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Urban form, shrinking cities, and residential carbon emissions: Evidence from Chinese city-regions

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HIGHLIGHTS

- Shrinking cities tend to be less energy efficient than their growing counterparts.
- Shrinking cities need to consider the environmental effects of shrinkage.
- Urban compactness is negatively associated with residential CO_2 emissions.
- Intra-city polycentricity is negatively correlated with gas-related CO_2 emissions.

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ABSTRACT

This paper analyzes the relationship between urban form, shrinking cities, and residential carbon emissions, based on information collected for prefectural-level and above Chinese cities for the years of 2005, 2010, and 2015. After controlling for a number of urban form and socioeconomic variables (e.g., size, compactness, and polycentricity), this paper pays attention to residential carbon emissions in 'shrinking cities', which have experienced population loss and are a recent urban phenomenon in China. Everything else being equal, shrinking cities tend to be associated with less energy efficient than their growing counterparts, suggesting that these cities may not only be 'battling' with shrinking populations and economies but also need to consider the environmental issues.

1. Introduction

Sustainable urban form is often conceptualized and pursued as a supplementary solution to carbon emissions reduction in addition to technological and market-based 'fixes' [1,2]. Specifically, the spatial distribution of people, economic activities, and land uses is closely related to residential carbon emissions, most notably through the housing and transportation sectors [1–4]. Against this backdrop, planning visions such as polycentric urban form and compact cities are often regarded as ideal-typical urban patterns and associated with environmental sustainability [1,5,6]. Furthermore, few empirical studies have examined the relationship between urban form and carbon emissions within the context of urban shrinkage [7,8]. A city that is experiencing continuous population decline or 'urban shrinkage' may be less energy efficient than another growing city of the same population size [9,10]. For example, while the shrinking urban economy may be consuming less energy, a declining and often more sparsely distributed population may increase the demand for daily travel and costs for infrastructure network maintenance [11,12]. Specifically, Moss [11] (p.436) emphasizes technical and economic issues brought by "overcapacity in urban infrastructure systems in regions subject to dramatic socio-economic restructuring". Therefore, März et al. [12] question whether conventional carbon reduction strategies can be applied to shrinking cities. Further analyses are required to identify whether shrinking cities spur or alleviate environmental challenges [7,8].

While many 'postindustrial' cities in the US and Europe have

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experienced 'urban shrinkage' for decades and even rounds of 'right-sizing' and 'restoration' [13,14], shrinking cities are emerging in China [15,16]. For example, Yang and Dunford [16] have employed multiple population measures and observed that 88 of 336 Chinese prefectural-level cities had experienced population loss between 2000 and 2010, within the context of rapid urbanization at the national level. In a more recent book-length treatise [17], Long, Gao, and colleagues have recorded the overall trends and characterized significant individual cases of shrinking cities in China. Specifically, drawing upon Shrinking Cities International Research Network (SCiRN)'s definition, Long and Gao [18] (p.10) have identified 180 shirking cities from 653 Chinese cities (at different administrative levels) and suggested that identified shrinking cities "are not limited to a specific region like northeastern China or central China…most shrinking cities are small- to medium-sized cities". Much debates have focused on the causes of urban shrinkage [18,19], as Long and Gao [18] have suggested (1) resource-depleted cities; (2) lagging economies in central and western regions; (3) erstwhile industrial cities that are enduring economic transition as major types of shrinking cities in China. Further analyses have started to pay attention to socioeconomic correlates of urban shrinkages, such as the aging population structure [20] and (distributive effects of) transport infrastructure [21]. Overall, the relevant empirical literature needs to be further advanced, and more specifically the environmental dimensions of shrinking cities have been less well studied (see however [8]). Furthermore, analyses of the relationship between urban form and carbon emissions in China are often restricted to cross-sectional studies of major cities due to data availability [5].

Therefore, this study assesses the associations between urban form, urban shrinkage, and residential carbon emissions across Chinese cities for the years of 2005, 2010, and 2015. Specifically, the study controls for urban size, compactness, and polycentricity. The analysis focuses on residential CO_2 emissions, as industrial emissions largely depend on the industrial structure [22]. The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and highlights key research gaps. Section 3 introduces the data and methods. Section 4 presents the empirical findings and discusses potential policy implications. We conclude by identifying the limitations of this study and avenues for future studies.

2. Literature review

2.1. Urban form, socioeconomic structure, and carbon emissions

Previous analyses of urban form and carbon emissions have often examined the role of city size [1,2,5,23]. Many studies have found a 'scaling' relationship between population size and energy consumption of cities [24]. More recently, studies start to pay attention to other dimensions of urban spatial structure, such as urban compactness [1,6] and polycentricity [5,6,25]. For example, compact cities have been linked to urban heat island mitigation strategies [23] and associated with reduced carbon emissions [5]. Meanwhile, polycentric urban development emphasizes the emergence of multiple urban centers within a given area as well as the balanace of 'importance' among these centers [26–28]. Initially proposed within European and North American contexts, the drive for 'urban polycentricity' has gained momentum in Chinese academic and policy circles [29,30]. Specifically, in many masterplans, multiple employment and population centers outside the traditional urban cores have been proposed [29]. While urban polycentricity has been conceptually linked with improved environmental outcomes, the empirical literature seems to be inconclusive [5]. For example, it is unclear whether a more polycentric urban pattern would spur longer and more frequent travel between individual centers and thus increase emissions or whether it could enable more centers to reach 'critical mass' and promote a more efficient public transit system [2,31]. Still, Ewing and Rong [31] suggest that green space between multiple centers can help mitigate heat island effects, which are highly related to the temperature in the city and influence electricity consumption. Lee and Lee [2] find that polycentric development can help reduce CO_2 emissions by enhancing land use mixtures and shortening communication distances. By contrast, Zheng et al. [32] imply that urban polycentricity is often associated with greater housing supply and larger living spaces, which may, in turn, contribute to more electricity consumption and CO_2 emissions. Veneri [6] and more recently, Wang et al. [5] found that a more polycentric urban form is not necessarily associated with reduced CO_2 emissions. Furthermore, analyses may account for emissions from different sectors, for example, Li et al.'s [33] study of transportation-related emissions suggests that in large urban areas developing polycentric urban patterns might be less significant for mitigating passenger transport.

Additionally, existing studies have often assessed the association between socioeconomic characteristics, geographical factors, and CO_2 emissions. For example, Zhang et al. [22] and Wangpattarapong et al. [34] identify that the annual average rainfall is associated with residential CO_2 emissions, suggesting that the influence may be through household appliances and transport modal choices. Still, empirical evidence indicates that higher levels of gross domestic product (GDP), larger weights of tertiary industry, and larger proportion of young residents are usually significantly related to higher residential energy consumption [35,36]. Furthermore, the positive associations between private car ownership and energy consumption and CO_2 emissions have been identified at multiple levels [37]. Using scenario simulations with an integrated model, Liu et al. [38] reveal that technological investment and compact urban spatial patterns may facilitate the balancing of economic development and emission reduction. Xie et al. [39] find that the provision of transportation infrastructure increases carbon emissions for large and medium-sized cities. Furthermore, socioeconomic development, such as cultivating awareness of energy-saving, may facilitate emissions reduction [40].

Therefore, given the complexity of the interactions between urban form, socioeconomic characteristics, and residential carbon emissions, it is necessary to accumulate more empirical evidence across different geographical areas. One of the major contributions to the field of applied energy is therefore to empirically examine such complicated relationships in the context of urbanizing China while considering the emerging phenomenon of shrinking cities, which will be introduced with details in the next section.

2.2. Shrinking cities and carbon emissions

Shrinking cities generally refer to urban areas that have undergone long-term population loss and lagging economies [14]. Such a phenomenon was initially found in Europe (e.g., many Eastern German cities after the unification as well as erstwhile industrial cities; Turok and Mykhnenko [41]), the US (e.g., cities in the 'rust belt'), and more recently in China [16]. Although similar phenomena can be observed around the world, remarkable diversities exist beneath such similarities at the surface [42,43]. As noted above, existing studies have debated the definitions, underlying processes, socioeconomic consequences, as well as policy responses of shrinking cities [17,43]. While the literature has emphasized the environmental significance of urban shrinkage [9,12], the empirical assessment of the relationship between shrinking cities and environmental impacts could be further advanced.

Extending from März et al.'s [12] framework, urban shrinkage could affect residential carbon emissions through different channels. Many existing studies have found a positive relationship between economic development and energy use. Following this logic, lagging economies in shrinking cities often lead to decreasing income levels and reduced energy use. For example, März et al. [12] have detailed the reduction in energy use in a shrinking German city, though their analysis does not differentiate between industrial and residential energy uses. Relatedly, Satterthwaite [44] suggests that increasing levels of consumption rather than population growth have more significant impacts on carbon emissions. Furthermore, within the North American and European contexts, recent literature has identified the relevance of vacant lands in shrinking cities for carbon reduction [13]. Specifically, Schilling and Logan [13] (p.455) suggest that "shrinking cities should transition to the new green economy by converting their vacant and abandoned properties to create new and different economic opportunities", which include using vacant lands for biofuel, urban forests, and urban farming.

However, a city experiencing a continuous population loss or 'urban shrinkage' may be less energy efficient than another growing city of the same population size [9,10,12]. First, urban shrinkage often results in more sparsely distributed population and economic activities, as compared to 'growing' cities of the same size. Lower densities of population and economic activities are often associated with (1) greater job-housing imbalance, longer commuters, and increased energy consumption for transportation; (2) higher energy demands for heating and cooling [12]. Second, infrastructure networks such as pipelines, electricity grids, and central heating in shrinking cities face the imminent problems of overcapacity and inefficiency [11,12]. As Moss [11] notes, many of these technologies and infrastructure networks have 'over-capacity', as they are planned and developed for 'growing cities'. However, the combination of reduced demands by shrinking cities and the infrastructure networks developed for a larger population result in technical, economic, and environmental issues. For example, for electricity grids and central heating systems, such underused networks may entail costly maintenance and energy loss during the transmission process [11]. Lastly, the geography of cities matters [2], as cities in colder locations may require more energy for heating [12]. This is particularly relevant for the Chinese case, as existing studies suggest that many old industrial towns in China's northeastern provinces are undergoing urban shrinkage [16]. These cities could be 'double whammed' in the sense that their resource- and manufacturing-driven economies are lagging while their cold winters require central heating [17].

To sum up, whether shrinking cities are associated with more or fewer carbon emissions is inconclusive. Furthermore, existing studies about the relationship between urban form and CO_2 emissions have overlooked cities with different development trajectories [8]. Exploring such a question with a longitudinal dataset of a sizeable set of Chinese city-regions is the main contribution being attempted here.

3. Data and methods

3.1. Data sources

Energy use and carbon emissions: For individual cities, we estimate residential CO_2 emissions based on gas, electricity, transportation, and heating energy consumption reported in the Chinese City Statistical Yearbooks as well as emissions factors from the Intergovernmental Panel on Climate Change (IPCC) [22]. According to IPCC and related studies [5,22], residential CO_2 emissions are mainly derived from energy consumption. Meanwhile, Zhang et al. [22] note that industrial emissions at the city level are more associated with industrial structures rather than urban form. Existing studies often use city-level statistics about energy consumption to estimate total residential CO_2 emissions, as the major alternative method, household-level surveys, is often time-consuming and resource-intensive [45]. More recently, remote sensing-based methods have been developed to estimate gridded CO_2 emissions, though these methods cannot easily separate residential and industrial emissions [46]. More detailed discussions about CO_2 emission for China can be found in Shan et al. [47]. Furthermore, the influence of urban form on residential CO_2 emissions in different subsectors is not necessarily the same. For example, Yuan et al. [48] and Zheng et al. [32] suggest that the influence on transport-related and electricity-related CO_2 emissions is different. Therefore, following Zhang et al. [22], we adopt a four-type categorization of residential CO_2 emissions as well as estimate energy use in individual categories by synthesizing information from statistical yearbooks, official reports, and previous academic studies (e.g., China City Statistical Yearbook; China Urban Construction Statistical Yearbook; China Energy Statistical Yearbook; and China Statistical Yearbook for Regional Economy).

Urban form: The measurement of urban form is at the city level as well. We rely on gridded population distribution data from Landscan^{TM} High-Resolution Global Population Data [49] as well as land use/cover information from the National Administration of Surveying, Mapping and Geoinformation of China. While the Landscan dataset is used to characterize polycentricity, the land use/cover dataset is used for calculating compactness. The LandScan dataset provides estimates of population density at approximately 1 km-by-1 km scale, thus allowing for the characterization of population distribution within cities and avoiding the complications brought by administrative boundary adjustment [50].

Socioeconomic and geographic variables: Information about GDP, population, and industrial composition for individual cities (*shiyu*) is gathered from Chinese City Statistical Yearbooks. The above datasets are collected for 2005, 2010, and 2015. Climate variables such as monthly average temperature and rainfall for the period of 1970–2000 are acquired from the *World Climate* website (http://www.worldclim.org/) and sampled for individual cities using GIS spatial analytical tools. Our analysis focuses on Chinese cities at the prefectural level and above [5]. Due to data availability, we can collect information for 271 Chinese cities (Appendix A). Specifically, for the analysis of emissions from residential electricity, gas, and transportation sectors, our sample includes 727 emissions records for the 271 cities in the three selected years. For the analysis of emissions from central heating, as not all Chinese cities are equipped with such service, we have collected emissions records for 136 cities during the study period. This study has constructed samples with about two-thirds of the Chinese cities at the prefectural level and above, and most of them are located in densely populated central and eastern China.

3.2. Methods

3.2.1. Estimating CO_2 emissions of urban residents

Overall, we have replicated Zhang et al.'s [22] methodology and expanded the estimation of residential carbon emissions to include multiple years. For individual cities, the direct residential CO_2 emissions (DCE; following the terminologies used in Zhang et al. [22]) are measured as the sum of four consumption sources: electricity (EDCE), gas (GDCE), transport (TDCE), and central heating (CDCE). Specific formulas for calculating individual components of residential CO_2 emissions are reported in Table 1.

We report the gist of Zhang et al.'s [22] approach here to make the current study self-standing. First, for residential electricity emissions (EDCE), the electricity consumption of residents for individual cities is gathered from *China City Statistical Yearbook*, and the emissions rates are reported in *Regional Grid Baseline Emissions Factors.* In other words, different electricity emissions factors are used for individual cities based on the regional grid to which they belong. Second, for gas-related emissions (GDCE), information about liquefied gas, coal gas, and natural gas consumption is from the *China Urban Construction Statistical Yearbook*. The corresponding carbon emissions factors are obtained from the *IPCC National Greenhouse Gas Emissions Inventory Guidebook* 2006. Third, for emissions-related to central heating, the heating areas of individual cities are collected from *China Urban Construction Statistical Yearbook,* while unit coal consumption for heating is reported in *Energy Conservation Design Standard* in China. Fourth, for transport-related emissions, the analysis accounts for taxis, buses, and private vehicles. The number of buses and taxis is compiled from *China City Statistical Yearbook*. Following Zhang et al. [51], bus speed and fuel factors are set at 16 km/h and 32 L/100 km, respectively. Similarly, we set annual taxi mileage and corresponding fuel factor at 12,000 km and

Table 1
Estimation methods for EDCE, GDCE, TDCE, and CDCE (Recreated based on Zhang et al. [22]).

$EDCE = E_1 \times EF_{1i}$	$GDCE = \sum_{i=1}^{r} F_r \times NV_r \times EF_r$	$TDCE = \sum_{i=1}^{s} Q_s \times L_s \times \alpha_s \times EF_s + EF_{S2} \times E_2 \times Q_{s2}/Q_{s2}^{'}$	$CDCE = S \times N \times EF_0$
E_1 represents the electricity consumption of an urban population. EF_{1i} is the urban emissions factor.	r indicates the type of residential gas use. F_r denotes the consumption of individual types of gas. NV_r is the calorific value of individual types of gas.	s is the type of considered public vehicles. Q_s is the amount of individual types of public vehicles. L_s is the annual mileage of individual types of public vehicles. α_s is the fuel factor of individual types of public vehicles. EF denotes the corresponding carbon emissions factor. Q_{s2} and $Q_{s2}^{'}$are the numbers of private vehicles in individual cities and corresponding provinces, respectively. E_2 represents the household gasoline consumption in the province.	S represents the heating area of individual cities. N corresponds to the coal consumption for central heating. EF_0 denotes the carbon emissions factor of standard coal.

10 L/100 km, respectively [52]. As for the private vehicles, statistics are mostly provided as provincial aggregates, and city-level tallies are only reported in *China Statistical Yearbook for Regional Economy* for 2006–2013. Therefore, we use 2006 and 2010 private vehicle numbers from *China Statistical Yearbook for Regional Economy* to estimate transport emissions in 2005 and 2010. For 2015, we rely on provincial and municipal yearbooks as well as statistical bulletins.

3.2.2. Measuring urban shrinkage in China

The key independent variable in this study is a dummy variable to indicate whether a corresponding city has experienced a long-term population loss between 2005 and 2015. A value of 1 indicates urban shrinkage, and 0 otherwise. As the definition and measurement of 'shrinking cities' within the Chinese context are still subject to debates (see for example the different numbers of shrinking cities as identified in different studies such as Yang and Dunford [23], Long and Gao [18], and Wu and Li [53]), a dummy variable may be more robust than specific population counts. Similarly, in Xiao et al. [8], cities are categorized into individual groups of growing and shrinking cities. To further ensure the robustness of our analysis, we have employed three ways to identify shrinking cities. The first two measures are based on the population figures in city districts (*shiqu*) and the whole cities (*shiyu*) as reported in *China City Statistical Yearbook*. For the ease of international readers, Chinese administrative cities are akin to city-regions in the US and European contexts [50], which consist of 'urban districts' as well as outlying towns, villages, and rural areas. As there is a mismatch between the administratively and functionally defined urban populations in Chinese cities, we use population figures for both city districts and the whole cities to improve robustness (see Chan [54] for a detailed discussion on *de jure* and *de facto* population in Chinese cities). The third list of prefectural-level and above cities that have experienced shrinkage during 2007–2016 is reported by Wu and Li [53], which has accounted for different definitions of the 'urban population'. The three lists contain 60, 30, and 22 shrinking cities for our analysis, respectively. For a more detailed account of geographical patterns of urban shrinkage in China, see Long and Gao [18].

3.2.3. Compiling urban form, geographic, and socioeconomic correlates

Similar to [5], the first urban form variable is the compactness of developed areas in individual cities. Compactness (COMP) reflects the degree of concentration of urban development from a land use/cover perspective. The calculation method of the compactness indicator is based on the minimum circumscribing circle [55,56]. As there might be several noncontiguous developed areas within a city, we use the average compactness ratio to assess the overall compactness of development [5]:

$$COMP = \frac{1}{n}\sum_{k=1}^{n}\frac{A_k}{A_k^c} \tag{1}$$

where n is the number of 'urbanized' areas in a city; A_k is the area of the kth urbanized area; A_k^c is the area of the minimum circle of the kth urbanized area. As mentioned above, the urbanized areas (i.e., A_k) are identified based on land use data from the National Administration of Surveying, Mapping and Geoinformation of China. A higher compactness variable corresponds to more concentrated urban development and vice versa.

Our analysis also accounts for the patterns of intra-city polycentric urban development (POLY). Following Liu et al. [30], we identify individual population centers within individual cities and evaluate whether the population is evenly distributed across the population centers:

$$POLY = 1 - \frac{\sigma_{abs}}{\sigma_{\max}} \tag{2}$$

where $POLY$ denotes the polycentricity of individual cities; σ_{abs} is the standard deviation of the population size of all the centers within the corresponding city; population centers within individual cities are identified as contiguous densely populated grids in the Landscan dataset (See Liu et al. [30] for more details); $\sigma_{\max}$is the standard deviation of population size in a 'hypothetical' two-center city, with one center of zero population and the other with 'maximum' population. $POLY$ ranges from 0 to 1, with values of 0 and 1 pointing to a total lack of polycentricity and absolute polycentricity, respectively.

Furthermore, relevant socioeconomic and climate variables are used as control variables. Population size (POP), per capita GDP (PGDP), and percent of tertiary industry in total GDP (WTI) are gathered from China City Statistical Yearbooks of corresponding years. Also, information about annual average temperature (ATEMP) and per capita paved road (PROAD) enter the model selection process. The natural logarithm of each of these variables is taken to control for nonstationarity and heteroskedasticity issues. Summary statistics of key variables are listed in Table 2.

3.2.4. Regression analysis

Building upon previous studies [5,57], a panel model is employed to link urban form and socioeconomic variables with residential CO_2 emissions in selected cities.

$$y_{it} = \beta x_{it} + \delta x_{it\_m} \times x_{it\_n} + \varnothing z_i + \varepsilon_{it} \tag{3}$$

where y_i is the dependent variable and, in our cases, represents the residential CO_2 emissions of city i; x_{it} is a vector representing the independent variables, including urban form indicators (compactness and

Table 2
Descriptive statistics of key variables.

Variable	unit	Obs	Mean	Std.Dev.	Min	Max
DCE	10,000 tons	727	1830.48	3539.25	44.23	42595.58
GDCE	10,000 tons	727	159.94	372.82	0.67	3764.08
EDCE	10,000 tons	727	1003.85	1976.86	21.52	20858.51
CDCE	10,000 tons	337	773.34	1435.19	5.21	11906.02
TDCE	10,000 tons	727	308.17	688.01	7.49	9618.22
POP	10,000 people	727	147.24	186.49	14.62	2129.09
PGDP	10,000 yuan	713	45056.82	31964.62	3420.00	249040.00
PROAD	m/people	722	10.83	7.54	0.74	105.02
WTI	%	725	0.43	0.11	0.10	0.80
TEMP	degree	337	10.33	3.90	−0.99	19.99
COMP	N/A	727	0.52	0.08	0.20	0.74
POLY	N/A	727	0.21	0.25	0.00	1.00

polycentricity), geographic and socioeconomic correlates (population, GDP per capita, the proportion of tertiary industry in GDP, annual average temperature and annual average precipitation); z_i are time-invariant variables, including a dummy variable to capture whether the city has been 'shrinking' in the study period, another dummy indicating whether the city has central heating services, as well as the average monthly temperature; and ε_i is the error term. x_{it_m} and x_{it_n} are the potential factors with interactive effects on residential CO_2 emissions. In this study, interaction effect assumptions are made that the relationships between urban form indexes and residential CO_2 emissions depend on levels of population size.

The regression is run for DCE as well as the four individual components. The models for heating energy consumption include only 136 cities, as citywide central heating is not provided in southern China. The VIF results indicate that variables do not suffer a high degree of multicollinearity. As the Breusch-Pagan LM test is significant, we choose random-effects models over pooled OLS for our panel analysis. In our models, the shrinking variable is time-invariant. Therefore, we include the between effects (BE) estimator for supplementary estimates as the random-effects results are weighted averages of BE and fixed effects estimators (Appendices B–D).

4. Results and discussions

4.1. Overall findings

The three sets of models with different urban shrinkage dummy variables are presented in Tables 3–5. We first discuss the significance of variables other than the urban shrinkage dummy and compare our results with previous studies. First, population size (POP) and GDP per capita (PGDP) are positively correlated with residential CO_2 emissions in China, which is consistent with the existing literature [5,51,57,58]. This relationship applies to total carbon emissions (DCE) as well as residential emissions in most sectors. Specifically, the influence of population size is in line with existing studies on the 'scaling' law [22,59], with the coefficients for population size in nearly all models smaller than 1.

Second, our results imply that cities with a higher proportion of tertiary sector is associated with more energy consumption [22], which is partly consistent with Li et al. [57]'s finding where an improvement of technological level increases carbon emissions, and industrial structure is not the main factor in carbon emissions in high emissions regions. Relatedly, a higher proportion of the tertiary sector may reflect a higher level of wealth of the city, which is consistent with the wealth effect of carbon emissions [5,51]. Furthermore, a higher proportion of the tertiary sector may be associated with more urban consumptions and travel, as energy consumption and private car ownership are positively associated with CO_2 emissions [37]. Along this line, Xiao et al. [8] have observed that even in 'rapidly shrinking cities' one of the main reasons for the recent increase in carbon emissions is the growing tertiary industry. Nevertheless, a higher level of urban consumption and upgrade of lifestyle may increase the adoption intention of smart energy monitors, which may optimize residential energy usage in the long run [60].

Third, in line with Liu et al. [56] and Fang et al. [1], compactness is negatively associated with residential carbon emissions. This result may be due to the fact that compact areas could lead to the higher efficiency of city operations and less energy consumption. In particular, the influence of compactness is statistically significant for transportation and electricity-related residential energy use. As the compactness ratio can be related to a suite of urban settlement parameters, it may provide a direct 'handle' for emission-mitigation planning practices [55].

Fourth, intra-city polycentricity (POLY) is only significant for gas-related energy consumption. Indeed, polycentricity is marginally significant in a previous study [5]. Wang et al. [5] (p. 6) have discussed the "*potential trade-off effects between urban compactness and polycentricity…as the polycentricity measure focuses on population distribution at the city level and does not reflect subcenters within the built-up area* [2] *… For many Chinese cities, a more polycentric urban pattern at the city level often means a relatively small and thus less dense central urban district.*" The interaction effect between polycentricity and population size on residential carbon emissions is not statistically significant. Different

Table 3
Correlates of residential carbon emissions with the urban shrinkage dummy variable measured based on city-district population.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	DCE	TDCE	EDCE	GDCE	CDCE
Ln (POP)	0.903***	0.915***	0.976***	1.055***	0.769***
	(0.0302)	(0.0433)	(0.0333)	(0.0450)	(0.111)
Ln (PGDP)	0.572***	0.396***	0.560***	0.431***	0.927***
	(0.0244)	(0.0524)	(0.0253)	(0.0369)	(0.0639)
WTI	1.363***	0.766***	1.337***	0.684**	1.491***
	(0.164)	(0.220)	(0.211)	(0.303)	(0.369)
COMP	−0.368**	−0.758***	−0.501**	−0.0744	0.629
	(0.167)	(0.290)	(0.205)	(0.321)	(0.444)
POLY	−0.0862	0.119	−0.0416	−0.278**	−0.0840
	(0.0639)	(0.0933)	(0.0654)	(0.122)	(0.190)
Urban Shrinkage (Shrinking = 1)	0.0909**	−0.0353	0.0738	0.0249	0.150*
	(0.0443)	(0.0573)	(0.0540)	(0.0774)	(0.0855)
Central Heating (Heating = 1)	0.389***				
	(0.0419)				
Ln (PROAD)		0.266***			
		(0.0651)			
TEMP					−0.596
					(0.379)
Constant	−3.946***	−4.003***	−4.541***	−5.426***	−7.252***
	(0.299)	(0.527)	(0.331)	(0.452)	(0.979)
Breusch and Pagan LM test	160.87***	205.69***	145.80***	124.07***	96.04***
Observations	713	708	713	713	332
Number of groups	271	271	271	271	136

Robust standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

Table 4
Correlates of residential carbon emissions with the urban shrinkage dummy variable measured based on city-wide population.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	DCE	TDCE	EDCE	GDCE	CDCE
Ln (POP)	0.913***	0.925***	0.984***	1.046***	0.771***
	(0.0300)	(0.0441)	(0.0336)	(0.0456)	(0.113)
Ln (PGDP)	0.581***	0.394***	0.567***	0.432***	0.948***
	(0.0243)	(0.0519)	(0.0249)	(0.0371)	(0.0639)
WTI	1.415***	0.760***	1.376***	0.685**	1.599***
	(0.169)	(0.219)	(0.215)	(0.304)	(0.386)
COMP	−0.337**	−0.769***	−0.470**	−0.0693	0.738*
	(0.167)	(0.287)	(0.206)	(0.320)	(0.448)
POLY	−0.0875	0.117	−0.0415	−0.273**	−0.120
	(0.0640)	(0.0937)	(0.0658)	(0.123)	(0.187)
Urban Shrinkage (Shrinking = 1)	0.246***	0.0951	0.197***	−0.112	0.525
	(0.0778)	(0.115)	(0.0665)	(0.108)	(0.346)
Central Heating (Heating = 1)	0.379***				
	(0.0406)				
Ln (PROAD)		0.265***			
		(0.0648)			
TEMP					−0.537
					(0.356)
Constant	−4.142***	−4.033***	−4.701***	−5.382***	−7.772***
	(0.302)	(0.523)	(0.335)	(0.466)	(1.018)
Breusch and Pagan LM test	146.05***	202.38***	137.65***	125.84***	86.38***
Observations	713	708	713	713	332
Number of groups	271	271	271	271	136

Robust standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

CO_2 datasets reveal that a high concentration of CO_2 emissions is usually in polycentric urban regions of China [46]. We also note that such a relationship at different spatial scales may result in a different pattern [61].

4.2. Shrinking cities and residential carbon emissions

In the models of total residential carbon emissions (i.e., DCE), everything else being equal, urban shrinkage is positively correlated with CO_2 emissions, suggesting that shrinking cities might be associated with less energy efficiency than growing cities of similar sizes. This

Table 5
Correlates of residential carbon emissions with the urban shrinkage dummy variable from Wu and Li [53].

	(1)	(2)	(3)	(4)	(5)
VARIABLES	DCE	TDCE	EDCE	GDCE	CDCE
Ln (POP)	0.901***	0.927***	0.971***	1.050***	0.752***
	(0.0319)	(0.0436)	(0.0346)	(0.0460)	(0.117)
Ln (PGDP)	0.579***	0.391***	0.566***	0.433***	0.946***
	(0.0242)	(0.0520)	(0.0249)	(0.0370)	(0.0638)
WTI	1.394***	0.750***	1.360***	0.693**	1.575***
	(0.172)	(0.219)	(0.219)	(0.302)	(0.384)
COMP	−0.329*	−0.764***	−0.470**	−0.0687	0.775*
	(0.169)	(0.289)	(0.205)	(0.320)	(0.452)
POLY	−0.0853	0.115	−0.0397	−0.275**	−0.121
	(0.0643)	(0.0938)	(0.0657)	(0.123)	(0.188)
Urban Shrinkage (Shrinking = 1)	0.142*	0.187*	0.0420	−0.0755	0.512*
	(0.0817)	(0.110)	(0.0868)	(0.111)	(0.290)
Central Heating (Heating = 1)	0.388***				
	(0.0417)				
Ln (PROAD)		0.270***			
		(0.0658)			
TEMP					−0.572
					(0.369)
Constant	−4.044***	−4.024***	−4.598***	−5.421***	−7.572***
	(0.299)	(0.524)	(0.330)	(0.454)	(1.007)
Breusch and Pagan LM test	161.52***	199.87***	150.08***	124.98***	100.98***
Observations	713	708	713	713	332
Number of groups	271	271	271	271	136

Robust standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

relationship holds with all three dummies of shrinkage (model 1 in Tables 3–5). As noted earlier, März et al. [12] have suggested reduced energy use in shrinking German cities. Similarly, carbon emissions are lowest in rapidly shrinking cities among the different groups of cities, as analyzed in Xiao et al. [8]. Existing studies have often associated urban shrinkage in China with lagging economic development [17], while Satterthwaite [44] suggests that levels of consumption exert a more significant influence on carbon emissions. More relevant to our purpose here, our results imply that controlling for variables about absolute population size (POP) and socioeconomic development (PGDP), a city that is experiencing continuous population loss or 'urban shrinkage' may be less energy efficient than another growing city of the same population size [9,10]. One potential underlying factor, as pointed out in the literature on 'right-sizing' cities and infrastructure networks [12,13], is that an oversupply of infrastructure and sparsely distributed populations may lead to more energy use [9]. However, no significant interactive effects of urban shrinkage and population size on total residential carbon emissions observed.

Furthermore, joint reading of the three sets of models based on our three urban shrinkage dummies suggests that the significance of urban shrinkage may be most in central-heating related energy use (model 5 in Tables 3–5). The urban shrinkage dummy variables are positive and significant for two models of CDCE. Because average monthly rainfall and temperature variables are highly correlated, only the temperature variable is included in the reported models. For robustness checking purposes, if the averaged monthly temperature is substituted by the average rainfall (see, for example [22,34]), the urban shrinkage dummy variables will be significant in all three models of CDCE. This seems to be in line with Moss's [11] observation that many of the infrastructure networks developed under urban growth scenarios have 'over-capacity'. Specifically, as noted above, for central heating systems, the combination of reduced demands in shrinking cities and a central heating network previously developed for a larger/growing population may lead to rising maintenance costs and increased transmission loss, *ceteris paribus* [12]. Furthermore, the urban shrinkage dummies are significant for TDCE and EDCE, each in one model. Such finding echoes with the reasoning that lower densities of population and economic activities in shrinking cities are often associated with greater job-housing imbalance, longer commuters, and increased energy consumption for transportation, and higher energy demands for heating and cooling [9,12].

4.3. Interaction effects on residential carbon emissions

Table 6 provides the results of the interaction effects between population size, compactness, polycentricity, and urban shrinkage. Overall, there is a significant negative interaction effect between population size and compactness. A joint interpretation of the coefficients in Tables 3–6 reveals that although population size is positively associated with carbon emissions, as a city's compactness increases, the positive effect of population size on carbon emissions decreases [1]. In other words, urban compactness potentially mitigates the effect of population size on carbon footprint [5]. When other covariates are held, urban compactness can reduce the CDCE of the population by about 1.017% for cities with an average population. In other words, population size strengthens the potential impact of compactness on CDCE. For cities with one million population, urban compactness is associated with 3.98% more reduction of CDCE; for cities with a population of five million, such number can reach 5.62%. Such interaction effects imply a positive role of compact urban development on energy efficiency. Indeed, this finding resonates with the results of a case study of 30 provincial capital cities of China [1]. Provincial capital cities in China are usually the largest city regarding population size in that province. One possible reason is that a large and densely populated city is more likely to establish a broader range of public transport with more efficient road network systems [1].

Furthermore, Table 6 examines the interaction effects between per capita GDP, compactness, polycentricity, and urban shrinkage. With a significantly negative interaction effect between per capita GDP and urban shrinkage, it suggests that while urban shrinkage itself is associated with higher carbon emissions, urban shrinkage may complicate the sitatuion and mitigate the positive role of economic growth on carbon emissions (notably in TDCE), whose relationship has been well researched (e.g., [35,36]). Specifically, when comparing shrinking cities with their non-shrinking counterparts, the DCE associated with economic growth (PDGP) in shrinking cities is 0.189% lower. Put differently, while shrinking cities may have high carbon emissions due to the legacy of their infrastructure (such as electricity and heating facilities), the economic structure of those cities may have been shifted, which may, in turn, affects carbon emissions (see however [8]).

4.4. Summary of empirical results

Our analysis points to the significance of urban form for residential CO_2 emissions. First, our analysis is consistent with previous analyses of urban compactness [1,5]. In fact, many ongoing urban policies, such as '*sanjizhong*' and '*jiyue jieyue*', have been proposed to increase land use efficiency and promote population concentration, which will, in turn, lead to more compact urban patterns [62]. This approach is also consistent with the recent shift in focus from urban expansion to urban

Table 6
Results of interaction effects.

	Interactive effects	DCE	TDCE	EDCE	GDCE	CDCE
City district shrinkage	COMP × Ln (POP)	−0.558**	−0.579*	−0.533**	−1.006**	−0.887
	POLY × Ln (POP)	0.0812	−0.114	0.0628	0.0304	0.330
	Urban Shrinkage × Ln (POP)	−0.131	0.101	−0.0823	0.129	−0.0919
	COMP × Ln (PGDP)	0.0414	0.0779	0.212	−0.0990	−0.169
	POLY × Ln (PGDP)	−0.0514	0.141	−0.0472	−0.294**	−0.140
	Urban Shrinkage × Ln (PGDP)	−0.189***	−0.214**	−0.195***	−0.0776	−0.228*
City wide shrinkage	COMP × Ln (POP)	−0.551**	−0.564	−0.528*	−1.025**	−0.962
	POLY × Ln (POP)	0.0531	−0.112	0.0408	0.0417	0.305
	Urban Shrinkage × Ln (POP)	−0.227	0.237	−0.289*	0.0186	−0.979*
	COMP × Ln (PGDP)	0.0402	0.0593	0.203	−0.0811	−0.150
	POLY × Ln (PGDP)	−0.0646	0.138	−0.0569	−0.285**	−0.116
	Urban Shrinkage × Ln (PGDP)	−0.114*	−0.229***	−0.109	−0.0715	−0.0902
Shrinkage measured by Wu and Li [53]	COMP × Ln (POP)	−0.581***	−0.579*	−0.545**	−1.008**	−1.017*
	POLY × Ln (POP)	0.0810	−0.106	0.0607	0.0271	0.361
	Urban Shrinkage × Ln (POP)	−0.0141	−0.0197	0.0877	−0.0744	−0.279
	COMP × Ln (PGDP)	0.0591	0.0655	0.229	−0.0915	−0.109
	POLY × Ln (PGDP)	−0.0484	0.137	−0.0446	−0.291**	−0.127
	Urban Shrinkage × Ln (PGDP)	−0.0993*	−0.358***	−0.0836	−0.263**	−0.203**

redevelopment [63]. Of course, we do not suggest an overall concentration of population and economic activities, as this will inevitably incur high agglomeration costs [64]. Second, our analysis only identifies the negative associations between higher levels of intra-city polycentirícty and reduced GDCE (see also [5]). Along this line, research about the influence of urban polycentricity on economic productivity indicates that Chinese polycentric urban development may not necessarily contribute to urban productivity [62]. Similarly, a recent study of multiscalar polycentricity of China has revealed that intra-city monocentriy and inter-city polycentricity are associated with better urban economic productivity [61]. Third, in line with the literature on urban shrinkage, our models find that shrinking cities tend to be associated with more residential emissions than growing cities of the same population size, controlling for other urban forms and socio-economic correlates. Specifically, such a relationship is more significant in energy use for heating. This result may be due to "overcapacity in technical networks that emerged in the context of 'shrinking' processes" [11] (p.437). While China is still undergoing rapid urbanization, recent studies have noticed population loss in a number of cities [15,17], thus calling for the need to consider the environmental, social, and economic dimensions of shrinking cities. The phenomenon of shrinkage in China has its characteristics [17,65]. For example, shrinking and growing are processes that can be observed in a parallel [66]. Still, as opposed to many case studies in European and North American cities, Wu and Wang [66] have found that residents may feel safer and a higher living quality after the population loss in a recent case study of Yiwu City.

5. Conclusions

The analysis uses a large sample of Chinese cities for the years 2005, 2010, and 2015 to assess the relationship between residential carbon emissions and urban spatial structure. Being consistent with and extending from the existing literature, our analysis points to the following findings. First, urban compactness is negatively associated with residential CO_2 emissions [1,56]. Second, polycentricity is correlated with fewer emissions but only statistically significant for a few models, which is possibly due to a trade-off effect between urban compactness and polycentricity at the selected scale of measurement [5]. Third, population size, GDP per capita, and the proportion of tertiary sector are often significantly related to residential emissions [2,3]. Most importantly, our analysis pays attention to carbon emissions in 'shrinking cities', which have experienced population loss and are a recent urban phenomenon in China [15,17]. Everything else being equal, shrinking cities tend to be less energy efficient (in residential energy consumption) than their growing counterparts, suggesting that these cities not only are 'battling' with declining populations but also need to consider the environmental effects of shrinkage [11,12]. Analysese of interaction terms also suggest complex relationships between economy, urban shrinkage, and carbon emissions [8]. Our analysis also points out that among the four selected sectors of energy use, the association between urban shrinkage and central-heating related residential carbon emissions seems to be more significant. However, as noted above, Xiao et al. [8] have suggested that the increases in carbon emissions in 'rapidly shrinking cities' may be due to a shift towards secondary/tertiary sectors.

Our study has the following limitations, which also lays the foundation for future studies. First, there are caveats in our collection of emissions data, despite our efforts in following and extending previous appraoches (e.g., [1,2,22]). For example, we only consider coal for central heating, while coal is increasingly used for such purpose [67]. Second, the polycentric urban development in this study focuses on 'population centers' and is approximated from a morphological perspective. By contrast, future studies may characterize urban polycentricity based on employment centers and through functional flows. Such studies are increasingly feasible given the emergence of the new urban data environment [68]. Third, the urban form may affect not only residential CO_2 emissions but also air pollutants. Comprehensively analyzing the influence of urban forms on CO_2 emissions and polluting gases is necessary, and an integrated available urban development strategy should be pursued. Still, we understand that residential carbon emissions are a limited part of overall carbon emissions for many shrinking cities [8]. Relatedly, while existing analyses are constrained by the quality of statistical yearbooks and government reports in China, our models can be refined with new data sources about emissions and pollution in China [46,48]. Finally, pointing to the nexus among urban form, shrinkage, and residential carbon emissions, this paper serves as a call for more in-depth and integrated quantitative/qualitative studies [17,60,69].

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CRediT authorship contribution statement

Xingjian Liu: Conceptualization, Methodology, Investigation, Validation, Writing - original draft, Writing - review & editing. **Mingshu Wang:** Conceptualization, Methodology, Investigation, Validation, Writing - original draft, Writing - review & editing. **Wei Qiang:** Methodology, Investigation, Validation, Writing - original draft, Writing - review & editing. **Kang Wu:** Writing - original draft, Writing - review & editing. **Xiaomi Wang:** Methodology, Investigation, Validation.

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.

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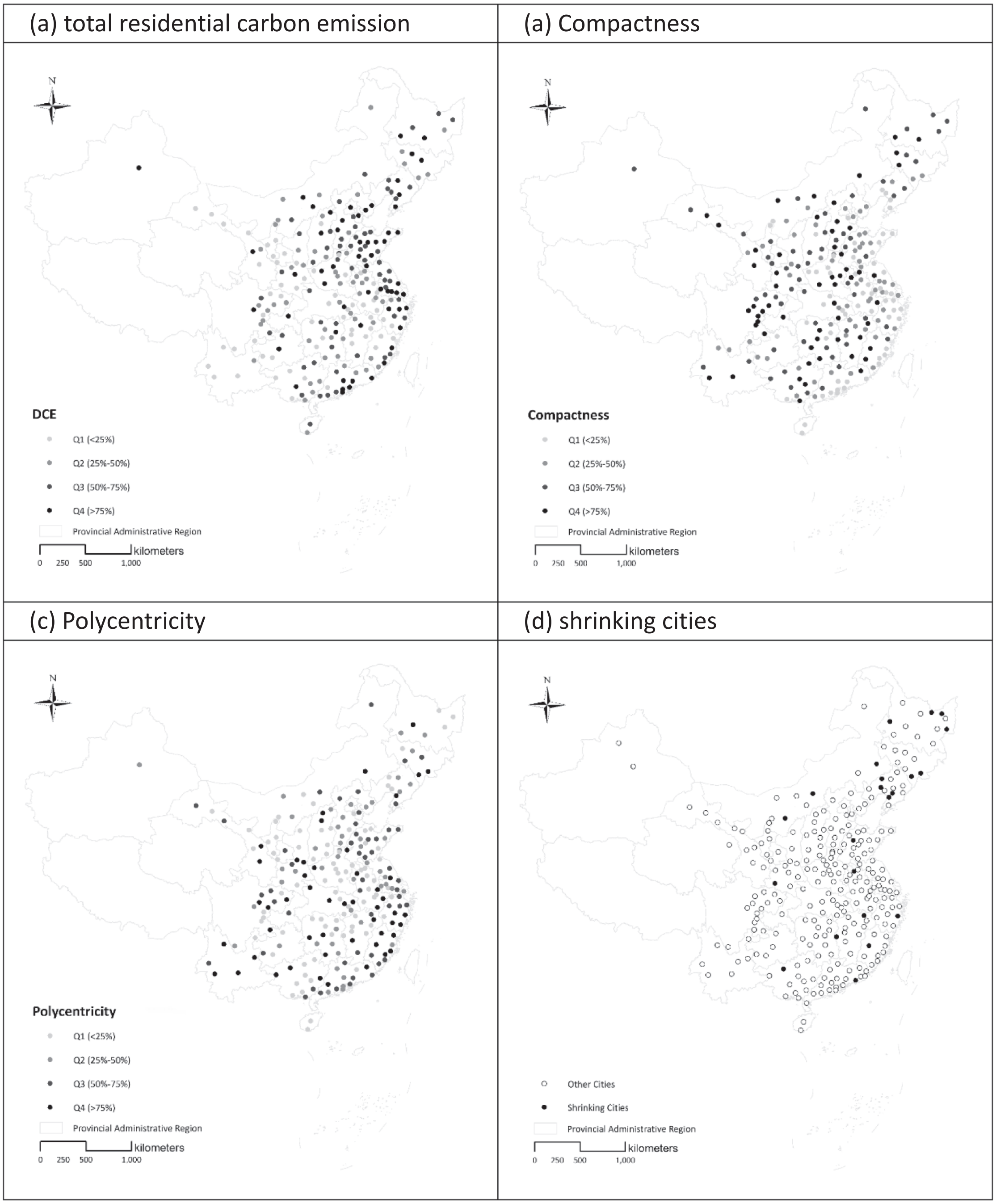
Appendix A. Maps of (a) total residential carbon emissions; (b) compactness; and (c) polycentricity for the year of 2015 as well as (d) shrinking cities (based on Wu and Li [53]).



Appendix B. Correlates of residential carbon emissions with the urban shrinkage dummy variable measured based on city-district population (BE estimation).

	(1)	(2)	(3)	(4)	(5)
VARIABLES	DCE	TDCE	EDCE	GDCE	CDCE
Ln (POP)	0.943***	0.963***	1.034***	1.086***	0.529***
	(0.0289)	(0.0470)	(0.0305)	(0.0487)	(0.149)
Ln (PGDP)	0.619***	0.399***	0.558***	0.608***	1.007***
	(0.0399)	(0.0851)	(0.0422)	(0.0674)	(0.193)

WTI	1.569***	1.232***	1.428***	0.758**	2.725***
	(0.208)	(0.333)	(0.220)	(0.352)	(0.974)
COMP	−0.694**	−0.397	−0.764**	−1.863***	0.623
	(0.347)	(0.546)	(0.368)	(0.587)	(1.675)
POLY	0.155	0.232	0.177*	0.195	−0.335
	(0.0942)	(0.148)	(0.0989)	(0.158)	(0.482)
Urban Shrinkage (Shrinking = 1)	0.185**	−0.0152	0.165*	−0.118	0.413
	(0.0843)	(0.133)	(0.0887)	(0.142)	(0.351)
Central Heating (Heating = 1)	0.463***				
	(0.0426)				
Ln (PROAD)		0.436***			
		(0.101)			
Temp					−0.511***
					(0.145)
Constant	−4.639***	−5.070***	−4.741***	−6.600***	−7.731***
	(0.530)	(0.899)	(0.562)	(0.897)	(2.429)
Observations	713	708	713	713	332
Number of groups	271	271	271	271	136

standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Appendix C. Correlates of residential carbon emissions with the urban shrinkage dummy variable measured based on city-wide population (BE estimation)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	DCE	TDCE	EDCE	GDCE	CDCE
Ln (POP)	0.956***	0.972***	1.046***	1.086***	0.554***
	(0.0282)	(0.0471)	(0.0302)	(0.0491)	(0.148)
Ln (PGDP)	0.640***	0.414***	0.575***	0.605***	1.053***
	(0.0391)	(0.0856)	(0.0418)	(0.0680)	(0.194)
WTI	1.627***	1.261***	1.472***	0.747**	2.802***
	(0.203)	(0.333)	(0.217)	(0.352)	(0.962)
COMP	−0.571*	−0.373	−0.663*	−1.912***	0.943
	(0.336)	(0.544)	(0.360)	(0.586)	(1.651)
POLY	0.180**	0.236	0.205**	0.179	−0.242
	(0.0909)	(0.147)	(0.0967)	(0.157)	(0.476)
Urban Shrinkage (Shrinking = 1)	0.304***	0.132	0.258***	−0.0693	0.523*
	(0.0667)	(0.107)	(0.0704)	(0.114)	(0.280)
Central Heating (Heating = 1)	0.440***				
	(0.0417)				
Ln (PROAD)		0.428***			
		(0.101)			
Temp					−0.478***
					(0.146)
Constant	−5.016***	−5.299***	−5.061***	−6.540***	−8.635***
	(0.523)	(0.912)	(0.561)	(0.912)	(2.489)
Observations	713	708	713	713	332
Number of groups	271	271	271	271	136

standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1.

Appendix D. Correlates of residential carbon emissions with the urban shrinkage dummy variable from Wu and Li [53] (BE estimation)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	DCE	TDCE	EDCE	GDCE	CDCE
Ln (POP)	0.942***	0.974***	1.030***	1.088***	0.546***
	(0.0290)	(0.0468)	(0.0307)	(0.0487)	(0.148)
Ln (PGDP)	0.617***	0.394***	0.555***	0.609***	0.982***
	(0.0399)	(0.0846)	(0.0424)	(0.0674)	(0.189)
WTI	1.561***	1.217***	1.423***	0.762**	2.518***
	(0.209)	(0.331)	(0.222)	(0.352)	(0.952)
COMP	−0.618*	−0.361	−0.704*	−1.909***	1.253
	(0.347)	(0.542)	(0.369)	(0.586)	(1.671)
POLY	0.168*	0.217	0.191*	0.186	−0.277
	(0.0941)	(0.146)	(0.0991)	(0.157)	(0.477)
Urban Shrinkage (Shrinking = 1)	0.134*	0.204*	0.0673	−0.0659	0.516*
	(0.0757)	(0.118)	(0.0798)	(0.127)	(0.308)
Central Heating (Heating = 1)	0.465***				
	(0.0427)				
Ln (PROAD)		0.451***			
		(0.101)			
Temp					−0.510***
					(0.143)

Constant	−4.642***	−5.128***	−4.718***	−6.608***	−7.792***
	(0.532)	(0.892)	(0.566)	(0.899)	(2.403)
Observations	713	708	713	713	332
Number of groups	271	271	271	271	136

standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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