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The Effect of Urban Agglomeration Expansion on $PM_{2.5}$ Concentrations: Evidence from a Quasi-natural Experiment

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Abstract: This study constructs a quasi-natural experiment based on the expansion of the Yangtze River Delta urban agglomeration (YRDUA) of China in 2010 to investigate the impact and inner mechanism of urban agglomeration expansion on fine particulate matter ($PM_{2.5}$) concentrations through propensity scores in difference-in-differences models (PSM-DID) using panel data from 286 prefecture-level cities in China from 2003 to 2016. The results show that 1) urban agglomeration expansion contributes to an overall decrease in $PM_{2.5}$ concentration, which is mainly achieved from the original cities. For the new cities, on the other hand, the expansion significantly increases the local $PM_{2.5}$ concentration. 2) In the long term, the significant influence of urban agglomeration expansion on $PM_{2.5}$ concentration lasts for three years and gradually decreases. A series of robustness tests confirm the applicability of the PSM-DID model. 3) Cities with weaker government regulation, a better educated population and higher per capita income present stronger $PM_{2.5}$ reduction effects. 4) Urban agglomeration expansion affects the $PM_{2.5}$ concentration mainly through industrial transfer and population migration, which cause a decrease in the $PM_{2.5}$ concentration in the original cities and an increase in the $PM_{2.5}$ concentration in the new cities. Corresponding policy suggestions are proposed based on the conclusions.

Keywords: urban agglomeration expansion; fine particulate matter ($PM_{2.5}$) concentration; quasi-natural experiment; propensity scores in difference-in-differences models (PSM-DID); Yangtze River Delta Urban Agglomeration, China

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1 Introduction

During the past few decades, urbanization has become an irreversible trend that underlies the evolution of human society (Li et al., 2018; Lawrence, 2019; Onyebueke et al., 2020). China, the world's largest developing country and an emerging economy with rich growth potential, has been experiencing a rapid process of urbanization ever since its reform and opening up (Wu et al., 2014), with its urbanization rate increasing from 17.92% in 1978 to 60.60% in 2019 (National Bureau of Statistics of China, 2020). Urbanization has aided China's social and economic growth, but it has also hastened the exploitation of scarce resources, resulting in many environmental problems (Liang et al., 2019), such as natural habitat loss (He et al., 2014), water contamination (Chen et al., 2011) and air pollution (Ebenstein et al., 2017; Ulpiani, 2021). The Chinese government has launched numerous major projects to prevent further atmospheric deterioration. As a result, pollutants such as SO_2 and CO_2 have greatly decreased (Zhou and Li, 2021). $PM_{2.5}$, a fine particulate matter characterized

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by small particles with a strong active state and wide diffusion, still remains a key concern that brings environmental and socioeconomic issues (Maji et al., 2020). The harm of $PM_{2.5}$ concentrations is self-explanatory. $PM_{2.5}$ can easily absorb hazardous chemicals, such as PAHs and Hg, which not only reduces atmospheric visibility and affects public activities (Cao et al., 2015) but also poses a serious threat to human health and daily life (Schulze et al., 2017; Fulgar et al., 2018), causing massive amounts of economic damage and death (Song et al., 2017; Yang et al., 2022). According to Han and Qian (2021), every 10 g/m^3 increase in $PM_{2.5}$ concentration raises the mortality rate by approximately 3.8% yearly in China.

Recently, an increasing number of academics have focused on socioeconomic contributors (Feng et al., 2022) and considered urbanization to be one of the most important indicators affecting $PM_{2.5}$ pollution (Siddique and Kiani, 2020), thereby providing a solid foundation for our study. The relevant conclusions can be divided into three groups based on the literature. That is, urbanization can increase $PM_{2.5}$ concentrations, alleviate $PM_{2.5}$ concentrations or have nonlinear effects on $PM_{2.5}$ concentrations. According to the first perspective, the process of urbanization involves various socioeconomic factors that directly generate severe urban diseases, such as heavy traffic, residential emissions, and resource consumption (Mccarty and Kaza, 2015), which inevitably increase the $PM_{2.5}$ concentrations (Zhang et al., 2019). Li et al. (2016) and Shi et al. (2020) empirically verified this viewpoint through China-based cases. The second viewpoint is that urbanization helps reduce $PM_{2.5}$. Urbanization provides a unified market environment for cities to share production factors and resources, helps in reducing $PM_{2.5}$ pollution through the centralized treatment of pollutants and the promotion of green technologies (Feldman, 1999). Moreover, urbanization can promote local government's environmental regulation through residents' consumption, habit preferences and public opinion pressure (Luo et al., 2018), which are effective in alleviating $PM_{2.5}$ (Li et al., 2019). The third perspective posits that the correlation between urbanization and $PM_{2.5}$ is nonlinear and complex (Ji et al., 2018; Zeduo et al., 2022). This opinion is mainly based on the classical theory of the environmental Kuznets curve (EKC), which states that urbanization has structural effects, scale effects, and technical effects on environmental pollution, and the ultimate result is determined by the interaction of various forces. EKC theory has been empirically confirmed by research on $PM_{2.5}$ concentrations in developing countries (Ding et al., 2019). Wu et al., (2018) found that the relationship between urbanization and $PM_{2.5}$ concentration in China has an inverted U-shape.

However, the existing literature mainly conducted analyses at the regional or city level, with few studies explicitly investigated the effect and mechanisms of urbanization from the perspective of urban agglomerations. Urban agglomeration is a collection of multiple cities radiating from the core circle to the periphery (Fan et al., 2017), with the links among previously separated cities becoming increasingly complex (Brezzi and Veneri, 2015). Compared with city areas, urban agglomerations are facing a more severe problem of $PM_{2.5}$ concentration but have received less attention overall (Du et al., 2018). The Chinese government has proposed several policy documents and planning outlines for promoting urban agglomeration expansion in recent decades (Liu and Leng, 2020), which has been considered a vital practice of urbanization in China (Liang and Cong, 2020; Huan et al., 2022). Given these factors, an in-depth investigation of the relationships between urban agglomeration expansion and $PM_{2.5}$ concentration must be conducted. Moreover, urban agglomeration expansion is the prominent policy tool used by the government to attain certain economic aspirations (You and Chen, 2019). The available studies mostly used the aggregate index (Liu et al., 2016) or commodity relative price information (Zhang et al., 2020) to represent the level of urbanization or urban agglomeration expansion, and described its effects through classical ordinary least squares, geographic detector models, spatial models and so on (Lin et al., 2014; Du et al., 2019), which may not only bring statistically significant biases caused by differences in quantization, time and numbers of observations (Wang et al., 2012), but also ignored the administrative significance of urban agglomeration expansion (Liu and Wu, 2017). Last but not least, relevant studies have neglected the heterogeneities between original cities (the cities that form the basis of the urban agglomeration, including the core cities) and new cities (the cities generally spatially surround the original cities) according to their chronological order of joining urban agglomerations (Shen et al., 2019). New cities have lower engagement in the development of urban agglomerations and tend to receive less public, policy and scholarly attention than the original cities that form the basis of a cluster. Therefore, distinguishing the effects between original cities and new cities is helpful for obtaining differential interpretations of the causal relationship.

This paper attempted to fill these gaps by investigating the influential effect and mechanisms of urban agglomeration expansion and $PM_{2.5}$ concentration through propensity score matching with difference in differences (PSM-DID), which can fully consider the policy implications of urban agglomeration expansion in China, and effectively prevent errors caused by the measurement and the endogeneity of parameter estimation (Zhang et al., 2022). The robustness of influential effect and mechanisms results was further verified by serious tests, such as the placebo test and the synthetic control method (SCM). In addition, this paper distinguished the heterogeneous impacts of urban agglomeration expansion on $PM_{2.5}$ concentrations between original cities and new cities, which helps in proposing targeted solutions for local governments to promote green and sustainable development in urban agglomeration areas. This paper takes the expansion of Yangtze River Delta Urban Agglomeration (YRDUA) of China as the ideal quasi-natural experimental platform for the following reasons. First, the expansion policy of the YRDUA has strong exogeneity, which makes predicting exactly when the expansion will occur difficult for local governments, and neither can regional industries respond accordingly. Second, different cities join the YRDUA at different times, which is conducive to eliminating the interference of other factors and reducing the endogeneity of parametric estimation overall. Based on the above discussion, this study considers the quasi-natural experiment of YRDUA expansion in 2010 to explore the effect and inner mechanism of urban agglomeration expansion on $PM_{2.5}$ concentration, based on an initial sample of 286 prefecture-level cities in China between 2003 and 2016.

The corresponding findings and conclusions can provide a scientifically sound basis and enlightenment for the high-quality and sustainable development of urban agglomerations in China and other countries. This paper provides a new insight for $PM_{2.5}$ reduction from the policy measure of urban agglomeration expansion, along with its influential mechanisms from both theoretical and empirical perspectives. In addition, the heterogeneous effect of urban agglomeration expansion on $PM_{2.5}$ between original cities and new cities will shed light on the targeted solutions of $PM_{2.5}$ control for different participants in the expansion progress of urban agglomeration.

2 Materials and Methods

2.1 Study area

The Yangtze River Delta (YRD) is an important part of the plain in the middle and lower reaches of the Yangtze River located in eastern China (Fig.1a). This region geographically comprises Jiangsu, Zhejiang, and Anhui provinces and Shanghai municipality. Fourteen cities in Jiangsu and Zhejiang provinces established the ‘Joint Directors of Economic Coordination’ in 1992 to strengthen economic cooperation and promote sustainable development in the YRD. In 1997, the local governments of the 14 cities above and Taizhou, a city that had just been promoted to the prefecture level in Jiangsu Province, voluntarily formed an emerging cross-regional organization, the City Economic Coordination Association (CECA), which is fully responsible for coordinated economic development in the YRD. Cities submit their application to join the urban agglomeration and wait for the approval of the CECA. After Taizhou in Zhejiang Province was admitted as a full member in 2003, the CECA of 16 cities officially formed the urban agglomeration of the YRD, or the YRDUA (Regional Economic Plan of the YRD, National Development and Reform Commission, 2005 and 2010 editions). In 2010, six pilot cities formally joined the YRDUA. Since then, the process of a steady expansion in the YRDUA has continued, with eight additional pilot cities participating in YRDUA expansion after being certified by the CECA in 2013, followed by four cities in 2018 and seven cities in 2019.

This paper selects the YRDUA expansion in 2010 to construct the quasi-natural experimental for the following reasons: first, this expansion extends to the administrative division of Anhui Province for the first time, making a breakthrough in the administrative relationship of the YRDUA from ‘two provinces and one city’ to ‘three provinces and one city’. In addition, the six

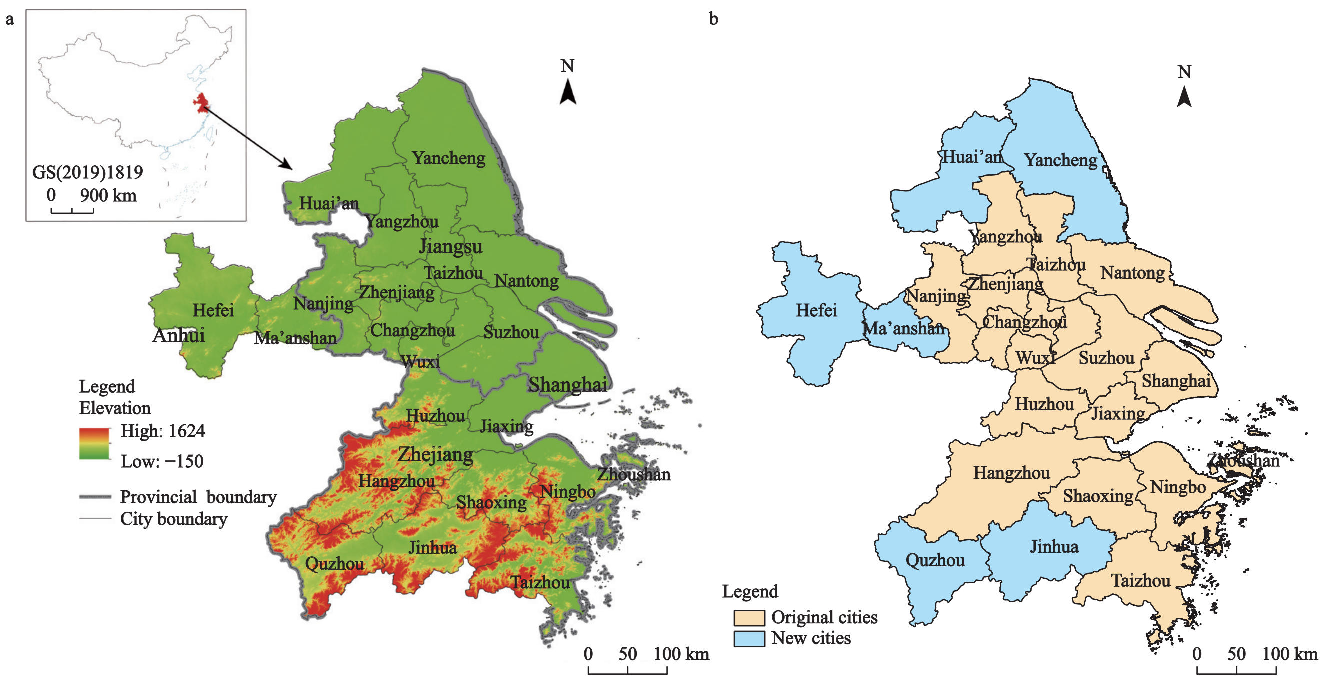

Fig. 1 Location and administrative division of the Yangtze River Delta Urban Agglomeration (YRDUA), China (a) and the distinction between original cities and new cities in 2010 (b)

new cities evenly cover Jiangsu, Zhejiang and Anhui provinces, which is helpful for comprehensively investigating the impact of urban agglomeration expansion. Second, six years passed between the first and the last year of the study period, such that sufficient time of observational data could be obtained. Third, the Development Plan of the YRDUA issued by the National Development and Reform Commission (NDRC) of China in 2016 involved few of the cities designated by the CECA in 2013, but it involved most of the cities designated by the CECA in 2010. The development plan issued by the NDRC represents the volition of the central government, while the CECA reflects the local government's strategic appeal to joining the YRDUA (Liu and Wu, 2017). The apparent decoupling of plans between central and local governments may lead to bias in the regression results, and the expansion in 2010 best reflected the unified development plan of the local and central governments for the YRDUA. Thus, this paper selects 22 cities participating in the YRDUA expansion in 2010 as the research samples for the quasi-natural experiment. Among them, 16 cities that formed the core area of the YRDUA represent the original cities, the six cities that joined the YRDUA in 2010 represent new cities, and the original and new cities are collectively referred to as all cities (Fig. 1b).

2.2 Methods and variables

2.2.1 Quasi-experimental analysis with PSM-DID

The difference-in-differences (DID) method is usually regarded as the most effective approach for studying quasi-natural experiments or evaluating the effects of exogenous shocks, such as economic crises, political instability, or policy implementation (Li et al., 2018). The completely randomized assignment of group status is one of the most important assumptions of DID, otherwise, the outcome can be seriously biased. However, pilot cities are chosen for certain reasons, such as geographical location and economic level, and are not randomly selected. In order to alleviate the endogeneity issues caused by selection bias, this paper chooses the method of propensity score matching (PSM) and adds enhancements to the DID method to eliminate selection bias and accurately estimate the effect of urban agglomeration expansion on $PM_{2.5}$. Although the PSM method can settle the problem of selection bias, it can not address the endogeneity problem caused by the omission of dependent variables (Tucker, 2010). On the other hand, the DID method can handle the problem of endogeneity, but it can not solve the bias problem. Therefore, this paper combines the above two methods as PSM-DID. The relevant regression is constructed as Eq. (1).

$$\ln hp_{it}{}^{PSM} = \alpha_0 + \alpha_1 Treat_{it} \times Time_{it} + \sum_{i=1}^{N} X_{it} + \lambda_i + \lambda_t + \varepsilon_{it} \tag{1}$$

where i (i = 1, 2,..., N) represents cities; t denotes years; hp represents the $PM_{2.5}$ concentration; *Treat* represents a dummy variable reflecting whether the 286 prefecture-level cities in China participated in the YRDUA expansion 2010; the value of *Treat* is a dummy variable sets as 1 for cities that participated in the expansion and 0 otherwise; *Time* represents a year dummy variable indicating the expansion of the YRDUA in 2010, where 2010 and the following years receive the value 1 and years before 2010 receive the value 0. *Treat* × *Time* is the intersection of dummy variables. α_0 is the constant term; α_1 reflects the influence of urban agglomeration expansion on the $PM_{2.5}$ concentration; X_{it} represents the control variables; λ_i and λ_t are city-fixed effects and time-fixed effects, respectively; and ε_{it} denotes the stochastic disturbance term. To eliminate the effect of heteroscedasticity, the natural logarithm of hp was calculated. This paper also controls some other urban characteristic variables and meteorological elements that could influence $PM_{2.5}$ concentration, aiming to obtain the unbiased estimator α_1, ensure the robustness of the results, and eventually form the set of control variables X_{it} along with the covariates, which will be further defined below.

2.2.2 Mechanism analysis model

This paper adopted mechanism analysis to recognize the conduction pathway of urban agglomeration expansion on $PM_{2.5}$ concentration to obtain more in-depth results than the baseline regression results. The logic of mechanism analysis is divided into the following three steps (Baron and Kenny, 1986):

$$M_{it} = \theta_0 + \theta_1 Treat_{it} \times Time_{it} + \sum_{i=1}^{N} X_{it} + \varepsilon_{it} \tag{2}$$

$$\ln hp_{it} = \beta_0 + \beta_1 Treat_{it} \times Time_{it} + \sum_{i=1}^{N} X_{it} + \varepsilon_{it} \tag{3}$$

$$\ln hp_{it} = \gamma_0 + \gamma_1 Treat_{it} \times Time_{it} + \gamma_2 M_{it} + \sum_{i=1}^{N} X_{it} + \varepsilon_{it} \tag{4}$$

where M_{it} is the mechanism variable (i.e., the mediation variable), θ_1 denotes the impact of urban agglomeration expansion on M_{it}, β_1 represents the total effects of urban agglomeration expansion on $PM_{2.5}$ concentration, γ_1 represents the direct effect of urban agglomeration expansion on $PM_{2.5}$ concentration, γ_2 indicates the impact of M_{it} on $PM_{2.5}$ concentration when urban agglomeration expansion is controlled. θ_0, β_0 and γ_0 are the constant terms. ε_{it} and X_{it} represent the regression residual and control variables, respectively. Only when the coefficients of α_1, β_1 and γ_2 are significant and γ_1 becomes nonsignificant or less significant can it be proven that urban agglomeration expansion affects $PM_{2.5}$ concentration through M_{it}. A mechanistic analysis will be conducted based on PSM matching in the empirical part; in that case, the coefficients of Eq. (3) will be the same as those of Eq. (1).

2.3 Variables and data description

(1) Explanatory variables. The interaction term *Treat* × *Time* indicates whether the city belongs to treatment group that participate in the expansion and whether the year was before or after the expansion. According to the research of Baycan (2013) and Liu and Wu. (2017), the treatment group can be further divided into three groups, new cities, original cities and all cities. Specifically, the group of original cities refers to the 16 cities composing the CECA of the YRD before 2010, the group of new cities refers to the six surrounding cities that officially joined the YRDUA in 2010, and the group of all cities includes both groups.

(2) Explained variable. The fixed-site monitoring used to acquire the official data of $PM_{2.5}$ concentrations in China can hardly capture the spatial changes of $PM_{2.5}$ concentration (Zhong et al., 2013). More importantly, the countrywide fixed-site monitoring of $PM_{2.5}$ concentrations did not exist in China until 2013 (Lin et al., 2018) and thus can not be used to detect the influence of urban agglomeration expansion that occurred in 2010. Therefore, this paper adopted the data provided by Professor Aaron Van Donkelaar of Dalhousie University as the raw data (http://fizz.phys.dal.ca/~atmos/martin/?page_id=140), and they provide the yearly average $PM_{2.5}$ concentrations from 1998 to 2016. The remote sensing data were obtained by integrating ground observations with the aerosol optical depth (AOD) collected from various satellite products, which has been proven to be an accurate model for large-scale $PM_{2.5}$ globally (Van Donkelaar et al., 2016). Additionally, the zonal statistics tool in ArcGIS 10.3 software was adopted to derive data on the annual average $PM_{2.5}$ concentrations of 286

prefecture-level cities in China between 2003 and 2016 based on vector maps.

(3) Control variables. Based on the relevant literature on $PM_{2.5}$ concentration and data availability, this paper controls for the following variables: 1) urbanization (*urb*). The level of urbanization was denoted by the proportion of the nonagricultural population in the total population (Panayotou, 1997). 2) Economic development (ln*gdp*). To assess regional economic progress, the natural logarithm of GDP per capita was utilized and deflated at the constant price of 2003, the start year of the study period. 3) Research investment (ln*inno*). This study adopted the natural logarithm of the fraction of local governments' fiscal expenditure spent on scientific research to measure the variation in research investment across cities. 4) Trade openness (*open*). The ratio of the total amount of foreign capital actually used to regional GDP was used to express the level of trade openness, and foreign capital actually used was calculated in RMB by the real exchange rate of the RMB against the USD. 5) Green space per capita (ln*green*). It was calculated by the natural logarithm of green space area per person in each city. 6) Industrial structure (ln*ind*). As secondary industries consume more energy than the agricultural and service sectors, strongly affecting the $PM_{2.5}$ concentration (Jiang et al., 2017), the industrial structure is represented by the logarithm of the secondary industrial production value in GDP. 7) Natural factors. In addition to the socioeconomic factors mentioned below, natural factors can impact the air flow and dynamic circumstances of particulate matter propagation, which indirectly affect the $PM_{2.5}$ concentration (Li et al., 2015). For example, temperature can influence the transformation of $PM_{2.5}$-related secondary pollutants (Megaritis, 2014). Therefore, to reduce omitted variable bias, natural indicators were also considered as control variables in this paper, including elevation (ln*ele*), meteorological indicators such as horizontal wind speed of 10 m (*ws*), specific humidity (ln*hum*) and annual average temperature (*temp*). The data of social-economic variables mainly comes from China City Statistical Yearbook (National Bureau of Statistics of China, 2004–2017), the data of environmental variables mainly comes from Geospatial Data Cloud, China (http://www.gscloud.cn), which is obtained from the meteorological monitoring stations in each city.

(4) Mechanism variables. In this paper, industrial transfer and population migration are selected as the mechanism variables. 1) Industrial transfer (*indtr*) is an economic process that involves the partial or complete transfer of specific industries and production share from one area to another from the perspective of location (Wang et al., 2021). Considering that the important sources of $PM_{2.5}$, such as fossil fuel burning and building dust, mainly originate from secondary industry (Jiang et al., 2018), this paper chooses secondary industry as the measurement sample. Due to the lack of complete data on location changing information of enterprises in China, industrial transfer is generally defined as the change in industry share or employment share. Therefore, referring to the practice of Liu and Zeng (2018), the ratio of the secondary industrial output value of a city to the average output value of all the sample cities was adopted to represent the industrial transfer index in this paper. 2) The essence of population migration (*pden*) is that a certain portion of the people moves from one region to another (Han and Qian, 2021), which can cause an increasing concentration of the population in the inflow region. Because of the limitations of population data at the prefecture level in China and with reference to relevant literature, population concentration was selected to represent the direction and level of population migration in this study. The ratio of annual total population to built-up area was adopted to estimate population concentration (*pden*) (He, 2019). The relevant data are from the China City Statistical Yearbook (National Bureau of Statistics of China, 2004–2017).

Finally, based on balanced panel data from 2003 to 2016, 286 prefecture-level cities of China were chosen as the samples after excluding cities with a serious lack of data such as those in Tibet, Hong Kong, Macao and Taiwan, accounting for 4004 city-year observations. The observation time started in 2003 mainly because Taizhou (Jiangsu Province) joined the CECA of the YRD in that year and formed part of the earliest '16 central cities' of the YRDUA. Except for the mechanism variables and indices that contain values less than 1 (*urb*, *open*, *temp*, *ws*), the other variables were all subjected to natural logarithm transformation to prevent the effects of heteroscedasticity and nonstationarity. Multiple interpolation was used to fill in the missing values. Table 1 contains the statistical description of the indicators.

Table 1 Variable description

Classification	Variable	Mean	Max	Min	S. D.	Obs.
Dependent variable	$PM_{2.5}$ concentration (ln*hp*)	3.675	4.702	1.141	0.514	4004
Control variable	Economic development (ln*gdp*)	3.674	4.701	1.141	0.514	4004
	Degree of urbanization (*urb*)	0.508	1.000	0.001	0.331	4004
	Research investment (ln*inno*)	2.753	3.901	0.039	0.573	4004
	Industrial structure (ln*ind*)	3.875	4.511	2.086	0.286	4004
	Trade openness (*open*)	2.078	21.579	0.001	2.344	4004
	Green space per capita (ln*green*)	3.284	7.314	0.086	0.744	4004
	Elevation (ln*ele*)	6.099	7.048	0.693	0.999	4004
	Wind speed (*ws*)	4.198	4.534	3.386	0.167	4004
	Specific humidity (ln*hum*)	4.198	4.534	3.386	0.167	4004
	Average annual temperature (*temp*)	14.805	27.000	−0.540	5.215	4004
Mechanism variable	Industrial transfer (*indtr*)	2.579	15.650	0.028	1.358	4004
	Population migration (*pden*)	5.365	9.907	1.016	0.512	4004

3 Results

3.1 Baseline regression

3.1.1 Propensity score matching

The main purpose of this study was to establish a strictly exogenous policy variable based on the YRDUA expansion in 2010 and analyze its effect on the $PM_{2.5}$ concentration of the three treatment groups. To minimize the interference from selection bias and to verify the correctness of the regression, this paper first conducted PSM on 286 city samples, including 22 cities in the treatment group and 264 cities in the control group. The matching factors were those affecting the likelihood of a city being chosen to participate in the YRDUA expansion in 2010. This study contained five matching variables. The process of index selection and data processing was described above.

The nearest neighbor matching method was adopted to compare the kernel density of propensity scores between the treatment group and the control group before and after matching and is represented in Fig. 2a and Fig. 2b, respectively. The kernel density curves of the treatment group and control group clearly show a great difference before matching, which means that some of the cities in the control group have an extremely high or low likelihood of being chosen as pilot cities. After matching and removing the samples that failed to meet the common support assumption, the two kernel density curves closely overlapped, indicating that the cities in the treatment group and control group are relatively close in terms of the matching variables, and the neighbor-matching method gained high accuracy in identifying the suitable cities for the control group.

The balance test of matching variables was further conducted to reveal the changes in matching variables before and after PSM (Table S1, http://egeoscien.neigae.ac.cn/article/2023/2). The results show that the estimated bias of all variables significantly decreased to within 15%. Furthermore, the *P* values of the matching variables were all greater than 5% after matching, suggesting that no considerable difference exists between the treatment and control groups. Therefore, the matching approach selected in this study is reasonable, and the remaining samples are suitable for further investigation based on the DID method.

3.1.2 Parallel trend test

As another important hypotheses of DID, parallel trend requires treatment group and control group exhibit similar fluctuation patterns before the implication of the policy, so as to ensure the effectiveness of the regression (Christodoulakis et al., 2000). Fig. 3 displays the average trends of the $PM_{2.5}$ concentration of the treatment group (black line) and control group from 2003 to 2016. The level of $PM_{2.5}$ concentration in the treatment group is obviously greater than that in the control group, as the black line is higher than the gray dotted line, which indicates that the level of $PM_{2.5}$ concentration in the YRDUA was worse than the average concentration in the other areas in China. As for the trend lines, the treatment group and control group basically had a simil-

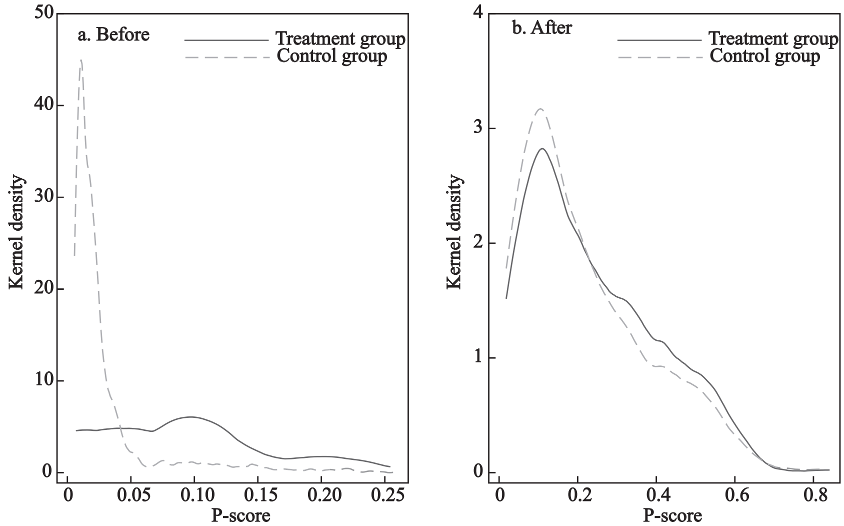

Fig. 2 Kernel density function matching diagram for identifying the suitable control group samples of the Yangtze River Delta Urban Agglomeration, China

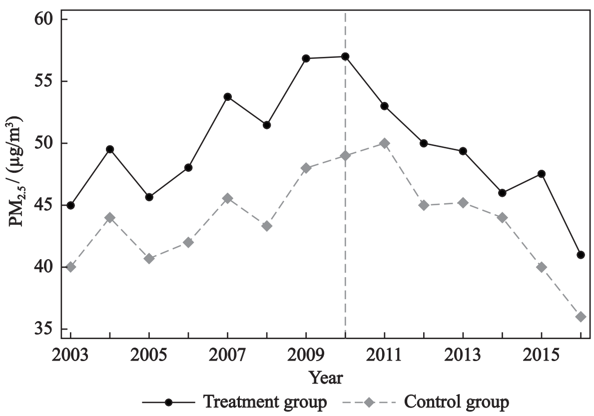

Fig. 3 Parallel trend of $PM_{2.5}$ concentration between the treatment group and the control group of China from 2003–2016

ar variation trend before 2010, manifesting as the two lines being nearly parallel, which lends credence to the assumption of a common trend. However, after the YRDUA expansion in 2010, the $PM_{2.5}$ concentration of the treatment group sharply decreased, in contrast with the continuous rising trend presented by the control group after 2010. Moreover, the gap between the two groups narrowed, indicating that the $PM_{2.5}$ concentration of the treatment group was suppressed after 2010, which generates a preliminary finding that urban agglomeration expansion may reduce the $PM_{2.5}$ concentration. This finding will be further verified through the following empirical analysis.

3.1.3 Results of baseline regression

Table 2 shows the results of the three treatment groups based on Eq. (1). The coefficient of *Treat* × *Time* in column (1) is significantly negative with a coefficient of −0.045, which means that urban agglomeration expansion reduced the $PM_{2.5}$ concentration by 4.5% overall. The coefficient of *Treat* × *Time* in column (3) is significantly negative with a value of −0.051, indicating that urban agglomeration expansion reduced the $PM_{2.5}$ concentration by 5.1% in the original cities. The coefficient of *Treat* × *Time* in column (5) is significantly positive with a value of 0.020, which means that urban agglomeration expansion increased the $PM_{2.5}$ concentration by 2% in the new cities. After introducing the control variables, the coefficients of *Treat* × *Time* in columns (2), (4) and (6) decrease to a certain extent, but their direction and significance remain unchanged. In addition, the coefficient of original cities has a higher absolute value than the coefficient of all cities, regardless of whether the control variables are considered. The above result shows that urban agglomeration expansion has significantly reduced the $PM_{2.5}$ concentration of the whole cluster, and the inhibition effect mainly comes from the decrease in the $PM_{2.5}$ concentration in the original cities, while the $PM_{2.5}$ concentration of the new cities has increased since the cities joined the urban cluster.

Except for wind speed (*ws*), the other control variables have statistically significant effects on $PM_{2.5}$ concentration. In general, an increasing wind velocity helps decrease the local $PM_{2.5}$ concentration by accelerating the diffusion of air pollutants (Li et al., 2019); however, as it may also cause an increase in the $PM_{2.5}$ concentration in surrounding areas, the total effect is nonsignific-

Table 2 Estimation results (coefficient) of urban agglomeration expansion influencing $PM_{2.5}$ concentration in the Yangtze River Delta Urban Agglomeration, China

Variable	All cities		Original cities		New cities	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × *Time*	−0.045***(−3.16)	−0.027**(−2.24)	−0.051***(−3.23)	−0.040**(−2.62)	0.020**(2.23)	0.016*(1.75)
ln*gdp*		0.064***(4.81)		0.059***(4.86)		0.067***(4.20)
urb		0.008**(2.08)		0.004**(2.19)		0.006**(2.01)
ln*ind*		0.096**(2.98)		0.095**(2.94)		0.095**(2.99)
open		0.008***(4.95)		0.007***(4.91)		0.008***(5.35)
ln*inno*		−0.014*(−1.78)		−0.014*(−1.75)		−0.014*(−1.72)
ln*green*		−0.012**(−2.15)		−0.011**(−1.97)		−0.011**(−1.99)
temp		0.025***(3.95)		0.024***(3.92)		0.025***(3.97)
ln*ele*		−0.004*(−1.89)		−0.004**(−2.01)		−0.002*(−1.68)
ws		−0.001(−0.37)		−0.003(−0.28)		−0.001(−0.23)
ln*hum*		−0.020***(−3.95)		−0.022***(−3.94)		−0.018***(−3.07)
Constant	3.608***(20.35)	3.369***(8.20)	3.608***(20.17)	3.364***(8.18)	3.608***(19.73)	3.348***(8.14)
Control variables	N	Y	N	Y	N	Y
City-fixed effect	Y	Y	Y	Y	Y	Y
Year-fixed effect	Y	Y	Y	Y	Y	Y
Obs.	2970	2970	2970	2970	2970	2970

Notes: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. Standard errors are in parentheses. Columns (1), (3) and (5) are the regression results of urban agglomeration expansion, while the regression results of further resetting the control variables are shown in columns (2), (4) and (6). Y is the abbreviation for yes, N is the abbreviation for no; Variables explanation are shown in Table 1

ant. Research investment, economic development, green space per capita, regional altitude and humidity are conducive to reducing $PM_{2.5}$ concentrations during urban agglomeration expansion. Moreover, a higher level of urbanization, secondary industry proportion, trade openness and temperature can increase the concentration of $PM_{2.5}$. That is, developed cities with capital-intensive sectors, higher technical innovation performance and better greening projects can be more effective at reducing the $PM_{2.5}$ concentration.

3.1.4 Time trend test

Fig. 3 reveals that the variation tendency of $PM_{2.5}$ concentration between the treatment and control groups is reasonable for the parallel trend assumption, but a more rigorous empirical approach is still required to prove it statistically. Moreover, the results of the baseline regression can only show the average influence of urban agglomeration expansion on the $PM_{2.5}$ concentration during the period of investigation but can not reflect the difference in the influence over time. Based on the event study approach (Jacobson et al., 1993), this paper tests the time trend effect of urban agglomeration expansion and constructs the following model:

$$\ln hp_{it} = \alpha_0 + \sum_{s=-3}^{3} \alpha_s Treat_{is} \times Time_{is} + \sum_{i=1}^{N} X_{it} + \lambda_i + \lambda_t + \xi_{it} \tag{5}$$

where $Treat_{is}$ × $Time_{is}$ indicates a dummy variable for the year when YRDUA expansion was implemented, which is 2010 in this paper. When s is negative, it refers to s years before 2010; when s is positive, it refers to s years after 2010. α_0 is the constant term; a_s represents the influence coefficient of urban agglomeration expansion on $PM_{2.5}$ concentration.

The results of the time trend test on urban agglomeration expansion in the three treatment groups of all cities, original cities and new cities are shown in Fig. 4. The X axis represents the time series, current represents the year 2010 when YRDUA expansion was implemented, pre_1–pre_3 represents 1–3 yr before 2010, and $post_1$–$post_3$ represents 1–3 yr after 2010. It can be seen that all of the α_s before 2010 in the three treatment groups are nonsignificant, which means that no discernible change in $PM_{2.5}$ concentration exists between cities in the treatment group and the control group and that the change in $PM_{2.5}$ concentration of the treatment group was indeed caused by the YRDUA expansion rather than other unobservable factors. The parallel trend assumption holds. After 2010, the α_s of $post_1$–$post_3$ was significantly less than zero in the treatment groups of all cities (Fig. 4a) and original cities (Fig. 4b), with slope of the connection line of $post_1$, $post_2$, and $post_3$ for the original cities larger than the corresponding slope for all cities. Moreover, in the treatment group of new cities, α_s is significantly greater than zero (Fig. 4c). The above result first reveals that the $PM_{2.5}$ concentration in all cities and the original cities has significantly decreased, while the $PM_{2.5}$ concentration of the new cities has significantly increased since the urban agglomeration expansion in 2010. Second, the overall $PM_{2.5}$ concentration reduction effect of urban agglomeration expansion mainly comes from the original cities, which verifies the conclusion of the baseline regression. Third, the effect of urban agglomeration expansion on $PM_{2.5}$ concentration remains significant for three years and gradually decreases over time.

3.2 Robustness tests

Several experiments were conducted to test the robustness of the baseline regression, which includes changing the PSM matching method, conducting a placebo test and changing the time window.

(1) Changing the matching method. In this paper, kernel matching and radius matching are used to identify suitable cities for the control group, and then the baseline regression is re-run. In theory, the estimated results would be similar to those in the baseline regression regardless of which matching method is employed (Vandenberghe and Robin, 2004). The corresponding regression results (Table S2, http://egeoscien.neigae.ac.cn/article/2023/2) show that the coefficient of *Treat* × *Time* based on two matching methods is significantly negative for both groups of all cities and original cities, indicating that urban agglomeration expansion has an obvious reduction effect on $PM_{2.5}$ concentration in all cities and the original cities. The results of both matching methods are significantly positive in regard to the new cities, indicating that urban agglomeration expansion has significantly increased the $PM_{2.5}$ concentration in the new cities. This finding is consistent with the results in benchmark regression, which verifies the correctness of the main results.

(2) Placebo Test. This paper further conducts a placebo test to examine whether the results are significantly influenced by unobservable factors at the city-year level, referring to the research of Cai et al., (2016). The prior arguments will be questioned or even rejected if the answer is yes. Specifically, this paper randomly selects 22 of the 286 cities as the new treatment group and assumes that these 22 cities participated in YRDUA expansion in 2010, while the other cities serve as the corresponding control group. The results of random sampling need to ensure that the interaction term *Treat* × *Time* has no effect on the $PM_{2.5}$ concentration. Any significant findings will indicate biased regression results and suggest that the variation in $PM_{2.5}$ concentration in the treatment group was not caused by the YRDUA expansion. The stack sampling method was used to perform the regression (Table S1). Although the PSM-DID model selects 'counterfactual' samples that have characteristics as similar to those of the treatment group as possible through the propensity score matching method. However, it also results in the loss of a large number of random samples, which could not meet the purpose of

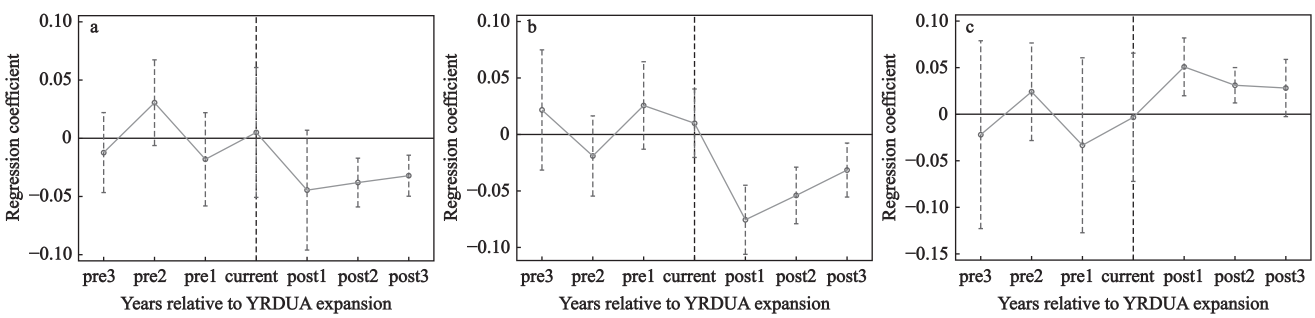

Fig. 4 Time trend analysis of urban agglomeration expansion influencing $PM_{2.5}$ concentration in the treatment groups of all cities (a), original cities (b) and new cities (c) in the Yangtze River Delta Urban Agglomeration, China

random sampling in the placebo test. Therefore, a common DID model was used for the placebo test.

The average value and *P* value of the coefficients through 500 random samplings are shown in Fig. 5. The coefficients of *Treat* × *Time* are mostly distributed near the value of 0, and most of their *P* values are larger than 0.1, indicating that they are not significant. Moreover, the real estimated value of the regression (red dotted line) was an evident outlier in the placebo test. The above results reveal that the change in $PM_{2.5}$ concentration in the treatment group was unlikely to be driven by unobservable factors at the city-year level; therefore, the regression results are robust.

(3) Changing the width of the time window. This method was adopted to increase the window width from 1 to 4 years before and after 2010 and then conduct a PSM-DID test based on Eq. (1), to observe whether any difference exists in the influence of urban agglomeration expansion on the $PM_{2.5}$ concentration in the three treatment groups compared with the results of the baseline regression. Table 3 exhibits the relevant results. Changing the time window width does not change the direction of the effect of urban agglomeration expansion in the three treatment groups, which verifies that the results of the baseline regression are reliable and stable. When the window width is 1–3 years before and after urban agglomeration expansion, as shown in columns (1)–(3), the coefficients of *Treat* × *Time* in the three treatment groups are significant; when the window width is the fourth year before and after the expansion, as shown in column (4), the coefficients of *Treat* × *Time* in the three treatment groups become negative and nonsignificant, suggesting that the significant effect of urban agglomeration expansion on the $PM_{2.5}$ concentration could last for three years. For the changing trend of the values of *Treat* × *Time*, the absolute values of all cities and the original cities continue decreasing, with the absolute value of the original city greater than that of all cities. For new cities, the coefficients also show a positive decreasing value. This finding verifies the robustness of the baseline results and time trend analysis results.

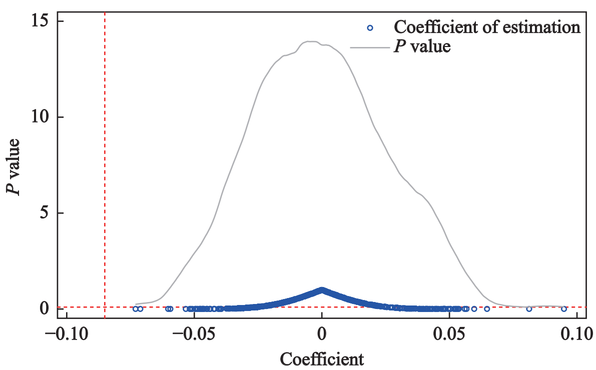

Fig. 5 Placebo Test of urban agglomeration expansion influencing $PM_{2.5}$ concentration in the Yangtze River Delta Urban Agglomeration, China

3.3 Heterogeneity analysis

Each city has its own distinct form of transformation and growth priorities. Given the diverse growth modes and levels in China, heterogeneity exists in regard to the influence of urban agglomerations on $PM_{2.5}$ concentrations. Therefore, for cities with different characteristics, how will urban agglomeration expansion affect $PM_{2.5}$ concentrations?

The specific urban characteristics and index construc-

Table 3 Estimation result (coefficient) of urban agglomeration expansion influencing $PM_{2.5}$ concentration in the Yangtze River Delta Urban Agglomeration, China after changing the width of the time window

Treatment groups	2009–2011 (1)	2008–2012 (2)	2007–2013 (3)	2006–2014 (4)
All cities	$-0.121^{***}(-4.83)$	$-0.073^{***}(-3.79)$	$-0.065^{***}(-4.03)$	$-0.017(-1.13)$
Original cities	$-0.144^{***}(-4.47)$	$-0.104^{***}(-3.56)$	$-0.080^{***}(-3.59)$	$-0.036(-1.46)$
New cities	$0.031^{*}(1.77)$	$0.027^{**}(1.90)$	$0.021^{**}(2.12)$	$-0.001(-0.32)$
Control variables	Y	Y	Y	Y
City-fixed effect	Y	Y	Y	Y
Year-fixed effect	Y	Y	Y	Y
Obs.	2002	1400	2574	1847

Notes: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. Standard errors are in parentheses. Y is the abbreviation for yes tion are as follows: 1) Government regulation. Under the theoretical hypothesis of the 'promotion tournament', local governments are motivated to adopt a series of regulatory measures, such as financial subsidies and household registration systems, to promote local economic development and restrict the transfer of factors and industries to places with higher efficiency (Zhao and Wei, 2015). Thus, the influence of urban agglomeration expansion on $PM_{2.5}$ concentration is affected by the degree of local government regulation. The variable is represented by the proportion of government budget spending in the gross regional product. 2) Education level of residents. In this paper, the popular rate of higher education was used to represent education level. Education and access to clean domestic fuels are well recognized to be related (O'Neill et al., 2012). Compared with the average population, residents with a higher level of education have a stronger consciousness of environmental protection, and their demand preferences for fuel shift toward cleaner fuels, which helps reduce the $PM_{2.5}$ concentration during urban agglomeration expansion. The ratio of college students per 10 000 people was used to measure this variable. 3) Household consumption level. The higher the consumption level is, the more accepting of green products residents will be, which is beneficial to environmental governance and inhibits the $PM_{2.5}$ concentration. Per capita disposable income was used to reflect the consumption level. The data are from the China City Statistical Yearbook (National Bureau of Statistics of China, 2004–2017). The indicators were divided into high-level and low-level groups, and then group regression was performed based on Eq. (1).

The test results shown in columns (1)–(6) of Table 4 reveal that, urban agglomeration expansion can decrease the $PM_{2.5}$ concentration more effectively in original cities with a low level of government regulation, a high level of population education and high per capita consumption. Meanwhile, a high level of government regulation, a low level of population education and low per capita consumption aggravate the deteriorating impact of urban agglomeration expansion on the $PM_{2.5}$ concentration in new cities according to the results in columns (7)–(12).

3.4 Mechanism analysis

$PM_{2.5}$ is composed of primary emissions and secondary formation (Hao et al., 2019). The former refers to atmospheric particulate matter that is directly released by pollution sources, such as incomplete combustion of fossil fuel, biomass burning, ground dust and petroleum residues, which are mainly affected by population activities (Zhao et al., 2016). The latter refers to the secondary sources of particulate matter, such as sulfate, ammonium salt and secondary organic aerosol (SOA), which is generated by the oxidation of gaseous contaminants (such as NO_x, SO_2, O_3, NH_3, and VOCs) mainly from industrial activities (Kanakidou et al., 2005). Based on the research of developed cities in China, Liu et al. (2020) revealed that the industrial and residential sectors were the top two sources of $PM_{2.5}$ concentrations, especially for the YRDUA, which is economically developed and has intensive industries in China. Based on the above analysis, the main mechanisms from

Table 4 Heterogeneity analysis of different city characteristics in the the Yangtze River Delta Urban Agglomeration, China

Treatment group	Variable	Government regulation		Education level		Consumption level	
		High level (1)	Low level (2)	High level (3)	Low level (4)	High level (5)	Low level (6)
Original cities	*Treat* × *Time*	$-0.090^{*}(-1.79)$	$-0.012^{**}(-2.08)$	$-0.055^{***}(-5.39)$	$-0.015(-1.39)$	$-0.086^{***}(-5.99)$	$0.013(0.55)$
	Control variables	Y	Y	Y	Y	Y	Y
	Obs.	55	2926	124	420	166	2857
	Variables	Government regulation		Education level		Consumption level	
		High level (7)	Low level (8)	High level (9)	Low level (10)	High level (11)	Low level (12)
New cities	*Treat* × *Time*	$0.027^{**}(2.13)$	$-0.008(-0.24)$	$-0.004(-0.90)$	$0.025^{**}(2.57)$	$-0.019(-0.83)$	$0.056^{***}(8.37)$
	Control variables	Y	Y	Y	Y	Y	Y
	Obs.	42	2928	42	2928	42	2928

Notes: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. Standard errors are in parentheses. Y is the abbreviation for yes urban agglomeration expansion that affect $PM_{2.5}$ concentration can be narrowed down to the following two channels: industrial transfer and population migration.

3.4.1 Industrial transfer

The results of the mechanism analysis are shown in Table 5. Columns(1)–(3), (4)–(6) and (7)–(9) indicate the coefficients corresponding to Eq. (2)–(4) of all cities, original cities and new cities, respectively. The coefficients of *Treat* × *Time* in columns (1), (4) and (7) are significantly negative, negative and positive, respectively. For the absolute value of the coefficients, the value of the original cities is larger than that of all cities, while the new cities have the smallest value. The coefficients of *Treat* × *Time* in columns (2), (5), and (8) are the same as the results in columns (2), (4) and (6) of the baseline regression. Moreover, the significantly positive coefficients of *indtr* in columns (3), (6) and (9) signal the impact of industrial transfer on $PM_{2.5}$ concentration when urban agglomeration expansion is controlled, while the coefficient of *Treat* × *Time* represents the direct effect of urban agglomeration expansion on $PM_{2.5}$ concentration (γ_1), with their absolute value and significance level decreasing compared with the coefficients in columns (2), (5) and (8).

These results verify that *indtr* is the mediating variable with positive effect. Secondary industries include mostly pollution-intensive industries, and with their transfer and aggregation in a certain area, the resulting energy consumption, industrial emissions and overcrowding exacerbate regional haze pollution (Luo et al., 2018). Urban agglomeration expansion can significantly promote the transfer trend of secondary industry mainly from original cities to new cities and even regions farther outside the urban cluster, as the increasing rate of industrial transfer in new cities is less than the decreasing rate in original cities, which causes an overall decline in *indtr* for the whole urban cluster. Therefore, $PM_{2.5}$ concentration can be dispersed or transmitted from original cities to neighboring areas, including new cities, through the mechanism of industrial transfer during urban agglomeration expansion, which causes a decrease in the $PM_{2.5}$ concentration in original cities and an increase in the $PM_{2.5}$ concentration in new cities.

The synthetic control method (SCM) was further selected to intuitively examine the long-term impact of urban agglomeration expansion on mechanism variables to provide more detailed evidence. The SCM can construct a 'counterfactual' synthetic group with roughly similar characteristics to the treatment group through a weighted average of multiple control units to simulate the mechanism variables of the pilot cities in the treatment group without considering the urban agglomeration expansion (Abadie et al., 2010).

Fig. 6 displays *indtr* and its synthetic counterpart for all cities (Fig. 6a), original cities (Fig. 6b) and new cities (Fig. 6c), respectively. The vertical dotted line represents the starting year of urban agglomeration expansion, which was 2010. The path of *indtr* in the synthetic unit very closely tracks the trajectory of this variable in the treated unit before 2010, which suggests that the synthetic unit performs a reasonable approximation of the degree of *indtr* that would have happened in the treated unit in the absence of urban agglomeration expansion. The difference between the path in the treated unit and in its synthetic version after 2010 represents the effect of urban agglomeration expansion on *indtr*. In

Table 5 Mechanism analysis (coefficient) of urban agglomeration expansion influencing $PM_{2.5}$ concentration in the Yangtze River Delta Urban Agglomeration, China: Industrial transfer

Variable	All cities			Original cities			New cities		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat × *Time*	-0.061^{***}	-0.027^{**}	-0.023^{**}	-0.118^{***}	-0.040^{**}	-0.026^{**}	0.044^{**}	0.016^{*}	0.013^{**}
	(−7.85)	(−2.24)	(−2.10)	(−8.41)	(−2.62)	(−3.08)	(3.07)	(1.75)	(2.24)
indtr			0.028^{***}			0.024^{***}			0.031^{***}
			(3.93)			(3.52)			(4.57)
City-fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	2569	2569	2569	2569	2569	2569	2569	2569	2569

Notes: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. Standard errors are in parentheses. Y is the abbreviation for yes; *indtr*,industrial transfer

Fig. 6a and 6b, the two lines begin to diverge noticeably to the right of the dotted line. Although both the actual and synthetic lines show an upward trend, the actual path of *indtr* is located below its synthetic path, and the difference between the two lines for original cities is larger than that for all cities. In Fig. 6c, *indtr* in the synthetic unit continues to exhibit a moderate trend, and the real unit of the new cities experiences an uptrend. In addition, the rising trajectory of *indtr* in the new cities peaks in 2014 and starts to decrease, indicating that the trend of secondary industries being undertaken by the new cities is gradually decreasing. The above results verify the results shown in Table 5. Notably, the influence of urban agglomeration expansion on *indtr* in all cities and original cities has an 'expectation effect', with its negative impact on industry transfer beginning to emerge before the starting year of the expansion. This is mainly caused by the advance planning made by local governments before the expansion of the urban agglomeration (Lin et al., 2018). While industrial transfer usually takes a certain amount of time, no 'expectation effect' occurs regarding new cities.

3.4.2 Population migration

Table 6 exhibits the regression results of population migration as the mechanism variable in the three treatment groups. The coefficients of *Treat* × *Time* in columns (1) and (4) and (7) show that urban agglomeration expansion promotes the level of population concentration in the whole cluster, especially in original cities, and causes a decrease in new cities. The coefficients of *pden* in columns (3) and (6) are significantly negative, which indicates that the increase of population concentration helps reduce the $PM_{2.5}$ concentration in the groups of the original cities and all cities. The coefficient of *pden* in column (9) is negative but not significant, which means that the increase in population concentration in new cities has no considerable impact on the local $PM_{2.5}$. This may be because population concentration has a threshold effect on $PM_{2.5}$ concentration, and only a certain scale of population concentration can exert its agglomeration effect and scale effect to reduce the $PM_{2.5}$ concentration (Liu and Leng, 2020). As the popu-

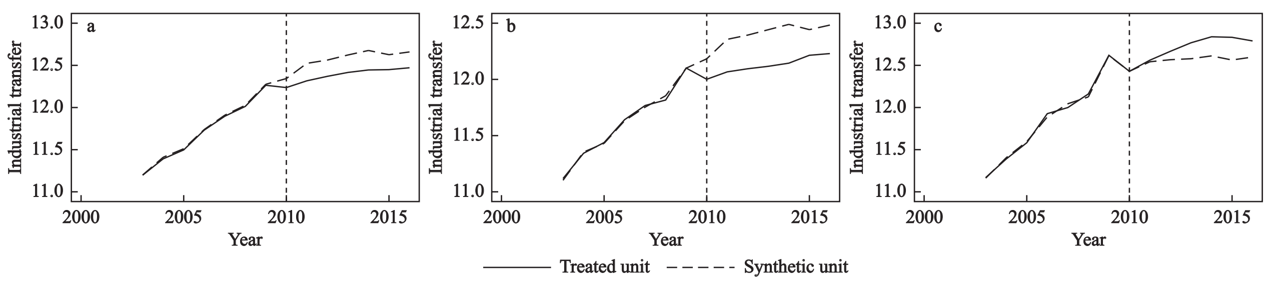

Fig. 6 Trends of industrial transfer in all cities (a), original cities (b) and new cities (c) of the Yangtze River Delta Urban Agglomeration, China: treated unit vs. synthetic unit

Table 6 Mechanism analysis (coefficient) of urban agglomeration expansion influencing $PM_{2.5}$ concentration in the Yangtze River Delta Urban Agglomeration, China: Population migration

Variables	All cities			Original cities			New cities		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat × *Time*	0.015^{**}	-0.027^{**}	-0.026^{**}	0.058^{***}	-0.040^{**}	-0.029^{**}	-0.034^{**}	0.016^{*}	0.014^{*}
	(2.18)	(−2.24)	(−2.61)	(3.29)	(−2.62)	(−3.08)	(−2.55)	(1.75)	(1.71)
pden			-0.022^{**}			-0.020^{**}			−0.013
			(−2.27)			(−2.47)			(−1.05)
Control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y
City-fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year-fixed effect	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	2569	2569	2569	2569	2569	2569	2569	2569	2569

Notes: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.1$. Standard errors are in parentheses. Y is the abbreviation for yes; *pden*, population migration lation outflow area after the expansion of urban agglomeration, the level of population concentration in new cities does not reach this threshold.

Fig. 7 displays *pden* and its synthetic counterpart in the groups of all cities (Fig. 7a), original cities (Fig. 7b) and new cities (Fig. 7c), respectively. Similarly, the synthetic unit and treated unit noticeably begin to diverge immediately after 2010 regarding all three treated units, while *pden* in the synthetic units continues to fluctuate moderately. The real treated unit of all cities and original cities experiences a rising trend, while the treated unit of the new cities experiences a sharp decline. In particular, the synthetic *pden* of the original cities has a downward trend, but urban agglomeration expansion promotes an increase in its real path. The actual path of *pden* in new cities gradually rebounds around 2012, and the gap between the actual and synthetic paths tends to narrow. The above results verify the results shown in Table 6. Moreover, the net effect of urban agglomeration expansion on the *pden* of new cities changes from increasing over time to gradually decreasing.

4 Discussion

With the rapid development of urbanization in China, the conflict between economic growth and environmental pollution in urban areas has become increasingly serious, with $PM_{2.5}$ being one of the most prominent problems. Although numerous articles have examined the relationship between urbanization and $PM_{2.5}$, few empirical studies have been conducted from the policy-based perspective, with urban agglomeration expansion being the vital practice of urbanization in China (Zhang and Wu, 2018). To address this drawback, this paper adopted the PSM-DID method to conduct a series of empirical tests to investigate the effect and inner mechanisms of urban agglomeration expansion on $PM_{2.5}$ concentrations based on the quasi-natural experiment of YRDUA expansion in 2010. The results of the parallel trend test revealed that before the expansion of the YRDUA in 2010, a similar trend of $PM_{2.5}$ concentration existed between cities in the YRDUA and other regions, with the level of $PM_{2.5}$ concentration in the YRDUA being considerably worse than that in the other areas. After expansion, the $PM_{2.5}$ concentration of cities in the YRDUA not only sharply decreased, the gap between the two groups also narrowed, indicating that urban agglomeration expansion may have a negative impact on the $PM_{2.5}$ concentration.

The results of the baseline regression verified the preliminary finding of the parallel trend test that urban agglomeration expansion helps to reduce the $PM_{2.5}$ concentration of the whole city cluster. Urban agglomeration expansion is manifested as the close interlinking of economic development through eliminating trade and administrative barriers, accelerating the intercity flow of production factors to achieve a more efficient allocation of resources, technology and capital (Liang and Cong, 2020). The intensive development model inevitably attracts the concentration of population, industries, and public services, stimulating infrastructure sharing and maximizing the scale and agglomeration effects to promote pollution reduction and improve environmental quality. In that case, urban agglomeration expansion is conducive to $PM_{2.5}$ reduction overall. However, not all city residents of the urban agglomeration can enjoy the dividends of the scale effect and agglomeration effect from the expansion. The characteristics of the original cities and new cities are clearly asymmetric, and the effects of urban agglomeration expansion on $PM_{2.5}$ concentration may differ between original cities and new cities. Baseline regression confirms that the inhibition

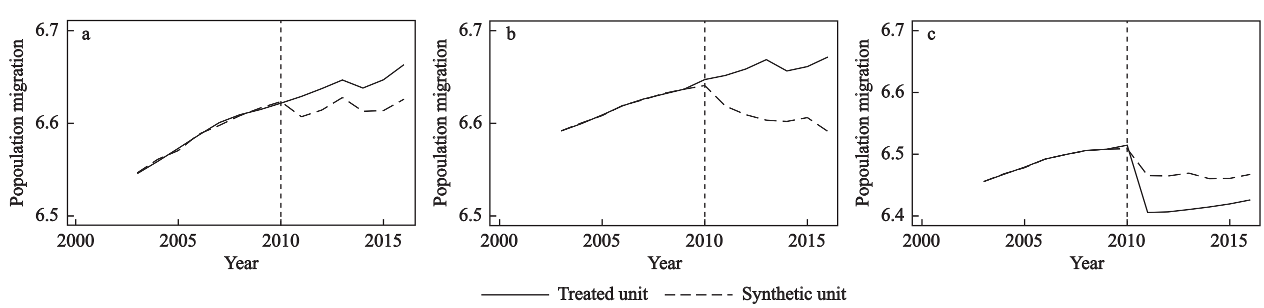

Fig. 7 Trends of population migration in all cities (a), original cities (b) and new cities (c) of the Yangtze River Delta Urban Agglomeration, China: treated unit vs. synthetic unit

effect mainly comes from original cities, while the $PM_{2.5}$ concentration of the new cities actually increased after the expansion. In addition, the significant effect of urban agglomeration expansion on the $PM_{2.5}$ concentration could last for three years according to the time trend test and robustness test, with the negative effect on $PM_{2.5}$ concentration in all cities and original cities gradually decreasing, and the positive effect in new cities gradually declining after 2010.

Mechanism analysis offered possible reasons for the above findings, that urban agglomeration inhibits $PM_{2.5}$ concentrations especially in original cities through industrial transfer and population migration. First, urban agglomeration expansion is conducive to the free flow of commodities and factors in a larger market (Zhao et al., 2021), which leads to the increase in production costs, such as pollution control and land costs, and the decrease of transfer and landing costs. The consequent production substitution effect, competition effect and division effect polluting industries in original cities to take the lead in transferring to peripheral new cities, which is generally accompanied by severe pollution and extensive energy consumption (Dong et al., 2020), that cause more $PM_{2.5}$ pollution to new cities. Some heavily polluting enterprises on the other hand, must be shut down, eliminated or transferred outside the cluster because their relocation and transfer costs are still too high after the expansion (You and Chen, 2019). All of these factors decrease the proportion of polluting industries overall, thus reduces their contribution to the $PM_{2.5}$ concentration in the urban agglomeration. As for population migration, urban agglomeration expansion reduces the cost of talent flow, intensifies the attractiveness of original cities and draws a large, high-quality labor force from new cities and the surrounding areas, seeking for better development conditions, educational resources and job opportunities (Wang et al., 2022). The concentration of a high-quality population enhances the productivity and innovation potential of the original cities, which helps lower the $PM_{2.5}$ concentration (Hao and Liu, 2016). What's more, population migration to more developed cities helps to reduce $PM_{2.5}$ concentration through a considerable increase in the use of clean household fuels and a decrease in the access to the prominent pollution sources of $PM_{2.5}$ such as biomass and coal overall (Zhong et al., 2021), which considerably lessens regional $PM_{2.5}$ emissions overall. In the long term, urban agglomeration expansion stimulated the economic development of the surrounding new cities (Niu et al., 2020). Economic development will attract a concentration of the labor force and weaken population outward migration (Wang et al., 2022). Meanwhile, new cities have stricter standards for undertaking secondary industries, especially those with heavy energy consumption and low efficiency, to form eco-industrial systems after joining urban agglomerations (Shen et al., 2019). Therefore, the net effect of urban agglomeration expansion on $PM_{2.5}$ gradually declines.

Results of the heterogeneity analysis reveal that, urban agglomeration expansion helps to inhibit $PM_{2.5}$ concentration more effectively in cities with lower levels of government regulation, higher levels of population education and higher consumption per capita. Strong government intervention impedes the transfer of production factors, such as labor and capital, to cities that are more economically efficient. Moreover, cities with strong government intervention tend to pursue short-term economic benefits while ignoring the long-term goals of environmental protection and industrial upgrading and transformation (Shi et al., 2018). Thus, a high level of government intervention could hinder the effect of $PM_{2.5}$ concentration reduction during urban agglomeration expansion. Personal income and education level have been found to strongly influence the choice of household energy (O'Neill et al., 2012). Education level indicates the threshold for mastering and using green technologies; only a highly educated labor force can apply these technologies to production activities. Cities with higher per capita consumption are also more willing to consume environmentally friendly but relatively expensive products in pursuit of a better life. Therefore, a high level of income and education can strengthen the reduction effect of urban agglomeration expansion on the $PM_{2.5}$ concentration. Urban agglomeration expansion also has a time-lag effect on the PM2.5 concentration.

In particular, urban agglomeration expansion weakens the administrative boundary barriers among cities, facilitates the flow of factors among regions and improves the ability to allocate and integrate. As a result, urban agglomeration expansion helps to reduce the $PM_{2.5}$ concentration in general through industrial transfer and population migration, which indicates that under the context of rapid urbanization and development pressure of both maintaining the economic growth rate and environmental quality, in addition to industrial upgrading, technological progress, etc., urban agglomeration expansion provides an effective path to optimize the reallocation of environmental factors among regions, which helps to achieve green and high-quality economic development. Moreover, to avoid the environmental burden brought by urban agglomeration expansion to new cities and other relatively underdeveloped areas as much as possible, local governments should strengthen the joint prevention and control of $PM_{2.5}$, such as setting unified standards for $PM_{2.5}$ detection and penalty systems of cities in urban agglomerations, building platforms for sharing information related to haze pollution, etc., to reduce the pollution pressure faced by new cities during the expansion process, and promote synergistic $PM_{2.5}$ reduction between the original cities and new cities. In addition, the effective impact of urban agglomeration expansion on $PM_{2.5}$ concentration has a decreasing trend overall; therefore, the step-by-step expansion of Chinese urban agglomeration should be actively promoted to continuously strengthen the economic and environmental effects of urban agglomeration expansion.

5 Conclusions

The expansion of the YRDUA of China in 2010 was used as a quasi-natural experiment in this study to analyze the effect of urban agglomeration expansion on $PM_{2.5}$ concentration, based on the panel data of 286 prefecture-level cities in China from 2003 to 2016. In order to overcome the endogenous problems, PSM-DID method was used to analyze the effect of urban agglomeration expansion on $PM_{2.5}$ concentration in the treatment groups of all cities, original cities and new cities, and go through a series of robustness tests. The heterogeneity tests and influential mechanism analyses of urban agglomeration expansion were also conducted to obtain more detailed findings. The most important conclusions are as followed.

1) After controlling for economic and environmental factors, the coefficient of urban agglomeration expansion on $PM_{2.5}$ concentration is −0.027 in the YRDUA, China. This means a significant effect that one-unit increase in urban agglomeration expansion can reduce $PM_{2.5}$ concentration by approximately 2.7% overall. Furthermore, the impact of urban agglomeration expansion on $PM_{2.5}$ concentration is −0.040 in original cities and 0.016 in new cities, indicating that the inhibition effect of urban agglomeration expansion on $PM_{2.5}$ is primarily manifested in original cities. Yet, a one-unit increase in urban agglomeration expansion will exacerbate $PM_{2.5}$ concentration in new cities by around 1.6%. 2) The effect of urban agglomeration expansion on $PM_{2.5}$ concentration remains significant for three years. With the economic development and stricter standards in new cities, the net effect of urban agglomeration expansion on $PM_{2.5}$ gradually decreases over time. 3) Urban agglomeration expansion has stronger inhibition on the $PM_{2.5}$ in cities with lower levels of government regulation, higher levels of population education and higher consumption per capita. 4) Urban agglomeration expansion can affect $PM_{2.5}$ concentration by promoting the transfer of heavy-polluting industries from original cities to new cities or areas outside the cluster, and stimulating population migration from new cities to original cities.

The following policy recommendations are made based on the conclusions.

(1) Urban agglomeration expansion can inhibit the effect of administrative boundaries between internal cities, improve the ability of cross-regional resource allocation, and then affect haze pollution through the spatial redistribution of industry and the labor force. This indicates that under the current pressure for green development, in addition to achieving eco-friendly development through technological transformation of the industry itself, expansion can be promoted to optimize resource redistribution, improve the resource allocation efficiency of industry and production factors, and thus suppress haze pollution on the whole. In summary, urban agglomeration expansion provides a new development form for China's urban agglomerations to achieve an eco-friendly and high-quality economy.

(2) Although new cities gain development dividends by joining urban agglomerations, they also bear pollution emissions from industrial transfer and the loss of high-quality populations, which can exacerbate haze pollution. Therefore, local governments should strengthen collaboration during the expansion process to prevent homogeneous industrial competition and keep undeveloped cities from falling into the trap of the low-end industrial chain to form a regional industrial coopera-

tion system with complementary functions and a reasonable spatial layout through intercity cooperation. Moreover, support for infrastructure development in underdeveloped new cities should be taken seriously. The improvement in roads, electricity, water conservancy and communications infrastructure needs to be accelerated in new cities, with the aim of creating better production and living conditions, reducing the impact of drivers motivating the transfer of production factors to advanced regions and preventing the siphon effect.

(3) Core cities in the urban cluster should strengthen their main position in spreading spillover effects in order to narrow the development gap and achieve green coordinated development with undeveloped cities. Local governments in the urban agglomeration should establish the concept of a community with shared interests to accomplish the symbiotic and integrated growth of the economy, society, and strengthen the cooperation in environmental governance, especially the coordinated control and prevention of air pollution between cities, to prevent pollution transfer from threatening the environmental quality in undeveloped cities during urban agglomeration expansion as much as possible and jointly create a remediation network to reduce $PM_{2.5}$ pollution within the city cluster. On this basis, the step-by-step expansion of urban agglomeration should be actively promoted to fully implement the strategies of New-Type Urbanization and high-quality development of urban agglomeration in China.

References

Abadie A, Diamond A, Hainmueller J, 2010. Synthetic control methods for comparative case studies: estimating the effect of California's tobacco control program. *Journal of the American statistical Association*, 105(490): 493–505. doi: 10.1198/jasa.2009.ap08746

Baron R M, Kenny D A, 1986. The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6): 1173–1182. doi: 10.1037/0022-3514.51.6.1173

Baycan O I, 2013. Air pollution, economic growth, and the European union enlargement. *International Journal of Economics and Finance*, 5(12): 121–126. doi: 10.5539/ijef.v5n12p121

Brezzi M, Veneri P, 2015. Assessing polycentric urban systems in the oecd: country, regional and metropolitan perspectives. *European Planning Studies*, 23(6): 1128–1145. doi: 10.1080/09654313.2014.905005

Cai X, Lu Y, Wu M et al., 2016. Does environmental regulation drive away inbound foreign direct investment? Evidence from a quasi-natural experiment in China. *Journal of Development Economics*, 123: 73–85. doi: 10.1016/j.jdeveco.2016.08.003

Cao Z Q, Sheng L F, Liu Q et al., 2015. Inter annual increase of regional haze-fog in North China Plain in summer by intensified easterly winds and orographic forcing. *Atmospheric Environment*, 122: 154–162. doi: 10.1016/j.atmosenv.2015.09.042

Chen F, Kusaka H, Bornstein R et al., 2011. The integrated WRF/urban modelling system: development, evaluation, and applications to urban environmental problems. *International Journal of Climatology*, 31(2): 273–288. doi: 10.1002/joc.2158

Christodoulakis N M, Kalyvitis S C, Lalas D P et al., 2000. Forecasting energy consumption and energy related CO_2 emissions in Greece: an evaluation of the consequences of the Community Support Framework II and natural gas penetration. *Energy Economics*, 22(4): 395–422. doi: 10.1016/S0140-9883(99)00040-7

Ding Y T, Zhang M, Qian X Y et al., 2019. Using the geographical detector technique to explore the impact of socioeconomic factors on $PM_{2.5}$ concentrations in China. *Journal of Cleaner Production*, 211: 1480–1490. doi: 10.1016/j.jclepro.2018.11.159

Dong F, Wang Y, Zheng L et al., 2020. Can industrial agglomeration promote pollution agglomeration? Evidence from China. *Journal of Cleaner Production*, 246: 118960. doi: 10.1016/j.jclepro.2019.118960

Du Y Y, Sun T S, Peng J et al., 2018. Direct and spillover effects of urbanization on $PM_{2.5}$ concentrations in China's top three urban agglomerations. *Journal of Cleaner Production*, 3: 72–83.

Du Y Y, Wan Q, Liu H et al., 2019. How does urbanization influence $PM_{2.5}$ concentrations? Perspective of spillover effect of multidimensional urbanization impact. *Journal of Cleaner Production. 220*, 974–983. doi: 10.1016/j.jclepro.2019.02.222

Ebenstein A, Fan M, Greenstone M et al., 2017. New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy. *Proceedings of the National Academy of Science of the United States of America*, 114(39): 10384–10389. doi: 10.1073/pnas.1616784114

Fan P, Xu L, Yue W et al., 2017. Accessibility of public urban green space in an urban periphery: the case of Shanghai. *Landscape and Urban Planning*, 165: 177–192. doi: 10.1016/j.landurbplan.2016.11.007

Feldman M P, 1999. The new economics of innovation, spillovers and agglomeration: a review of empirical studies. *Economics of Innovation and New Technology*, 8(1): 5–25. doi: 10.1080/10438599900000002

Feng R, Wang K, Wang F, 2022. Quantifying influences of administrative division adjustment on $PM_{2.5}$ pollution in China's mega-urban agglomerations. *Journal of environmental management*, 302: 113993. doi: 10.1016/j.jenvman.2021.113993

Fulgar C, Sun X L, Li W et al., 2018. Time lag histological changes following acute exposure to China and California fine particulate matter ($PM_{2.5}$) indoor and outdoor air pollution. *American Thoracic Society*, A1917–A1917.

Han Yiyang, Qian Cunhua, 2021. Study on the impact of population flow on environmental pollution under the background of new urbanization. *Ecological Economy*, 37(3): 207–214. (in Chinese)

Hao Y F, Meng X P, Yu X P et al., 2019. Quantification of primary and secondary sources to $PM_{2.5}$ using an improved source regional apportion method in an industrial city, China. *Science of the Total Environment*, 706: 135715. doi: 10.1016/j.scitotenv.2019.135715

Hao Y, Liu Y M, 2016. The influential factors of urban $PM_{2.5}$ concentrations in China:a spatial econometric analysis. *Journal of Cleaner production*, 112: 1443–1453. doi: 10.1016/j.jclepro.2015.05.005

He C Y, Liu Z F, Tian J et al., 2014. Urban expansion dynamics and natural habitat loss in China: a multiscale landscape perspective. *Global Change Biology*, 20(9): 2886–2902. doi: 10.1111/gcb.12553

He Xionglang, 2019. Population concentration, industrial agglomeration and environmental pollution: a research based on two types of environmental pollution. *Journal of Southwest University for Nationalities (Humanities and Social Sciences Edition)*, 2: 87–97. (in Chinese)

Huan H, Zhu Y, Liu J, 2022. A quasi - natural experiment research regarding the impact of regional integration expansion in the Yangtze River Delta on foreign direct investment. *Growth and Change*, . doi: 10.1111/grow.12627

Jacobson L S, LaLonde R J, Sullivan D G, 1993. Earnings losses of displaced workers. *American Economic Review*, (83): 4685–709.

Ji X, Yao Y, Long X, 2018. What causes $PM_{2.5}$ pollution? Cross-economy empirical analysis from socioeconomic perspective. *Energy Policy*, 119: 458–472.

Jiang J, Ye B, Xie D et al., 2017. Provincial-level carbon emission drivers and emission reduction strategies in China: combining multi-layer LMDI decomposition with hierarchical clustering. *Journal of Cleaner Production*, 169: 178–190. doi: 10.1016/j.jclepro.2017.03.189

Jiang P, Yang J, Huang C et al., 2018. The contribution of socioeconomic factors to $PM_{2.5}$ pollution in urban China. *Environmental Pollution*, 233: 977–985. doi: 10.1016/j.envpol.2017.09.090

Kanakidou M, Seinfeld J H, Pandis S N et al., 2005. Organic aerosol and global climate modelling: a review. *Atmospheric Chemistry and Physics*, 5: 1053–1123. doi: 10.5194/acp-5-1053-2005

Lawrence R J, 2019. *Human Ecology in The Context Of Urbanisation. In Integrating Human Health into Urban and Transport Planning. Scotland: Springer*, Cham: 89–109.

Li G D, Fang C L, Wang S J et al., 2016. The effect of economic growth, urbanization, and industrialization on fine particulate matter ($PM_{2.5}$) concentrations in China. *Environmental Science and Technology*, 50(21): 11452–11459. doi: 10.1021/acs.est.6b02562

Li G, He Q, Shao S et al., 2018. Environmental non-governmental organizations and urban environmental governance: evidence from China. *Journal of Environmental Management. 206*, 1296–1307. doi: 10.1016/j.jenvman.2017.09.076

Li H, Zhang M, Li C et al., 2019. Study on the spatial correlation structure and synergistic governance development of the haze emission in China. *Environmental Science and Pollution Research*, 26: 12136–12149. doi: 10.1007/s11356-019-04682-5

Li Z, Chao C, Ping W et al., 2015. Influence of atmospheric fine particulate matter ($PM_{2.5}$) pollution on indoor environment during winter in Beijing. *Building and Environment*, 87: 283–291. doi: 10.1016/j.buildenv.2015.02.008

Liang Jun, Cong Zhennan, 2020. Can urban agglomeration expansion increase the intensity of Foreign Direct Investment? Quasi-natural experiments from the Yangtze River Delta. *Forum of World Economics and Politics*, (4): 137–154. (in Chinese)

Liang L W, Wang Z B, Li J X, 2019. The effect of urbanization on environmental pollution in rapidly developing urban agglomerations. *Journal of Cleaner Production*, 237: 117649. doi: 10.1016/j.jclepro.2019.117649

Lin C Q, Liu G, Lau A K H et al., 2018. High-resolution satellite remote sensing of provincial $PM_{2.5}$ trends in China from 2001 to 2015. *Atmospheric environment*, 180: 110–116. doi: 10.1016/j.atmosenv.2018.02.045

Lin G, Fu J, Jiang D et al., 2014. Spatial-Temporal variation of $PM_{2.5}$ concentrations and their relationship with geographic and socioeconomic factors in China. *International journal of environmental research and public health*, 11: 173–186. doi: 10.3390/ijerph110100173

Lin Xixi, Zhang Haifeng, Zhang Minghong, 2018. The Influence of urban economic circle on regional economic growth: based on the Center-periphery theory. *World Economic Literature*, (4): 66–83. (in Chinese)

Liu Binquan, Cheng Kai, Ma Zhanxin, 2016. Research on the effects of urbanization on logistics carbon emissions changes. *China Population, Resource and Environment*, 26(3): 54e60. (in Chinese)

Liu Yaobin, Leng Qingsong, 2020. Urbanization, population agglomeration and haze changes: based on threshold regression and spatial partition. *Ecological Economy*, 36(3): 92–97. (in Chinese)

Liu Youjin, Zeng Xiaoming, 2018. The impact of property tax on industrial transfer: empirical evidence from Chongqing and Shanghai. *China Industrial Economics*, 11(6): 98–119. (in

Chinese)

Liu Naiquan, Wu You, 2017. Can the enlargement in Yangtze River Delta boost regional economic common growth. *China Industrial Economics*, 6: 79–97.

Liu B, Sun X, Zhang J et al., 2020. Characterization and spatial source apportionments of ambient PM_{10} and $PM_{2.5}$ during the heating period in Tianjin, China. *Aerosol and Air Quality Research*, 20(1): 1–13. doi: 10.4209/aaqr.2019.06.0281

Luo K, Li G D, Fang C L et al., 2018. $PM_{2.5}$ mitigation in China:socioeconomic determinants of concentrations and differential control policies. *Journal of Environmental Management*, 213: 47–55. doi: 10.1016/j.jenvman.2018.02.044

Maji K J, Li V O, Lam J C, 2020. Effects of China's current Air Pollution Prevention and Control Action Plan on air pollution patterns, health risks and mortalities in Beijing 2014−2018. *Chemosphere*, 260: 127572. doi: 10.1016/j.chemosphere.2020.127572

Mccarty J, Kaza N, 2015. Urban form and air quality in the United States. *Landscape and Urban Planning*, 139: 168–179. doi: 10.1016/j.landurbplan.2015.03.008

Megaritis A G, Fountoukis C, Charalampidis P E et al., 2014. Linking climate and air quality over Europe: effects of meteorology on $PM_{2.5}$ concentrations. *Atmospheric Chemistry and Physics*, 14(18): 10283–10298. doi: 10.5194/acp-14-10283-2014,2014

National Bureau of Statistics of China (NBSC), 2004−2017. *China City Statistical Yearbook*. Beijing: China Statistics Press. (in Chinese)

National Bureau of Statistics of China (NBSC), 2020. *China Statistical Yearbook*. Beijing: China Statistics Press. (in Chinese)

Niu Fangqu, Yang Xinyu, Wang Fang, 2020. Urban agglomeration formation and its spatiotemporal expansion process in China: from the perspective of industrial evolution. *Chinese Geographical Science*, 30(3): 532–543. doi: 10.1007/s11769-020-1094-3

O'Neill B C, Ren X, Jiang L et al., 2012. The effect of urbanization on energy use in India and China in the iPETS model. *Energy Economics*, 34: S339–45. doi: 10.1016/j.eneco.2012.04.004

Onyebueke V, Walker J, Lipietz B et al., 2020. Urbanisation-induced displacements in peri-urban areas: clashes between customary tenure and statutory practices in Ugbo-Okonkwo Community in Enugu, Nigeria. *Land Use Policy*, 99: 104884. doi: 10.1016/j.landusepol.2020.104884

Panayotou T, 1997. Demystifying the environmental kuznets curve: turning a black box into a policy tool. *Environment and Development Economics*, 2(4): 465–484. doi: 10.1017/S1355770X97000259

Schulze F, Gao X, Virzonis D et al., 2017. Air quality effects on human health and approaches for its assessment through microfluidic chips. *Genes*, 8(10): 244. doi: 10.3390/genes8100244

Shen Y, Zhang L, Fang X et al., 2019. Spatiotemporal patterns of recent $PM_{2.5}$ concentrations over typical urban agglomerations in China. *Science of the Total Environment*, 655: 13–26. doi: 10.1016/j.scitotenv.2018.11.105

Shi Daqian, Ding Hai, Wei Ping et al., 2018. Can smart city construction reduce environmental pollution. *Chinese Industrial Economy*, 6: 117–133.

Shi K F, Shen J W, Wang L et al., 2020. A multiscale analysis of the effect of urban expansion on $PM_{2.5}$ concentrations in China: evidence from multisource remote sensing and statistical data. *Building and Environment*, 174: 106778. doi: 10.1016/j.buildenv.2020.106778

Siddique H M A, Kiani A K, 2020. Industrial pollution and human health: evidence from middle-income countries. *Environmental Science and Pollution Research*, 27(11): 12439–12448. doi: 10.1007/s11356-020-07657-z

Song C B, He J J, Wu L et al., 2017. Health burden attributable to ambient $PM_{2.5}$ in China. *Environmental Pollution*, 223: 575–586. doi: 10.1016/j.envpol.2017.01.060

Tucker J W, 2010. Selection bias and econometric remedies in accounting and finance research. *Journal of Accounting Literature*, 29: 31–57.

Ulpiani G, 2021. On the linkage between urban heat island and urban pollution island: three-decade literature review towards a conceptual framework. *Science of the total environment*, 751: 141727. doi: 10.1016/j.scitotenv.2020.141727

Van Donkelaar A, Martin R V, Brauer M et al., 2016. Global estimates of fine particulate matter using a combined geophysical-statistical method with information from satellites, models, and monitors. *Environmental Science & Technology*, 50(7): 3762–3772. doi: 10.1021/acs.est.5b05833

Vandenberghe V, Robin S, 2004. E Evaluating the effectiveness of private education across countries: a comparison of methods. *Labour Economics*, 11(4): 487–506. doi: 10.1016/j.labeco.2004.02.007

Wang J, Feng J, Yan Z et al., 2012. Nested high‐resolution modeling of the impact of urbanization on regional climate in three vast urban agglomerations in China. *Journal of Geophysical Research: Atmospheres*, 117(D21). doi: 10.1029/2012JD018226

Wang S X, Wang S X, Chen W et al., 2021. Exploring the path of inter-provincial industrial transfer and carbon transfer in China via combination of multi-regional input-output and geographically weighted regression model. *Ecological Indicators*, 125: 107547. doi: 10.1016/j.ecolind.2021.107547

Wang Y, Yin S, Fang X et al., 2022. Interaction of economic agglomeration, energy conservation and emission reduction: evidence from three major urban agglomerations in China. *Energy*, 241: 122519. doi: 10.1016/j.energy.2021.122519

Wu J G, Xiang W N, Zhao J Z, 2014. Urban ecology in China: historical developments and future directions. *Landscape and Urban Planning*, 125: 222–233. doi: 10.1016/j.landurbplan.2014.02.010

Wu J S, Zheng H Q, Zhe F et al., 2018. Study on the relationship between urbanization and fine particulate matter ($PM_{2.5}$) concentration and its implication in China. *Journal of Cleaner Production*, 182: 872–882. doi: 10.1016/j.jclepro.2018.02.060

Yang X, Wang W, Su X et al., 2022. Analysis of the influence of land finance on haze pollution: an empirical study based on 269 prefecture-level cities in China. *Growth and Change*, in press. doi: 10.1111/grow.12638

You Jihong, Chen Xiqiang, 2019. Whether regional integration cooperation leads to pollution transfer. *China Population, Resources and Environment*, 29(6): 118–129.

Zeduo Z, Wei Z, Mou Y et al., 2022. Evolutionary relationship between the $PM_{2.5}$ concentration and urbanization in the Yellow River Ecological and Economic Zone. *Environmental and Sustainability Indicators*, 16: 100198.

Zhang J, Wang W, Gao L et al., 2022. Can the coal-to-gas/electricity policy improve air quality in the Beijing-Tianjin-Hebei Region?—empirical analysis based on the PSM-DID. *Atmosphere*, 13(6): 879. doi: 10.3390/atmos13060879

Zhang K, Shao S, Fan S, 2020. Market integration and environmental quality: Evidence from the Yangtze River Delta region of China. *Journal of Environmental Management*, 261: 110208. doi: 10.1016/j.jenvman.2020.110208

Zhang P, Wu J, 2018. Impact of mandatory targets on $PM_{2.5}$ concentration control in Chinese cities. *Journal of Cleaner Production*, 197: 323–331. doi: 10.1016/j.jclepro.2018.06.189

Zhang Z Y, Shao C F, Guan Y et al., 2019. Socioeconomic factors and regional differences of PM2.5 health risks in China. *Journal of Environmental Management*, 251: 109564. doi: 10.1016/j.jenvman.2019.109564

Zhao Yong, Wei Houkai, 2015. The government intervention, the division of labor of the function of the space of the city group, and the difference in district: on the effectiveness of regional policy in China. *Management World*, 8(4): 14–28. (in Chinese)

Zhao J, Zhu D, Cheng J et al., 2021. Does regional economic integration promote urban land use efficiency? Evidence from the Yangtze River Delta, China. *Habitat International*, 116: 102404. doi: 10.1016/j.habitatint.2021.102404

Zhao Y, Zhang Y Y, Fu P Q et al., 2016. Non-polar organic compounds in marine aerosols over the northern South China Sea: influence of continental outflow. *Chemosphere*, 153: 332–339. doi: 10.1016/j.chemosphere.2016.03.069

Zhong L, Louie P K K, Zheng J et al., 2013. Science-policy interplay: Air quality management in the Pearl River Delta region and Hong Kong. *Atmospheric Environment*, 76: 3–10. doi: 10.1016/j.atmosenv.2013.03.012

Zhong Y, Chen J, Zhao Q et al., 2021. Temporal trends of the concentration and sources of secondary organic aerosols in $PM_{2.5}$ in Shanghai during 2012 and 2018. *Atmospheric Environment*, 261: 118596. doi: 10.1016/j.atmosenv.2021.118596

Zhou A, Li J, 2021. Analysis of the spatial effect of outward foreign direct investment on air pollution: evidence from China. *Environmental Science and Pollution Research*, 28(37): 50983–51002. doi: 10.1007/s11356-021-13960-0