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Regional polycentric spatial patterns and air pollution: An empirical study of German metropolitan regions

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ABSTRACT

This study empirically examines the effectiveness of polycentric urban spatial patterns in reducing air pollution across German metropolitan regions, using satellite-based air quality measures, multi-year datasets and a multi-spatial scale research design. Our findings suggest that polycentric development does not significantly impact regional air pollution overall. However, an intra-regional analysis reveals that urban cores in more polycentric regions experience higher pollution levels compared to their monocentric counterparts. When disaggregating by regional size, we find that polycentricity has no influence on air quality in smaller regions. However, this relationship does not hold as regional size increases, with additional polycentric development leading to higher pollution levels in medium and large regions, particularly in urban core areas. Although we find that differences in population density can explain pollution in the peripheries of polycentric regions, this explanation does not extend to urban core areas. In this case, we find that differences in air quality may be due to the cumulative effects of congestion in larger urban cores, where strong functional links among multiple centers intensify commuting demands and traffic congestion more than in peripheral areas. This prolonged and more congested travel likely contributes to higher pollution levels in urban core areas of polycentric regions. In contrast, smaller regions may avoid these negative externalities because their scale of commuting is insufficient to generate the extended travel times and congestion.

1. Introduction

Despite growing emphasis on livability and sustainability, urban areas continue to emit a disproportionate amount of airborne toxins that degrade air quality and harm human health. This exposure is unevenly distributed, often higher in marginalized neighborhoods and communities (Schweitzer & Zhou, 2010). While the causes of regional air quality issues are complex, urban form and spatial patterns are key factors (McCarty & Kaza, 2015). In this paper, we examine the role that polycentric spatial patterns play in explaining ambient air quality in German metropolitan regions. Regional polycentricity, an increasingly common description of contemporary spatial development patterns around the globe, is also an oft-cited goal of various spatial development policies to advance sustainability and equity goals (e.g., ESDP, 1999; EU Ministers, 2020; European Union, 2011). Although research has explored the economic and equity impacts of polycentricity (W. Li et al., 2018; Y. Li & Liu, 2018; E. J. Meijers & Burger, 2010; Ouwehand et al., 2022; Sun et al., 2019; Wang et al., 2019), not much is known about the supposed environmental benefits. In this paper, we address this gap, empirically examining the relationship between polycentricity and ambient air quality in German metropolitan regions.

Studies on the relationship between urban spatial patterns and air quality generally models pollutants using accessible datasets for pollutants such as nitrogen dioxide, carbon dioxide, particulate matter, and ozone, and often compiling these into a composite air quality index (Borck & Schrauth, 2021). Measures of urban form are quite diverse and utilize wide-ranging datasets including census and economic measures as well as remotely sensed data. These range from aggregate measures such as population size (Glaeser & Gottlieb, 2009), population density (Borck & Schrauth, 2021; Carozzi & Roth, 2023), population centrality (Clark et al., 2011), road density (Clark et al., 2011), change in night-time lights (as a proxy for urbanized area) (Larkin et al., 2017), percent vegetation (Bechle et al., 2017), percent impervious surface (Bechle et al., 2017; Larkin et al., 2017) and landscape metrics such as contiguity of urban area (Bechle et al., 2017), land use complexity (Bereitschaft & Debbage, 2013), and the number of urban patches or mean patch area,

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among others (Bereitschaft & Debbage, 2013; McCarty & Kaza, 2015). Composite measures are also utilized. For example, Stone (2008) and Schweitzer and Zhou (2010) utilize a composite sprawl index compiled from several variables including street connectivity, density, land use mix, and the degree of regional centeredness (Ewing et al., 2018), while Bereitschaft and Debbage (2013) compare and contrast various sprawl indices.

City planners have long debated the relationship between urban spatial patterns and air pollution. On one hand, concentrated economic activity can increase emissions and result in greater pollution exposure (Ahlfeldt & Pietrostefani, 2019; Carozzi & Roth, 2023; Schweitzer & Zhou, 2010). On the other hand, low-density sprawl often leads to more vehicular trips and vehicle mileage traveled (VMT), producing higher ambient air pollution concentrations (Bereitschaft & Debbage, 2013; Stone, 2008). This dilemma has prompted city planners to seek innovative solutions that can simultaneously address the drawbacks of both compact development and urban sprawl.

In this paper, we examine whether a more polycentric spatial pattern may offer a solution. In theory, polycentric urban regions (PURs) distribute urban socio-economic activities across multiple nodes as opposed to relying on a single center (Kloosterman & Lambregts, 2001; E. Meijers, 2005). Compared with a traditional monocentric region where population is highly concentrated, a polycentric configuration can effectively reduce the density and congestion in urban core(s) (Parr, 2004; Veneri, 2010), thereby lowering pollutant concentration levels. Multiple compact cores may also mitigate pollution from traffic and energy emissions typically associated with sprawl (Sun et al., 2020). Advocates argue that a polycentric pattern fosters the co-location of residences and workplaces, thereby reducing pollution from car usage, long-distance commute, and associated traffic congestion (Giuliano & Small, 1993; Marcińczak & Bartosiewicz, 2018; Susilo & Maat, 2007; Veneri, 2010; Zhao et al., 2011).

However, critics note that polycentricity does not necessarily mitigate pollution. Some studies suggest that polycentrism in face resembles decentralized sprawl (Tsai, 2005), and whether negative externalities associated with sprawl also occur in polycentric regions or not requires further empirical justification. Regarding travel patterns, polycentric regions are often characterized by intensive functional linkages both between urban core(s) and between urban core(s) and peripheral areas, resulting in substantial inter-municipality commuting and general-purpose trips. A wide set of studies in the US and Europe found that polycentricity facilitates long-distance commute and/or longer travel time (Ewing, 1997; Melo et al., 2012; Schwanen et al., 2004; M. Wang & Debbage, 2021). Moreover, dispersed centers and relatively low population densities are not conducive to creating a walkable built environment and fail to achieve the critical mass required for public transit services. As a result, a polycentric pattern may ultimately lead to increased traffic-related air pollution. These theoretical debates underscore the need for further empirical research to evaluate whether polycentricity can efficiently mitigate air pollution.

This study empirically investigates whether a polycentric urban structure can mitigate air pollution, analyzing data from 50 German metropolitan regions over a period spanning over 20 years, from 1998 to 2019. In addition to institutional and political support for polycentrism (Schmidt et al., 2021; Schmidt & Buehler, 2007), the co-existence of well-established mature monocentric (e.g., Berlin and Munich) and polycentric regions (e.g., Rhine-Ruhr and Rhine-Neckar) makes Germany an ideal context for studying the outcomes of polycentric development.

We conduct cross-sectional analyses for each year individually rather than employing a fixed-effect panel model, due to the lack of temporal variations in our key variable of interest, (polycentricity). Therefore, our models compare variations across regions instead of examining changes in each over multiple years to estimate the influence of polycentricity. Air quality was measured using satellite-derived PM2.5 concentrations, which offer continuous measurements of ambient air pollution concentration at a 1 km-by-1 km spatial resolution. We utilized PM2.5 (particulate matter with a diameter $\leq 2.5\mu m$) as a proxy pollutant. Fine particles can penetrate the respiratory system, causing respiratory, cardiovascular, and chronic diseases, and thus pose a greater threat to public health compared to other pollutants.

The rest of the paper is organized as follows: The next section introduces the study area, methods, and dataset. Next, we present our regression results, including baseline regressions at regional and intra-regional scales, as well as regressions for two moderating variables: region size and inter-municipal commuting ratio. The final section offers conclusions and discusses policy implications.

2. Methods, data, and study regions

2.1. Study area

Regional delineation is of great importance, as it determines the appropriate functional urban areas necessary to operationalize polycentricity, and the spatial scale for measuring and aggregating granular air pollution data (Li & Schmidt, 2024a, 2024b; Thomas et al., 2021). For this study, we utilize German urban regions (*Großstadtregionen*) as the basis for investigating the environmental outcomes of polycentricity. The Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR) defines Großstadtregionen as regions composed of one or more urban cores, each with a population exceeding 100,000, along with surrounding peripheries that maintain strong commuting linkages with these core cities. These regions are good representatives of the regional labor markets, which reflects intra-regional functional links and air quality across the entire area. The final regional delineation consists of 50 regions and 254 districts within these regions, with each district classified as either an urban core or a periphery (see

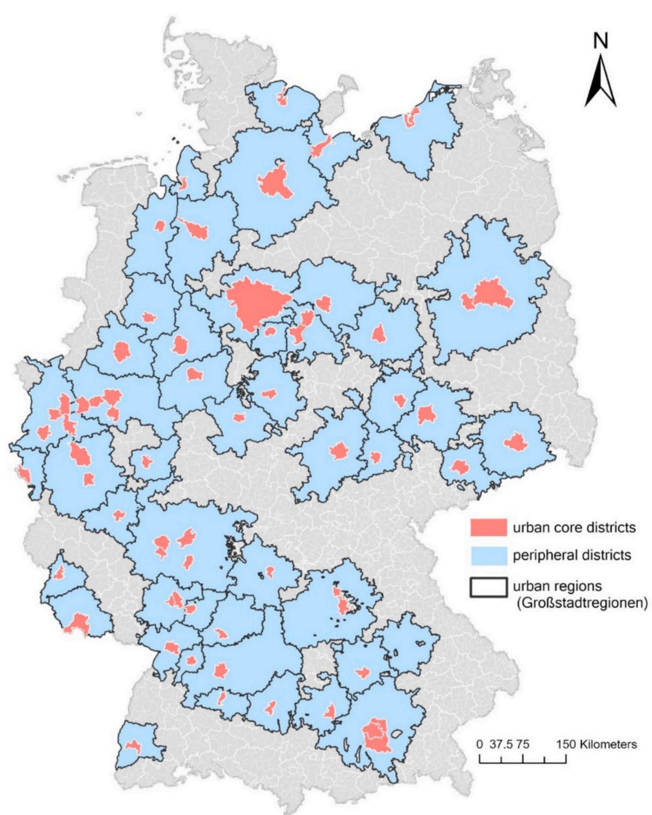

Fig. 1. The re-delineated German urban regions following the borders of districts. Urban cores are marked in red, and the peripheries are blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 1).

2.2. Operationalizing polycentricity

Measuring polycentricity has been a source of extensive debate in the literature, largely due to the lack of clarity regarding how urban centers are defined and how the balance between these centers is measured (Derudder et al., 2021; Münter & Volgmann, 2021; Thomas et al., 2021). In this study, we adopt the municipal association (*Verbandsgemeinde*) as the basic spatial unit for quantifying polycentricity, employing two widely used morphological metrics. Morphological polycentricity utilizes patterns of employment distribution within a region and operationalizes polycentricity following the standard deviation method introduced by Green (2007). The method is expressed in eq. (1):

$$P_i(n) = 1 - \sigma_n/\sigma_{\max} \; (n = 2, 3, 4) \tag{1}$$

Where $P_i(n)$ is the degree of polycentricity for region i considering the top n centers; σ_n presents the standard deviation of the employment for the top n centers; and $\sigma_{\max}$ presents the maximum standard deviation of employment considering an absolute monocentric two-center scenario; That is, one center has employment zero, and another has the maximum employment in the urban region.

We employ the rank-size distribution method following Meijers and Burger (2010) and Wang et al. (2019) as a robustness check. This methos measures how quickly size declines when ordering cities from largest to smallest. The indicator is calculated as follows:

$$\ln(Size) = \alpha + \beta \ln(Rank) \tag{2}$$

where β quantifies the degree of polycentricity. The flatter the slope, the more polycentric the urban region. Size is measured as the total employment of a municipality, and rank is determined by the order of total employment within an urban region.

According to Zhang and Derudder (2019), polycentricity measures are sensitive to the number of centers incorporated. In this study, we focus on a fixed number of major centers within each region, ranked by total employment, as polycentricity is typically evaluated based on the size distribution of a few large cities. Specifically, we calculate polycentricity values for the top two, three, and four centers in each region, then average these values to derive the final polycentricity indices for the measures we constructed. This approach follows with the methodology employed by Meijers and Burger (2010), Ouwehand et al. (2022), and Wang et al. (2019).

2.3. Empirical estimation strategy

The econometric approach to test the influence of polycentrism on air pollution begins with a cross-sectional analysis at the regional scale. Our dependent variable is the regional average PM2.5 concentration, weighted by population. This better reflects the actual exposure of individuals, and prioritizes where more people live, rather than a simply average that treats all areas equally regardless of population distribution. This variable is constructed by aggregating spatial cells into regional level observations, integrating satellite-based pollution concentration estimates with population data from census. The population-weighted average of PM2.5 concentration is calculated using the following weighted average formula:

$$PM2.5_r = \sum_{i=1}^{N_r} PM2.5_{r,i} * \frac{Pop_{r,i}}{\sum_{j=1}^{N_r} Pop_{r,j}} \tag{3}$$

Where i indexes grid cells within region r, N_r is the number of cells within region r, $Pop_{r,j}$ is the population on grid cell i and $PM2.5_{r,i}$ is average yearly PM2.5 concentration on the grid cell i.

At the regional scale, our major estimating equation regressing the population-weighted average PM2.5 exposure for region r ($PM25_{r,t}$) on regional polycentricity $Poly_r$ is expressed as follows:

$$PM25_r = \alpha_0 + \alpha_1 Poly_r + \boldsymbol{X}_r \beta + \mu_r + \epsilon_r \tag{4}$$

where $\boldsymbol{X_r}$ incorporate a vector of control variables that are related to PM2.5 concentration based on literature, including population density (*popden*), total commuting volume, ratio of green spaces within a region (*ROG*), windspeed (*ws*), annual average temperature (*mntemp*), annual average precipitation (*prep*), GDP per capita (*gdppc*), employment in the tertiary sectors (*thempo*) as control for industrial structure, and unemployment rate (*unemp*). We also included regional dummy variables—east, north, west, and south—to control for public policies related to air pollution and other unobservable variations across regions.

We further perform an intra-regional regression analysis, differentiating between urban core(s) and peripheral districts, to investigate whether polycentrism has a positive or negative impact on air quality in these areas. The model follows a similar structure to the regional-scale equation but is applied at the district level.

$$PM25_d = \alpha_0 + \alpha_1 Poly_r + \alpha_2 Core_d + \boldsymbol{X}_d \beta + \mu_d + \nu_s + \epsilon_d \tag{5}$$

Where $PM25_d$ and control variables ($\boldsymbol{X_d}$) are disaggregated to the district level, except for $Poly_r$, which is calculated only at the regional scale. This variable can be interpreted as the increasing or decreasing impacts of polycentrism on air pollution exposure if a district, either an urban core or periphery, is embedded in a more polycentric urban region. In addition, we also include a dummy variable to indicate whether a district is an urban core or a peripheral area, as well as a state fixed effect (ν_s) to control for the state-specific unobserved variations.

To further unravel the mechanisms underlying our findings, we examined how region size and the inter-municipal commuting ratio moderate the relationship between polycentricity and air quality by incorporating two interaction terms, specifically *poly*region size* and *poly*commute*.

We utilized regional population size in *poly*region size* because previous studies suggest that population and/or population density can influence the impact of polycentricity on various sustainable outcomes. For instance, Han et al. (2020) demonstrated that polycentric development can alleviate air pollution in large, high-density cities, while showing no significant effect in smaller areas. Similarly, Li and Schmidt (2024a, 2024b) observed that a polycentric spatial pattern mitigates urban heat island effects only in large regions within central business districts. The second moderating variable, the inter-municipal commuting ratio (Ratio of Commuters), was chosen due to its central role in the air pollution debate, as commuting patterns often vary significantly across different urban spatial configurations. Therefore, commuting patterns should be considered a key factor influencing air pollution. Additionally, we explored how the moderating effects differ in magnitude between urban cores and peripheral areas by incorporating the triple interaction term, *poly*commuting*UrbanCore,* and between regions of different sizes by incorporating *poly*commuting*size*.

2.4. Instrumental variables (IV) approach

Many studies have documented the potential endogeneity between urban spatial patterns and air pollution (Borck & Schrauth, 2021; Carozzi & Roth, 2023; Wu et al., 2022) primarily due to reverse causality. For instance, regions with poor air quality might strategically adopt polycentric planning to alleviate congestion and emissions, thereby generating a reverse causal effect. To address this endogeneity issue inherent in the OLS model, we employ an instrumental variable (IV) approach with two-stage least square (2SLS) estimation. Following previous work (e.g., W. Li et al., 2023; Meijers & Burger, 2010), the two IVs we selected are the historical spatial structure for German regions, which measures the degree of polycentricity using the 1871 census at the municipality level, and the terrain curvature, defined as the second derivative of elevation.

A core principle that the IV strategy should follow is the exclusion restriction, which requires the chosen instruments to influence current air quality only through their impact on contemporary urban spatial structure. We argue that our IVs met this condition because Germany has undergone substantial historical transformations over the past 150 years, including significant economic disruptions, extensive population relocations, and urban rebuilding triggered by two World Wars. Therefore, the degree of polycentricity dating back to 1871 is very unlikely to directly affect the current air pollution level, except through shaping modern polycentricity. In addition, existing research has demonstrated that geographic and topographic characteristics, such as elevation, slope, and curvature, play an important role in shaping present-day urban spatial structure, but do not exert direct influence on present-day air pollution level (M. Wang et al., 2019). Therefore, the historical degree of polycentricity and topographic factor could serve as valid IVs in our empirical analysis.

2.5. Datasets

The socio-economic datasets (1998–2019) come from the INKAR data platform[1] of the Federal Institute for Research on Building, Urban Affairs, and Spatial Development (BBSR). The commuting flow data used to measure the inter-municipal commuting ratio are collected from the Federal Employment Agency of Germany and is only available for 2007 and 2017. The climate and weather-related variables, such as annual average temperature (*mntemp*), annual average precipitation (*prep*) are collected from the Climate Data Center (CDC)[2] of the Deutscher Wetterdienst (DWD). Both datasets have a spatial resolution of 10 km by 10 km. The annual mean PM2.5 grided dataset at the 0.01-degree spatial resolution[3] is collected from the Atmospheric Composition Analysis Group (Van Donkelaar et al., 2021). The dataset estimates the ground-level fine particulate matter (PM2.5) from 1998 to 2022 by combing aerosol optical depth (AOD) retrievals from multiple sensors with the GEOS-Chem chemical transport model, and subsequently calibrated by the station-based readings using a geographically weighted regression (GWR). The dataset is primarily intended to aid in large scale studies (Van Donkelaar et al., 2021), and it is suitable for the regional scale like this one. One of the instrumental variables, the degree of polycentricity, is derived from the 1871 municipality-level population census compiled by Roesel (2022).[4] The other instrumental variable, terrain curvature, is computed using NASA's SRTM DEM product. The descriptive statistics of the variables (using 2017 datasets as an example) are available in Table 1 below.

Table 1
Descriptive statistics and data sources of variables collected for the year 2017.

Variables (in logarithmic form)	Mean	SD	Median	Min	Max
Regional-scale variables					
Population weighted pm2.5	2.448	0.078	2.432	2.251	2.687
Polycentricity (Poly)	−1.347	0.462	−1.298	−2.32	−0.328
Population density	7.801	0.218	7.762	7.401	8.223
Total Commuting volume	12.388	0.944	12.229	10.548	14.535
Ratio of green spaces	−1.208	0.478	−1.111	−2.282	−0.269
Mean temperature (annual)	4.589	0.059	4.596	4.467	4.719
Mean precipitation (annual)	6.711	0.138	6.729	6.309	7.025
GDP per capita	3.648	0.218	3.610	3.299	4.237
Tertiary employment (%)	4.293	0.102	4.310	3.921	4.459
Unemployment rate	1.674	0.391	1.734	0.722	2.302
Wind speed	0.145	0.186	0.151	−0.233	0.502
IV: Polycentricity (in 1871)	−0.381	0.503	−0.410	−1.607	0.641
IV: topography (curvature)	−1.984	0.042	−1.982	−2.129	−1.85
Number of observations (N)	50				
Intra-regional scale variables					
PM2.5 at district level	2.458	0.088	2.457	2.193	2.714
Polycentricity (Poly)	−1.303	0.541	−1.288	−2.32	−0.328
UrbanCore (dummy variable)	0.232	0.423	0.000	0	1
Population density	7.934	0.347	7.935	7.135	8.868
Total Commuting volume	10.981	0.664	10.948	9.525	13.23
GDP per capita	3.567	0.357	3.506	2.942	5.109
Tertiary employment (%)	4.276	0.132	4.289	3.816	4.538
Unemployment rate	1.609	0.451	1.666	0.372	2.638
Mean temperature (annual)	4.609	0.075	4.611	4.316	4.759
Mean Precipitation (annual)	6.689	0.178	6.694	6.23	7.292
Ratio of Commuters	−1.188	0.335	−1.179	−2.048	−0.371
IV: Polycentricity (in 1871)	−0.388	0.538	−0.280	−1.607	0.641
IV: topography (curvature)	−1.987	0.042	−1.983	−2.129	−1.85
Number of observations (N)			254		

Notes: (1) all variables, including dependent variables, are log-transformed. (2) the descriptive statistics are based on the datasets in 2017.

3. Results and findings

Before proceeding to the discussion of our regression results, it is important to note that all regression models in this section (Tables 2, 3, and 4) are estimated using two-stage least square (2SLS), with the historical degree of polycentricity in 1871 and terrain curvature as instrumental variables. We report the 2SLS results because this approach addresses endogeneity issue and establishes clear causal relationships. Thus, we place greater trust in the 2SLS models. For reference, corresponding OLS results are provided in Appendices 2, 3, and 4, and the OLS results are largely consistent with the 2SLS outcomes. To validate our IVs, we conducted a series of instrumental variable tests, including the Cragg-Donald (CD) F-test for weak instruments, the Sargan-Hansen over-identification test for instrument exogeneity, and the Endogeneity test for assessing the necessity of IV estimation. Overall, the diagnostics results presented across Tables 2, 3, and 4 confirm that our instrumental variables are sufficiently strong and valid. Model (5) in Table 4 shows relatively lower CD F-test statistics, primarily due to the complexity introduced by the three-way interaction terms.

3.1. Baseline results—regional and intra-regional regressions

We begin our analysis with a regional-scale regression as shown in model (1) of Table 2, which examines whether a higher level of polycentric development can help to mitigate air pollution (PM2.5) across the 50 German metropolitan regions. As shown, our variable of interests, *Poly*, is not statistically significant, suggesting that higher levels of polycentrism are not associated with lower levels of air pollution. For robustness, we extend our regional-scale cross-sectional analysis beyond a single year (2017) to cover the period spanning from 1998 to 2019. We find that none of the coefficients for our variable of interests are statistically significant during this time period (see Fig. A1). Based on these results, we conclude that higher polycentricity does not contribute to reduced air pollution across German metropolitan regions.

Recent studies on polycentricity indicate that its effects may vary based on the intra-regional interactions between urban cores and peripheral districts (W. Li et al., 2023). To examine these varying impacts within regions, we decompose each region into urban core(s) and

[1] https://www.inkar.de/
[2] https://opendata.dwd.de/climate_environment/
[3] https://sites.wustl.edu/acag/datasets/surface-pm2-5/#V5.GL.04
[4] The Germany local population to construct the instrumental variable is available at: https://leopard.tubraunschweig.de/receive/dbbs_mods_00071017.

Table 2
2SLS regressions to test the impacts of polycentricity on air pollution at both regional and intra-regional scale.

Variables (in logarithmic form)	Regional scale	Intra-regional scale		
	(1)	(2)	(3)	(4)
	All regions	All districts	Urban Core	Periphery
Poly	−0.022	0.0008	0.0656**	−0.0111
	(0.023)	(0.0112)	(0.0233)	(0.012)
Population density	0.091	0.0471*	−0.0312	0.0533*
	(0.071)	(0.019)	(0.0439)	(0.0238)
Total commuting volume	0.046**	0.0156*	0.0664**	0.0054
	(0.013)	(0.0074)	(0.013)	(0.0092)
Ratio of Greenspace	0.02			
	(0.023)			
Mean temperature (annual)	1.312	0.4083**	0.1503	0.4512**
	(0.677)	(0.0709)	(0.1388)	(0.079)
Mean precipitation (annual)	−0.398**	−0.1069**	−0.1308*	−0.0987**
	(0.102)	(0.027)	(0.0567)	(0.0292)
GDP per capita	−0.017	−0.0246*	−0.0059	−0.0335*
	(0.057)	(0.0123)	(0.0239)	(0.0156)
Tertiary employment	−0.173	−0.0875*	−0.0915*	−0.0412
	(0.129)	(0.0341)	(0.0449)	(0.0443)
Unemployment	0.01	0.0259	0.0285	0.0197
	(0.048)	(0.0146)	(0.0314)	(0.0182)
UrbanCore		−0.0109		
		(0.0117)		
Windspeed	−0.019	0.0331	0.1472	0.0181
	(0.155)	(0.0543)	(0.1195)	(0.0604)
Region fixed effects	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y
Constant	9.752**	1.16**	2.5578**	0.8023
	(2.363)	(0.4336)	(0.8316)	(0.4846)
Observations	49	252	58	194
R-squared	0.644	0.7207	0.8671	0.705
IV tests:				
Cragg-Donald (CD) F-test	49.056	285.136	33.974	245.303
Sargan-Hansen statistics	0.537	2.096	0.685	0.946
Endogeneity test	0.271	4.786*	1.481	10.194**

Notes: a). the variable (ROG), ratio of urban green spaces is missing for all models at the intra-regional scale. b). All modes include Region and State fixed effects to account for unobserved, location-specific factors that may influence air pollution.
Standard errors are in parentheses: ** $p < 0.01$, * $p < 0.05$.

peripheries. Before focusing specifically on urban core(s) or peripheries, model (2) provides a general result at the intra-regional scale, encompassing all districts, regardless of core or periphery status. This model indicates that being situated in a more polycentric context does not improve the air quality for that district, a finding consistent with results at the regional scale. In contrast, model (3), which focuses on urban cores, shows a statistically significant result suggesting that core districts in polycentric contexts experience higher pollution levels than those in monocentric settings. This finding remains robust over the period from 1998 to 2019, with significance in all years except from 2001 to 2005 (see Fig. A2). Therefore, we conclude that an urban core in a more polycentric setting is more likely to face higher air pollution, contradicting our hypothesis that urban core(s) might benefit from polycentrism through a more efficient and evenly distributed spatial pattern.

Model (4) investigates the influence of regional polycentrism on peripheral districts and finds no statistically significant effect. This result remains consistent across all years from 1998 to 2019. Thus, we conclude that peripheral districts situated in a broader and more polycentric region do not exhibit differences in air pollution levels compared to those in monocentric regions. This outcome also contradicts our initial hypothesis that peripheral districts in polycentric settings would integrate more closely with surrounding urban cores and experience increased air pollution as a result.

Table 3
Intra-regional analysis regarding the moderating effects of region size on air pollution (2SLS regressions with instrumental variables).

Variables (in logarithmic form)	(1)	(2)	(3)
	All district	UrbanCore district	Periphery district
Poly (benchmark: small)	−0.0585	−0.0596	−0.0633
	(0.0314)	(0.0684)	(0.0347)
Poly × Medium-size region	0.082*	0.1585*	0.0636
	(0.0391)	(0.0751)	(0.0432)
Poly × Large-size region	0.0694*	0.1383*	0.0674*
	(0.0305)	(0.0622)	(0.034)
Medium-sized region	0.0909	0.2031*	0.0608
	(0.0487)	(0.0975)	(0.0532)
Large-sized region	0.1133**	0.1856*	0.1018*
	(0.0399)	(0.0867)	(0.0436)
Control variables	Y	Y	Y
Region fixed effects	Y	Y	Y
State fixed effects	Y	Y	Y
Constant	1.8666**	2.641**	1.8557**
	(0.4473)	(0.7563)	(0.5444)
Observations	252	57	194
R-squared	0.7611	0.9157	0.7445
IV tests:			
Cragg-Donald (CD) F-test	37.464	5.862	35.862
CD 10 % relative bias	7.77	7.77	7.77
Sargan-Hansen statistics	3.588	4.697	0.789
Endogeneity test	15.398**	4.837	14.220**

Note: a). All regression models include a set of control variables including population density, total population, GDP per capita, employment in tertiary industry, unemployment rate, mean temperature (annual), and mean precipitation (annual). b). All modes include Region and State fixed effects to account for unobserved, location-specific factors that may influence air pollution.
Standard errors are in parentheses: ** $p < 0.01$, * $p < 0.05$.

In addition to our findings regarding polycentricity, we observe that population density, a key determined of air pollution (Borck & Schrauth, 2021; Carozzi & Roth, 2023), is significant in the peripheral district model (model 4) but insignificant in the urban core district model (model 5). Conversely, commuting volume demonstrates the opposite pattern; significant for urban core districts but not in peripheral areas. This result suggests that commuting volume is a more critical factor influencing air pollution in urban cores, whereas population density has a greater impact on pollution levels in peripheral districts.

3.2. Mechanism analysis I: Population density and region size

The previous section presented results indicating that polycentricity does not reduce air pollution at either the regional or intra-regional scale. In this section, we explore why polycentric development has not reduced air pollution as initially hypothesized and why urban cores in more polycentric settings experience higher pollution levels, while peripheral districts remain unaffected, as shown in the baseline regression results.

In Table 3, we empirically test the moderating effects of population size on the relationship between polycentrism and air quality. Model (1), which includes all districts (regardless of core or periphery status), suggests that polycentric development does not significantly reduce air pollution in districts within small regions, according to the coefficient *Poly (benchmark: small)*. However, as a region's size increases, the impact of polycentricity on air pollution gradually shifts from neutral to positive, as shown by the coefficients of the interaction terms *Poly×Medium-size region* and *Poly×Large-size region*. Put differently, polycentricity do not effectively reduce air pollution in districts embedded within smaller regions but instead contribute to increased pollution levels in districts situated within medium and large-sized regions.

Model (2) and (3) further examine the heterogeneous impacts of region size in urban core(s) and peripheries. According to model (2),

Table 4
Intra-regional analysis regarding the moderating effects of Urban core/peripheries and region size on air pollution (2SLS regressions with instrumental variables).

Variables (in logarithmic form)	(1)	(2)	(3)	(4)	(5)	(6)
	All Districts	All Districts	All Districts	All Districts	UrbanCore	Peripheral
	Commute	Poly× Commute	Poly× Commute ×UrbanCore	Poly× Commute ×Size	Poly× Commute ×Size	Poly× Commute ×Size
Poly	−0.0011	0.0584	−0.0011	−0.1542	−0.6181	−0.3176
	(0.0112)	(0.0308)	(0.0384)	(0.0837)	(0.3457)	(0.1702)
RaCommute	0.0582**	0.1241**	0.0688	−0.0302	−0.4948	−0.1807
	(0.0158)	(0.036)	(0.0434)	(0.0857)	(0.4515)	(0.1658)
Poly×RaCommute		0.0484*	0.0027	−0.0859	−0.6761	−0.1858
		(0.0238)	(0.0295)	(0.0605)	(0.3569)	(0.1142)
UrbanCore×Poly×RaCommute			0.1066*			
			(0.0469)			
Medium×Poly×RaCommute				0.0846	0.5172	−0.0753
				(0.1019)	(0.3058)	(0.1674)
Large×Poly×RaCommute				0.1521*	0.8624*	0.2237*
				(0.0646)	(0.3679)	(0.1123)
UrbanCore			0.1531			
			(0.0801)			
Medium-size region				0.1501	0.4893	−0.1525
				(0.16)	(0.4852)	(0.3127)
Large-size region				0.3419**	0.998**	0.5343*
				(0.1208)	(0.4637)	(0.2399)
Control Variables	Y	Y	Y	Y	Y	Y
Region fixed effects	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y
Constant	1.9469**	2.1252**	1.9024**	2.8872**	3.9267*	3.3777**
	(0.6008)	(0.6012)	(0.6351)	(0.6376)	(2.1086)	(0.8242)
Observations	252	252	252	252	58	194
R-squared	0.7296	0.7349	0.7389	0.7835	0.8912	0.7708
IV tests:						
Cragg-Donald (CD) F-test	281.340	127.547	57.030	15.190	4.323	14.882
Sargan-Hansen statistics	3.065	2.881	2.940	9.418	5.62	6.565
Endogeneity test	3.687	3.197	8.318	15.852*	22.894**	20.490**

Notes: a). To ensure the clarity and readability of this table, we have removed some interaction terms that are not relevant to the conclusions, including UrbanCore×Poly and UrbanCore×Commute in Model (3); Medium×Poly, Large×Poly, Medium×Commute, and Large×Commute in Models (4), (5), and (6). The complete regression table, including all variables, can be found in the supplemental materials. b). All regression models include a set of control variables including population density, total population, GDP per capita, employment in tertiary industry, unemployment rate, mean temperature (annual), and mean precipitation (annual). Standard errors are in parentheses: ** $p < 0.01$, * $p < 0.05$.

polycentricity has no significant influence on the urban core(s) of small regions; however, in medium- and large-sized regions, polycentricity worsens air quality in urban cores, as indicated by the coefficients of variables *Poly×Medium-size region* and *Poly×Large-size region*. Model (3) focuses on peripheries, finding that increased polycentricity is associated with greater air pollution only in the peripheries of large-sized

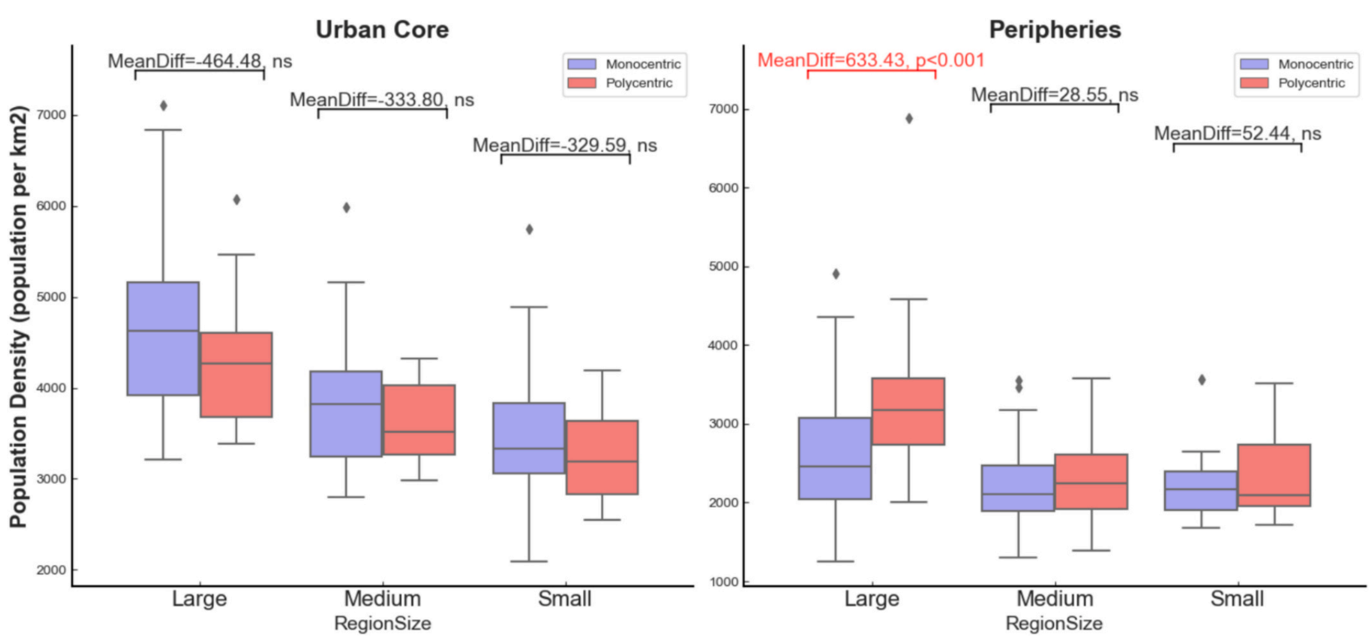

Fig. 2. heterogeneity analysis of density in terms of region sizes. Statistically significant results are marked in red.

regions, with no effect on the peripheries of small and medium-sized regions.

The findings in Table 3 highlight the heterogeneous effect of a region's size on the relationship between polycentricity and air pollution. Polycentricity significantly increases air pollution in urban core(s) of medium- and large-sized regions and in peripheries only within large-sized regions. One possible explanation is differences in population density, as previous studies have suggested that higher population density leads to increased air pollution (Borck & Schrauth, 2021; Carozzi & Roth, 2023). Larger polycentric regions may offer spatial spillovers that benefit peripheral areas through the nearby urban core, a phenomenon known as the 'borrowed size effect'. As such, the urban core of larger regions may not only stimulate economic growth and density in peripheries but also contribute to increased air pollution. In fact, when we compare the population densities of the peripheral areas of larger regions, we find a statistically significant difference between monocentric and polycentric regions. The peripheries of larger polycentric regions have higher population densities compared with medium and smaller regions (see Fig. 2, right side). This observation could explain the significance of the *Poly×Large-size region* variable in the model 3 focusing on peripheral district (Table 3).

However, we find no statistically significant difference in population density between the urban cores of monocentric and polycentric regions in both medium and large-sized regions Fig. 2, left side). This suggests that density cannot be the explanation for why *Poly×Medium-size region* and *Poly×Large-size region* in model 2 (Table 3) are significant and positive in terms of their relationship to air quality. Therefore, factors other than density may play a role here. In the next section, we explore the inter-municipal commuting ratio as an explanation.

3.3. Mechanism analysis II: Commuting patterns

Another possible variable that may moderate the impacts of polycentrism on air pollution is the inter-municipal commuting ratio (*RaCommute*), calculated by dividing the total inter-municipal commuting trips (both in- and out-commuting) by the total residential population within each district. This variable reflects the proportion of potential long-distance commuting generated by residents and incoming workers within a district, and serves as an important proxy for car usage, traffic congestion, and associated emissions.

For illustrative purposes, we select a paradigmatic monocentric region (Munich) and a polycentric region (*Düsseldorf-Duisburg-Krefeld-Mönchengladbach*) to visualize their commuting patterns (Fig. 3). A comparison of these regions reveals distinct differences: Munich exhibits a radial pattern, characterized by flows directed primarily from peripheries toward the urban core, whereas Düsseldorf-Duisburg-Krefeld-Mönchengladbach displays a network-like commuting structure. In the following analysis, we will further explore which commuting pattern, when interacting with urban spatial structure, is more effective in reducing travel-related pollution.

In Table 4, we examine the moderating effect of commuting patterns on the influence of polycentricity on air quality through regression analysis. To ensure the clarity and readability of this table, we have removed certain interaction terms that are not relevant to the conclusions. In Model (1), the commute variable (see *RaCommute*) is positive and statistically significant, suggesting that a higher proportion of inter-municipal trips contributes to increased local pollution, regardless of whether the area is an urban core(s) or peripheral districts.

In model (2), we add an interaction term, *Poly×Commute*, which is positive and statistically significant. This result suggests that, in a more polycentric environment, a unit increase in commuting ratio is associated with a higher level of air pollution than in a more monocentric setting. This finding suggests that commuting patterns in polycentric regions are less efficient and less environmentally sustainable. Possible reasons could include longer commuting distances and travel times, increased reliance on private vehicles, and higher congestion levels, all of which contribute to reduced commuting efficiency.

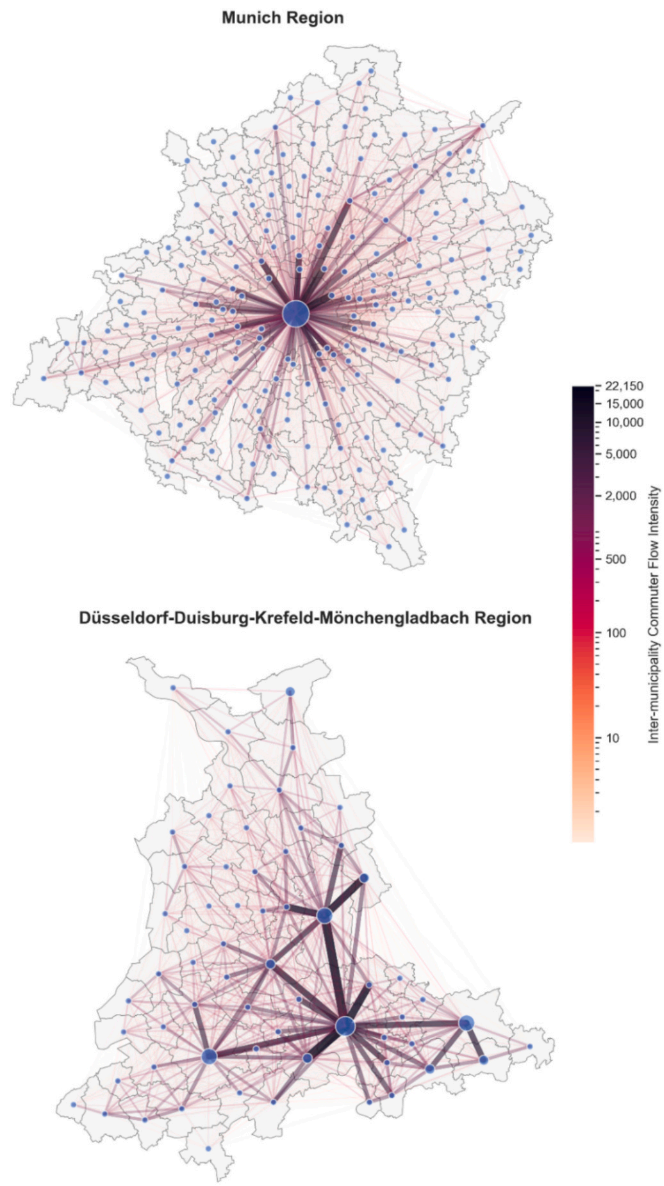

Fig. 3. Commuting flow patterns for two regions: the monocentric Munich region and the polycentric region of Düsseldorf-Duisburg-Krefeld-Mönchengladbach.

Model (3) examines whether the moderating effect of inter-municipal commuting ratio differs between urban core(s) and peripheral districts by including the triple-interaction term, *Poly×Commute×UrbanCore*, which is positive and statistically significant. This indicates that the influence of inter-municipal commuting ratio on air pollution is greater for urban core(s) than for peripheral districts in a polycentric region. This may be due to the cumulative effects of congestion in urban cores where a marginal increase in per capita commuting exacerbates traffic congestion more than in peripheral areas. We conclude that urban core(s) are less efficient and sustainable than peripheral districts in optimizing commuting patterns, which may explain the higher levels of pollution in polycentric urban cores compared to peripheral districts.

In model (4), we examine whether the moderating effect of the inter-municipal commuting ratio varies by region size through the inclusion of the triple-interaction terms: *Poly×Commute×Medium* and *Poly×Commute×Large*. The *Poly×Commute×Large* interaction is positive and statistically significant, while the $Poly \times Commute \times Medium$ interaction is significant at the 10 % level but not at the 5 % level. These coefficients suggest that the influence of commuting on polycentricity ($Poly \times Commute$) increases with a region's size. Large-sized polycentric regions may experience greater increases in commuting time, distance, and congestion compared to smaller regions. This potential difference could help explain the findings in Model (1) of Table 3, where polycentricity contributes to air pollution in larger regions.

Model (5) and (6) further break down the effects of $Poly \times Commute \times Medium$ and $Poly \times Commute \times Large$ for of urban core(s) and peripheral districts, respectively. Our results suggest that polycentricity does not significantly influence air quality in smaller regions, as indicated by the insignificant $Poly \times Commute$ coefficient. In Model (5), the positive and significant coefficient of variable $Large \times Poly \times Commute$ demonstrates that urban core(s) in large regions are particularly susceptible to the moderating effect ($Poly \times Commute$). This is possibly due to the greater cumulative impact of congestion in urban cores of large regions as inter-municipal commuting increases. This triple-interaction term also suggests that commuting-related pollution is amplified in urban cores of large, polycentric regions, helping explain why these areas experience higher pollution levels than monocentric counterparts, even when density differences are not statistically significant (see Model 2 in Table 3). Finally, the significant and positive coefficient for $Large \times Poly \times Commute$ in Model (6) suggests that the moderating effect ($Poly \times Commute$) is especially pronounced in peripheries of large-sized regions. This is likely due to longer and more congested travels associated with peripheries that are functionally connected to the nearby urban cores and benefit from their spatial spillovers.

4. Discussion

To synthesize the multi-dimensional effects we observed above, Table 5 summarizes the heterogeneous impacts of polycentricity by region size (small, medium, and large) and intra-regional locations (urban core vs. periphery), with overall marginal effects presented in the final column and row. Overall, our baseline model reveals no significant impact of polycentric structure on regional air quality. This outcome is consistent with the mixed findings from previous studies, which vary depending on pollution measures and study contexts. Several studies, focusing on Chinese regions, found polycentricity is conductive to reducing pollution concentrations of PM2.5 and CO2 emissions (F. Li & Zhou, 2019; P. Liu et al., 2022; Sun et al., 2020; Xia et al., 2024); whereas studies by Y. Li et al. (2020) on Chinese prefectural regions and Lee and Lee (2014) on US urbanized areas reported that polycentricity increased pollution levels. Similarly, Burgalassi and Luzzati (2015) found no significant impact of polycentricity on PM10 in Italian NUTS-2 regions.

However, when disaggregating regions into urban cores and peripheries, and differentiating by region size, our findings reveal differences. For urban core districts (row 1, Table 5) in small-sized regions, polycentric development does not significantly influence air pollution, indicating that neither polycentric nor monocentric structures effectively reduce pollution at smaller spatial scales. This suggests that urban cores in smaller regions have not yet reached a critical threshold of agglomeration diseconomies, and therefore, whether development is polycentric or monocentric does not matter for urban cores. In contrast, urban cores within medium and large-sized polycentric regions exhibit significantly higher air pollution levels compared to monocentric counterparts. Our modeling results (Table 4) demonstrate that this is primarily due to commuting accumulation; a unit increase in inter-municipal commuting ratio leads to a greater increase in air pollution in polycentric regions compared to monocentric ones. Urban cores within polycentric regions, therefore, are comparatively less efficient in managing commuting-related emissions.

For peripheral districts, our results indicate that polycentric development in small and medium-sized regions does not significantly affect air pollution compared to monocentric regions. This suggests differences in commuting volumes and population density in these peripheral areas have not reached critical levels to noticeably influence air quality. However, peripheral districts within large & polycentric regions show significantly increased air pollution. The population density comparison in Fig. 2 and commuting ratio models in Table 4 suggests two primary reasons for this increase: first, peripheral districts within polycentric regions experience spillover effects from adjacent urban cores, thereby displaying higher population density and pollution levels; second, polycentric peripheries involves higher commuting volumes due to stronger interactions with urban cores, and these commuting activities cause increased pollution per commuting unit compared to monocentric regions.

While existing studies have addressed related themes, few have explicitly explored how effects differ between urban cores and peripheral areas. However, several China-based studies have investigated factors that mediate the impact of polycentricity on air pollution, such as population density (Han et al., 2020), population (Y. Li et al., 2019), economic development (Y. Li et al., 2020; Xia et al., 2024), industrial structure (Y. Li et al., 2020; Wu et al., 2022), and congestion (Sun et al., 2020). Some of these findings are closely aligned with ours. For example, Li et al. (2019) found that polycentric structure exacerbates congestion in large cities, echoing our finding regarding commuting-related pollution in large regions. W. Li et al. (2023) confirms the spillover effects from adjacent urban cores to peripheries, which resonates to our observation that peripheries in polycentric context have higher population density and thus pollution levels than monocentric ones. Nevertheless, other China-based studies generally view polycentric development positively, and quite a few find it effective for redistributing populations, polluting industries, and congestion levels (e.g., Han et al., 2020; Y. Li et al., 2020; Wu et al., 2022).

The differences in outcomes between studies conducted in Germany and China may stem from several factors. First, spatial development patterns in China and Germany vary significantly in terms of spatial scale, population density, and historical urbanization context. Chinese urban regions are characterized by larger size, higher population density, more rapid urbanization, and dynamic commuting patterns, with more pronounced agglomeration diseconomies. In such contexts, polycentric urban development—emphasizing multiple urban centers rather than a single dominant core—can more effectively redistribute population, alleviate congestion, and mitigate pollution compared to monocentric structures. By contrast, German metropolitan regions are typically smaller, with established urban structures, commuting patterns, and more stable growth rates. Consequently, the effectiveness of

Table 5
Heterogeneous Effects and Mechanisms of Polycentricity on PM2.5 Concentration across Region Sizes and Intra-regional Locations (Urban Core vs. Periphery).

Poly ↑	Small region	Medium region	Large region	All regions
Urban core	not significant	significant increase in PM2.5 *(due to commuting accumulation)*	significant increase in PM2.5 *(due to commuting accumulation)*	significant increase in PM2.5 *(driven by medium & large regions)*
Peripheries	not significant	not significant	significant increase in PM2.5*(spillover: higher density & commuting accumulation)*	not significant
All districts (UrbanCore + Peripheries)	not significant	significant increase in PM2.5 *(effects of commuting)*	significant increase in PM2.5 *(joint effects of commuting & density)*	not significant

polycentric strategies in pollution mitigation may be limited, as negative externalities may not accumulate significantly in such settings. For example, the largest prefectural regions in China, such as Beijing and Shanghai, have populations exceeding 20 million, while the largest metropolitan region in our study, Berlin-Potsdam, has a population of approximately 5 million. Thus, there is a notable mismatch in urban scales and sizes; what constitutes a large-sized region in Germany may only be classified as medium or small-sized in China, which significantly influences observed outcomes regarding the effectiveness of polycentric development. Second, industrial structures and environmental governance may also contribute to the differing results. Chinese urban regions often face greater challenges from heavily polluting industries, such as manufacturing and coal-based energy production (G. Wang, 2020), leading to localized environmental pressure. In these scenarios, polycentric structures can effectively redistribute industrial activities to reduce local pollutant concentrations. German regions, on the other hand, often have stricter environmental regulations, more balanced industrial distribution, and advanced technological standards (X. Liu et al., 2021). We argue that such conditions potentially limit the environmental benefits achieved through polycentric urban structures.

5. Conclusion

This study empirically investigates whether a polycentric urban spatial pattern can help mitigate air pollution across 50 metropolitan regions in Germany, utilizing satellite-based air quality measurements, multi-year datasets (2018–2019), and a multi-spatial scale research design. One unique contribution of our research is the disaggregation of intra-regional locations into urban core and peripheral districts. Our findings reveal that polycentric development does not significantly influence air pollution levels in small-sized cities, but it contributes to increased pollution in urban core and large-sized regions.

We also conducted a mechanism analysis to investigate potential explanations related to region size, population density, and commuting patterns. Differences in population density partially account for the elevated pollution levels observed in peripheral areas of polycentric regions; however, this factor does not explain patterns in urban core areas. Instead, our results suggest that differences in commuting patterns between polycentric and monocentric regions, rather than population density, are more closely associated with higher pollution levels in urban cores. A higher proportion of inter-municipal commuting trips is consistently linked to greater air pollution, regardless of whether the district is part of the core or periphery. This effect is especially pronounced in the urban cores of medium and large regions, as well as in the peripheral districts of large regions.

Our findings contrast with studies from other geographical contexts, such as Han et al. (2020) and Sun et al. (2020), which found that polycentricity reduces pollution and mitigates agglomeration diseconomies in Chinese regions. The performance of polycentric development varies across regions and spatial scales, with observed differences in its impacts on economic productivity, regional disparities, and commuting patterns. Policymakers should therefore recognize that the outcomes of polycentric strategies are often context-specific and path-dependent. Rather than being a one-size-fits-all solution to spatial and regional challenges, polycentricity involves trade-offs that must be carefully weighed against diverse policy goals. For instance, while polycentricity may be less effective in reducing air pollution or managing commuting patterns in some settings, it may still play a valuable role in mitigating urban heat island effects or promoting regional equity. (Jin & Xu, 2024a; Jin & Xu, 2024b; Li & Schmidt, 2024a, 2024b).

Lastly, methodological differences across studies, such as varying definitions of urban centers and measurement for polycentricity, may partially explain the divergent empirical findings. Future comparative research would benefit from harmonizing methodologies to ensure consistency and comparability. Furthermore, future research should adopt harmonized definitions of regions and conduct cross-national comparative research to better evaluate and compare the empirical effects of polycentricity in diverse geographical contexts.

CRediT authorship contribution statement

Wenzheng Li: Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Stephan Schmidt:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **Jintao Gu:** Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1

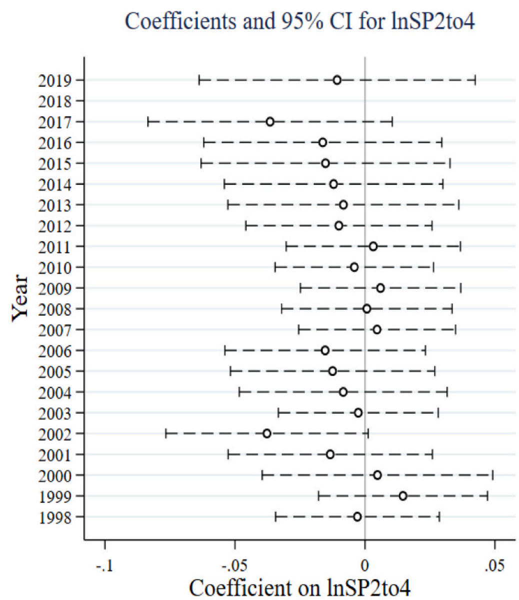

Fig. A1. regional-scale analysis—coefficients and 95 % confidence intervals (CIs) of cross-sectional regressions (1998–2019) examining the influence of polycentricity on PM2.5 levels. Solid circles represent statistically significant results, whole hollow circles indicate results are not statistically significant.

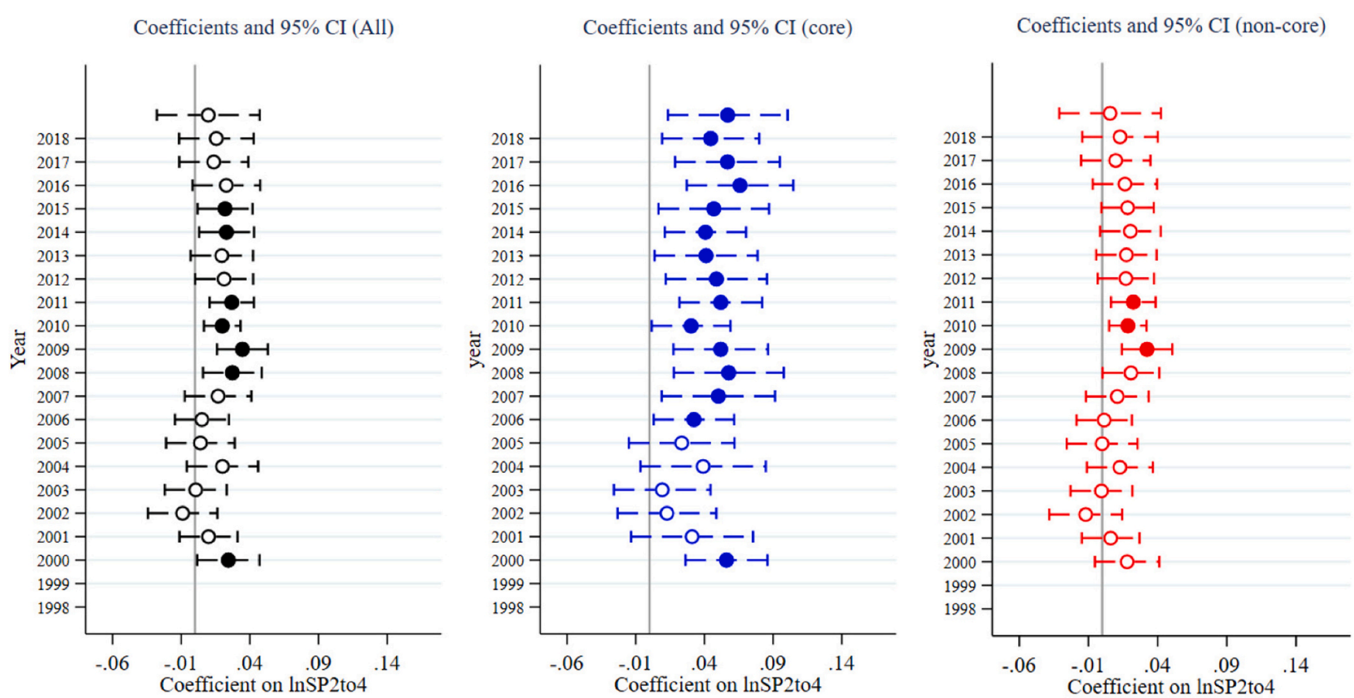

Fig. A2. intra-regional scale analysis—coefficients and 95 % CIs of cross-sectional regressions (1998–2019) examining the influence of polycentricity on PM2.5 levels. (a) coefficients of regressions incorporating all districts; (b) coefficients of regressions only incorporating urban core districts; (c) coefficients of regressions only incorporating peripheral districts.

Appendix 2

Table 2
OLS Regressions to test the impacts of polycentricity on air pollution at both regional and intra-regional scale.

Variables (in logarithmic form)	Regional scale	Intra-regional scale		
	(1)	(2)	(3)	(4)
	All regions	All districts	UrbanCore	Periphery

(continued on next page)

Table 2 (*continued*)

Variables (in logarithmic form)	Regional scale	Intra-regional scale		
	(1)	(2)	(3)	(4)
	All regions	All districts	UrbanCore	Periphery
Poly	−0.0275	0.0145	0.0527*	0.0081
	(0.0222)	(0.0117)	(0.0231)	(0.0128)
Population density	0.0954	0.0441*	−0.0289	0.0471*
	(0.1037)	(0.0186)	(0.0498)	(0.0236)
Total Commute	0.0452**	0.0169*	0.0642**	0.0062
	(0.0139)	(0.0073)	(0.0164)	(0.009)
Ratio of Greenspace	0.0199			
	(0.024)			
Mean temperature (annual)	1.3201	0.4092**	0.1663	0.4572**
	(0.7229)	(0.0901)	(0.1439)	(0.0977)
Mean precipitation (annual)	−0.4057*	−0.1034**	−0.1295	−0.0955*
	(0.1505)	(0.0352)	(0.0758)	(0.0375)
GDP per capita	−0.0213	−0.0234	−0.0022	−0.0304
	(0.0441)	(0.0135)	(0.0307)	(0.0176)
Tertiary employment	−0.1865	−0.0719*	−0.0921	−0.0288
	(0.1082)	(0.0343)	(0.0484)	(0.047)
Unemployment	0.0128	0.0199	0.0295	0.0133
	(0.0362)	(0.0154)	(0.0325)	(0.02)
Wind speed	−0.0218	0.0182	0.184	−0.0045
	(0.1457)	(0.0663)	(0.1411)	(0.0724)
UrbanCore		−0.0125		
		(0.0125)		
Region fixed effects	Y	Y	Y	Y
State fixed effects		Y	Y	Y
Constant	9.8694**	1.0996*	2.4506*	0.764
	(3.3819)	(0.5537)	(0.9696)	(0.5795)
Observations	50	253	59	194
R-squared	0.6446	0.7221	0.8686	0.7103

Notes: a). the variable (ROG), ratio of urban green spaces is missing for all models at the intra-regional scale. b). All modes include Region and State fixed effects to account for unobserved, location-specific factors that may influence air pollution.
Robust standard errors are in parentheses: ** $p < 0.01$, * $p < 0.05$.

Appendix 3

Table 3
Intra-regional analysis regarding the moderating effects of population density on air pollution (OLS regressions).

Variables (in logarithmic form)	(1)	(2)	(3)
	All district	UrbanCore	Periphery
Poly (benchmark: small)	−0.0458*	−0.0647	−0.0385
	(0.0194)	(0.053)	(0.0244)
Poly × Medium-size region	0.0714**	0.1188	0.0567
	(0.026)	(0.0639)	(0.0315)
Poly × Large-size region	0.0738**	0.1098*	0.0613*
	(0.0203)	(0.0459)	(0.0259)
Medium-sized region	0.082*	0.1474	0.06
	(0.0316)	(0.0835)	(0.0382)
Large-sized region	0.1259**	0.1553*	0.1036**
	(0.0269)	(0.0655)	(0.0334)
Control variables	Y	Y	Y
Region fixed effects	Y	Y	Y
State fixed effects	Y	Y	Y
Constant	1.8231**	2.1114	1.8718**
	(0.5983)	(1.0852)	(0.6981)
Observations	253	59	194
R-squared	0.7617	0.8903	0.7483

Note: a). All regression models include a set of control variables including population density, total population, GDP per capita, employment in tertiary industry, unemployment rate, mean temperature (annual), and mean precipitation (annual). b). All modes include Region and State fixed effects to account for unobserved, location-specific factors that may influence air pollution.
Robust standard errors are in parentheses: ** $p < 0.01$, * $p < 0.05$.

Appendix 4

Table 4
Intra-regional analysis regarding the moderating effects of Urban core/peripheries and region size on air pollution (OLS regressions).

Variables (in logarithmic form)	(1) All Districts Commute	(2) All Districts Poly× Commute	(3) All Districts Poly× Commute ×UrbanCore	(4) All Districts Poly× Commute ×Size	(5) UrbanCore Poly× Commute ×Size	(6) Peripheral Poly× Commute ×Size
Poly	0.0114	0.0658*	0.0203	−0.2047**	−0.5688*	−0.223*
	(0.0116)	(0.0285)	(0.0435)	(0.0588)	(0.2102)	(0.1042)
RaCommute	0.0545**	0.117**	0.0603	−0.0777	−0.3267	−0.0936
	(0.0176)	(0.0326)	(0.0435)	(0.0572)	(0.2417)	(0.0937)
Poly× RaCommute		0.0455*	0.0124	−0.1191**	−0.4827*	−0.1241
		(0.0208)	(0.0302)	(0.0402)	(0.1985)	(0.0669)
UrbanCore×Poly×RaCommute			0.0748*			
			(0.0347)			
Medium×Poly×RaCommute				0.1572*	0.4035	0.0094
				(0.0654)	(0.2637)	(0.1135)
Large×Poly×RaCommute				0.1821**	0.5547*	0.172*
				(0.0462)	(0.2143)	(0.0722)
UrbanCore			0.0994			
			(0.0598)			
Medium-size region				0.2816*	0.5854	0.0121
				(0.1092)	(0.3281)	(0.2162)
Large-size region				0.4284**	0.7889**	0.4506**
				(0.0889)	(0.2818)	(0.1583)
Control Variables	Y	Y	Y	Y	Y	Y
Region fixed effects	Y	Y	Y	Y	Y	Y
State fixed effects	Y	Y	Y	Y	Y	Y
Constant	1.7741**	1.9679**	1.7036**	2.654**	1.9016	3.7312**
	(0.6385)	(0.6085)	(0.5704)	(0.6495)	(1.3957)	(0.9427)
Observations	253	253	253	253	59	194
R-squared	0.7293	0.7348	0.7339	0.7837	0.9086	0.7805

Notes: a). To ensure the clarity and readability of this table, we have removed some interaction terms that are not relevant to the conclusions, including UrbanCore×Poly and UrbanCore×Commute in Model (3); Medium×Poly, Large×Poly, Medium×Commute, and Large×Commute in Models (4), (5), and (6). The complete regression table, including all variables, can be found in the supplemental materials. b). All regression models include a set of control variables including population density, total population, GDP per capita, employment in tertiary industry, unemployment rate, mean temperature (annual), and mean precipitation (annual). Robust standard errors are in parentheses: ** $p < 0.01$, * $p < 0.05$.

Appendix 5. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2025.106676.

Data availability

Data will be made available on request.

References

Ahlfeldt, G. M., & Pietrostefani, E. (2019). The economic effects of density: A synthesis. *Journal of Urban Economics, 111*, 93–107. https://doi.org/10.1016/j.jue.2019.04.006

Bechle, M. J., Millet, D. B., & Marshall, J. D. (2017). Does Urban Form Affect Urban NO_2? Satellite-Based Evidence for More than 1200 Cities. *Environmental Science & Technology, 51*(21), 12707–12716. https://doi.org/10.1021/acs.est.7b01194

Bereitschaft, B., & Debbage, K. (2013). Urban Form, Air Pollution, and CO_2 Emissions in Large U.S. Metropolitan Areas. *The Professional Geographer, 65*(4), 612–635. https://doi.org/10.1080/00330124.2013.799991

Borck, R., & Schrauth, P. (2021). Population density and urban air quality. *Regional Science and Urban Economics, 86*, Article 103596. https://doi.org/10.1016/j.regsciurbeco.2020.103596

Burgalassi, D., & Luzzati, T. (2015). Urban spatial structure and environmental emissions: A survey of the literature and some empirical evidence for Italian NUTS 3 regions. *Cities, 49*, 134–148. https://doi.org/10.1016/j.cities.2015.07.008

Carozzi, F., & Roth, S. (2023). Dirty density: Air quality and the density of American cities. *Journal of Environmental Economics and Management, 118*, Article 102767. https://doi.org/10.1016/j.jeem.2022.102767

Clark, L. P., Millet, D. B., & Marshall, J. D. (2011). Air Quality and Urban Form in U.S. Urban Areas: Evidence from Regulatory Monitors. *Environmental Science & Technology, 45*(16), 7028–7035. https://doi.org/10.1021/es2006786

Derudder, B., Liu, X., Wang, M., Zhang, W., Wu, K., & Caset, F. (2021). Measuring polycentric urban development: The importance of accurately determining the 'balance' between 'centers.'. *Cities, 111*, Article 103009. https://doi.org/10.1016/j.cities.2020.103009

ESDP (Ed.). (1999). *ESDP—European Spatial Development Perspective: towards balanced and sustainable development of the territory of the European Union*. Office for Official Publications of the European Communities.

Ewing, R. (1997). Is Los Angeles-Style Sprawl Desirable? *Journal of the American Planning Association, 63*(1), 107–126. https://doi.org/10.1080/01944369708975728

Ewing, R., Tian, G., & Lyons, T. (2018). Does compact development increase or reduce traffic congestion? *Cities, 72*, 94–101. https://doi.org/10.1016/j.cities.2017.08.010

Giuliano, G., & Small, K. A. (1993). Is the Journey to Work Explained by Urban Structure? *Urban Studies, 30*(9), 1485–1500. https://doi.org/10.1080/00420989320081461

Glaeser, E. L., & Gottlieb, J. D. (2009). The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States. *Journal of Economic Literature, 47*(4), 983–1028. https://doi.org/10.1257/jel.47.4.983

Green, N. (2007). Functional Polycentricity: A Formal Definition in Terms of Social Network Analysis. *Urban Studies, 44*(11), 2077–2103. https://doi.org/10.1080/00420980701518941

Han, S., Sun, B., & Zhang, T. (2020). Mono- and polycentric urban spatial structure and PM2.5 concentrations: Regarding the dependence on population density. *Habitat International, 104*, Article 102257. https://doi.org/10.1016/j.habitatint.2020.102257

Jin, Y., & Xu, Y. (2024a). Carbon reduction of urban form strategies: Regional heterogeneity in Yangtze River Delta. *China. Land Use Policy, 141*, Article 107154. https://doi.org/10.1016/j.landusepol.2024.107154

Jin, Y., & Xu, Y. (2024b). The divergent effects of polycentric urban form on urban carbon emissions: Spatial balance and spatial dispersion in Chinese cities. *Urban Climate, 55*, Article 101862. https://doi.org/10.1016/j.uclim.2024.101862

Kloosterman, R. C., & Lambregts, B. (2001). Clustering of economic activities in polycentric urban regions: the case of the Randstad. *Urban studies, 38*(4), 717–732.

Larkin, A., Geddes, J. A., Martin, R. V., Xiao, Q., Liu, Y., Marshall, J. D., … Hystad, P. (2017). Global Land Use Regression Model for Nitrogen Dioxide Air Pollution. *Environmental Science & Technology, 51*(12), 6957–6964. https://doi.org/10.1021/acs.est.7b01148

Lee, S., & Lee, B. (2014). The influence of urban form on GHG emissions in the U.S. household sector. *Energy Policy, 68*, 534–549. https://doi.org/10.1016/j.enpol.2014.01.024

Li, F., & Zhou, T. (2019). Effects of urban form on air quality in China: An analysis based on the spatial autoregressive model. *Cities, 89*, 130–140. https://doi.org/10.1016/j.cities.2019.01.025

Li, W., & Schmidt, S. (2024a). The spatial-temporal evolution of urban development patterns in Chinese cities: Dynamics and interpretations. *Growth and Change, 55*(2), Article e12722. https://doi.org/10.1111/grow.12722

Li, W., & Schmidt, S. (2024b). Can spatial patterns mitigate the urban heat island effect? Evidence from German metropolitan regions. *Environment and Planning B: Urban Analytics and City Science*. , Article 23998083241227500. https://doi.org/10.1177/23998083241227500

Li, W., Schmidt, S., & Siedentop, S. (2023). Can polycentric urban development simultaneously achieve both economic growth and regional equity? A multi-scale analysis of German regions. *Environment and Planning A: Economy and Space*. , Article 0308518X231191943. https://doi.org/10.1177/0308518X231191943

Li, W., Sun, B., Zhao, J., & Zhang, T. (2018). Economic performance of spatial structure in Chinese prefecture regions: Evidence from night-time satellite imagery. *Habitat International, 76*, 29–39. https://doi.org/10.1016/j.habitatint.2018.05.006

Li, Y., & Liu, X. (2018). How did urban polycentricity and dispersion affect economic productivity? A case study of 306 Chinese cities. *Landscape and Urban Planning, 173*, 51–59. https://doi.org/10.1016/j.landurbplan.2018.01.007

Li, Y., Xiong, W., & Wang, X. (2019). Does polycentric and compact development alleviate urban traffic congestion? A case study of 98 Chinese cities. *Cities, 88*, 100–111. https://doi.org/10.1016/j.cities.2019.01.017

Li, Y., Zhu, K., & Wang, S. (2020). Polycentric and dispersed population distribution increases PM2.5 concentrations: Evidence from 286 Chinese cities, 2001–2016. *Journal of Cleaner Production, 248*, Article 119202. https://doi.org/10.1016/j.jclepro.2019.119202

Liu, X., Hadiatullah, H., Tai, P., Xu, Y., Zhang, X., Schnelle-Kreis, J., … Zimmermann, R. (2021). Air pollution in Germany: Spatio-temporal variations and their driving factors based on continuous data from 2008 to 2018. *Environmental Pollution, 276*, Article 116732. https://doi.org/10.1016/j.envpol.2021.116732

Liu, P., Zhong, F., Yang, C., Jiang, D., Luo, X., Song, X., & Guo, J. (2022). Influence mechanism of urban polycentric spatial structure on PM2.5 emissions in the Yangtze River Economic Belt, China. *Journal of Cleaner Production, 365*, Article 132721. https://doi.org/10.1016/j.jclepro.2022.132721

Marcińczak, S., & Bartosiewicz, B. (2018). Commuting patterns and urban form: Evidence from Poland. *Journal of Transport Geography, 70*, 31–39. https://doi.org/10.1016/j.jtrangeo.2018.05.019

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

Meijers, E. (2005). Polycentric Urban Regions and the Quest for Synergy: Is a Network of Cities More than the Sum of the Parts? *Urban Studies, 42*(4), 765–781. https://doi.org/10.1080/00420980500060384

Meijers, E. J., & Burger, M. J. (2010). Spatial Structure and Productivity in US Metropolitan Areas. *Environment and Planning A: Economy and Space, 42*(6), 1383–1402.

Melo, P. C., Graham, D. J., & Noland, R. B. (2012). The effect of labour market spatial structure on commuting in England and Wales ‡. *Journal of Economic Geography, 12* (3), 717–737. https://doi.org/10.1093/jeg/lbr011

EU Ministers. (2020). *Territorial Agenda 2030. A future for all places* (pp. 1–32). https://ec.europa.eu/regional_policy/en/information/publications/brochures/2021/territorial-agenda-2030-a-future-for-all-places last accessed, August 1st, 2022.

Münter, A., & Volgmann, K. (2021). Polycentric regions: Proposals for a new typology and terminology. *Urban Studies, 58*(4), 677–695. https://doi.org/10.1177/0042098020931695

Ouwehand, W. M., van Oort, F. G., & Cortinovis, N. (2022). Spatial structure and productivity in European regions. *Regional Studies, 56*(1), 48–62. https://doi.org/10.1080/00343404.2021.1950912

Parr, J. (2004). The Polycentric Urban Region: A Closer Inspection. *Regional Studies, 38* (3), 231–240. https://doi.org/10.1080/003434042000211114

Roesel, F. (2022). The German Local Population Database (GPOP), 1871 to 2019. *Jahrbücher für Nationalökonomie und Statistik, 0*(0). https://doi.org/10.1515/jbnst-2022-0046

Schmidt, S., & Buehler, R. (2007). The Planning Process in the US and Germany: A Comparative Analysis. *International Planning Studies, 12*(1), 55–75. https://doi.org/10.1080/13563470701346592

Schmidt, S., Li, W., Carruthers, J., & Siedentop, S. (2021). Planning Institutions and Urban Spatial Patterns: Evidence from a Cross-National Analysis. *Journal of Planning Education and Research, 44*(3), 1186–1197. https://doi.org/10.1177/0739456X211044203

Schwanen, T., Dieleman, F. M., & Dijst, M. (2004). The Impact of Metropolitan Structure on Commute Behavior in the Netherlands: A Multilevel Approach. *Growth and Change, 35*(3), 304–333. https://doi.org/10.1111/j.1468-2257.2004.00251.x

Schweitzer, L., & Zhou, J. (2010). Neighborhood Air Quality, Respiratory Health, and Vulnerable Populations in Compact and Sprawled Regions. *Journal of the American Planning Association, 76*(3), 363–371. https://doi.org/10.1080/01944363.2010.486623

Stone, B. (2008). Urban sprawl and air quality in large US cities. *Journal of Environmental Management, 86*(4), 688–698. https://doi.org/10.1016/j.jenvman.2006.12.034

Sun, B., Han, S., & Li, W. (2020). Effects of the polycentric spatial structures of Chinese city regions on CO2 concentrations. *Transportation Research Part D: Transport and Environment, 82*, Article 102333. https://doi.org/10.1016/j.trd.2020.102333

Sun, B., Li, W., Zhang, Z., & Zhang, T. (2019). Is polycentricity a promising tool to reduce regional economic disparities? Evidence from China's prefectural regions. *Landscape and Urban Planning, 192*, Article 103667. https://doi.org/10.1016/j.landurbplan.2019.103667

Susilo, Y. O., & Maat, K. (2007). The influence of built environment to the trends in commuting journeys in the Netherlands. *Transportation, 34*(5), 589–609. https://doi.org/10.1007/s11116-007-9129-5

Thomas, R., Schmidt, S., & Siedentop, S. (2021). Toward comparative polycentricity scores: Assessing variations in regional delineation and subcenter identification. *Environment and Planning B: Urban Analytics and City Science*. https://doi.org/10.1177/23998083211065765, 239980832110657.

Tsai, Y.-H. (2005). Quantifying Urban Form: Compactness versus "Sprawl.". *Urban Studies, 42*(1), 141–161. https://doi.org/10.1080/0042098042000309748

European Union. (2011). Towards an Inclusive, Smart and Sustainable Europe of Diverse Regions. on 19th May 2011 in gödöllő, Hungary. In *Territorial Agenda of the European Union 2020*.

Van Donkelaar, A., Hammer, M. S., Bindle, L., Brauer, M., Brook, J. R., Garay, M. J., … Martin, R. V. (2021). Monthly Global Estimates of Fine Particulate Matter and Their Uncertainty. *Environmental Science & Technology, 55*(22), 15287–15300. https://doi.org/10.1021/acs.est.1c05309

Veneri, P. (2010). Urban Polycentricity and the Costs of Commuting: Evidence from Italian Metropolitan Areas. *Growth and Change, 41*(3), 403–429. https://doi.org/10.1111/j.1468-2257.2010.00531.x

Wang, G., Deng, J., Zhang, Y., Zhang, Q., Duan, L., Hao, J., & Jiang, J. (2020). Air pollutant emissions from coal-fired power plants in China over the past two decades. *Science of the Total Environment, 741*, 1–9, 140326.

Wang, M., & Debbage, N. (2021). Urban morphology and traffic congestion: Longitudinal evidence from US cities. *Computers, Environment and Urban Systems, 89*, Article 101676. https://doi.org/10.1016/j.compenvurbsys.2021.101676

Wang, M., Derudder, B., & Liu, X. (2019). Polycentric urban development and economic productivity in China: A multiscalar analysis. *Environment and Planning A: Economy and Space, 51*(8), 1622–1643. https://doi.org/10.1177/0308518X19866836

Wu, K., Chen, X., Anwar, S., & Alexander, W. R. J. (2022). Polycentric agglomeration and haze pollution: Evidence from China. *Environmental Science and Pollution Research, 30* (13), 35646–35662. https://doi.org/10.1007/s11356-022-24383-w

Xia, X., Sun, H., Tang, J., & Xu, L. (2024). Can polycentric urban spatial structures reduce pollution aggregation? *Ecological Indicators, 166*, Article 112461. https://doi.org/10.1016/j.ecolind.2024.112461

Zhang, W., & Derudder, B. (2019). How sensitive are measures of polycentricity to the choice of 'centres'? A methodological and empirical exploration. *Urban Studies, 56* (16), 3339–3357. https://doi.org/10.1177/0042098019843061

Zhao, P., Lu, B., & De Roo, G. (2011). The impact of urban growth on commuting patterns in a restructuring city: Evidence from Beijing. *Papers in Regional Science, 90* (4), 735–755. https://doi.org/10.1111/j.1435-5957.2010.00343.x