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Article

The Effects of Urban Polycentricity on Particulate Matter Emissions From Vehicles: Evidence From 102 Chinese Cities

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Abstract
This article analyzes the impact of the level of urban polycentricity (UP) on particulate matter emissions from vehicles (PMV) across 102 prefecture-level cities in China between 2011 and 2015. We adopt a spatial panel modeling approach to our measures of UP and PMV, controlling for (possible) intervening effects such as population density and economic output. We observe an inverted U-shaped relationship between both measures: When UP is low, an increase in polycentricity is associated with higher levels of PMV; however, when UP reaches a certain threshold, the increase in polycentricity is associated with a reduction in PMV. We find a similar relationship between economic output and PMV and demonstrate how the effects of population density on PMV consist of two opposite processes that likely offset each other. Nonetheless, jointly, population density and UP have a significant effect on PMV. We use our results to discuss policy implications and identify avenues for further research.

Keywords
China; pollution reduction; polycentricity; urban spatial structure; vehicle emissions

Issue
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1. Introduction

Since the onset of its gradual reform and opening-up policies, China’s urbanization rate has rapidly increased from 18% in 1978 to 64% in 2020 (National Bureau of Statistics of China, 2021). This fast-paced urbanization has gone hand in hand with a rising number of motor vehicles: There are now more than 370 million motor vehicles in China, many of which are used in or around cities. China is now the country with the largest number of motor vehicles in the world. This sharp increase implies that in 2020 more than 15 million tons of air pollutants were generated through exhaust emissions (Ministry of Ecology and Environment [MEE] of the People’s Republic of China, 2021), which has resulted in deteriorating air quality and economic losses equivalent to 4.3% of China’s total GDP (World Bank, 2007). In this article, we will focus on a specific category of these pollutants: small particulate matter from vehicle (PMV) emissions, defined as having an aerodynamic equivalent diameter ≤100 µ. It has been demonstrated that these PMV emissions constitute a significant threat to public health: PMV contains heavy metals which can be toxic to humans, such as cadmium, chromium, nickel, and lead (Mainka, 2021; Zhao & Zhao, 2012). PMV can be deposited in the human lungs after inhalation, and subsequently, enter other tissues through blood circulation; this then leads to lesions in organs and cellular DNA damage (Zhang et al., 2015), thus increasing the chances of developing diseases such as cancer (Kong et al., 2012).

Confronted with these problems, a variety of measures have been implemented to reduce vehicle emissions, such as completely replacing fossil fuel vehicles (FFVs) with electric vehicles (EVs). Because EVs do not emit exhaust gases, they only produce fairly limited amounts of PMV through tire-road friction and brake wear (Timmers & Achten, 2016). In recent years, EVs have gained popularity in China from both the government and the consumer side. For example, the Chinese government has introduced a subsidy policy to encourage the purchase of EVs, which contributed to China now being the world's largest EVs market (Lin & Wu, 2018). In addition to this transformation, there are also indirect solutions, for example, policies and interventions aimed at regulating the spatial structure of cities through macro-level policy instruments and mitigating PMV pollution through a polycentric urban structure (Wang & Zhang, 2020). Indeed, promoting urban polycentricity (UP) has become a normative territorial development goal (Y. Li et al., 2019) and includes narratives stressing its potential to alleviate environmental challenges (Wang et al., 2020). Since the release of the 13th Five-Year Plan (see Appendix A in the Supplementary File), a variety of policies aimed at building urban polycentric structures have been devised, such as the Beijing Urban Master Plan launched in 2017.

Analyzing UP is hampered by the fact that there is no universally accepted definition (Meijers & Sandberg, 2008). A straightforward interpretation is that a given area can be considered polycentric if its population or employment is dispersed across several centers of roughly equal importance (Rauhut, 2017). In China, UP has become a prominent feature of the urban-regional landscape (Y. Li & Derudder, 2022), with most Chinese regions being polycentric to some extent (Zhang et al., 2017). Most UP studies have focused on its putative economic contribution (Meijers & Burger, 2010; Zhang et al., 2017), but there has also been some research on the relationship between UP and environmental pollution (Burgalassi & Luzzati, 2015; Chen et al., 2021). It is to the latter literature we seek to contribute with this article.

To date, most of the studies on the relation between UP and environmental pollution have focused on what are arguably some of the most well-known pollutants: $PM_{2.5}$ and PM_{10}, representing particulate matter emissions with an aerodynamic diameter smaller than 2.5 μm and 10 μm, respectively. A specific focus on PMV is a worthwhile addition to these analyses for several complementary reasons. First, PMV has in part different sources than $PM_{2.5}$ and PM_{10}, with vehicle emissions being only one of several major sources of $PM_{2.5}$ and PM_{10}. In most Chinese cities, the primary sources of $PM_{2.5}$ and PM_{10} are fossil fuel emissions (MEE of the People's Republic of China, 2019) and soil dust, respectively (Wang et al., 2012). As a result, the conclusions drawn from research on the effects of UP on $PM_{2.5}$ and/or PM_{10} cannot directly inform our understanding of the effects of studies of UP on PMV. Second, the fact that there is only one major source of PMV allows for a clear and straightforward analytical framework and subsequent interpretation. By focusing primarily on how urban-spatial structure affects car use, it is possible to reasonably conjecture how and why UP can impact PMV. This advantage is not likely to exist in studies of the effects of UP on other pollutants.

Against this background, the purpose of this article is to extend earlier research on the environmental effects of urban-spatial structure by examining to what extent (changes in) PMV can be traced back to (changes in) UP across 102 prefecture-level Chinese cities. We investigate both the direct and indirect effects of UP on PMV and adopt an explicitly spatial perspective by exploring the role of population density and a range of other factors in mediating this association. The analysis of the nature and the degree of these effects is based on a stepping-stone framework: We begin by discussing the direct correlates of PMV (the number of cars and the demand for car use), followed by an analysis of how UP indirectly affects the direct correlates of PMV, and subsequently PMV itself. The remainder of this article is organized as follows. Section 2 takes stock of the literature that allows hypothesizing how and why UP may exert an influence on PMV. In Section 3, we describe the data, regression model, and methodology, after which the results are discussed in Section 4. Finally, Section 5 summarizes our main findings, suggests some policy recommendations, and puts forward some possible avenues for further research.

2. Literature Review

2.1. Definition and Construction of Urban Polycentricity

There are different interpretations and specifications of the nature of UP. For example, at the intra-urban scale, UP points to the balance of the distribution of population and economic activities among different areas within the city (Liu et al., 2018); at the inter-urban scale, it refers to the balanced interaction between multiple, proximately located cities within a region. The UP concept can even be extended to the continental scale, as shown by the European Spatial Development Perspective where polycentricity was put forward as a general development plan for promoting balanced and sustainable development in the EU. In addition to differentiation in spatial scales, UP can be approached from morphological and functional perspectives. Morphological UP focuses on the distribution and size (in terms of population, employment, etc.) of centers (Brezzi & Veneri, 2015). Accordingly, an area can be regarded as morphologically polycentric if its population/employment is mainly concentrated in two or more centers (Riguelle et al., 2007). Meanwhile, functional UP refers to the balance and the connections between the centers in a given area (Green, 2007).

This article focuses on the intra-urban scale, adopting a morphological perspective to UP: We envisage UP as the degree to which the "importance" of (sub)centers is evenly distributed (Y. Li & Liu, 2018), with the importance constituted by indicators such as population, employment, and gross domestic product (Green, 2007).

2.2. Impact of Urban Polycentricity on Pollutants

Research on the possible impact of UP on pollutants is inconclusive at best (Han et al., 2020), and different (possible) relationships have been put forward in the literature. Burgalassi and Luzzati (2015) found no evidence of UP impacting pollution in Italian NUTS-2 regions. Focusing on the case of Île-de-France, Etuman et al. (2021) argued that UP reduces transportation-related emissions by reducing commuting distance in the city, but increases the demand for cars outside the city and therefore entails more emissions. In the case of the US metropolitan areas, S. Lee and Lee (2014) showed a positive relationship between UP and transport-related pollution. In contrast, Castells-Quintana et al. (2021) found heterogeneous impacts of UP on pollutants in light of city size: they found that polycentric structures are associated with lower levels of CO_2 emissions per capita and $PM_{2.5}$ emissions per capita, but only in larger cities. Similar uneven results have been reported in the Chinese context. Y. Li et al. (2020) showed positive effects of UP on $PM_{2.5}$ concentrations, while UP was found to reduce $PM_{2.5}$ concentrations (Han et al., 2020; He et al., 2022) as well as other pollutants: UP has been shown to be associated with lower levels of CO_2 concentrations (Sun et al., 2020), as well as PM_{10} concentrations and SO_2 concentrations (Sha et al., 2020; She et al., 2017). More fine-grained empirical studies pointed out that UP can alleviate traffic congestion in high-population-density areas while increasing air pollution in low-population-density areas (Zhang et al., 2017). Importantly, Y. Li et al. (2019) and Chen et al. (2021) found that the relationship between UP and pollution is not monotonic: When the level of UP is low, UP helps reduce traffic congestion and therefore pollution; when the level is high, UP increases pollution.

2.3. Mechanisms of Urban Polycentricity's Influence on Matter Emissions From Vehicles

The above-mentioned studies do not directly address PMV. This is relevant given that the different nature of PMV's origins may influence the overall association. Because PMV comes mainly from vehicle emissions, the discussion can be recast into a related one: How and why can UP affect vehicle emissions? Previous research is less divided here: Despite using different methods and empirical settings, most studies of the (alleged) impact of UP on pollution reduction focus on the jobs-housing balance as a key explanatory mechanism (Castells-Quintana et al., 2021; Park et al., 2020; Sun et al., 2019; Tao et al., 2019; Wang et al., 2017). The term "jobs-housing balance" has multiple meanings, but in the UP literature, it is commonly interpreted as the spatial (mis-)match between the quantity of employment and housing across a specific region (Peng, 1997). The assumed mechanism at play is that higher levels of UP are associated with more sub-centers with a larger population, more housing options, and more job opportunities. Residents in those sub-centers are subsequently more likely to obtain jobs near where they live and/or labor finds housing near where they work, which means that a jobs-housing balance is broadly achieved. As a result, residents will have less demand for cross-center commuting, resulting in less car usage and lower PMV generation. In addition, the decline in commuting demand in sub-centers would also alleviate traffic congestion, hence reducing the commuting time (X. Li et al., 2018; Y. Li et al., 2019; Sun et al., 2013) and therefore PMV generation.

Finally, it should be noted that there is also an ancillary explanation for the mitigation of PMV through UP, based on the suggestion that more sub-centers lead to lower pollutant concentrations which are then more easily self-cleared (Wang & Zhang, 2020).

2.4. Intervening Socio-Economic Factors

The potential effects of UP on PMV are influenced by a range of intervening processes. For example, the level of vehicle ownership is likely a direct influencing factor of PMV. In addition, there are possibly opposing relationships between PMV and population density: Higher population densities are often related to more private vehicles, which brings more traffic congestion, extends the commute time, and results in more pollutants (Bechle et al., 2011). However, higher population densities may also go hand in hand with more job opportunities and smaller job-housing distances as well as better public transportation systems. As a result, residents who live in areas with a higher population density will have less need to travel by private car and will therefore produce less pollution (Duranton & Turner, 2018; Saeidizand et al., 2022).

In addition, previous studies also identified a range of other factors contributing directly or indirectly to (changes in) missions. For example, the level of economic development can have both a positive and a negative relationship with PMV. In cities with a larger GDP, residents tend to buy more private vehicles (Paulley et al., 2006) and may therefore be generating more PMV. On the other hand, larger levels of GDP also commonly entail more environmental investments, such as acquiring more air pollution control equipment that removes hazardous air pollutants (Y. Li et al., 2020; Lin et al., 2012). This may be construed as economic growth leading to higher preferences for environmental quality and therefore more attention being paid to pollution control and cleaning technology (Dasgupta et al., 2002). Although in China, GDP is closely correlated with foreign direct investment (FDI; Büthe & Milner, 2008), the latter can also affect PMV independently, and this is because local governments may adopt looser environment-related policies to facilitate FDI (Cole et al., 2006), while on the other hand, advanced pollution treatment technologies and equipment often arrive under the form of foreign investment (Markusen & Venables, 1997).

Furthermore, industry sector factors such as the proportion of manufacturing industry output in GDP are often found to be directly correlated with pollution (Lin & Zhu, 2018). However, given that PMV does not originate from factories it is hard to envisage a direct relation. Contrary to the other pollutants, PMV may be negatively related to industry sectors, since large levels of industrialization mean that factories or industrial areas will be more concentrated, which can be associated with better urban public transportation systems and transport accessibility, thus helping to reduce the people's commuting demand and decrease the average transportation distance of industrial products (Gordon et al., 1989) and therefore PMV.

2.5. Hypothesized Effects Based on Existing Studies

Figure 1 summarizes the hypothesized effects of UP and possible intervening processes on PMV. Vehicle ownership has a direct influence, while the other factors indirectly change PMV through one or more routes.

The figure also shows that three factors (population density, GDP, and FDI) may be hypothesized to have either a positive and/or a negative impact. As a result, a regression result that is not significant may be somewhat misleading in that can imply that positive and negative effects offset each other. Hence, drawing on earlier studies (e.g., Han et al., 2020), we will use regression models with interaction and quadratic terms to help better explore these factors. In the next section, we describe and operationalize these dimensions.

3. Analytical Framework

3.1. Empirical Setting

Our analysis focuses on 102 prefecture-level cities in China, with data spanning the period from 2011 to 2015.

Although there are 293 prefecture-level cities in China, only 109 of them, mainly located in the eastern and central regions of mainland China (see Appendix A in Supplementary File), have their PMV data observed and recorded by the MEE of the People's Republic of China (because of missing data on other socioeconomic factors, only 102 cities are studied in this article). Note that the selection is made by the ministry, and we were unable to identify exactly why and how the 109 cities were chosen. As a result, our sample is not random, and sampling biases cannot be excluded. However, this is the most comprehensive dataset to date, and we, therefore,

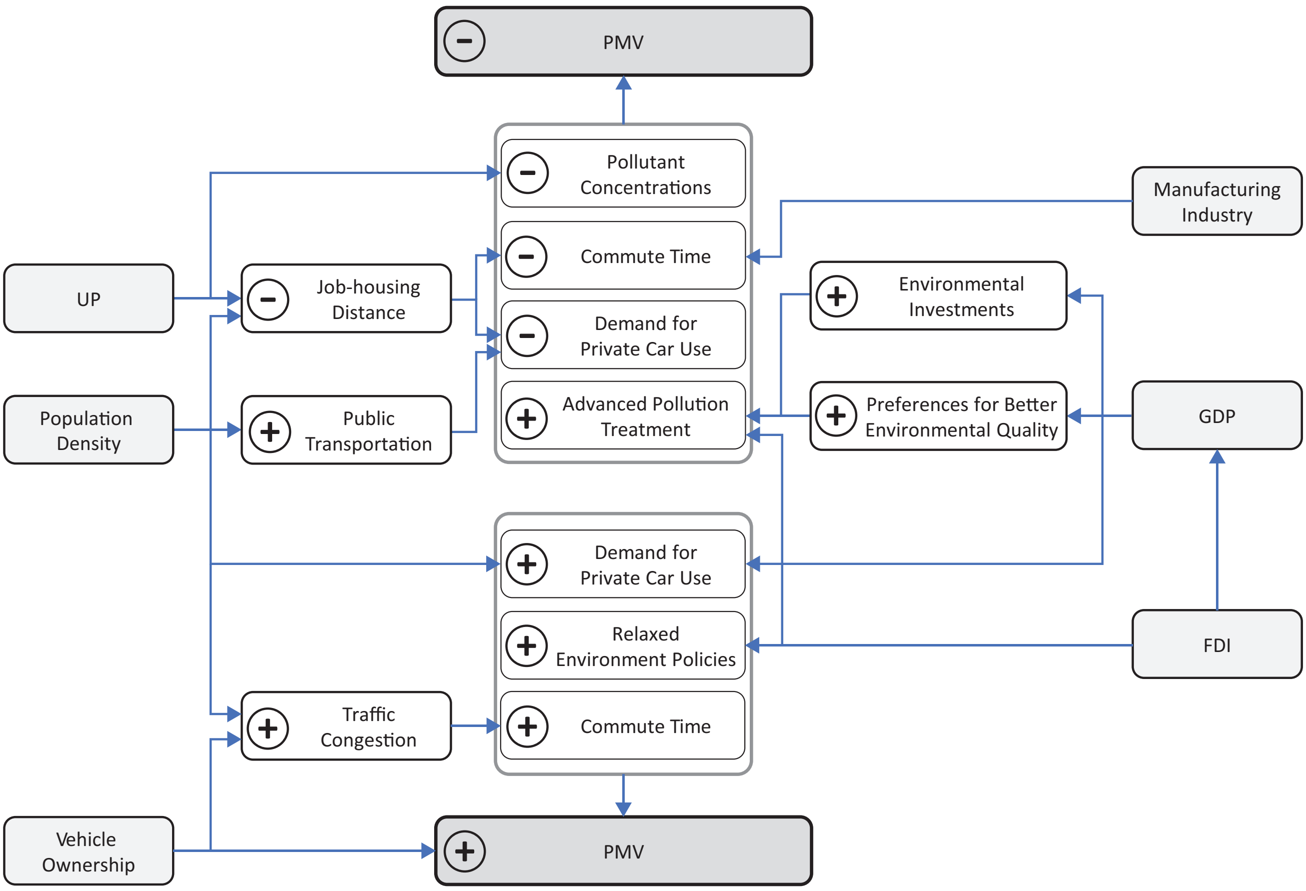

Figure 1. Hypothesized drivers of PMV.

proceed under the assumption that our analyses can inform our understanding of whether and how UP influences PMV.

Figure 2 shows that many cities are clustered, and interactions between those geographically clustered cities lead to the formation of urban agglomerations (Fang & Yu, 2017). Cities in these urban agglomerations become increasingly dependent on each other (Liu et al., 2016) and generate myriad economic and non-economic links, including trade, capital, information, and labor migration flows. As a result, the PMV of a city is likely to be influenced by its neighboring cities. This influence is known as the spatial spillover effect and should be considered in our models. In Section 3.5, we will therefore explicitly discuss how we capture this spatial spillover effect.

3.2. PMV Data

The PMV data are measured according to the *Technical Compilation Guide for Emissions of Atmospheric Pollutants from Road Motor Vehicles* (MEE of the People's Republic of China, 2014a). The guideline classifies vehicles according to their engine displacement, fuel consumption, and other relevant factors. In addition, it quantifies the number of vehicles in each category. Subsequently, the average annual distance traveled and the emissions per unit distance traveled for each type of vehicle are calculated. Finally, the PMV emission for each of the 109 cities can be estimated with the subsequent formula:

$$TPMV_i = \sum_j N_{i,j} \times EF_{i,j} \times VKT_{i,j}$$

$$\text{With: } EF_{i,j} = BEF_j \times \vartheta_i \times \rho_i \times \sigma_j \times \tau_j \quad (1)$$

Where $TPMV_i$ denotes the total amount of PMV emission of the city i, $N_{i,j}$ represents the number of type-j vehicles registered in city i. $EF_{i,j}$ is the amount of PMV emission generated per unit distance traveled for the type-j vehicle, and $VKT_{i,j}$ is the average annual distance traveled for type-j vehicles and BEF_j is the comprehensive reference emission factor, which is adjusted by the urban environmental correction factor (ϑ_i), the average speed correction factor (ρ_i), the degradation correction factor (σ_j), and the usage condition factor (τ_j) such as load coefficient and fuel quality.

Note that in this article we do not investigate the relationship between UP and the total amount of PMV emission. Rather, we examine PMV per capita. Because the total quantity of PMV emission is largely determined by urban dimension. As a result, research on this indicator would potentially obscure the impact of factors other than the urban dimension on PMV. Analyzing PMV per capita allows for a stronger association between PMV pollution and human commuting—one of the

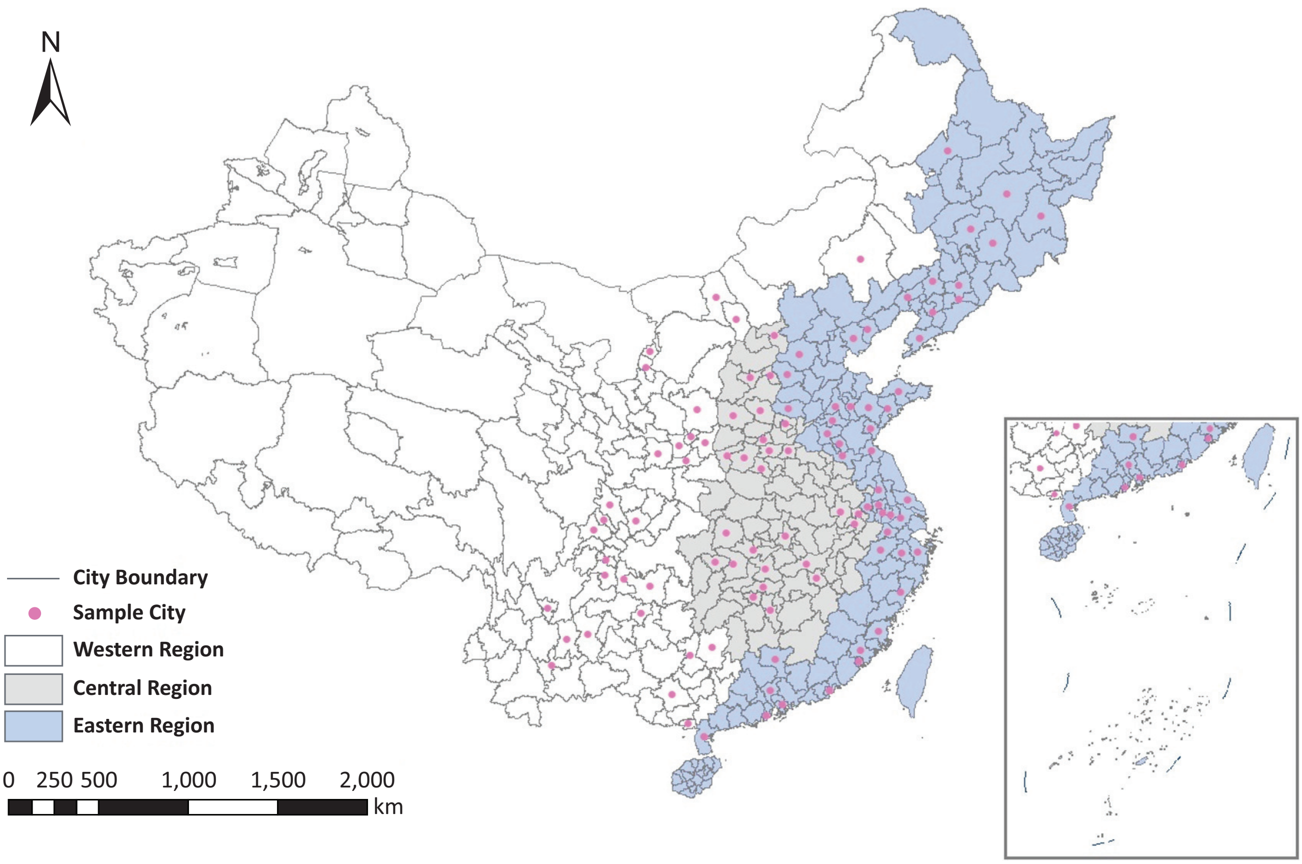

Figure 2. Research area.

key conduits connecting UP and PMV. And finally, this approach also aligns with the specification of the other socioeconomic factors in our study, such as GDP per capita and vehicle ownership per capita.

Figure 3 shows a decreasing trend of PMV over the five years, with the maximum value and mean value decreasing by 49.1% and 20.6%, respectively. Handan, Yan'an, Tangshan, Shenzhen, and Shijiazhuang had very high PMV values (>0.8) in 2011, while in 2015, only Handan's PMV value exceeded 0.8. The number of cities with PMV values below 0.1 went from seven in 2011 to 27 in 2015. The fastest decreases in PMV over the five years were found in Yan'an and Tangshan, with decreases of 0.864 and 0.411, respectively, while Dalian and Yinchuan witnessed the largest increases in PMV at 0.102 and 0.286.

3.3. Measuring Urban Polycentricity

To measure UP, it is first necessary to identify the population center(s). Drawing on Y. Li and Liu (2018), our first step is to identify potential population centers based on grid cells of approximately 1 km × 1 km in the LandScan population dataset. We use local Moran's I (Anselin, 1995) with an inverse distance weighting matrix to estimate the spatial autocorrelation pattern for each grid. The H-H grids (high-density grids surrounded by other high-density grids) are initially identified as potential population centers. Second, to filter out the smaller centers, we deleted potential population centers containing less than three grids or having a population that does not exceed 100,000 inhabitants. We calculate UP based on the thus-identified centers. Following B. Lee and Gordon (2007) and Y. Li et al. (2019), UP can be expressed as the proportion of the population of centers across the population of all centers:

$$UP = \frac{Pop_{sub}}{Pop_{main} + Pop_{sub}} \qquad (2)$$

Where Pop_{main} denotes the population of the most populous center in the city, and Pop_{sub} represents the population of the sub-centers—the larger the population of the sub-centers relative to the main center, the higher the level of UP.

Figure 4 shows the changes in UP from 2011 to 2015. We can observe that the overall level of UP in China does not demonstrate a major increasing or decreasing trend over the five years. However, the bar chart reveals a weak rising in the UP trend in eastern China, increasing from 0.285 to 0.298 (+4.56%).

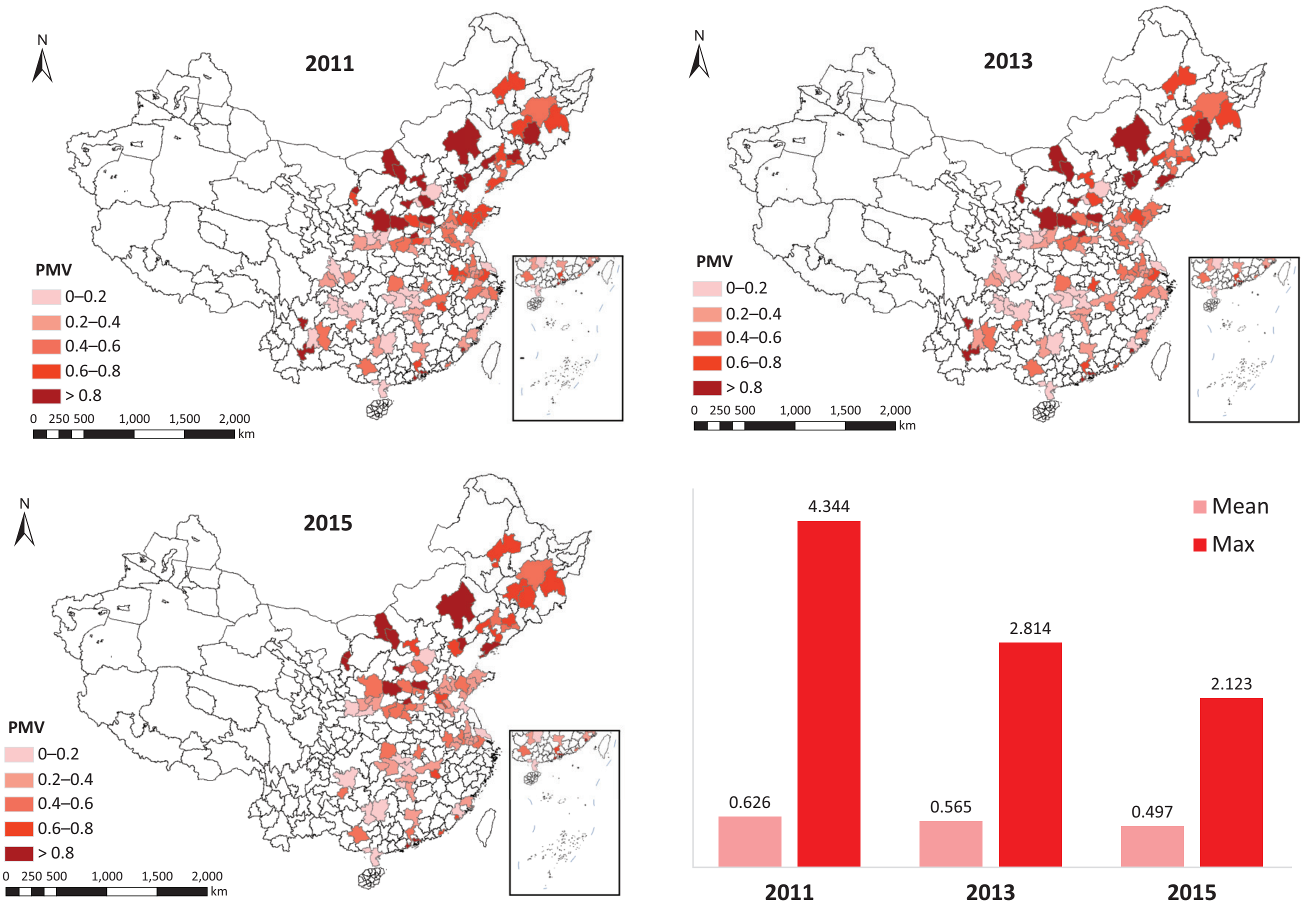

Figure 3. PMV between 2011 and 2015. Note: The unit of PMV is kilograms.

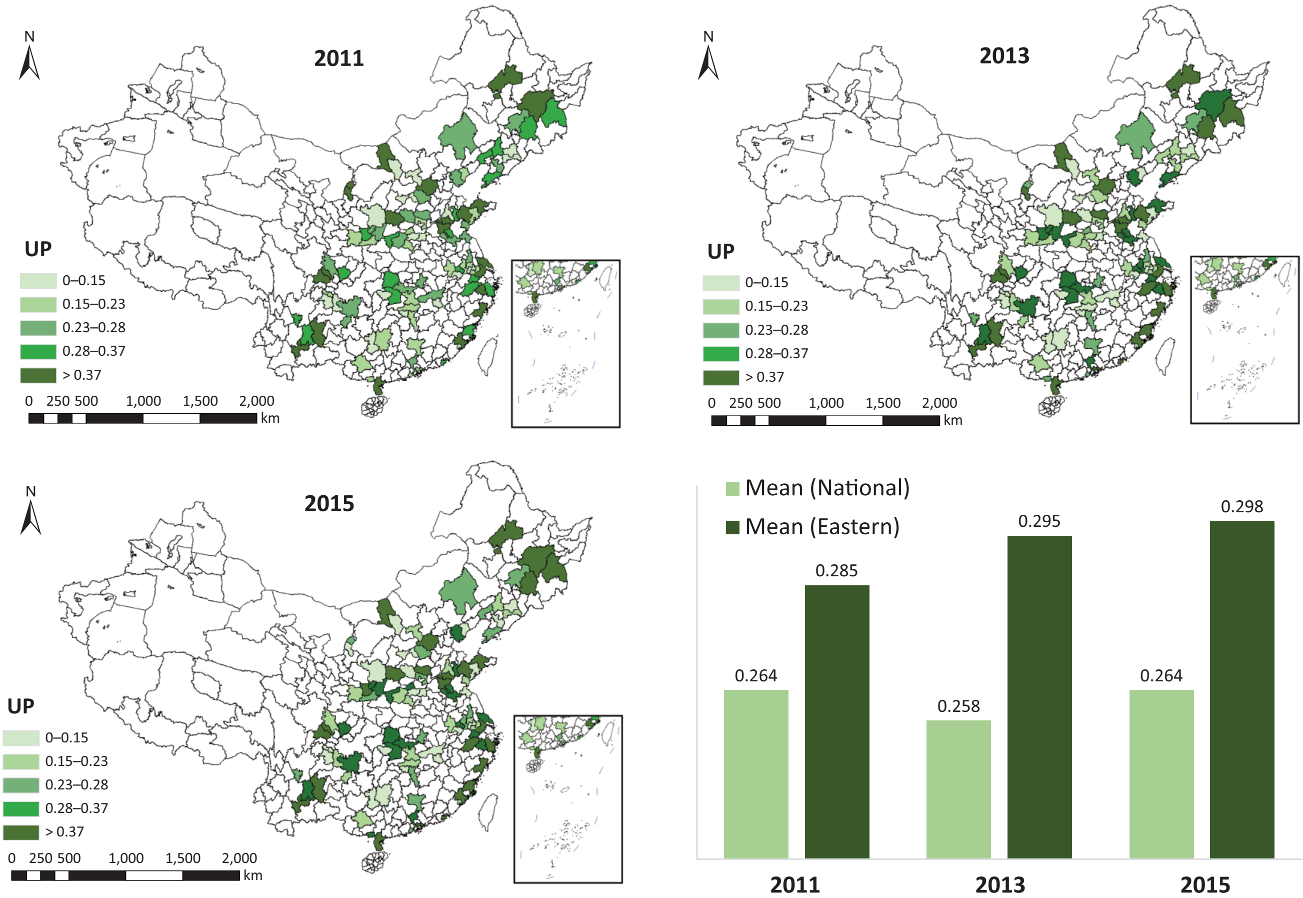

Figure 4. UP between 2011 and 2015.

3.4. Datasets

To analyze the impact of UP on PMV, we select five control variables, listed in Table 1 alongside the dependent variable (*PMV*) and the core independent variable (*UP*). In addition, for robustness checks, we consider another pollutant (*NOx*) that mainly emerges from vehicles alongside industrial emissions as the dependent variable.

Note that the minimum value of PMV equaling zero does not imply there are no PMV pollutants, but rather that the PMV density is too low to be measured by the gravimetric method. Meanwhile, a UP value of zero means that the city only has one population center. The variable *Car* contains both FFVs that emit PMVs and EVs that do not emit PMVs. Therefore, we cannot separate both types. However, the share of EVs was very small

Table 1. Descriptive statistics (number of observations = 510).

Variables	Mean	Standard deviation	Minimum	Maximum	Definition	Unit
PMV [a]	0.568	0.556	0	4.344	Particulate matter emissions from vehicles per capita	Kilogram
UP [b]	0.258	0.129	0	0.881	Urban polycentricity	No unit
GDP [c]	31536	15548	8074	91473	Gross regional product per capita, modified by GDP deflator based on 2000	Yuan
Density [c]	532.0	358.2	51.85	2648	Population density	Person/km^2
Industry [c]	52.03	8.700	24.3	75.9	The share of manufacturing output in GDP	%
FDI [c]	270.5	366.2	1.590	2356	FDI per capita	Dollar
Car [c]	0.141	1.165	0.135	1.000	Vehicle ownership per capita	Unit
NOx [a]	5.700	4.041	1.151	30.78	Nitrogen oxide emissions per capita	Kilogram

Sources: [a] MEE of the People's Republic of China (2011, 2012, 2013, 2014b, 2015); [b] Calculated based on LandScan grid data (Bright et al., 2016); [c] National Bureau of Statistics of China (2011, 2012, 2013, 2014, 2015).

during the study period (about 1%), so the variable *Car* can be approximated to represent the number of FFVs per capita.

Because some variables are likely to be correlated (e.g., FDI and GDP), we checked for multicollinearity. According to the variance inflation factors (VIF) test, the VIF values of all variables are less than five, with the mean VIF value being 2.07, indicating that there was no significant multicollinearity in our dataset.

3.5. Empirical Model

To investigate the impact of UP on PMV and take the spatial spillover effects into account, we use a time and individual fixed spatial error model based on panel datasets (see Appendix B in Supplementary File for more details on the selection of spatial models), in which PMV is examined as a function of a series of socio-economic factors and with the spatial spillover effects captured in the stochastic disturbances:

$$\begin{aligned} PMV_{i,t} &= C + \beta_1 UP_{i,t} + \beta_2 Ln\left(GDP_{i,t}\right) + \beta_3 \left[Ln\left(GDP_{i,t}\right)\right]^2 \\ &+ \beta_4 Ln\left(Density_{i,t}\right) + \beta_5 Industry_{i,t} + \beta_6 Ln\left(FDI_{i,t}\right) \\ &+ \beta_7 Ln\left(Car_{i,t}\right) + \gamma_i + \varphi_t + u_{i,t}, \\ &\text{with: } u = \lambda W u_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

Where C is a constant term, β represents the coefficients of the independent variables, γ_i and φ_t are the individual fixed effect (FE) and the time FE, respectively, $u_{i,t}$ and $\varepsilon_{i,t}$ are the stochastic disturbances term, W is the row-normalized k-nearest (k = 4) spatial-weighting matrix, and λ is the spatial coefficient. $\left[Ln\left(GDP_{i,t}\right)\right]^2$ is used to study the possible nonlinear relationship between GDP and PMV (Y. Li & Liu, 2018). We use the logarithms of the variables in order to reduce the influence of extreme values and heteroskedasticity. Exceptions are *Industry* as this is percentual data and *PMV* and *UP* as they contain a large number of zeros.

As in many UP analyses, the above model may suffer from endogeneity issues (Chen et al., 2021; Y. Li & Liu, 2018). There are two main possible causes of endogeneity: omitted variables and bidirectional causality. In our case, omitted variables are largely controlled by time and individual FEs in the panel model, and they are therefore unlikely to cause biased estimates. In addition, the UP data is calculated from 5-year-period population data. Large-scale population changes due to PMV are unlikely to occur during this short period, suggesting that the effect of PMV on UP should be either non-existent or very weak, and thus bidirectional causality is unlikely to be a major factor. Accordingly, endogeneity issues will not significantly weaken the validity of our model. Given the low chances of endogeneity being an issue in our model, we treat UP as an exogenous variable. Nonetheless, we also empirically analyzed the endogeneity problem using instrumental variable estimation. The instrumental variable is the interaction terms of the number of rivers and the exchange rate. These estimation results (see Appendix C in Supplementary File) validated the robustness of our model.

Drawing on previous studies (e.g., Y. Li et al., 2019; Zhang et al., 2017), we also construct extended models by adding quadratic and interaction terms to the spatial error model, including *UP*UP*, *UP* × *Density*, *UP* × *GDP*, and *UP* × *Industry*. These terms can help to a more comprehensive analysis of the effect of UP and other factors on PMV. For example, adding *UP* × *Density* to the model helps to further explore how *UP* and *Density* jointly influence PMV: Positive (or negative) coefficients of *UP* × *Density* indicate that UP and PMV offset (or enhance) each other's PMV-reducing impacts.

4. Empirical Results

Table 2 shows the regression results for the spatial error model models. Model 1 is the benchmark model as described in equation (3), Models 2–5 are the extended models, and Model 6 is the NO_x analysis introduced for robustness checks.

In benchmark Model 1, the core variable *UP* is negative at the 1% significance level, suggesting that after controlling for other variables, a city is indeed less PMV-polluted if it has a higher level of UP. This result is consistent with earlier studies (e.g., Sun et al., 2020; Zhang et al., 2017). However, our finding contrasts with Y. Li et al. (2020), which may be due to their focus on $PM_{2.5}$, which has multiple sources/components.

As for the control variables, the coefficients for *GDP* and GDP^2 are positive and negative, respectively, suggesting that the functional relationship between *PMV* and *GDP* is best described as an inverted U-shaped curve. When a city's economic size achieves a certain threshold, an increase in GDP will be associated with a reduction in PMV. *Density* influences PMV (significant at the 10% level), suggesting that the negative effects (related to a shorter commute time and less vehicle demand) of population density on PMV likely exceed their positive effects (related to traffic congestion and a longer commute). The coefficient for *Industry* is negative at the 10% level, which might be because the concentrated industrial areas can increase transport accessibility, and thus reduce the commuting/transportation distance for people/industrial products, and consequently lower PMV. *Car* is significantly positive because it is directly related to *PMV*. In addition, FDI is not significant: it is either unrelated to PMV, or the two opposite effects of FDI on PMV (see Figure 1) offset each other.

In Model 2, the higher log-likelihood value indicates a more considerable explanatory power. *UP* is positive and *UP* × *UP* is negative, indicating an inverted U-shaped relationship—a polycentric structure reduces a city's PMV only when UP exceeds a threshold value of 0.222 (= 1.623/(−3.650 × 2)). A possible explanation could be that a lower level of UP implies that

Table 2. Regression results.

Dependent variable	PMV					NO_x
Models	1	2	3	4	5	6
UP	−0.792***	1.623***	−4.796***	−1.351	−3.166**	−0.522***
GDP	4.680***	5.473***	5.397***	4.585***	4.565***	6.510***
GDP^2	−0.206***	−0.241***	−0.237***	−0.200***	−0.199***	−0.280***
Density	−0.680*	−0.871**	−1.121***	−0.667*	−0.667*	−0.677**
Industry	−0.014*	−0.017**	−0.017**	−0.014*	−0.026**	−0.022***
Car	0.204***	0.152**	0.194***	0.204***	0.202***	0.149**
FDI	0.042	0.029	0.038	0.042	0.040	−0.054**
UP × UP		−3.650***				
UP × Density			0.700***			
UP × GDP				−0.076***		
UP × Industry					0.045*	
Constant	0.220***	0.216***	0.221***	0.222***	0.221***	0.196***
λ	−0.141*	−0.071*	−0.125*	−0.143*	−0.135*	0.259***
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Log-likelihood	34.504	46.994	36.809	34.407	35.920	83.806
Observations	510	510	510	510	510	510

Notes: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

the sub-centers have less population, housing, and job opportunities, and therefore less likely to achieve the jobs-housing balance. As a result, residents will have a greater need for cross-center commuting and therefore generate more PMV. Another reason might be that the sub-centers with relatively smaller populations may not have a well-established public transportation system so residents' commuting needs are more likely to be met by private vehicles.

In Model 3, *UP × Density* and *Density* are significantly positive and negative, respectively, suggesting that Model 3 provides a more comprehensive explanation for the impact of population density on PMV. This result shows that UP and population density interact in reducing PMV pollution—the PMV reduction effect of UP is reduced as the population density increases. This is consistent with the studies of X. Li et al. (2018) and Y. Li et al. (2019). Accordingly, we could argue that for areas with high population density, it is better to maintain a high level of polycentricity to reduce PMV.

In Model 4, *UP × GDP* is negatively significant but *UP* is not significant, implying that UP's effect on PMV might be indirect, and dependent upon the level of urban economic development. Specifically, the higher the GDP, the greater the effect of UP on PMV reduction. The finding can be corroborated by the study of Y. Li et al. (2020): A polycentric structure may play a larger role in reducing PMV in cities with higher levels of economic development.

In Model 5, *UP × industry* is positively significant at the 10% level, implying that UP will increase PMV when the share of manufacturing output in GDP exceeds 70.35% (*Industry* = 3.166/0.045). In our case, only Panzhihua and Yan'an reach this threshold. This implies that a monocentric instead of a polycentric urban structure might be more suitable for predominantly industrial cities in the case of PMV reduction. Because the polycentric structure might decentralize factories and industrial areas, increasing the transportation distance of industrial products between different industrial areas, and therefore generating more demand for vehicles and more PMV.

In the above models, the spatial coefficient *λ* is consistently negative and significant at the 10% level, which can be interpreted as the PMV of a city being negatively influenced by some omitted factors of the surrounding cities, such as inter-urban trade, labor migration, and regional (environmental) policies. In other words, if we ignore these unobservable spillovers, our regression models will likely lead to biased estimates. We can therefore argue that the spatial error models are indeed appropriate and necessary for our study.

In Model 6, we replaced PMV with NO_x. The result shows that the significance and direction (positive or negative) of the coefficients for most variables did not change. This finding reaffirms the reduction effect of UP on pollutants emitted from FFVs. It also implies that our analytical framework (e.g., in the choice of spatial model and control variables) is reasonable and the results presented by our empirical models are robust.

5. Conclusions and Policy Implications

The purpose of this article has been to contribute to the longstanding debate on what kind of urban-spatial structure is conducive to PMV reduction. To this end, we engaged in a spatial panel econometric analysis of 109 prefectural-level cities in China. Our regression results reveal that a polycentric structure can help reduce PMV. In addition, the relationship between UP and PMV follows an inverted U-shaped pattern, meaning that for lower levels of UP, more UP increases the level of PMV, but UP starts leading to decreases in PMV when it exceeds a threshold value. We also analyzed the different roles a polycentric structure played in different types of cities. We find that polycentric urban structures can help reduce PMV for cities with high population density and high levels of economic development, and the monocentric structure which may lead to less PMV for the ones with the low level of economic development and industry-dominated cities.

Based on our findings, we propose the following policy recommendations:

1. A polycentric structure does not always contribute to PMV pollution reduction, and it may even bring about more pollution in certain cities. Therefore, policymakers should not blindly implement polycentric-related policies. Rather, such policies should above all be applied to less-industrialized cities with higher levels of economic development and population density.
2. Promoting a polycentric structure should not only focus on the number of sub-centers but on also the development of these sub-centers. If the sub-centers do not have sufficient population, employment, and public infrastructure potential, more sub-centers will create more cross-center commuting thus resulting in more PMV pollution.

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Conflict of Interests

The authors declare no conflict of interests.

Supplementary Material

Supplementary material for this article is available online in the format provided by the authors (unedited).

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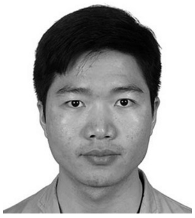

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