the functional-coefficient model are that government-led MA can increase technology spillover, and industrial park-like construction is valuable. But the park's structure needs to consider the synergy between industries to improve management efficiency and expand the MA effect.

4. Robustness test and heterogeneity analysis

4.1. Robustness test

In this section, we do the relevant robustness tests. Firstly, we consider the robust standard error in the regression to reduce the impact of heteroscedasticity. Secondly, we use other methods to re-measure the GFTP and replace the original dependent variable. There are many ways to measure GTFP, and we use the MLPI model to measure GTFP in Section 3. In this chapter, we will use the LPI model to re-measure the GTFP and replace it with the dependent variable. We keep the remaining core explanatory and control variables unchanged and perform basic panel and partial linear regression. Table 8 shows the results. We can find that the main results of the basic panel regression do not change when we replace the explanatory variables, and the regression coefficient of MA remains significantly positive and essentially unchanged in value. The significance of the remaining control variables is roughly similar to the results in Table 4, where the impact of HC is negative but still insignificant. The results of the partial linear regression have shown in Fig. 6, where only the nonlinear part is reported, and the curve shape is the same as that of Fig. 5(A). we can also find that the coefficients of the core explanatory variables gradually decrease as the GDP per capita increases. Based on the results of the basic panel model and the nonlinear regression, we can obtain similar regression results as before, indicating that the main regression results of this paper are robust.

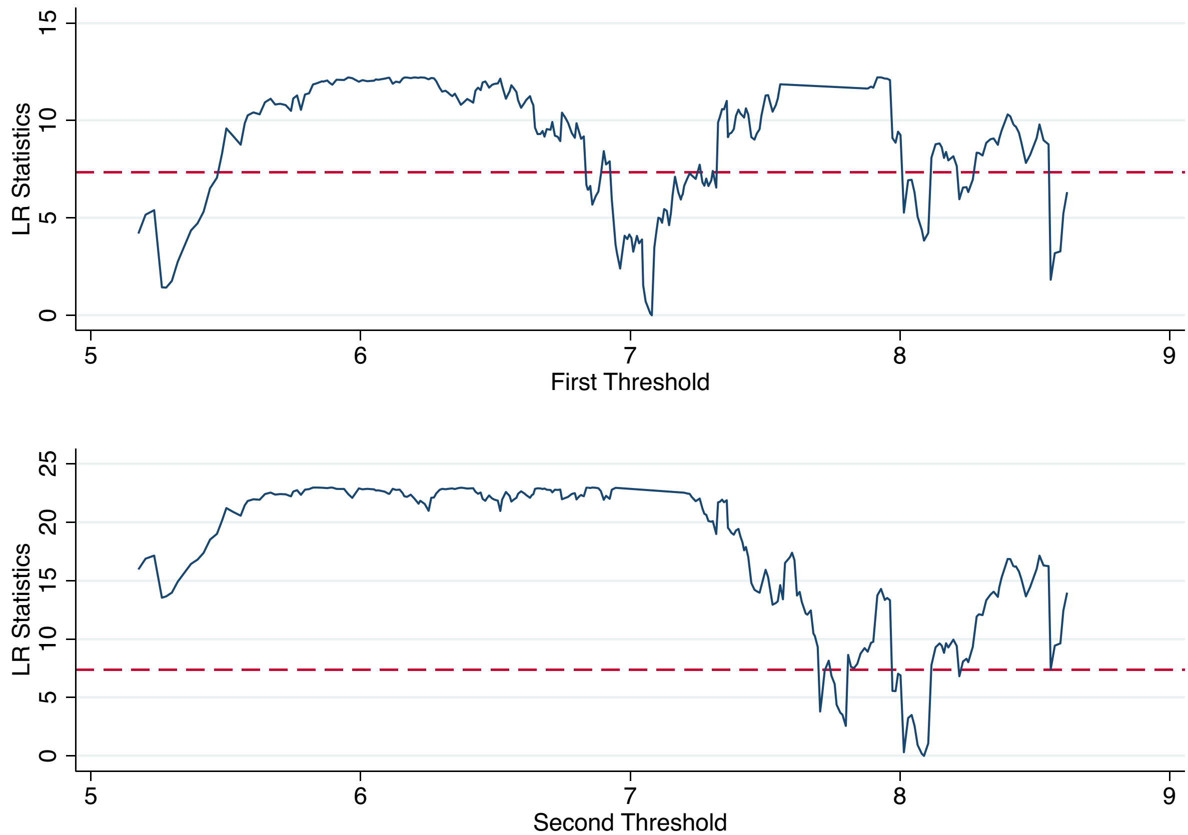

Fig. 4. Confidence interval construction in the double threshold model.
Notes: The curve represents the LR statistic, and the red dashed part represents the critical value. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.2. Regional heterogeneity

To further verify the robustness of the above results, we grouped the 243 cities into eastern, central, and western cities according to their location, and the list of grouped cities is shown in Table A1 in Appendix. As shown in Fig. 7, the impact parameters of MA and GTFP show an overall increasing trend followed by a decreasing trend in the eastern, central, and western regions. The trend means that as the economic level increases, MA significantly promotes GTFP for the region with a lower economic level. However, as the economic level further improves, the growth benefits in the graph gradually decrease. Competitive effects lead to a crowding impact within the industry, reducing the scale of growth. And when the PGDP is close to 0.07, 0.05, and 0.03, the parameters of the eastern, central, and western regions reach inflection points. A comparative analysis of the regional differences shows that the absolute value of the parameter inflection points affects the benefits in the following order: western cities > central cities > eastern cities. The western regions are more backward in the manufacturing chain and have a more apparent peak-boosting effect. The smaller the size, the greater the overall growth.

However, we also find that the western region has a faster decline after the inflection point than other regions. Within the range of 0.05 PGDP decline after the inflection point, the parameter effects decline rate of regional cities is as follows: western cities (50%) > eastern cities (25%) > central cities (23%). The western cities have a considerably higher downward trend than the central and east regions. The rapid growth in the parameter effects also leads to a similarly rapid decline. It proves that if the industry is smaller, the manufacturing industry is easier to agglomerate and quickly reach a crowded state. Meanwhile, the economic growth rate of the western cities is lower than that of the eastern and central regions, which means that the central and eastern regions can enjoy the exact value of technological spillover "dividends" for a more extended period with the same value of PGDP growth. MA can bring more stable output limited to a larger scale and more consistently stabilize the upgrading of the industrial chain.

More interestingly, although the marginal parameter effects in all regions show a decreasing trend, the regional decline changes are different. The final benefit of central cities is still positive, but it is close to 0 in the eastern cities. And the final benefit of western cities even shows a negative value. The results show that transferring manufacturing from the east region to the central region is better for the overall economic benefits. The central region has a better industrial chain and sufficient human capital, which is more conducive to economic growth. Meanwhile, although the transfer of manufacturing to the western region can bring the highest marginal benefits, the transfer scale needs to be strictly controlled due to the remote geographical distance and high transfer costs.

4.3. Scale heterogeneity

Finally, we group cities by population. And large cities (over 6.2 million), medium-sized cities (2.55 million-6.2 million), and small cities (<2.55 million) are used to distinguish population heterogeneity. Table A2 in the appendix shows the list of grouped cities. As shown in Fig. 8, the overall trend of the parameter changes is gradually decreasing for both large, medium, and small cities. The initial values of the

Table 7
Regression results of panel threshold models.

Variable	(1) lnGTFP	(2) lnGTFP	(3) lnGTFP
lnMA*I(u < 0.6439)	0.0338*** (0.007)		
lnMA*I(u > 0.6439)	0.0189** (0.008)		
lnMA*I(u < 0.5409)		0.0363*** (0.007)	
lnMA*I(0.7075 > u > 0.5409)		0.0251*** (0.007)	0.0222*** (0.008)
lnMA*I(u > 0.7075)		0.0098 (0.008)	0.0060 (0.008)
lnMA*I(u < 0.2437)			0.0455*** (0.008)
lnMA *I(0.5409 > u > 0.2437)			0.0336*** (0.007)
lnIS	0.0237** (0.010)	0.0216** (0.010)	0.0261*** (0.008)
lnHC	0.0032 (0.003)	0.0026 (0.003)	0.0020 (0.003)
lnSTI	0.0125*** (0.002)	0.0128*** (0.002)	0.0127*** (0.002)
lnSE	0.0222*** (0.007)	0.0139* (0.007)	0.0100 (0.007)
lnGC	−0.0306*** (0.008)	−0.0271*** (0.008)	−0.0261*** (0.008)
Constant	0.2212*** (0.079)	0.2165*** (0.078)	0.2254*** (0.078)
Observations	3888	3888	3888
Number of the cities	243	243	243

Notes: (1) Standard errors in parentheses (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Estimated values in different runs are similar but not identical, because of the randomness of bootstrap sampling. The present value is the result of random seed 42.

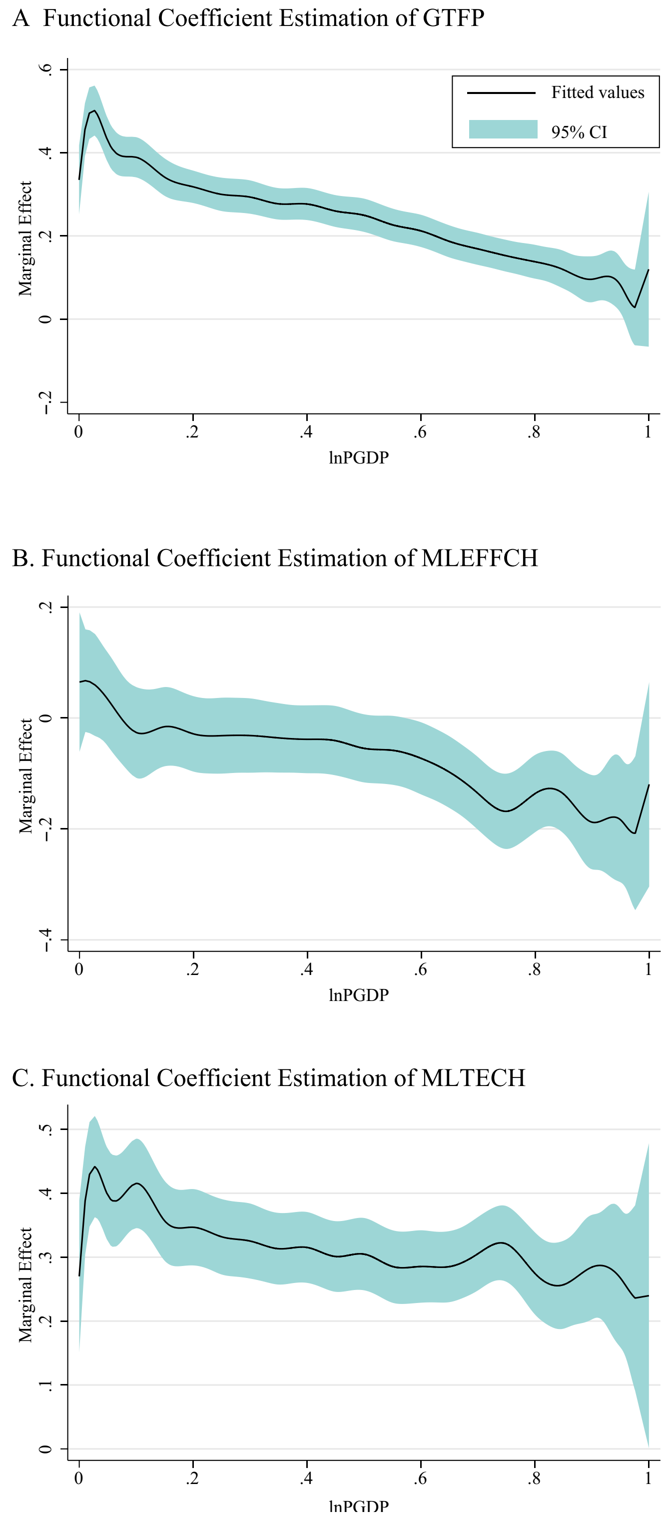

Fig. 5. Functional coefficients estimates.

parameters of large and medium cities indicate that population positively affects GTFP growth, which is consistent with the results of model II. Besides, the variation range of nonlinear parameters in small-scale cities is much smaller. We can get the reason from the results of model II. when the cities have more population, the parameter of the interaction term is positive. So the marginal effect of MA decrease when the cities have small-scale population and increase in large-scale population case. That is why the nonlinear parameter is much smaller for small cities. The results obtained by grouping regression are consistent with the previous conclusions.

For the results grouped by population, the marginal effect of MA on GTFP decreases with the increase in the economic level. And the parameter decreases fastest in cities with a medium population. A valid explanation is that densely populated areas are conducive to producing labor-intensive products. With the continuous improvement of the economic level, manufacturing enterprises will gradually transform from labor-intensive to capital-intensive. So the population advantage will gradually weaken, and the impact of MA on GTFP will also weaken progressively due to the lifting effect. In particular, the marginal impact falls more slowly in cities with smaller populations.

We also find that meddle cities have the highest and slowest inflection points of the marginal efficiency parameter. Meddle cities mainly consist of non-core significant cities in urban agglomerations. Therefore, manufacturing industries in big cities should gradually shift to the periphery of urban agglomerations. Both overpopulation and underpopulation of cities inhibit the positive impact of spillover. So cities with medium-sized populations can avoid crowded competition's regressive benefits.

5. Conclusions and policy implications

5.1. Conclusions

Controversial conclusions about the effect of MA on GTFP lead us to reconsider their relationship. Our study analyzes this question from three aspects. First, MA and GTFP have a nonlinear relationship. Second, the relationship between MA and GTFP is dynamically affected by economic levels. Finally, population and regional development significantly influence the heterogeneity analysis. We use the linear panel model, linear panel model with interaction terms, threshold panel data model, and PLFC model to construct the relationships between MA and GTFP. Especially the four models we consider are a progressive relationship. The main conclusions are as follows:

Table 8
Robustness test: baseline model.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	GTFP	GTFP	GTFP	GTFP	GTFP
lnMA	0.0474***	0.0283***	0.0168***	0.0196***	0.0191***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
lnIS	0.0185**	0.0281***	0.0134*	0.0131*	0.0131*
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
lnTEC		0.0149***	0.0105***	0.0140***	0.0141***
		(0.001)	(0.001)	(0.002)	(0.002)
lnKL			0.0159***	0.0313***	0.0325***
			(0.002)	(0.006)	(0.006)
lnFISC				−0.0239***	−0.0242***
				(0.007)	(0.007)
lnHC					−0.0021
					(0.002)
Constant	0.1602***	−0.0731***	−0.1570***	0.0521	0.0551
	(0.017)	(0.023)	(0.026)	(0.066)	(0.066)
Observations	3888	3888	3888	3888	3888
R-squared	0.024	0.070	0.078	0.082	0.082
Number of city	243	243	243	243	243
City FE	Yes	Yes	Yes	Yes	Yes

Notes: (1) Robust standard errors in parentheses; (2) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

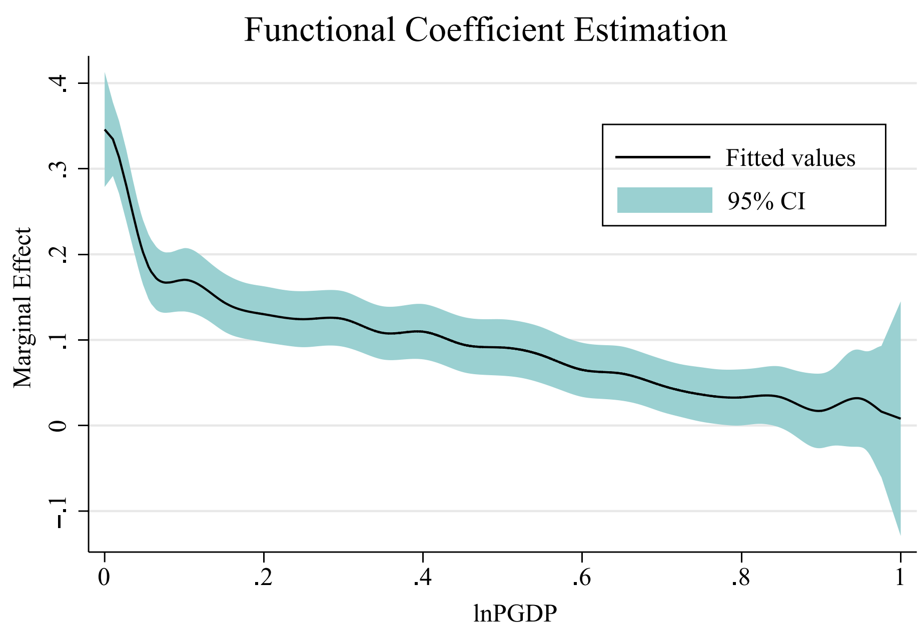

Fig. 6. Partially linear panel model regression of robustness test.

(1) There is a nonlinear relationship between MA and GTFP, which changes with the economic level. The influence of the economic level has a threshold effect. And when the economic level reaches a critical value (threshold value), the influence of MA on GTFP has an inflection point. According to the results of the PLFC model, the impact of MA on GTFP is close to the shape of an inverted U. And MA can increase GTFP effectively at a low economic level. However, with the continuous improvement of the economic level, the effect is still positive, but the efficiency of promotion brought about by MA gradually decreases.
(2) By regressing GTFP with MLTECH and MLEFFCH, we can find that the promotion effect of MA on MLEFFCH gradually decreases, which leads to a gradual decline in the regression coefficient of GTFP. Therefore, cities with a relatively developed economy have a complete industrial system, and the efficiency of MA will gradually decrease, resulting in a congestion effect.
(3) The results of model II and heterogeneity analysis show that the population, region, and economic conditions restrict the impact of MA on GTFP. But the rate of decline and the inflection point vary significantly across regional factors. For example, the western cities have a considerably higher downward trend than the central and east regions. The rapid growth in the parameter effects also leads to a similarly rapid decline. It proves that if the industry is smaller, the MA is easier to reach a crowded state. The conclusions of these differences will provide valuable suggestions for the government.

5.2. Policy implications

From the findings mentioned above, this study proposes the following implications:

(1) The government needs to develop differentiated policies for cities based on the city's economic level. MA has good marginal spillover to GTFP for cities with backward economic levels. The government should improve the infrastructure construction and

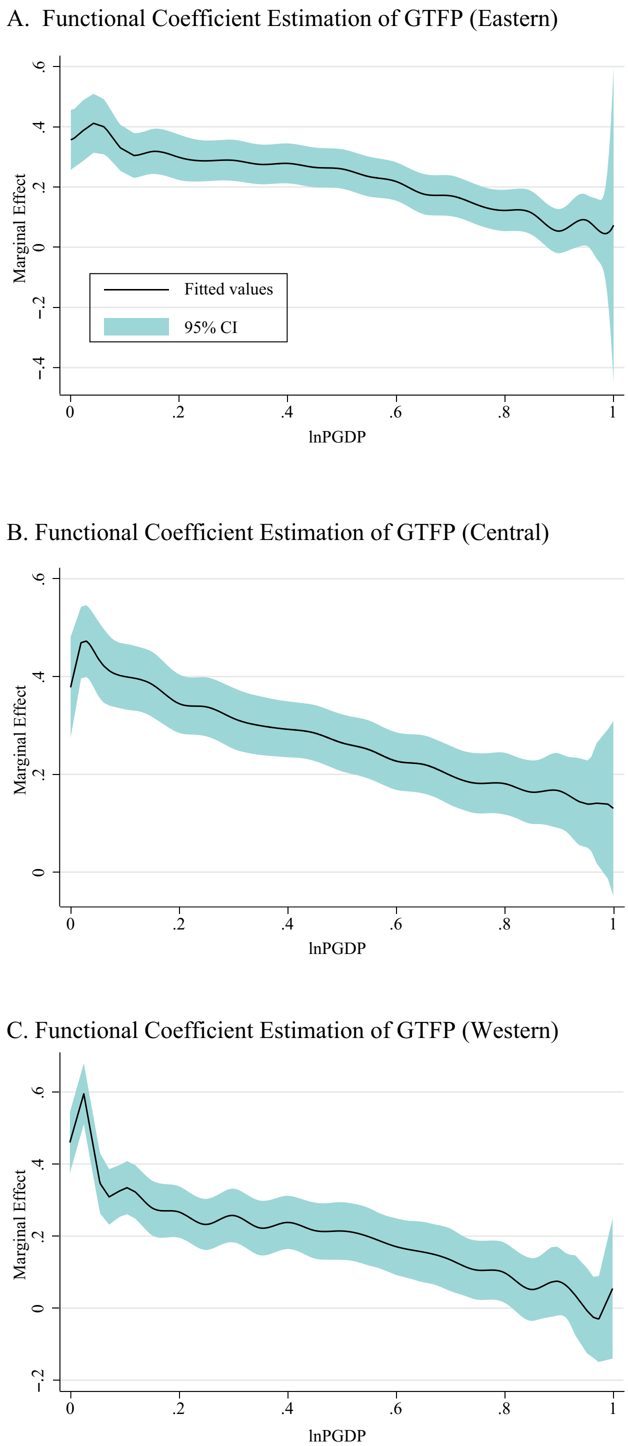

Fig. 7. Functional coefficients estimates of different groups by region.

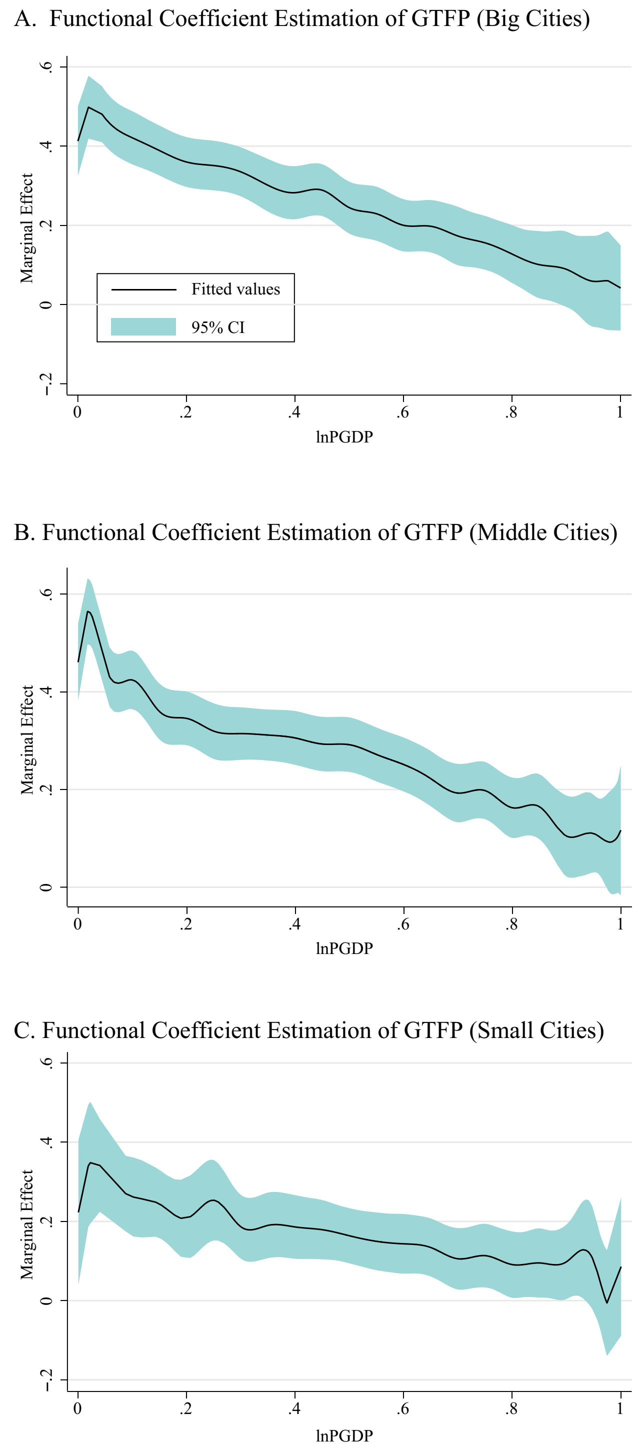

Fig. 8. Functional coefficients estimates of different groups by size.

investment environment for MA. With the city's economic development, the marginal benefit of MA to GTFP gradually diminishes. For economically developed cities, the government needs to avoid the crowding effect of MA. Therefore, these cities must promote urban transformation by optimizing the industrial structure and introducing high-end manufacturing.

(2) Different stages of MA require various policies. In the early stage of MA, the government should provide a comfortable environment for industrial growth. For instance, we could establish industrial parks to promote the development of MA. Subsequently, the government should guide the coordinated development of different industries to increase the marginal benefit of MA on GTFP. But the marginal benefit of MA to GTFP is mainly driven by technology when the city's economy develops to a high level. Therefore, the government should reasonably regulate investment flows in urban development's middle and late stages. For instance, we could curb high-polluting enterprises on the negative list. And the development of technology has become the most critical factor in improving the city's GTFP.

(3) The government should invest more resources to improve technology. The results of our research prove that technology is the most essential factor for the continuous improvement of GTFP.

However, the results in Figs. 2 and Figs. 3 show that technology has not progressed significantly compared to management efficiency. Therefore, the government needs to increase investment in the technology industry and establish an effective industrial cluster. In addition, the company could optimize the production technology, such as adopting mechanical cluster production and artificial intelligence to replace traditional management technology, which could improve GTFP and achieve the goal of "carbon neutrality".

(4) The government should promote the construction of manufacturing city clusters and the transfer of MA. China's Yangtze River Delta urban agglomeration and Pearl River Delta urban agglomeration have formed a spatial pattern with the central city as the gathering center. The government should transfer part of the manufacturing industry in major cities to adjacent medium-sized cities. At the same time, the government needs to consider the city's location advantages in urban MA planning.

Inclusion and diversity

While citing references scientifically relevant for this work, we actively worked to promote gender balance in our reference list. The author list of this paper includes contributors from the location where the research was conducted who participated in the data collection, design, analysis, and/or interpretation of the work.

CRediT authorship contribution statement

Congcong Du: Writing – original draft, Visualization, Software, Methodology, Data curation. **Yunhui Cao:** Writing – original draft, Software, Methodology, Data curation. **Yushan Ling:** Writing – review & editing, Visualization, Validation. **Zebin Jin:** Visualization, Data curation. **Shibo Wang:** Methodology, Data curation. **Daoping Wang:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Conceptualization.

Declaration of competing interest

None.

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Appendix A. Appendix

Table A1
City Groups by Region.

Eastern Cities	Beijing, Tianjin, Shenyang, Dalian, Anshan, Fushun, Benxi, Dandong, Jinzhou, Yingkou, Fuxin, Liaoyang, Panjin, Tieling, Chaoyang, Huludao, Shanghai, Nanjing, Wuxi, Xuzhou, Changzhou, Suzhou, Nantong, Lianyungang, Yancheng, Yangzhou, Zhenjiang, Taizhou, Suqian, Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Quzhou, Zhoushan, Taizhou, Lishui, Fuzhou, Xiamen, Putian, Sanming, Quanzhou, Zhangzhou, Nanping, Longyan, Ningde, Jinan, Qingdao, Zibo, Zaozhuang, Dongying, Yantai, Weifang, Jining, Taian, Weihai, Rizhao, Laiwu, Linyi, Dezhou, Liaocheng, Binzhou, Heze, Guangzhou, Shaoguan, Shenzhen, Zhuhai, Shantou, Foshan, Jiangmen, Zhanjiang, Maoming, Zhaoqing, Huizhou, Shanwei, Heyuan, Yangjiang, Qingyuan, Zhongshan, Chaozhou, Jieyang
Central Cities	Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Boding, Zhangjiakou, Chengde, Cangzhou, Zhangjiakou, Chengde, Cangzhou, Langfang, Hengshui, Hengshui, Taiyuan, Datong, Yangquan, Changzhi, Jincheng, Shuozhou, Jinzhong, Yuncheng, Xinzhou, Linfen, Hohhot, Baotou, Wuhai, Chifeng, Tongliao, Changchun, Jilin, Siping, Liaoyuan, Tonghua, Baishan, Songyuan, Baicheng, Harbin, Qiqihar, Jixi, Hegang, Shuangyashan, Daqing, Yichun, Jiamusi, Qitaihe, Mudanjiang, Heihe, Suihua, Hefei, Wuhu, Bengbu, Huainan, Maanshan, Huaibei, Tongling, Anging, Huangshan, Chuzhou, Fuyang, Suizhou, Liuan, Haozhou, Chizhou, Xuancheng, Nanchang, Jingdezhen, Pingxiang, Jiujiang, Xinyu, Yingtan, Ganzhou, Yichun, Fuzhou, Shangrao, Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Anyang, Hebi, Xinxiang, Jiaozuo, Puyang, Xuchang, Luohe, Sanmenxia, Nanyang, Shangqiu, Xinyang, Zhoukou, Zhumadian, Wuhan Huangshi, Shiyan, Yichang, Ezhou, Jingmen, Xiaogan, Jingzhou, Huanggang, Xianning, Suizhou, Changsha, Zhuzhou, Xiangtan, Hengyang, Zhaoyang, Yueyang, Changde, Zhangjiajie, Yiyang, Chenzhou, Yongzhou, Huaihua, Loudi
Western Cities	Chongqing, Chengdu, Zigong, Panzhihua, Luzhou, Deyang, Mianyang, Guangyuan, Suining, Neijiang, Leshan, Nanchong, Meishan, Yibin, Guang'an, Ya'an, Bazhong, Ziyang, Guiyang, Liupanshui, Zunyi, Anshun, Kunming, Qujing, Yuxi, Baoshan, Tongchuan, Baoji, Xianyang, Yan'an, Hanzhong, Yulin, Ankang, Lanzhou, Jiayuguan, Jinchnag, Baiyin, Tianshui. Xining, Yinchuan, Shizuishan, Wuzhong, Wulumqi, Kelamayi

Table A2
City groups by population size.

Big cities	Beijing, Tianjin, Shijiazhuang, Tangshan, Handan, Xingtai, Baoding, Cangzhou, Shenyang, Changchun, Harbin, Shanghai, Nanjing, Xuzhou, Suzhou, Nantong, Yancheng, Hangzhou, Wenzhou, Hefei, Anqing, Fuyang, Suzhou, Liu'an, Fuzhou, Quanzhou, Ganzhou, Jinan, Qingdao, Yantai, Weifang, Jining, Linyi, Liaocheng, Heze, Zhengzhou, Luoyang, Xinxiang, Nanyang, Shangqiu, Xinyang, Zhumadian, Wuhan Jingzhou, Changsha, Hengyang, Shaoyang, Yongzhou, Guangzhou, Zhanjiang, Maoming, Jieyang, Nanning, Yulin, Chongqing, Chengdu, Nanchong, Zunyi, Qujing Xi'an
Meddle cities	Qinhuangdao, Zhangjiakou, Chengde, Langfang, Hengshui, Taiyuan, Datong, Changzhi, Jinzhong, Yuncheng, Xinzhou, Linfen, Chifeng, Tongliao, Dalian, Anshan, Jinzhou, Tieling, Chaoyang, Huludao, Jilin, Siping, Songyuan, Qiqihar, Daqing, Mudanjiang, Suihua, Wuxi, Changzhou, Lianyungang, Yangzhou zhenjiang, taizhou, suqian, ningbo, jiaxing, huzhou, shaoxing, jinhua, quzhou, taizhou, lishui, wuhu, bengbu, chuzhou, xuancheng, putian, sanming, zhangzhou, nanping, longyan, ningde, nanchang, jujiang, yichun, fuzhou, zibo, zaozhuang, taian, rizhao, dezhou, kaifeng Pingdingshan, Anyang, Jiaozuo, Puyang, Xuchang, Luohe, Huangshi, Shiyan, Yichang, Jingmen, Xianning, Zhuzhou, Xiangtan, Yueyang, Changde, Yiyang, Chenzhou, Huaihua, Shaoguan, Shenzhen, Shantou, Foshan, Jiangmen, Zhaoqing, Huizhou, Shanwei, Heyuan, Yangjiang, Qingyuan, Chaozhou. Liuzhou, Guilin, Wuzhou, Qinzhou, Guigang, Baise, Hechi, Laibin, Zigong, Luzhou, Deyang, Mianyang, Guangyuan, Suining, Neijiang, Leshan, Meishan, Yibin, Guang'an, Ziyang, Guiyang, Liupanshui, Kunming, Baoshan, Baoji, Xianyang, Hanzhong, Yulin, Ankang Lanzhou, Tianshui
Small cities	Yangquan, Jincheng, Shuozhou, Hohhot, Baotou, Wuhai, Fushun, Benxi, Dandong, Yingkou, Fuxin, Liaoyang, Panjin, Liaoyuan, Tonghua, Baishan, Baicheng, Jixi, Hegang, Shuangyashan, Yichun, Jiamusi, Qitaihe, Heihe, Zhoushan, Huainan, Maanshan, Huaibei, Tongling, Huangshan, Chizhou. Xiamen, Jingdezhen, Pingxiang, Xinyu, Yingtan, Dongying, Weihai, Laiwu, Hebi, Sanmenxia, Ezhou, Suzhou, Zhangjiajie, Zhuhai, Zhongshan, Beihai, Fangchenggang, Haikou, Sanya, Panzhihua, Ya'an, Yuxi, Tongchuan, Yan'an, Jiayuguan, Jinchang, Baiyin, Xining, Yinchuan, Shizuishan, Wuzhong, Wulumuqi, Kelamayi

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107352.

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