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The Heterogeneous Effects of Urban Form on CO_2 Emissions: An Empirical Analysis of 255 Cities in China

Chengye Jia [1,†], Shuang Feng [1,*,†], Hong Chu [1] and Weige Huang [2,*]

[1] School of Economics, Shandong University of Finance and Economics, Jinan 250014, China
[2] Wenlan School of Business, Zhongnan University of Economics and Law, Wuhan 430073, China
* Correspondence: sfeng@sdufe.edu.cn (S.F.); weige_huang@zuel.edu.cn (W.H.)
† These authors contributed equally to this work.

Abstract: Urban form is closely related to CO_2 emissions and the accurate estimation of the impact of urban form on CO_2 emissions plays an important role in tackling climate change caused by the emission of greenhouse gases. In this paper, we quantitatively investigate the effects of urban form on CO_2 emission and its efficiency from three perspectives: urban expansion, compactness, and complexity. By using panel quantile regression with fixed effects, we show that: (1) The estimation results about the relationship between urban form and CO_2 emission and its efficiency are consistent with the literature. (2) The partial effects of urban form without controlling for socioeconomic factors are heterogeneous throughout the conditional distribution of CO_2 emission and its efficiency. (3) Taking into consideration that the partial effects of urban form on CO_2 emission and its efficiency might depend on the magnitude of socioeconomic factors, we include interaction terms into our model and find that the interaction effects between socioeconomic factors and urban form are heterogeneous across cities with different levels of CO_2 emission and its efficiency. Our empirical findings shed light on the optimization of urban form in improving the CO_2 emission efficiency, providing policy makers with effective ways of reducing CO_2 emissions across cities with different levels of CO_2 emissions.

Keywords: CO_2 emissions; urban form; panel data quantile regression; heterogeneous interaction effect

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1. Introduction

Global warming, which refers to a gradual increase in the Earth's temperature, is associated with the frequency of catastrophic weather events that pose a severe threat to humanity. Excessive emission of carbon dioxide (CO_2) is believed to be closely related to climate change, especially global warming. Since the launch of reform and opening up, China has achieved remarkable economic growth and become the world's second-largest economy. This miraculous economic development, however, is coupled with environmental degradation, particularly an intensification of the greenhouse effect caused by CO_2 emissions in urban areas [1]. Being the largest energy consumer and CO_2 emitter since 2009, China has committed to achieving peak CO_2 emissions by 2030, reducing CO_2 emissions per unit GDP by 60% to 65% compared with the level in 2005, increasing the share of non-fossil energy consumption in total energy consumption to 20%, and targeting carbon neutrality by 2060 [2–4]. Although the Chinese government has proposed various policies to reduce CO2 emissions, more effort is needed, especially since China is still in the process of urbanization. Urbanization is closely related to urban form, which refers to the physical characteristics of a city, such as its size, shape, and arrangement of buildings, streets, open spaces, and transportation systems, and how they interact with each other. Urban form can significantly impact a city's social, economic, and environmental aspects [5], and is widely considered to be closely related to CO2 emissions. Accurately estimating the impact of urban form on CO_2 emissions plays a crucial role in addressing climate change caused by greenhouse gas emissions.

In this paper, we quantitatively investigate the effects of urban form on CO_2 emission and its efficiency from three perspectives: urban expansion, urban compactness, and urban complexity. By using the panel quantile regression method with fixed effects, we show that: (1) The estimation results about the relationship between urban form and CO_2 emission and its efficiency are consistent with the literature. (2) The partial effects of urban form without controlling for socioeconomic factors are heterogeneous throughout the conditional distribution of CO_2 emission and its efficiency. (3) Taking into consideration that the partial effects of urban form on CO_2 emission and its efficiency might depend on the magnitude of socioeconomic factors, we include interaction terms into our model and the interaction effects between socioeconomic factors and urban form are heterogeneous across cities with different levels of CO_2 emission and its efficiency.

Our study contributes to the literature in two important ways. The first contribution relates to the application of the methodology, namely, the panel quantile regression with fixed effects model, which makes our paper, to our knowledge, the first one to provide the heterogeneous effects of urban form on CO_2 emission and its efficiency. Secondly, our paper not only focuses on the heterogeneous effects of urban form but also explores the heterogeneous impact of the socioeconomic factors on the correlation between urban form and CO_2 emission and its efficiency. These contributions of our paper vis-à-vis the existing literature can be summarized as follows.

Our paper is related to the literature on the factors associated with CO_2 emission and its efficiency. Related studies demonstrate that the process of urbanization, which can be proxied by various spatial patterns and traditional factors such as socioeconomic factors, plays a major role in impacting CO_2 emissions.

A strand of literature which focuses on spatial planning, has recently received more attention. The authors show that the urban form plays an important role in mitigating CO_2 emissions. Urban form, which involves spatial patterns and organization of urban landscape elements, reflects the temporal and spatial interaction between human socioeconomic activities and natural environment in urban areas [6–8]. It can influence CO_2 emission and its efficiency, directly or indirectly, through impacting the structure of land use, urban infrastructure, urban transportation, urban heat island effects, household energy demand and efficiency, and carbon sinks [9–13]. Urban form does not usually change rapidly once formed, and its impact on CO_2 emissions is long-lasting and prominent. Salat and Bourdic [14] suggested that the energy consumption of suitable urban form is 50–60% less than that of undesirable urban form. In addition, CO_2 emissions of well-established but undesirable urban form are difficult to curb by conventional measures applied in the reduction of CO_2 emissions [15]. Thus, a better understanding of the connection between urban form and CO_2 emissions is required to keep a long-lasting, low-carbon, and sustainable path of development.

To investigate the effects of urban form on CO_2 emissions, the recent literature explores the impact of urban form from three aspects—urban expansion or size, urban compactness, and urban complexity—examining the relationship between urban form and CO_2 emissions. Being a carrier for urbanization, urban expansion or sprawl is depicted by the increase of urban build-up areas. Urban expansion is positively linked to CO_2 emissions under a background of population growth, increasing commuting distances, or increasing urban household energy consumption [16–18]. Urban compactness , which is an urban form of high density with mixed land uses, is designed with an efficient public transportation system to provide an urban layout with less need to travel by car, to support walking and cycling, giving citizens convenient access to services and facilities, and thus inducing low energy consumption [19,20]. A high level of urban compactness is found to effectively reduce CO_2 emissions [21–24]. Urban complexity refers to the irregularity of the shape of urban patches and is generally believed to have a positive impact on CO_2 emissions. Complex and irregular boundaries of urban land patches could increase the time and distance of common commuting, causing more energy consumption and CO_2 emissions [21]. Vice versa, less urban complexity tends to lower residential CO_2 emissions [25]. Accordingly, our paper concentrates on explaining the effects of urban form on CO_2 emission and its efficiency measured by CO_2 emissions per capita and per unit (CNY 10^4) GDP across cities and through time. The existing literature only considers the mean effects of urban form on CO_2 emissions. Little is known about their distributional effects or heterogeneous effects, which is proved to be critical for policy makers to design precise solutions to approach the task of reducing CO_2 emissions across cities with different levels of CO_2 emissions [18].

In addition to the contributions to the literature on the correlation of urban form and CO_2 emissions, as outlined above, we also extend the literature on the impact of socioeconomic factors on CO_2 emissions and on its relationship with urban form. Liu and Bae [1] analyzed the impact of energy intensity, real GDP, industrialization, and the proportion of renewable energy in energy usage on CO_2 emissions for China over the period from 1970 to 2015. They found that energy intensity, industrialization, and real GDP are positively related to CO_2 emissions whereas the impact of the proportion of renewable energy on CO_2 emissions is negative. Wang et al. [26] used global and local regression models to study the effects of different socioeconomic factors on CO_2 emissions. The estimation results of both models showed that the economic growth and energy consumption caused positive effects on CO_2 emissions. Pao and Tsai [27], however, found that the connection between economic growth and CO_2 emissions supports the Environmental Kuznets Curve (EKC) hypothesis. Other factors which were found to be relative to CO_2 emissions include technology, foreign direct investment (FDI), fiscal decentralization, and energy consumption structure [28–30].

Besides showing that socioeconomic factors, such as the growth of economy and the level of industrialization, are important determinants of CO_2 emissions and its efficiency, as mentioned above, we also extend this literature into the study of the heterogeneous interaction effects of socioeconomic factors. Specifically, unlike the current literature, our work looks at not only the mean (overall) effect of these social economic factors on CO_2 emissions, but also their heterogeneous impact on the correlation between urban form and CO_2 emissions. It is reasonable to consider that the effects of urban form on CO_2 emissions depend on the value of socioeconomic factors. In other words, these interaction effects might exert an opposite force which is large enough to change the direction of the effects of urban form on CO_2 emissions [31].

There is also a strand of literature focusing on the original definition of urbanization, i.e., the population shift from rural to urban areas, and exploring the effects on CO_2 emissions of various indicators which are associated with the increasing demand of energy caused by the increasing of urban population. For instance, Liu and Bae [1] showed that CO_2 emission is positively correlated with urbanization by raising the demand for transportation, building energy consumption, and infrastructure that uses carbon-intensive materials. Senbel and Church (2010) concluded that vehicle travel and buildings' energy consumption are the two main contributors to CO_2 emissions. Xu and Xu [32] pointed out that the transportation sector is a major contributor to global CO_2 emissions and accounted for 24.34% of the total CO_2 emissions in 2016. Li and Yu [33] showed that CO_2 emission from the transportation sector accounted for about 14% of the national CO_2 emissions in China in 2014. It is obvious that the demand for transportation in a city is positively correlated with the number of populations. In addition, urbanization usually promotes the construction of buildings to accommodate more population. The increase in the demand for carbon-intensive materials such as cement and steel during construction and heating and cooling of buildings contributes more CO_2 emissions [34]. Our paper, accordingly, includes the population density as a control and investigates the impact from the population density on the relationship between urban form and CO_2 emission and its efficiency with the panel quantile regressions.

The remainder of this paper is organized as follows. The next section presents the study area. Section 3 provides details of the steps for data preparation and introduces the fixed effects model of quantile regression. Section 4 collects the estimation results for the baseline and alternative regressions. Section 5 gives a discussion of the policy implication. The last section concludes the paper.

2. Study Area

Our study focuses on cities at prefecture level and above in China over five periods: 2000, 2005, 2010, 2015, and 2018. The number of cities varies across different years. This is because the values of CO_2 emissions are missing for some cities in a specific year. After removing cities with missing values, we have 103 cities in 2000, 154 cities in 2005, 236 cities in 2010, 231 cities in 2015, and 178 cities in 2018. According to the social and economic development status, the traditional geographical divisions divide China into four regions, which are the Northeast, East, Central part, and West.[1] Figure 1 displays the spatial and temporal distribution of cities studied in our paper and shows that all regions have been spatially covered by these cities in each year, although the number of cities varies temporally. Furthermore, compared with the literature which only studies provincial capitals [21] or medium and small-sized cities in a specific region [35], we include cities with different sizes, which makes our research more general. Hence, the study area constituted by these cities can give us a general picture of the effects of urban form on CO_2 emissions or CO_2 emission efficiency. In particular, a better understanding of the relationship between CO_2 emissions and urban form can be achieved through analyzing the heterogeneous effects of how urban forms vary across not only different levels of CO_2 emissions but also different regions and sizes, which enables policy makers and urban planners to create sustainable and low-carbon cities.

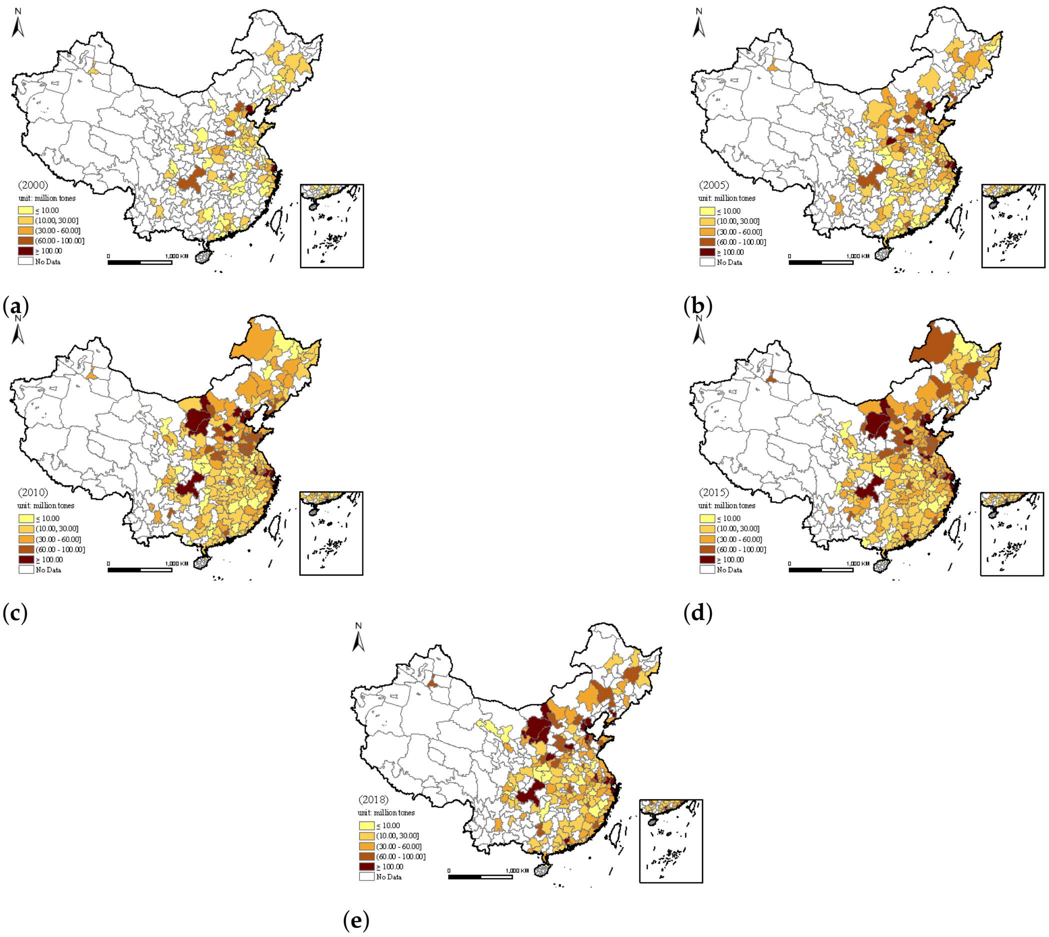


Figure 1. The Spatial and Temporal Distribution of CO_2 Emissions. (**a**) CO_2 Emissions in 2000, (**b**) CO_2 Emissions in 2005, (**c**) CO_2 Emissions in 2010, (**d**) CO_2 Emissions in 2015, (**e**) CO_2 Emissions in 2018. *Note:* The data for CO_2 emissions are from the Carbon Emission Accounts and Datasets (CEADs).

3. Data and Method

Our paper focuses on exploring the heterogeneous effects of urban form on CO_2 emissions and the CO_2 emission efficiency from three perspectives—urban expansion, urban compactness, and urban complexity. For this purpose, we use data on CO_2 emissions, the CO_2 emissions per capita, the CO_2 emissions per unit GDP, the urban form metrics measuring the dynamics of urban form, and other socioeconomic factors measuring the level of industrialization, economic development, and the population density. The data on CO_2 emissions are from the Carbon Emission Accounts and Datasets (CEADs) for emerging economies, ranging from 2000 to 2018 annually. Metrics used to quantify the urban form are calculated with ArcGIS and FRAGSTATS 4.2, based on the information of 255 cities from the Science Data Bank.[2] The information of the population density, GDP, and industrial structure is from the China City Statistical Yearbook (2000–2018). Our sample consists of 255 cities over five periods: 2000, 2005, 2010, 2015, and 2018. In the following three subsections, we outline the details for the dependent variables, CO_2 emissions and the CO_2 emission efficiency, the main independent variables—urban form metrics, and control variables—socioeconomic factors.

3.1. CO_2 Emissions and CO_2 Emissions Efficiency

The Carbon Emission Accounts and Datasets (CEADs) for emerging economies contains the data of CO_2 emissions at country, province, city and county level, respectively. As cities in China are at different stages of industrialization and have their distinctive paths of development, we focus on the inventories of cities' CO_2 emissions to explore the different patterns of cities' CO_2 emissions, and provide reasonable policy suggestions according to the cities' specific conditions. This paper uses the data on city-level CO_2 emissions calculated by Shan et al. [38–41]. The city-level CO_2 emissions are the sum of the energy-related CO_2 emissions and the process-related CO_2 emissions. Using the Intergovernmental Panel Climate Change (IPCC) territorial emission accounting approach, the information about the energy-related emissions are calculated based on 17 fuels and 47 socioeconomic sectors by Equation (1). The information about the process-related CO_2 emissions are calculated based on seven industrial processes by Equation (2). The energy-related emissions are calculated as follows:

$$\sum_i \sum_j CE_{ij} = \sum_i \sum_j AD_{ij} \times NCV_{ij} \times CC_i \times O_{ij} \tag{1}$$

where CE_{ij} is the CO_2 emissions induced by the combustion of fuel i in sector j and AD_{ij} (activity data) is the fossil fuel combustion by fuel and sector. NCV_{ij} is the heat value produced per physical unit of fossil fuel i combusted, CC_i is the carbon emissions per unit heat value when combusting per physical unit of fossil fuel i, and O_{ij} stands for the oxidation ratio of the fossil fuel combusted. The equation below is used to estimate the process-related CO_2 emissions.

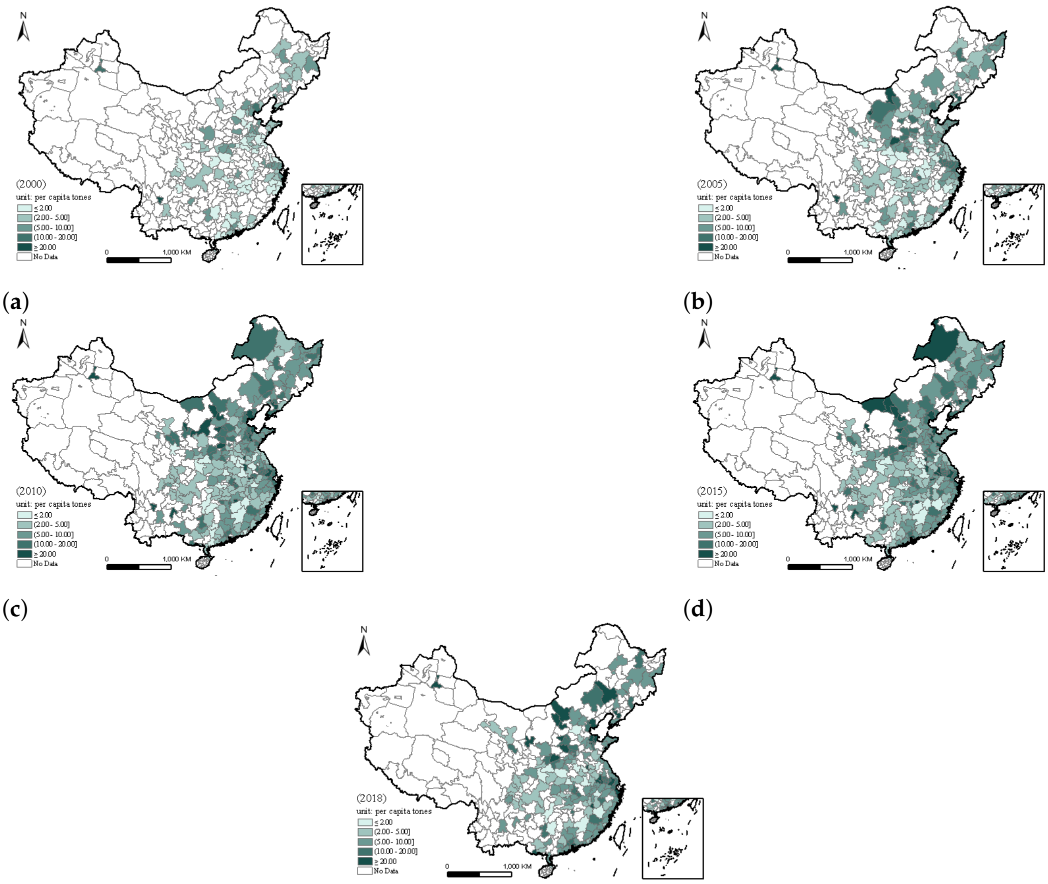
$$\sum_t CE_t = \sum_t AD_t \times EF_t \tag{2}$$

where AD_t and EF_t refer to industrial process t and its corresponding emission factor, respectively.

Besides using the quantity of CO_2 emissions, which is a direct measure employed in the literature, as the dependent variable, we include CO_2 emissions per capita and CO_2 emissions per unit GDP as dependent variables to proxy the CO_2 emission efficiency. Although economic development is typically associated with the improvements of living standards and well-being of people, it induces a very large amount of energy consumption and consequently causes environmental issues which in turn degrade the living environment and risk people's lives. Hence, it is of great importance to examine the effects on CO_2 emission efficiency with respect to urban form [22]) and make policies to reduce

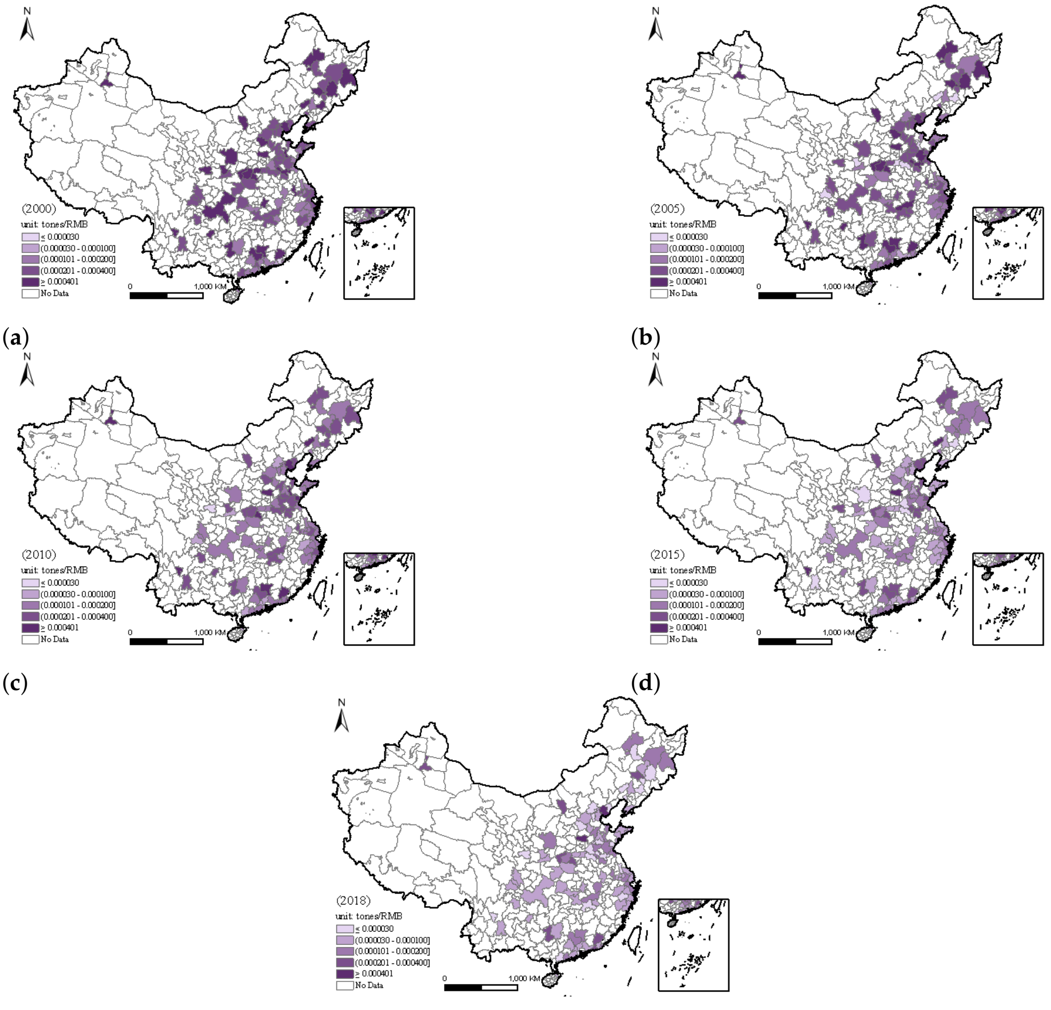
CO_2 emissions without sacrificing economic development. Based on the demographic information and the levels of economic development of cities studied here, we use the data on CO_2 emissions of the years 2000, 2005, 2010, 2015, and 2018 to compute the CO_2 emissions per capita and CO_2 emissions per unit GDP, respectively.

Figures 1–3 plot the spatial and temporal distribution of CO_2 emissions, CO_2 emissions per capita, and CO_2 emissions per unit GDP, respectively, to show their spatial changes from the year of 2000 to the year of 2018. As shown in the three figures, the study area covers the four regions of China. In particular, most of the cities for which we have data on CO_2 emissions are located in the central, east, and northeast areas of China. For the Western region, we have the information of Urumqi, the capital of Xinjiang autonomous region. Two facts of the spatial and temporal distribution of the dependent variables are summarized as follows: (1) For cities with data available, the CO_2 emissions and CO_2 emissions per capita are generally increasing over 2000–2018. In particular, for cities in the northeast, Inner Mongolia, the region of Beijing–Tianjin–Hebei, Shanxi Province, Shandong Province, and the region of Jiangsu–Zhejiang–Shanghai, as well as the municipality of Chongqing and the Great Bay Area of Guangdong–Hong Kong–Macau, the magnitude of the increase is much larger. (2) In contrast, the CO_2 emissions per unit GDP are generally decreasing over time while this decreasing has less spatial discrepancy.



(**a**) (**b**) (**c**) (**d**) (**e**)

Figure 2. The Spatial and Temporal Distribution of CO_2 Emissions per Capita. (**a**) CO_2 Emissions per Capita in 2000, (**b**) CO_2 Emissions per Capita in 2005, (**c**) CO_2 Emissions per Capita in 2010, (**d**) CO_2 Emissions per Capita in 2015, (**e**) CO_2 Emissions per Capita in 2018. *Note:* The data for CO_2 emissions per capita are from the Carbon Emission Accounts and Datasets (CEADs) and the China City Statistical Yearbook (2000–2018).



(**a**) (**b**) (**c**) (**d**) (**e**)

Figure 3. The Spatial and Temporal Distribution of CO_2 Emissions per Unit GDP. (**a**) CO_2 Emissions per Unit GDP in 2000, (**b**) CO_2 Emissions per Unit GDP in 2005, (**c**) CO_2 Emissions per Unit GDP in 2010, (**d**) CO_2 Emissions per Unit GDP in 2015, (**e**) CO_2 Emissions per Unit GDP in 2018. *Note:* The unit of measurement shown in this picture is CNY. The data for CO_2 emissions per unit GDP are from the Carbon Emission Accounts and Datasets (CEADs) and the China City Statistical Yearbook (2000–2018).

3.2. Urban Form Metrics

In order to quantify the relationship between urban form and CO_2 emissions, we choose ten metrics shown in Tables 1 and 2 to proxy the urban form from three perspectives: urban expansion, urban compactness, and urban complexity. In align with Fang et al. [21], Li et al. [22], we choose total area (TA) to describe urban expansion. TA equals the total area (m^2) of all patches of an urban area, divided by 10,000 (to convert to hectares), which indicates the overall size and the expansion of the urban area.

Urban compactness refers to the degree of aggregation of an urban area and is represented by patch density (PD), landscape division index (DIVISION), splitting index (SPLIT), the percentage of like adjacencies (PLADJ), and patch cohesion index (COHESION). PD equals the number of patches of the corresponding patch type divided by TA and reflects the fragmentation of an urban area. DIVISION, whose value lies in the range $[0, 1]$, equals the possibility that two randomly selected cells are not located in the same patch. SPLIT refers to the sparsity of urban patches. Specifically, the more compact the urban landscape, the lower the values of PD, DIVISION, and SPLIT. PLADJ, taking values between 0 and 100, is the percentage of cells adjacencies in a single patch type (cells bordering cells of the same patch type). The increase in PLADJ implies greater aggregation of the patches within the same patch type and across all patch types. COHESION measures the connectedness of patches in an urban area and takes value between 0 and 100 when there is only one patch type. Patch cohesion increases as the patches becomes more clustered within the same patch type and across patch types. The closer the values of both PLADJ and COHESION are to 100, the more compact an urban area is.

Urban complexity refers to the degree of irregularity of the perimeter of a specific patch type and is measured by landscape shape index (LSI), area-weighted mean shape index (SHAPE_AM), perimeter-area fractal dimension (PAFRAC), and area-weighted mean contiguity index (CONTIG_AM). Both LSI and SHAPE_AM measure the perimeter-to-area ratio for the urban area as a whole [42] and function as the measure of overall geometric complexity of urban area. The values of both LSI and SHAPE_AM are greater than or equal to 1. The urban area has the most regular shape when LSI or SHAPE_AM equals 1. PAFRAC, whose value lies between 1 and 2, equals 2 divided by the slope of regression line obtained by regressing the logarithm of patch area ($\ln a_{ij}$) against the logarithm of patch perimeter ($\ln p_{ij}$). PAFRAC approaches 1 for a simple shape and approaches 2 for a complex shape. CONTIG_AM (the range is between 0 and 1) measures the spatial connectedness of cells in patches to reflect the shape complexity of an urban area. Higher values of LSI, SHAPE_AM, PAFRAC, and CONTIG_AM are associated with greater irregularity of the shape of an urban area.

The ten metrics used here are calculated by using ArcGIS and FRAGSTATS 4.2, based on the information obtained from the Science Data Bank. Following the rules accepted by the United Nations (UN), this dataset is constructed by using the remote sensing technology to process the Landsat and Sentinel images, which covers urban built-up areas for 433 Chinese cities at five-year interval from 1990 to 2020. More details of the process of extracting urban built-up data can be found in Sun et al. [36], Jiang et al. [37].

Table 1. The Description of Urban Metrics.

Category	Landscape Metric	Abbreviation	Equation
Urban expansion	Total area	TA	$\sum_{i}^{m}\sum_{j=1}^{n} a_{ij}\left(\frac{1}{10{,}000}\right)$
Urban compactness	Patch density	PD	$\frac{\mathrm{n}}{\mathrm{A}}$
	Landscape division index	DIVISION	$1-\sum_{i=1}^{m}\sum_{j=1}^{n}\left(\frac{a_{ij}}{10{,}000\mathrm{A}}\right)^2$
	Splitting index	SPLIT	$\frac{(A)^2}{\sum_{i=1}^{m}\sum_{j=1}^{n} a_{ij}^2}$
	Percentage of like adjacencies	PLADJ	$\frac{\sum_{i=1}^{m} g_{ii}}{\sum_{i=1}^{m}\sum_{k=1}^{m} g_{ik}}(100)$
	Patch cohesion index	COHESION	$\left[1-\frac{\sum_{i=1}^{m}\sum_{j=1}^{n} P_{ij}^*}{\sum_{i=1}^{m}\sum_{j=1}^{n} P_{ij}^*\sqrt{a_{ij}^*}}\right]\left[1-\frac{1}{\sqrt{\mathrm{Z}}}\right]^{-1}(100)$
Urban complexity	Landscape shape index	LSI	$\frac{0.25\sum_{k=1}^{m} e_{ik}^*}{\sqrt{\mathrm{A}}}$
	Area-weighted mean shape index	SHAPE_AM	$\sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(\frac{0.25p_{ij}}{\sqrt{a_{ij}}}\right)\left(\frac{a_{ij}}{\mathrm{A}}\right)\right]$
	Perimeter-area fractal dimension	PAFRAC	$\frac{2}{\frac{[N\sum_{i=1}^{m}\sum_{j=1}^{n}(lnp_{ij}lna_{ij})]-[(\sum_{i=1}^{m}\sum_{j=1}^{n}lnp_{ij})(\sum_{i=1}^{m}\sum_{j=1}^{n}lna_{ij})]}{(N\sum_{i=1}^{m}\sum_{j=1}^{n}lnp_{ij}^2)-(\sum_{i=1}^{m}\sum_{j=1}^{n}lnp_{ij})^2}}$
	Area-weighted mean contiguity index	CONTIG_AM	$\sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(\frac{\frac{\sum_{r=1}^{x}C_{ijr}}{a_{ij}^*}-1}{v-1}\right)\left(\frac{a_{ij}}{\mathrm{A}}\right)\right]$

Table 2. Notation used in FRAGSTATS algorithms.

Subscripts	Definition	Symbols	Definition
i	$1, \cdots, m$ or m' patch types (classes)	a_{ij}	the area (m^2) of patch ij
j	$1, \cdots, n$ patches	p_{ij}	perimeter of patch ij
k	$1, \cdots, m$ or m' patch types (classes)	g_{ik}	the number of adjacencies between patch types i and k
q	$1, \cdots, p$ disjunct core areas	g_{ii}	the number of like adjacencies between pixels of patch type i
s	$1, \cdots, n$ patches, within specified neighborhood	c_{ijr}	contiguity value for pixel r in patch ij
n	number of patches of a class	e^*_{ik}	total length of edge in landscape between classes i and k
m	number of patch types	Z	total number of cells in an urban area
r	$1, \cdots, x$ pixels	P^*_{ij}	the perimeter of patch ij in terms of number of cell surfaces
v	sum of the values in a 3×3 moving window	a^*_{ij}	the area of patch ij in terms of number of cells
A	the total area (m^2) of an urban area		

In Figure 4, we show an example of the expansion of urban built-up areas over time. We first use the Google Earth Engine (GEE) to process and export the raw images of cities from Landsat 5, 7, and 8. Specifically, we obtain the images in 2005 and 2010 from Landsat 5, images in 2000 from Landsat 7, and images in 2005 and 2018 from Landsat 8. The cloud-free raw image for a city is composed of different raw images depicting different parts of the same city. After the composites were generated, we exported those images to Google Drive, from which we can download. Then we obtained the false color composite images with Band 5 (Red), 4 (Green), and 3 (Blue), as shown in Figure 4. The bluish-violet areas within the red rectangles indicate urban built-up areas. Based on the geographic information, we selected seven provincial capital cities in different parts of China to show the changes in urban built-up areas over time. Specifically, we chose Changchun and Xi'an as two representative cities in the Northeast and West parts of China, respectively. Jinan, Nanjing, and Shijiazhuang represent cities in the East part of China. Wuhan and Zhengzhou were chosen for the Central part. Figure 4 shows that the built-up areas have a tendency to expand over time along with the increase in CO_2 emissions shown in Figure 1. This reveals a close connection between urban form and CO_2 emissions.

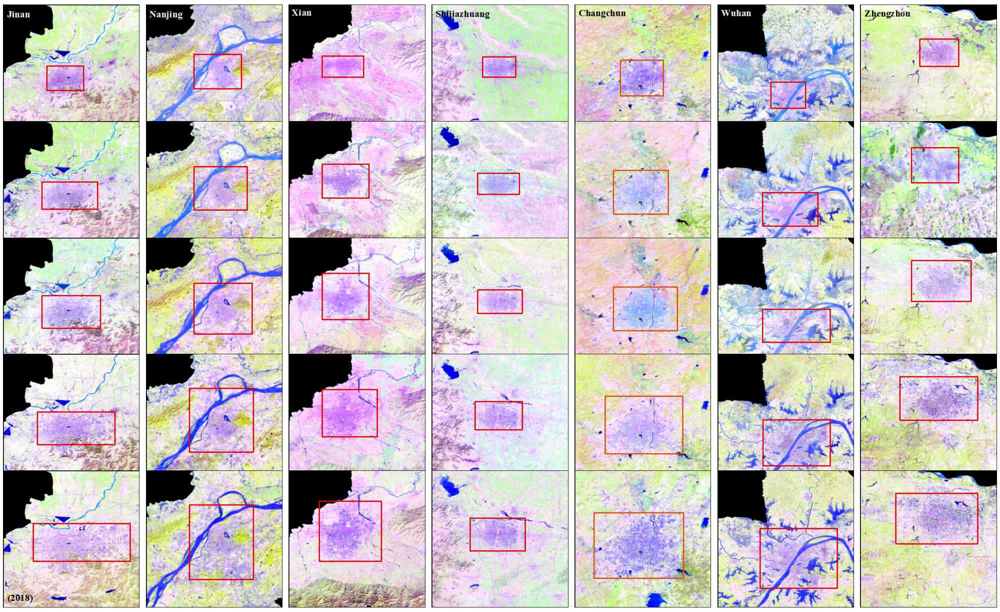


Figure 4. The Urban Expansion of Seven Representative Cities. Note: The images are composites of Band 5 (Red), 4 (Green), 3 (Blue). The bluish-violet areas within the red rectangles represent urban built-up areas. The names of representative cities are shown in the top-left corners of the images in the first row. The time of images are in the bottom-left corners in the first column. The raw images are downloaded from Landsat 5, 7, and 8 by using Google Earth Engine.

3.3. Socioeconomic Factors

Socioeconomic factors are believed to be not only closely related to CO_2 emissions but also urban form. We select the population density, the share of second industry in GDP, and the GDP per capita as the representative socioeconomic factors, which are thought to have significant impacts on CO_2 emissions and urban form [35,43,44]. In order to analyze the causal effects of urban form on CO_2 emissions across cities with different socioeconomic characteristics, we need to disentangle the pure effects of urban form on dependent variables mentioned in Section 3.1 from the effects of socioeconomic factors. Under the ceteris paribus assumption, we can sort out the causal effects by adding socioeconomic factors and their interaction term into our model.

3.4. Panel Quantile Regression with Fixed Effects Model

As mentioned earlier, the existing literature only considers the mean (overall) effects of driving factors on CO_2 emissions ([22,35]). Little is known about their distributional effects or heterogeneous effects which are the effects of the driving factors on the entire distribution of CO_2 emissions. For example, for two cities' urban planning policies with the same mean impact on CO_2 emissions, policymakers are likely to prefer a policy that tends to reduce CO_2 emissions in the higher tail of the distribution of the CO_2 emissions to one that tends to decrease CO_2 emissions in the middle or lower tail of the distribution of CO_2 emissions. Moreover, there exist some unobserved time-constant city-specific effects α_i that could not otherwise be controlled for by other explanatory variables in the model. Geographical features and city-specific culture can be included in the fixed effects.

To explore the heterogeneous effects of urban form on CO_2 emissions and CO_2 emission efficiency, we use the panel data quantile regression method proposed by Koenker [45]. Let i denote the cross section unit and t denote the time period. We can write the conditional quantile regression function as follows:

$$Q_{y_{it}}(\mu|x_{it}) = x_{it}^T\beta(\mu) + \alpha_i \tag{3}$$

where y_{it} and x_{it} are dependent and independent variables for city i at time t, respectively. α_i is an unobserved effect for city i which is correlated with independent variables. Suppose $\mu|x_i, \alpha_i \sim U[0,1]$ with $x_i = [x'_{i1}, \cdots, x'_{iT}]'$. Treating $\{\alpha_i\}_{i=1}^n$ as parameters to be jointly estimated with $\beta(\mu)$ for q different quantiles, the penalized estimators are proposed as follows:

$$(\tilde{\beta}, \{\tilde{\alpha}_i\}_{i=1}^n) = \operatorname{argmin} \sum_{k=1}^{q}\sum_{i=1}^{n}\sum_{t=1}^{T} w_k\rho_{\mu_k}\left[y_{it} - \alpha_i - x_{it}^T\beta(\mu_k)\right] + \lambda\sum_{i=1}^{n}|\alpha_i| \tag{4}$$

where $\rho_\mu(u) = u(\mu - I(u < 0))$ denote the check function in Koenker and Bassett Jr [46], and $I\{\cdot\}$ is the indicator function and equals one if the condition in the parentheses is satisfied. The weights w_k control the relative importance of the q quantiles $\{\mu_1, \cdots, \mu_q\}$ on the estimation of the $\{\alpha_i\}_{i=1}^n$. The fixed effects estimators α can be obtained when $\lambda \to 0$ and equal to zero when $\lambda \to \infty$.

4. Results

The existing empirical work ([22,35]) finds urban form to be an important determinant of the CO_2 emissions. However, few studies document how it impacts the CO_2 emissions from an aspect of the quantile analysis. Our paper, accordingly, fills this gap by examining the effects of changing in the urban expansion, urban compactness, and urban complexity on CO_2 emissions, CO_2 emissions per capita, and the economic efficiency, i.e., CO_2 emissions per unit (CNY 10^4) GDP, respectively.

4.1. The Distributions of CO_2 Emissions and CO_2 Emission Efficiency

In this subsection, we give the basic facts associated with the CO_2 emissions, the CO_2 emissions per capita, and the CO_2 emissions per unit GDP, respectively. Table 3(a)–(c) summarize the essential statistics, the number of observations, mean, standard deviation, and the minimum and maximum of the three dependent variables in our study. The following three features of our dependent variables deserve mention: (1) The mean as well as the standard deviation values of CO_2 emissions are increasing over time, indicating a general economic development but an increasing discrepancy of this development among different cities. The average quantity of CO_2 emissions increased from 19.14 million tonnes in 2000 to 47.42 million tonnes in 2018, with standard deviations of 20.59 million tonnes in 2000 and 56.32 million tonnes in 2018, respectively. (2) Unlike the quantity of CO_2 emissions, the CO_2 emissions per capita show a pattern of first increasing and then decreasing. It increased, on average, from 0.04 tonnes in 2000 to 0.13 tonnes in 2015 while slightly dropping to 0.12 tonnes in 2018. (3) The emissions per unit GDP exhibits a similar pattern that the CO_2 emissions per capita has. However, the inflection point appeared at an earlier time, the year of 2005. From 2005 to 2018, the CO_2 emissions per unit GDP decreased from 4.14×10^{-2} tonnes to 1.81×10^{-2} tonnes.

Table 3. Summary Statistics.

(a) CO_2 Emissions					
Year	**Number of Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
2000	103	19.14	20.59	1.35	117.97
2005	154	29.27	26.77	1.70	158.94
2010	236	34.99	32.58	1.34	195.50
2015	231	42.01	43.30	1.99	337.45
2018	178	47.42	56.32	1.76	415.98
(b) CO_2 Emissions Per Capita					
Year	**Number of Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
2000	103	0.04	0.04	0.00	0.27
2005	154	0.08	0.14	0.00	1.56
2010	236	0.10	0.13	0.01	1.23
2015	231	0.13	0.21	0.01	2.14
2018	178	0.12	0.18	0.00	1.56
(c) CO_2 Emissions Per Unit GDP					
Year	**Number of Obs.**	**Mean**	**Std. Dev.**	**Min**	**Max**
2000	103	0.0385	0.0337	0.0036	0.2460
2005	154	0.0414	0.0370	0.0040	0.2280
2010	236	0.0284	0.0230	0.0039	0.1470
2015	231	0.0217	0.0238	0.0017	0.2150
2018	178	0.0181	0.0193	0.0019	0.1040

Note: The units of measurement for the three dependent variables are displayed in the parentheses: CO_2 Emissions (Million Tones); CO_2 Emissions Per Capita (Tones per Capita); CO_2 Emissions Per Unit GDP (Tonnes/CNY 10^4)

In one word, as we can observe, the quantity of CO_2 emissions increases along time, and it becomes much more volatile. In addition, the process of CO_2 emissions has become much more efficiency as the CO_2 emissions per unit GDP started to decrease since 2005.

Moreover, our dependent variables are also featured by their characteristics of the dynamic distribution. Figure 5 displays the kernel density of the natural logarithm of CO_2 emissions, CO_2 emissions per capita, and CO_2 emissions per unit GDP by year, respectively. The short dash lines represent the mean values of each subsample sorted by year. (1) For the CO_2 emissions, the distribution of the sample shifts from the left to the right over time period 2000–2018, but the process of distribution shifting slows down in recent years, as we can see the distance between two consecutive vertical line of mean values becomes shorter. (2) The distribution of the CO_2 emissions per capita also shifts from the left to the right over time. However, this process looks like it has been at a standstill since 2015. (3) The distribution of the sample of the CO_2 emissions per unit GDP shifts from the right to the left, indicating a significant improvement of CO_2 emission efficiency. By looking at the kernel density of dependent variables, we draw the same conclusion as Table 3 that, though the quantity of CO_2 emissions increases along time, the process of CO_2 emissions has become much more efficient.

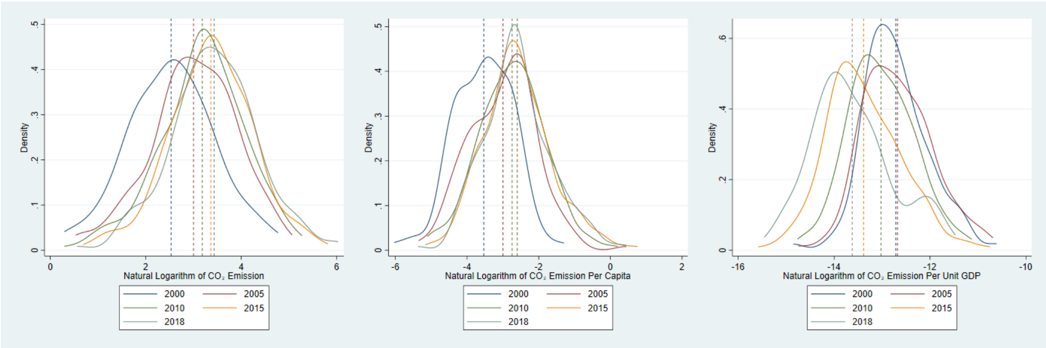


Figure 5. The Kernel Density of the Natural Logarithm of CO_2 Emissions, CO_2 Emissions per Capita, and CO_2 Emissions per Unit GDP. *Note:* The data for CO_2 emissions in the period 2000-2018 are from "The Carbon Emission Accounts and Datasets". The data for CO_2 emissions per capita and CO_2 emissions per unit GDP are from the Carbon Emission Accounts and Datasets (CEADs) and the China City Statistical Yearbook (2000–2018).

4.2. The Estimation Results of Panel Quantile Regression with Fixed Effects

For the main explanatory variable, urban form, we select one representative metric for each categorical map pattern. We use the total area (TA) in urban expansion as the first main explanatory variable. Then we conduct a correlation analysis to select metrics representing the other two categorical map patterns, urban compactness and urban complexity, to avoid a multicollinearity issue in the panel regression.

The results of the correlation analysis are presented in Figure 6. In the second map pattern, urban compactness, landscape division index (DIVISION), and splitting index (SPLIT) have insignificant correlation coefficients with TA, where the correlation coefficients are -0.05 and 0.04, respectively. As DIVISION and SPLIT are highly correlated (with a correlation coefficient 0.70), we choose DIVISION to represent urban compactness. In the third map pattern, urban complexity, perimeter-area fractal dimension (PAFRAC) has an insignificant correlation coefficient -0.09 with TA. Thus, we use TA, DIVISION, and PAFRAC to conduct the panel regressions in the following subsections. All the variables of urban form metrics, as well as the dependent variables, are in the form of natural logarithm.

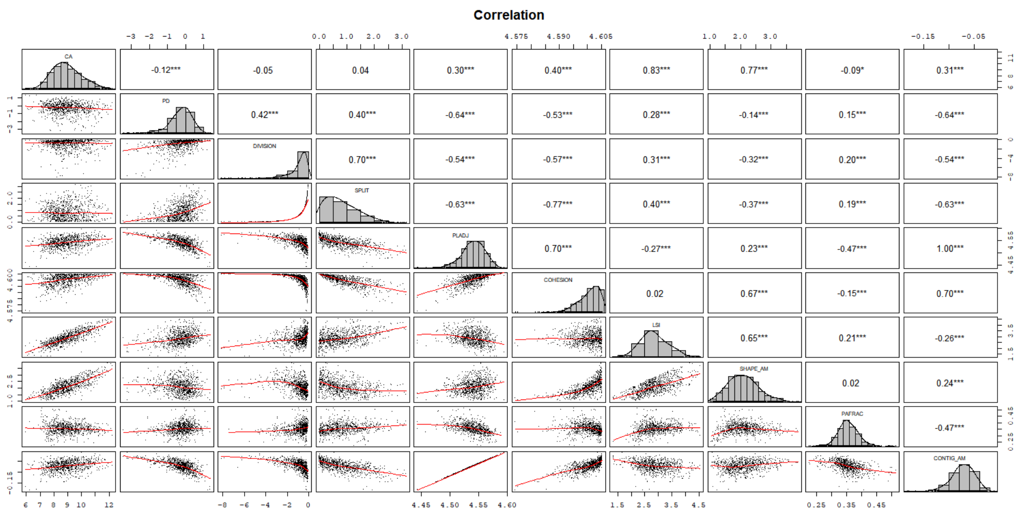


Figure 6. The Correlation Coefficients of the Urban Form Metrics.

4.2.1. The Empirical Analysis of Distributional Effects of Urban Form

We estimate a fixed effects model of quantile regression described in the previous section for selected metrics. For the purpose of comparison, we also provide the results of a fixed effects model, with mean (overall) estimated effects.

Table 4(a)–(c) contains the estimates with the results of the mean effects in the second column of each panel and with the results of quantile analysis in columns three to five, for the CO_2 emissions, the CO_2 emission per capita, and the CO_2 emission per unit GDP, respectively. The results show the directions as well as the magnitudes of the impacts of each urban form variable.

In Column 2 of Table 4(a), both TA and DIVISION have significant, positive effects on CO_2 emissions, with coefficients 0.75 and 0.06, respectively. Consistent with the literature [16–18], as the urban area expands, the quantity of CO_2 emissions increases. In general, the higher the values of DIVISION, the less compact the spatial pattern of urban landscape. Thus, our estimates can be interpreted as that less compact urban landscape pattern results in higher CO_2 emissions [21–24]. PAFRAC has a negative but insignificant effect on the CO_2 emissions, which suggests urban complexity has no impact on the CO_2 emissions when urban expansion and compactness are included.

The estimation results of quantile regression in Table 4(a) yield the same conclusion as the mean regression: both TA and DIVISION have significant, positive effects on CO_2 emissions while PAFRAC has a negative but insignificant effect on CO_2 emissions. Moreover, the estimation results of quantile regression show a significant monotonicity of the effects of TA and DIVISION on CO_2 emissions. The magnitude of the impact from TA decreases when the level of the CO_2 emissions increases (from 0.80 to 0.70). So does the impact of DIVISION (from 0.08 to 0.04). In particular, the impact of DIVISION becomes less significant at high levels of CO_2 emissions.

Table 4(b) presents the CO_2 estimations results for the emissions per capita in the same way as Table 4(a). In the second column of the mean effects, both TA and DIVISION have significant, positive effects on the CO_2 emissions per capita, with coefficients 0.66 and 0.06, respectively. As the urban area expands, CO_2 emissions per capita increases, and less compact urban landscape pattern results in higher CO_2 emissions per capita. PAFRAC has a positive but insignificant effect on CO_2 emissions per capita, which means urban complexity has no impact on CO_2 emissions per capita when urban expansion and compactness are included.

The estimation results of quantile regression in Table 4(b) provide the same conclusion as the overall regression in the second column: both TA and DIVISION have significant, positive effects on the CO_2 emissions per capita while PAFRAC has a positive but insignificant effect. Moreover, the estimation results of quantile regression show a significant monotonicity of the effects of TA and DIVISION on the CO_2 emissions per capita. The magnitude of the impact from TA (urban expansion) decreases when the level of the CO_2 emissions per capita increases (from 0.73 to 0.60), and so does the impact of DIVISION (from 0.09 to 0.04). However, the impact of DIVISION becomes insignificant at high levels of the CO_2 emissions per capita (at the third quantile in our regression).

The last panel of Table 4, Table 4(c), shows the estimation results for CO_2 emissions per unit (CNY 10^4) GDP in the same way as Table 4(a). The overall impacts of TA, DIVISION, as well as PAFRAC on the economic efficiency of CO_2 emissions, i.e., CO_2 emissions per unit GDP, are significant with coefficients -0.70, 0.04, and 1.25, respectively. As the urban area expands, CO_2 emissions per unit GDP decreases. Less compact urban landscape pattern results in higher CO_2 emissions per unit GDP. By comparing the estimated coefficients, PAFRAC has a much stronger impact on CO_2 emissions per unit GDP, which means compared with urban expansion and urban compactness, urban complexity has much larger influence on the economic efficiency of CO_2 emissions.

The estimation results of quantile regression in Table 4(c) draw the similar conclusion as the mean regression: both DIVISION and PAFRAC have positive effects on the CO_2 emissions per unit GDP while TA has a negative effect. Moreover, the estimation results of quantile regression show a significant monotonicity of these impacts. The magnitude of the negative impact of TA increases (from -0.68 to -0.71) when the level of CO_2 emissions per unit GDP increases, and so does the impact of PAFRAC (from 1.04 to 1.46). However, the magnitude of the impact of DIVISION decreases and becomes insignificant at high levels of CO_2 emissions per unit GDP. For a low economic efficiency of CO_2 emissions, urban complexity has a much stronger impact than urban compactness.

Table 4. The Heterogeneous Effects of Urban Form on Dependent Variables.

	(a) Dependent Variable: CO_2 Emissions			
	Mean	**0.25**	**0.50**	**0.75**
TA	0.75 ***	0.80 ***	0.74 ***	0.70 ***
	(0.04)	(0.06)	(0.04)	(0.05)
DIVISION	0.06 ***	0.08 ***	0.06 ***	0.04 *
	(0.02)	(0.03)	(0.02)	(0.02)
PAFRAC	−0.11	−0.08	−0.11	−0.14
	(0.50)	(0.76)	(0.47)	(0.60)
Obs.	817	817	817	817
	(b) Dependent Variable: CO_2 Emissions per Capita			
	Mean	**0.25**	**0.50**	**0.75**
TA	0.66 ***	0.73 ***	0.66 ***	0.60 ***
	(0.04)	(0.06)	(0.04)	(0.05)
DIVISION	0.06 ***	0.09 ***	0.06 ***	0.04
	(0.02)	(0.03)	(0.02)	(0.02)
PAFRAC	0.28	0.35	0.27	0.21
	(0.49)	(0.78)	(0.48)	(0.60)
Obs.	817	817	817	817
	(c) Dependent Variable: CO_2 Emissions per Unit GDP			
	Mean	0.25	0.50	0.75
TA	−0.70 ***	−0.68 ***	−0.70 ***	−0.701 ***
	(0.04)	(0.06)	(0.04)	(0.06)
DIVISION	0.04 *	0.05 *	0.04 *	0.02
	(0.02)	(0.03)	(0.02)	(0.03)
PAFRAC	1.25 **	1.04	1.24 **	1.46 *
	(0.56)	(0.79)	(0.56)	(0.79)
Obs.	817	817	817	817

Note: All variables listed in the table are converted into natural logarithmic forms. The estimated coefficients at each of the quantiles are given in the columns labeled by the corresponding quantiles. Standard errors are reported in the parentheses. * indicates statistically significant at the 10% level, ** indicates statistically significant at the 5% level, and *** indicates statistically significant at the 1% level.

4.2.2. The Empirical Analysis of Distributional Interaction Effects between Urban Form and Socioeconomic Factors

In our regressions, we examine other determinants of the CO_2 emission and its efficiency to isolate the effect of our main explanatory variables of urban form. In this subsection, we include three socioeconomic factors as controls. They are the population density, the value share of industry in GDP, and the GDP per capita. We allow for the possibility that the impact of urban form on the CO_2 emission and its efficiency depend on these socioeconomic variables. In particular, our regressions allow for the interaction of urban form metrics with each control variable, respectively. Except GDP per capita, the other two variables are in the form of natural logarithm.

The Heterogeneous Effects of Urban Form after Controlling for Socioeconomic Factors

Table 5(a)–(c) summarizes the estimation results of the fixed effects model and of the fixed effects model of quantile regression, when all control variables—population density (Pop_density), the industry share in GDP (Ind_GDP), and the GDP per capita (PGDP)—are included. We interpret our results by comparing them with the results of the impacts of urban form variables in Table 4(a)–(c). In Table 5 (a), both TA and DIVISION have positive effects on the CO_2 emissions, with a monotonicity of such effects along the distribution of the CO_2 emissions, which is consistent with the findings of Table 4(a). For the socioeconomic variables, the population density does not have a significant effect on the total amount of the CO_2 emissions. Although the industry share in GDP and the GDP per capita are positively correlated with the total amount of the CO_2 emissions, which is consistent with Liu and Bae [1], the effects are monotonically decreasing with respect to the level of CO_2 emissions. Table 5(b) shows the estimated results for the CO_2 emissions per capita. Compared with Table 4(b), both TA and DIVISION consistently have positive and decreasing effects. However, the impact from DIVISION becomes less significant for cities with high CO_2 emissions per capita. The industry share in GDP and the GDP per capita are consistently the two important determinants of CO_2 emissions per capita, with positive but decreasing effects along the distribution of CO_2 emissions per capita. For the CO_2 emissions per unit GDP, the effect of TA is consistently negative. However, the direction of the monotonicity of this effect is changed to decreasing and the magnitude of the overall effect shrinks to −0.32, over 50% less than that in Table 4(c). The correlations between DIVISION and the CO_2 emissions per unit GDP, and between PAFRAC and the CO_2 emissions per unit GDP are affected by including variables related to the process of industrialization and GDP. In the following paragraphs, we look into details of the impact from the socioeconomic variables on the relationship between urban form and the variables related to CO_2 emissions.

Table 5. The Heterogeneous Effects of Urban Form on Dependent Variables after Controlling for Socioeconomic Factors.

	(a) Dependent Variable: CO_2 Emissions			
	Mean	**0.25**	**0.50**	**0.75**
TA	0.71 ***	0.73 ***	0.71 ***	0.69 ***
	(0.05)	(0.09)	(0.06)	(0.08)
DIVISION	0.07 **	0.09 **	0.06 **	0.04
	(0.03)	(0.04)	(0.03)	(0.04)
PAFRAC	−0.43	−0.63	−0.40	−0.23
	(0.54)	(0.71)	(0.48)	(0.64)
Pop_density	−0.06	−0.07	−0.07	−0.13
	(0.19)	(0.26)	(0.17)	(0.23)
Ind_GDP	1.06 ***	1.03 ***	0.024 ***	0.89 ***
	(0.12)	(0.19)	(0.13)	(0.17)
PGDP	3.85×10^{-6} ***	3.87×10^{-6} ***	3.85×10^{-6} ***	3.84×10^{-6} ***
	(5.95×10^{-7})	(1.24×10^{-6})	(8.34×10^{-7})	(1.13×10^{-6})
Obs.	650	650	650	650
	(b) Dependent Variable: CO_2 Emissions per Capita			
	Mean	**0.25**	**0.50**	**0.75**
TA	0.66 ***	0.70	0.66 ***	0.63 ***
	(0.05)	(0.09)	(0.06)	(0.09)
DIVISION	0.07 **	0.11 **	0.07 **	0.04
	(0.03)	(0.05)	(0.03)	(0.05)
PAFRAC	−0.19	−0.40	−0.16	0.01
	(0.53)	(0.73)	(0.51)	(0.70)
Pop_density	0.10	0.20	0.08	−0.002
	(0.18)	(0.25)	(0.17)	(0.24)
Ind_GDP	0.99 ***	1.13	0.97 ***	0.86 ***
	(0.12)	0.19	0.13	0.18
PGDP	2.75×10^{-6} ***	2.80×10^{-6} **	2.75×10^{-6} ***	2.71×10^{-6} **
	(5.87×10^{-7})	(1.14×10^{-6})	(7.92×10^{-7})	(1.09×10^{-6})
Obs.	650	650	650	650
	(c) Dependent Variable: CO_2 Emissions per Unit GDP			
	Mean	**0.25**	**0.50**	**0.75**
TA	−0.32 ***	−0.33 **	−0.32 ***	−0.30 **
	(0.06)	(0.14)	(0.09)	(0.12)
DIVISION	0.04	0.07	0.04	0.01
	(0.04)	(0.05)	(0.03)	(0.05)
PAFRAC	0.71	0.37	0.72	1.06
	(0.61)	(0.98)	(0.65)	(0.88)
Pop_density	−0.10	−0.01	−0.10	−0.19
	(0.21)	(0.31)	0.20	0.27
Ind_GDP	−0.19	−0.01	−0.20	−0.38 *
	0.14	0.23	0.16	0.21
PGDP	-6.68×10^{-6} ***	-6.48×10^{-6} ***	-6.68×10^{-6} ***	-6.88×10^{-6} ***
	(6.74×10^{-7})	(1.60×10^{-6})	(1.06×10^{-6})	(1.43×10^{-6})
Obs.	650	650	650	650

Note: All variables tabulated in the table are converted into natural logarithmic forms except PGDP. The estimated coefficients at each of the quantiles are given in the columns labeled by the corresponding quantiles. Standard errors are reported in the parentheses. * indicates statistically significant at the 10% level, ** indicates statistically significant at the 5% level, and *** indicates statistically significant at the 1% level.

The Heterogeneous Interaction Effects between Urban Form and Population Density

Table 6(a)–(c) lists the estimation results of the quantile regressions with interactions of the population density for the CO_2 emissions, the CO_2 emissions per capita, and CO_2 emissions per unit GDP. In Table 6(a), as expected, both TA and DIVISION have positive effects on the CO_2 emissions, with a decreasing monotonicity of the impacts. However, those impacts are not significant due to the interaction with the population density. On the other hand, when considering the population density, PAFRAC becomes significantly, positively, correlated with the medium and low level CO_2 emissions, and this impact is negatively affected by the population density. The two impacts, which the urban complexity imposes on CO_2 emissions and which the population density imposes on the former one, are decreasing when CO_2 emissions increases.

Table 6. The Heterogeneous Effects of Urban Form on Dependent Variables after Controlling for Population Density.

	(a) CO_2 Emissions			**(b) CO_2 Emissions per Capita**			**(c) CO_2 Emissions per Unit GDP**		
	0.25	**0.50**	**0.75**	**0.25**	**0.50**	**0.75**	**0.25**	**0.50**	**0.75**
TA	0.62	0.48	0.38	0.77	0.69 *	0.63	0.34	0.74	1.06
	(0.61)	(0.40)	(0.53)	(0.66)	(0.41)	(0.52)	(0.81)	(0.59)	(0.83)
DIVISION	0.49	0.29	0.15	0.19	0.10	0.04	−0.06	−0.27	−0.45
	(0.46)	(0.30)	(0.40)	(0.50)	(0.31)	(0.40)	(0.57)	(0.41)	(0.58)
PAFRAC	10.34 *	9.04 **	8.18	9.02	7.27 **	6.06	7.80	6.39	5.22
	(5.75)	(3.76)	(4.99)	(6.21)	(3.83)	(4.90)	(9.21)	(6.62)	(9.40)
Pop_density	0.51	0.28	0.12	1.02	0.75	0.56	1.37	1.97 **	2.47 *
	(1.05)	(0.69)	(0.91)	(1.11)	(0.68)	(0.88)	(1.32)	(0.95)	(1.34)
TA × Pop_density	0.05	0.07	0.08	0.01	0.02	0.02	−0.16	−0.23 **	−0.29 **
	(0.10)	(0.06)	(0.09)	(0.11)	(0.07)	(0.08)	(0.13)	(0.09)	(0.13)
DIVISION × Pop_density	−0.06	−0.03	−0.01	−0.001	−0.01	0.01	0.02	0.05	0.07
	(0.07)	(0.05)	(0.06)	(0.08)	(0.050)	(0.06)	(0.09)	(0.06)	(0.09)
PAFRAC × Pop_density	−1.86 *	−1.65 ***	−1.51 *	−1.61	−1.31 **	−1.10	−1.23	−0.94	−0.70
	(0.98)	(0.64)	(0.85)	(1.06)	(0.66)	(0.84)	(1.55)	(1.11)	(1.58)
Obs.	650	650	650	650	650	650	650	650	650

Note: All variables except the interaction terms in the table are in natural logarithmic forms. The interaction term is the multiplication of two independent variables after being converted into natural logarithmic forms. The estimated coefficients at each of the quantiles are given in the columns labeled by the corresponding quantiles. Standard errors are reported in the parentheses. * indicates statistically significant at the 10% level, ** indicates statistically significant at the 5% level, and *** indicates statistically significant at the 1% level.

Table 6(b) presents the estimation results for the CO_2 emissions per capita in the same way. When CO_2 emissions per capita is low, urban form has no significant impacts. However, the estimates still show suggestive evidence that both TA and DIVISION have positive and decreasing effects on the CO_2 emissions per capita. Again, PAFRAC's effect becomes more significant when considering the population density, though the impact of population density on the relationship between PAFRAC and CO_2 emissions per capita is negative. Table 6(c) shows the estimation results for the CO_2 emissions per unit GDP. Without exception, when considering the population density, the impact of urban form becomes less significant, and the impact of the population density affects the correlation of TA most. However, a monotonicity of the estimates can be observed with the quantile analysis. In summary, the population density can significantly affect the relationship between urban complexity and CO_2 emissions, and the relationship between urban complexity and CO_2 emissions per capita. In addition, the population density can also monotonically alter the impact of urban expansion on the economic efficiency of the CO_2 emissions and for itself, and high population density will reduce the economic efficiency of the CO_2 emissions.

The Heterogeneous Interaction Effects between Urban Form and Share of Industry

Table 7 presents the estimation results for the impact of the value share of industry in GDP in the same way as Table 6 does. Table 7(a) shows the estimated coefficients for the CO_2 emissions. Except observing a decreasing, positive effect of TA (from 1.45 to 0.84), we find that the development of industry can significantly, positively, affect the correlation of DIVISION and the CO_2 emissions. Moreover, compared with the results in Table 4(a), the impact of DIVISION alters the direction, from positive to negative. In Table 7(b), we show the results when considering the impact of the value share of industry in GDP on the effect of urban form on the CO_2 emissions per capita. Both TA's positive effects and DIVISION's negative effects have the property of monotonicity. Moreover, the value share of industry in GDP increasingly, positively, affects the correlation between DIVISION and CO_2 emissions per capita (from 0.22 to 0.23). In Table 7(c), we find that the value share of industry in GDP increasingly, positively affects both the correlation between TA and CO_2 emissions per unit GDP and the correlation between DIVISION and CO_2 emissions per unit GDP. In one word, the share of industry in GDP can significantly affect the relationship between urban compactness and CO_2 emissions, and the relationship between urban compactness and CO_2 emissions per capita. In addition, the share of industry in GDP can also monotonically, significantly affect the correlation between urban expansion and the economic efficiency of the CO_2 emissions and for itself, a well-developed industrial city usually have a high economic efficiency of CO_2 emissions.

Table 7. The Heterogeneous Effects of Urban Form on Dependent Variables after Controlling for Share of Industry.

	(a) CO_2 Emissions			(b) CO_2 Emissions per Capita			(c) CO_2 Emissions per Unit GDP		
	0.25	**0.50**	**0.75**	**0.25**	**0.50**	**0.75**	**0.25**	**0.50**	**0.75**
TA	1.45 ***	1.12 ***	0.84 **	1.08 **	0.77 ***	0.54	−2.22 ***	−2.40 ***	−2.63 ***
	(0.41)	(0.28)	(0.38)	(0.44)	(0.28)	(0.36)	(0.44)	(0.39)	(0.68)
DIVISION	−0.68	−0.73 **	−0.77 *	−0.77	−0.83 ***	−0.87 **	−0.52	−0.64	−0.79
	(0.43)	(0.30)	(0.40)	(0.49)	(0.31)	(0.40)	(0.44)	(0.39)	(0.68)
PAFRAC	−0.80	−4.38	−7.49	0.12	−2.60	−4.62	6.12	0.60	−6.51
	(10.45)	(7.15)	(9.70)	(11.71)	(7.50)	(9.71)	(11.62)	(10.20)	(17.86)
Ind_GDP	2.66 *	1.51	0.51	2.01	1.04	0.32	−2.59	−3.65 **	−5.03 **
	(1.59)	(1.09)	(1.48)	(1.73)	(1.11)	(1.43)	(1.81)	(1.59)	(2.78)
TA × Ind_GDP	−0.17	−0.09	−0.03	−0.09	−0.02	0.02	0.41 ***	0.45 ***	0.51 ***
	(0.11)	(0.07)	(0.10)	(0.12)	(0.07)	(0.10)	(0.12)	(0.11)	(0.19)
DIVISION × Ind_GDP	0.19 *	0.20 **	0.21 **	0.22 *	0.23 ***	0.23 **	0.15	0.18 **	0.21
	(0.12)	(0.08)	(0.11)	(0.13)	(0.08)	(0.11)	(0.12)	(0.10)	(0.18)
PAFRAC × Ind_GDP	0.15	1.05	1.83	0.01	0.67	1.17	−1.42	0.08	2.00
	(2.67)	(1.82)	(2.48)	(2.99)	(1.91)	(2.48)	(3.02)	(2.65)	(4.65)
Obs.	817	817	817	817	817	817	817	817	817

Note: All variables except the interaction terms in the table are in natural logarithmic forms. The interaction term is the multiplication of two independent variables after being converted into natural logarithmic forms. The estimated coefficients at each of the quantiles are given in the columns labeled by the corresponding quantiles. Standard errors are reported in the parentheses. * indicates statistically significant at the 10% level, ** indicates statistically significant at the 5% level, and *** indicates statistically significant at the 1% level.

The Heterogeneous Interaction Effects between Urban Form and GDP per Capita

In Table 8(a)–(c), we use the original form of per capita GDP and do not take the natural logarithm of this socioeconomic variable. As for the distributional interaction effects of GDP per capita, we find that the estimated coefficients of CO_2 emissions per unit GDP with respect to all independent variables, except GDP per capita, are almost the same as those of CO_2 emissions per capita. This is caused by the natural logarithmic properties and linearity of the function specified in this paper. For more details, please see Appendix A.

Table 8(a) shows the estimated coefficients for CO_2 emissions. Consistent with the results mentioned above, TA has a decreasing, positive effect (from 0.60 to 0.54). We also find that TA's impact on CO_2 emissions is significantly, negatively, affected by per capita GDP, i.e., the living standard in one city. Moreover, the per capita GDP can impact the correlation between PAFRAC and CO_2 emissions at its median and lower levels. In Table 8(b), we show the results when considering the impact of the per capita GDP on the effect of urban form on CO_2 emissions per capita. TA's positive effects consistently have a property of decreasing monotonicity. Moreover, the per capita GDP near constantly, negatively, affects the correlation between TA and CO_2 emissions per capita, as well as the correlation between PAFRAC and CO_2 emissions per capita. In Table 8(c), both TA and DIVISION have the consistent impacts (increasing negative and decreasing positive, respectively) on the CO_2 emissions per unit GDP, as shown in Table 4(c). We also find that the per capita GDP increasingly, positively, affects the correlation between TA and the CO_2 emissions per unit GDP and decreasingly, negatively affects the correlation between DIVISION and CO_2 emissions per unit GDP. In sum, the per capita GDP can significantly affect the relationship between urban expansion and CO_2 emissions, and the relationship between urban complexity and CO_2 emissions. It can also affect the relationship between urban expansion and CO_2 emissions per capita, and the relationship between urban complexity and CO_2 emissions per capita. In addition, the per capita GDP can also monotonically, significantly affect the correlation between urban expansion and CO_2 emissions per unit GDP, and the correlation between urban compactness and CO_2 emissions per unit GDP.

Table 8. The Heterogeneous Effects of Urban Form on Dependent Variables after Controlling for GDP per Capita.

	(a) CO_2 Emissions			**(b) CO_2 Emissions per Capita**			**(c) CO_2 Emissions per Unit GDP**		
	0.25	**0.50**	**0.75**	**0.25**	**0.50**	**0.75**	**0.25**	**0.50**	**0.75**
TA	0.60 ***	0.57 ***	0.54 ***	0.56 **	0.51 ***	0.47 ***	−0.32 ***	−0.34 ***	−0.35 ***
	(0.09)	(0.06)	(0.07)	(0.08)	(0.06)	(0.07)	(0.08)	(0.07)	(0.12)
DIVISION	0.06	0.04	0.03	0.04	0.03	0.02	0.12 ***	0.08 **	0.04
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.06)
PAFRAC	−1.46	−0.85	−0.46	−1.20	−0.76	−0.44	1.05	1.44 *	1.90
	(0.96)	(0.62)	(0.80)	(0.89)	(0.59)	(0.78)	(0.90)	(0.80)	(1.40)
PGDP	2.14×10^{-6}	7.12×10^{-6}	0.10×10^{-4}	4.89×10^{-6}	8.45×10^{-6}	1.10×10^{-5}	-1.17×10^{-5}	-1.17×10^{-5} *	-1.16×10^{-5}
	(0.11×10^{-4})	(7.12×10^{-6})	(9.24×10^{-6})	(1.07×10^{-5})	(7.08×10^{-6})	(9.38×10^{-6})	(7.86×10^{-6})	(7.03×10^{-6})	(1.23×10^{-5})
TA × PGDP	-1.07×10^{-6}	-1.10×10^{-6} **	-1.12×10^{-6} *	-1.44×10^{-6} *	-1.44×10^{-6} **	-1.44×10^{-6} **	7.16×10^{-7} *	8.98×10^{-7} **	1.11×10^{-6} *
	(7.58×10^{-7})	(4.89×10^{-7})	(6.36×10^{-7})	(7.55×10^{-7})	(4.98×10^{-7})	(6.60×10^{-7})	(4.28×10^{-7})	(3.83×10^{-7})	(6.67×10^{-7})
DIVISION × PGDP	1.67×10^{-7}	1.17×10^{-7}	8.47×10^{-8}	4.42×10^{-7}	2.70×10^{-7}	1.44×10^{-7}	-7.82×10^{-7} **	-6.14×10^{-7} **	-4.17×10^{-7}
	(3.37×10^{-7})	(2.18×10^{-7})	(2.83×10^{-7})	(3.36×10^{-7})	(2.22×10^{-7})	(2.94×10^{-7})	(3.31×10^{-7})	(2.96×10^{-7})	(5.15×10^{-7})
PAFRAC × PGDP	3.64×10^{-5} **	2.16×10^{-5} **	1.20×10^{-5}	3.79×10^{-5} ***	2.65×10^{-5} ***	1.81×10^{-5}	-7.15×10^{-6}	-1.37×10^{-5}	-2.14×10^{-5}
	(1.62×10^{-5})	(1.05×10^{-5})	(1.36×10^{-5})	(1.42×10^{-5})	(9.38×10^{-6})	(1.24×10^{-5})	(1.45×10^{-5})	(1.30×10^{-5})	(2.27×10^{-5})
Obs.	817	817	817	817	817	817	817	817	817

Note: All variables except PGDP and interaction terms in the table are in natural logarithmic forms. The interaction term is the multiplication of two independent variables after being converted into natural logarithmic forms. The estimated coefficients at each of the quantiles are given in the columns labeled by the corresponding quantiles. Standard errors are reported in the parentheses. * indicates statistically significant at the 10% level, ** indicates statistically significant at the 5% level, and *** indicates statistically significant at the 1% level.

5. Discussion

Our study on the relationship between urban form and CO2 emissions, CO2 emissions per capita, and CO_2 emissions per unit GDP sheds light on the complex interplay between urbanization and environmental sustainability. As the world becomes increasingly urbanized, understanding the impact of urban form on carbon emissions is crucial for designing effective policies to mitigate climate change.

The estimation results in Section 4, find weak (i.e., not statistically significant) evidence that urban complexity decreases CO_2 emissions and increases CO_2 emissions per capita. We find strong evidence to support the following results: (1) Urban expansion increases the CO_2 emissions and CO_2 emissions per capita while decreases CO_2 emissions per unit GDP. This is in line with the commonly known fact that the external form of urban expansion involves large-scale construction of buildings and infrastructure to accommodate more population, thereby stimulating a surge in demand for not only the construction materials, the production of which emits a huge amount of CO_2 emissions but also the energy for household usage. The negative correlation between urban expansion and CO_2 emissions per unit GDP suggests that the expansion of urban built-up areas increases GDP more than CO_2 emissions and thus leads to the improvement of CO_2 emission efficiency through achieving the economies of scale. (2) Urban complexity increases CO_2 emissions per unit GDP. Urban complexity measures the irregularity of the shape of the land patches which could increase the time and distance of common commuting and the frequency of traffic congestion. The inefficiency of transportation will raise the cost of the production of goods and services, which means more CO_2 emissions are required for one unit of GDP and thus lower the CO_2 emission efficiency. (3) Urban compactness decreases CO_2 emissions, CO_2 emissions per capita and CO_2 emissions per unit GDP. This is consistent with the idea that urban compactness could potentially reduce CO_2 emissions by encouraging mixed land use. Mixed land use refers to a combination of residential, commercial, cultural, and institutional functions into a block or neighborhood accessible by walking and cycling. Thus, urban compactness can decrease the transportation CO_2 emissions by choosing low carbon travel modes and reducing heating-associated energy consumption in buildings by affecting the heat island effect [35]. Furthermore, compact urban form could promote the CO_2 emission efficiency through agglomeration economies [47].

To provide a more comprehensive understanding of the relationships between urban form and the dependent variables, we analyze the heterogeneous effects of urban metrics at different quantiles of the conditional distributions of the three dependent variables, respectively. We find strong evidence that the effects of TA are positive and monotonically decreasing as the levels of CO_2 emissions and CO_2 emissions per capita increase and negative and monotonically decreasing as the levels of CO_2 emissions per unit GDP increase. The urban compactness displays a similar pattern to TA except that urban compactness has a positive and monotonic decreasing impact as CO_2 emissions per unit GDP increases. For urban complexity, we find weak evidence that its impacts on CO_2 emissions and CO_2 emissions per capita both are monotonically decreasing. The impacts on CO_2 emissions are positive across the distribution of CO_2 emissions per capita and negative across the distribution of CO_2 emissions. Our results also show a positive and monotonic increase (statistically significant) in the effect on CO_2 emissions per unit GDP with respect to the urban complexity, implying that urban complexity plays an important role in improving CO_2 emission efficiency for cities with high level of CO_2 emissions inefficiency. In sum, we find strong evidence that the effects of TA and urban compactness on CO_2 emissions, CO_2 emissions per capita, and CO_2 emissions per unit GDP are heterogeneous and display monotonicity across the conditional distributions of these three dependent variables. The impacts of urban complexity on CO_2 emissions per unit GDP increase monotonically over the distribution of CO_2 emissions per unit GDP.

As previous research has shown that socioeconomic factors are closely related to changes in urban form [35], we analyzed the partial effects of urban form on dependent variables by controlling for the interaction terms between urban form and three key socioeconomic factors: the population density, the share of industry in GDP, and GDP per capita. However, unlike the study by Guo et al. [35], we believe that the effects of socioeconomic factors on the partial effects of urban form are not constant and may vary with the magnitude of the dependent variables. To account for this, we also examined the interaction effects between urban form and socioeconomic factors across the conditional distributions of the dependent variables, including CO2 emissions, CO2 emissions per capita, and CO_2 emissions per unit GDP.

Our study on the interaction effects between population density and urban metrics reveals that the magnitude of interaction effects between urban complexity and population density is monotonically decreasing with the increase in the levels of CO_2 emissions. The interaction effects between TA and population density are statistically significant at 0.50 and 0.75 quantiles and are monotonically decreasing with the increase in the quantiles of the conditional distribution of CO_2 emissions per unit GDP. These findings highlight the importance of considering the interaction effects between population density and urban metrics when designing policies to mitigate carbon emissions in urban areas. By understanding how these factors interact, policymakers can develop more effective strategies to promote sustainable urban development and reduce the negative impact of urbanization on the environment, especially for cities with high level of CO_2 emissions.

Then we examine the heterogeneous interaction effects between the share of industry in GDP and urban form variables. Our analysis reveals compelling evidence that the interaction effects between urban compactness and the share of industry in GDP are consistently increasing as the levels of CO2 emissions and CO2 emissions per capita increase. However, the differences among these effects at different quantiles of the conditional distributions of CO2 emissions and CO2 emissions per capita are negligible, allowing us to consider these effects as homogeneous. Additionally, we have found strong evidence supporting the conclusion that the interaction effects between TA and the share of industry in GDP are monotonically increasing along the distribution of CO_2 emissions per unit GDP. Overall, these findings suggests that, as the share of industry in GDP increases, it becomes increasingly important to consider the expansion and compactness of urban areas in order to mitigate the negative environmental impacts of industrial activity, especially for cities at high tail of the distribution of CO_2 emissions.

Moreover, we turn to the GDP per capita and find that the effects of TA are statistically significant at 0.25, 0.5, and 0.75 quantiles and monotonically decreasing along the distributions of the three dependent variables, respectively. We also find that the interaction effects of GDP per capita on the partial effects of urban compactness are statistically significant at 0.25 and 0.5 quantiles and monotonically increasing with the increase in the levels of CO_2 emissions per unit GDP while the interaction effects between urban complexity and GDP per capita are statistically significant at 0.25 and 0.5 quantiles and monotonically increasing as the levels of the distributions of CO_2 emissions and CO_2 emissions per capita rise, respectively.

Finally, our study could be extended by considering more socioeconomic characteristics to alleviate omitted variable bias and developing comprehensive indicators for each categorical map pattern of urban form to avoid multicollinearity without losing important information embedded in other metrics which are not selected in our paper. For example, principal component analysis, entropy evaluation methods, or other methods could be used to construct such comprehensive indicators by either extracting main characteristics of the urban form or taking the weighted average of urban metrics (proposed in this paper) in each aspect of urban form. By doing so, we can obtain a more complete picture of the relationships between urban form and carbon emissions and provide more robust evidence to inform policy-making for sustainable urban development.

6. Conclusions

Urban form is closely related to CO_2 emissions. In this paper, we use a panel quantile regression with fixed effects model to analyze the heterogeneous effects of urban form on CO_2 emission and its efficiency. It is commonly admitted that socioeconomic factors can affect the dependent variables—CO_2 emissions and CO_2 emission efficiency as well as these dependent variables' relationships with urban form.Accordingly, this paper also investigates the heterogeneous effects and the heterogeneous interaction effects of a socioeconomic factor by adding into the model this variable and the interaction terms between this variable and urban form variables.

We analyze the effects of urban form from three dimensions—urban expansion, urban compactness, and urban complexity, which are indexed by ten metrics and quantified by ArcGIS and FRAGSTATS. To avoid an issue of multicollinearity, we select three indexes—total area (TA), landscape vision index (DIVISION), and perimeter-area fractal dimension (PAFRAC), to represent urban expansion, urban compactness, and urban complexity, respectively. Our quantitative estimates from a panel of 255 cities over five periods 2000, 2005, 2010, 2015, and 2018, show that both TA and DIVISION can monotonically, positively, affect the CO_2 emissions and CO_2 emissions per capita, i.e., as the urban total area expands and becomes less compact, the CO_2 emissions and CO_2 emissions per capita increase, while these impacts are less strong for cities with an large amount of CO_2 emissions or cities in which citizens enjoy a high level of development measured by CO_2 emissions. Our results also show that TA has a monotonically negative impact on the economic efficiency of CO_2 emissions: urban expansion can significantly reduce the CO_2 emissions per unit GDP, thus improving the economic efficiency. On the other hand, PAFRAC, compared with TA, has a much stronger impact on the CO_2 emissions per unit GDP. As the CO_2 emissions per unit GDP increases, the impact of PAFRAC increases and becomes more significant. Specifically, a city with a more complex urban form usually has a low economic efficiency of CO_2 emissions.

In addition to the main results for the indices of urban form, our results for the impacts of socioeconomic factors are also statistically significant: The impacts of industry share in GDP and the GDP per capita are monotonically decreasing and positively correlated with the total amount of CO_2 emissions and the CO_2 emissions per capita. For the CO_2 emissions per unit GDP, the effect of TA is consistently negative but decreasing along the distribution of the CO_2 emissions per unit GDP, when considering socioeconomic factors. The impacts of DIVISION and PAFRAC are affected by the process of industrialization and living standard measured by per capita GDP. Industrialization and higher living standards imply higher economic efficiency of CO_2 emissions, which is specifically true for cities with high CO_2 emissions per unit GDP.

Our paper further looks into details of the impacts of socioeconomic variables on the relationship between urban form and the dependent variables related to CO_2 emissions. Our estimation results show that, for CO_2 emissions and CO_2 emissions per capita, their relationships with urban expansion and urban complexity are significantly affected by per capita GDP. Moreover, their relationships with urban compactness are affected by the level of industrialization. The relationship between CO_2 emissions per unit GDP and urban expansion is significantly influenced by all socioeconomic factors in this paper.

Overall, our findings are fairly robust in the sense that all results are consistent with urban planning intuition. Our approach of the quantile analysis, which is for the correlation between CO_2 emissions and urban form, sheds light on the optimization of urban form in improving the CO_2 emission efficiency and provides policy makers with effective ways to reduce CO_2 emissions across cities with different levels of CO_2 emissions.

While our paper has comprehensively investigated the effects of urban form on the distribution of CO_2 emission and its efficiency, it is important to acknowledge its limitations where further research is needed. First, our paper only examines three socioeconomic factors: industrial structure, population density, and GDP per capita. However, there may be other omitted variables that could cause bias in our estimation. Therefore, future research should consider additional socioeconomic characteristics to obtain a more comprehensive understanding of the effects of urban form on dependent variables. Additionally, while our paper proposes ten metrics, only three were selected due to multicollinearity issues. To address this, future research could develop comprehensive indicators for each categorical map pattern of urban form by utilizing methods such as principal component analysis, entropy evaluation, or weighted averaging of urban metrics in each aspect of urban form. This would help avoid multicollinearity while preserving important information embedded in other metrics that were not selected in our paper.

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Appendix A

Without loss of generality, we omit unobserved effects, error terms, and the indicators of urban form for simplicity. Define y_{it} as the dependent variables $ln\left(\frac{CO_2}{population}\right)_{it}$ or $ln\left(\frac{CO_2}{GDP}\right)_{it}$, and set $x_{it} = \left(ln(\frac{GDP}{population})_{it}, ln(\frac{population}{area})_{it}, ln(\frac{Industry}{GDP})_{it}\right)'$. We can rewrite the check function in Equation 4 as follows:

$$\rho_{\mu_k}(y_{it} - x'_{it}\beta(\mu_k)) = \rho_{\mu_k}\left(ln\left(\frac{CO_2}{population}\right)_{it} - \beta_1(\mu_k)ln(\frac{GDP}{population})_{it} - \beta_2(\mu_k)ln(\frac{population}{area})_{it} - \beta_3(\mu_k)ln(\frac{Industry}{GDP})_{it}\right)$$

Then the summation and difference of natural logarithmic properties give

$$\begin{aligned}&\rho_{\mu_k}\left(ln\left(\frac{CO_2}{population}\right)_{it} - \beta_1(\mu_k)ln(\frac{GDP}{population})_{it} - \beta_2(\mu_k)ln(\frac{population}{area})_{it} - \beta_3(\mu_k)ln(\frac{Industry}{GDP})_{it}\right)\\ =&\rho_{\mu_k}(ln(CO_2)_{it} - ln(population)_{it} - \beta_1(\mu_k)(ln(GDP)_{it} - ln(population)_{it})\\ &-\beta_2(\mu_k)(ln(population)_{it} - ln(area)_{it}) - \beta_3(\mu_k)(ln(Industry)_{it} - ln(GDP)_{it}))\end{aligned} \tag{A1}$$

Applying the same mathematical manipulation to the check function of $ln\left(\frac{CO_2}{GDP}\right)_{it}$ gives

$$\begin{aligned}&\rho_{\mu_k}\left(ln\left(\frac{CO_2}{GDP}\right)_{it} - \beta_1(\mu_k)ln(\frac{GDP}{population})_{it} - \beta_2(\mu_k)ln(\frac{population}{area})_{it} - \beta_3(\mu_k)ln(\frac{Industry}{GDP})_{it}\right)\\ =&\rho_{\mu_k}(ln(CO_2)_{it} - ln(GDP)_{it} - \beta_1(\mu_k)(ln(GDP)_{it} - ln(population)_{it}) - \beta_2(\mu_k)(ln(population)_{it} - ln(area)_{it})\\ &-\beta_3(\mu_k)(ln(Industry)_{it} - ln(GDP)_{it}))\\ =&\rho_{\mu_k}(ln(CO_2)_{it} - ln(population)_{it} - (\beta_1(\mu_k)+1)(ln(GDP)_{it} - ln(population)_{it})\\ &-\beta_2(\mu_k)(ln(population)_{it} - ln(area)_{it}))\end{aligned} \tag{A2}$$

The apparent discrepancy between Equations (A1) and (A2) is the difference in the coefficients of GDP per capita which are $\beta_1(\mu_k)$ in Equation (A1) and $\beta_1(\mu_k) + 1$ in Equation (A2) respectively.

Notes

[1] For details about provinces included in each region, please refer to the website of National Bureau of Statistics of China: http://www.stats.gov.cn/zt_18555/zthd/sjtjr/dejtjkfr/tjkp/202302/t20230216_1909741.htm, accessed on 1 January 2022

[2] The dataset of built-up areas from 1990 to 2020 is obtained from these two papers: Sun et al. [36] and Jiang et al. [37].

References

1. Liu, X.; Bae, J. Urbanization and industrialization impact of CO_2 emissions in China. *J. Clean. Prod.* **2018**, *172*, 178–186. [CrossRef]
2. Wang, Z.; Huang, W.; Chen, Z. The peak of CO_2 emissions in China: A new approach using survival models. *Energy Econ.* **2019**, *81*, 1099–1108. [CrossRef]
3. Fang, K.; Tang, Y.; Zhang, Q.; Song, J.; Wen, Q.; Sun, H.; Ji, C.; Xu, A. Will China peak its energy-related carbon emissions by 2030? Lessons from 30 Chinese provinces. *Appl. Energy* **2019**, *255*, 113852. [CrossRef]
4. Li, R.Y.M.; Wang, Q.; Zeng, L.; Chen, H. A study on public perceptions of carbon neutrality in China: Has the idea of ESG been encompassed? *Front. Environ. Sci.* **2023**, *10*, 1032. [CrossRef]
5. Živković, J. Urban Form and Function. In *Climate Action*; Leal Filho, W., Azeiteiro, U., Azul, A., Brandli, L., Özuyar, P., Wall, T., Eds.; Springer: Cham, Switzerland 2019; pp. 862–871. . [CrossRef]
6. Cui, S.; Xu, L.; Huang, Y.; Wang, J.; Li, Y.; Li, Y.; Yang, Y.; Zhou, Y. Progress and prospect of study on urban spatial patterns to cope with climate change. *Prog. Geogr.* **2015**, *34*, 1209–1218.
7. Cui, X.; Huang, W.; Deng, W.; Jia, C. Spatial Patterns, Drivers and Heterogeneous Effects of $PM_{2.5}$: Experience from China. *Pol. J. Environ. Stud.* **2022**, *31*, 5633–5647. [CrossRef]
8. Shan, L.; Jiang, Y.; Liu, C.; Zhang, J.; Zhang, G.; Cui, X. Conflict or Coordination? Spatiotemporal Coupling of Urban Population–Land Spatial Patterns and Ecological Efficiency. Front. *Public Health* **2022**, *10*, 890175.
9. Stone Jr, B.; Rodgers, M.O. Urban form and thermal efficiency: how the design of cities influences the urban heat island effect. *Am. Plan. Assoc. J. Am. Plan. Assoc.* **2001**, *67*, 186. [CrossRef]
10. Hankey, S.; Marshall, J.D. Impacts of urban form on future US passenger-vehicle greenhouse gas emissions. *Energy Policy* **2010**, *38*, 4880–4887. [CrossRef]

11. Ishii, S.; Tabushi, S.; Aramaki, T.; Hanaki, K. Impact of future urban form on the potential to reduce greenhouse gas emissions from residential, commercial and public buildings in Utsunomiya, Japan. *Energy Policy* **2010**, *38*, 4888–4896. [CrossRef]
12. Liu, X.; Sweeney, J. Modelling the impact of urban form on household energy demand and related CO_2 emissions in the Greater Dublin Region. *Energy Policy* **2012**, *46*, 359–369. [CrossRef]
13. Ou, J.; Liu, X.; Li, X.; Chen, Y. Quantifying the relationship between urban forms and carbon emissions using panel data analysis. *Landsc. Ecol.* **2013**, *28*, 1889–1907. [CrossRef]
14. Salat, S.; Bourdic, L. Urban complexity, efficiency and resilience. In *Energy Efficiency—A Bridge to Low Carbon Economy*; Morvaj, Z., Ed.; InTechOpen: Rijeka, Croatia, 2012; pp. 25–44.
15. Zhang, H.; Peng, J.; Wang, R.; Zhang, J.; Yu, D. Spatial planning factors that influence CO_2 emissions: A systematic literature review. *Urban Clim.* **2021**, *36*, 100809. [CrossRef]
16. Lee, S.; Lee, B. The influence of urban form on GHG emissions in the US household sector. *Energy Policy* **2014**, *68*, 534–549. [CrossRef]
17. Ye, H.; He, X.; Song, Y.; Li, X.; Zhang, G.; Lin, T.; Xiao, L. A sustainable urban form: The challenges of compactness from the viewpoint of energy consumption and carbon emission. *Energy Build.* **2015**, *93*, 90–98. . [CrossRef]
18. Zheng, S.; Huang, Y.; Sun, Y. Effects of Urban Form on Carbon Emissions in China: Implications for Low-Carbon Urban Planning. *Land* **2022**, *11*, 1343. [CrossRef]
19. Burton, E. Measuring urban compactness in UK towns and cities. *Environ. Plan. B Plan. Des.* **2002**, *29*, 219–250. [CrossRef]
20. Liu, Y.; Song, Y.; Song, X. An empirical study on the relationship between urban compactness and CO_2 efficiency in China. *Habitat Int.* **2014**, *41*, 92–98. [CrossRef]
21. Fang, C.; Wang, S.; Li, G. Changing urban forms and carbon dioxide emissions in China: A case study of 30 provincial capital cities. *Appl. Energy* **2015**, *158*, 519–531. [CrossRef]
22. Li, S.; Zhou, C.; Wang, S.; Hu, J. Dose urban landscape pattern affect CO_2 emission efficiency? Empirical evidence from megacities in China. *J. Clean. Prod.* **2018**, *203*, 164–178. [CrossRef]
23. Falahatkar, S.; Rezaei, F. Towards low carbon cities: Spatio-temporal dynamics of urban form and carbon dioxide emissions. *Remote. Sens. Appl. Soc. Environ.* **2020**, *18*, 100317. [CrossRef]
24. Sun, C.; Zhang, Y.; Ma, W.; Wu, R.; Wang, S. The Impacts of Urban Form on Carbon Emissions: A Comprehensive Review. *Land* **2022**, *11*, 1430. [CrossRef]
25. Makido, Y.; Dhakal, S.; Yamagata, Y. Relationship between urban form and CO_2 emissions: Evidence from fifty Japanese cities. *Urban Clim.* **2012**, *2*, 55–67. [CrossRef]
26. Wang, S.; Shi, C.; Fang, C.; Feng, K. Examining the spatial variations of determinants of energy-related CO_2 emissions in China at the city level using Geographically Weighted Regression Model. *Appl. Energy* **2019**, *235*, 95–105. [CrossRef]
27. Pao, H.T.; Tsai, C.M. Multivariate Granger causality between CO_2 emissions, energy consumption, FDI (foreign direct investment) and GDP (gross domestic product): evidence from a panel of BRIC (Brazil, Russian Federation, India, and China) countries. *Energy* **2011**, *36*, 685–693. [CrossRef]
28. Omri, A.; Nguyen, D.K.; Rault, C. Causal interactions between CO_2 emissions, FDI, and economic growth: Evidence from dynamic simultaneous-equation models. *Econ. Model.* **2014**, *42*, 382–389. [CrossRef]
29. Wang, S.; Wang, J.; Li, S.; Fang, C.; Feng, K. Socioeconomic driving forces and scenario simulation of CO_2 emissions for a fast-developing region in China. *J. Clean. Prod.* **2019**, *216*, 217–229. [CrossRef]
30. Xia, J.; Li, R.Y.M.; Zhan, X.; Song, L.; Bai, W. A study on the impact of fiscal decentralization on carbon emissions with U-shape and regulatory effect. *Front. Environ. Sci.* **2022**, *10*, 964327. [CrossRef]
31. Li, Y.; Xiong, W.; Wang, X. Does polycentric and compact development alleviate urban traffic congestion? A case study of 98 Chinese cities. *Cities* **2019**, *88*, 100–111. [CrossRef]
32. Xu, X.; Xu, H. The Driving Factors of Carbon Emissions in China's Transportation Sector: A Spatial Analysis. *Front. Energy Res.* **2021**, *9*, 225. [CrossRef]
33. Li, X.; Yu, B. Peaking CO_2 emissions for China's urban passenger transport sector. *Energy Policy* **2019**, *133*, 110913. [CrossRef]
34. Benhelal, E.; Zahedi, G.; Shamsaei, E.; Bahadori, A. Global strategies and potentials to curb CO_2 emissions in cement industry. *J. Clean. Prod.* **2013**, *51*, 142–161.
35. Guo, R.; Leng, H.; Yuan, Q.; Song, S. Impact of Urban Form on CO_2 Emissions under Different Socioeconomic Factors: Evidence from 132 Small and Medium-Sized Cities in China. *Land* **2022**, *11*, 713. [CrossRef]
36. Sun, Z.; Sun, J.; Guo, H.; Jiang, H.; Gao, J.; Jianbo, W. A dataset of built-up areas in Chinese cities in 2020. *Science Data Bank* **2021** . [CrossRef]
37. Jiang, H.; Sun, Z.; Guo, H.; Du, W.; Xing, Q.; Cai, G. A standardized dataset of built-up areas of China's cities with populations over 300,000 for the period 1990–2015. *Science Data Bank.* **2021** . [CrossRef]
38. Shan, Y.; Guan, D.; Liu, J.; Mi, Z.; Liu, Z.; Liu, J.; Schroeder, H.; Cai, B.; Chen, Y.; Shao, S.; et al. Methodology and applications of city level CO_2 emission accounts in China. *J. Clean. Prod.* **2017**, *161*, 1215–1225. [CrossRef]
39. Shan, Y.; Guan, D.; Hubacek, K.; Zheng, B.; Davis, S.J.; Jia, L.; Liu, J.; Liu, Z.; Fromer, N.; Mi, Z.; et al. City-level climate change mitigation in China. *Sci. Adv.* **2018**, *4*, eaaq0390. [CrossRef]
40. Shan, Y.; Liu, J.; Liu, Z.; Shao, S.; Guan, D. An emissions-socioeconomic inventory of Chinese cities. *Sci. Data* **2019**, *6*, 1–10.

41. Shan, Y.; Guan, Y.; Hang, Y.; Zheng, H.; Li, Y.; Guan, D.; Li, J.; Zhou, Y.; Li, L.; Hubacek, K. City-level emission peak and drivers in China. *Sci. Bull.* **2022**, *67*, 1910–1920. [CrossRef]
42. McGarigal, K. *FRAGSTATS Help*; University of Massachusetts: Amherst, MA, USA, 2015; Volume 182.
43. Liu, Y.; Zhou, Y.; Wu, W. Assessing the impact of population, income and technology on energy consumption and industrial pollutant emissions in China. *Appl. Energy* **2015**, *155*, 904–917. [CrossRef]
44. Tian, X.; Bai, F.; Jia, J.; Liu, Y.; Shi, F. Realizing low-carbon development in a developing and industrializing region: Impacts of industrial structure change on CO_2 emissions in southwest China. *J. Environ. Manag.* **2019**, *233*, 728–738. [CrossRef] [PubMed]
45. Koenker, R. Quantile regression for longitudinal data. *J. Multivar. Anal.* **2004**, *91*, 74–89. [CrossRef]
46. Koenker, R.; Bassett Jr, G. Regression quantiles. *Econom. J. Econom. Soc.* **1978**, 33–50. [CrossRef]
47. Yao, Y.; Pan, H.; Cui, X.; Wang, Z. Do compact cities have higher efficiencies of agglomeration economies? A dynamic panel model with compactness indicators. *Land Use Policy* **2022**, *115*, 106005. . [CrossRef]