

## Article

# Urban Management for Building-Sector Decarbonization: Focusing on the Role of Low-Carbon Policies

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**Abstract:** The building sector is a major source of anthropogenic carbon emissions worldwide. While existing studies have extensively explored the socioeconomic and technological impacts on carbon emissions generated from building operations, few have assessed the effectiveness of low-carbon policies in curbing the increasing trend of building sector carbon emissions. This study examines the impacts of low-carbon policy intensity on building sector carbon emissions using a two-way fixed effects model on a 6-year panel (2015–2020) dataset for 286 cities in China. Our findings indicate that, on average, the aggregated intensity of low-carbon policies fails to pose any significant impacts on carbon emissions from building operations. This is partly due to the variations in different types of policy. Specifically, a 10% increase in the intensity of energy conservation policy results in a 0.05% decrease in carbon emissions, whereas capacity utilization policies are associated with an increase in building-operation carbon emissions. Moreover, these policy–emission relationships vary across building types and end-use sources. In particular, energy conservation policies are negatively associated with emissions from cooking and heating, but positively related to emissions generated from appliances and cooling. In comparison, capacity utilization policies tend to encourage additional emissions from most sources. This study highlights the partial effectiveness of energy conservation policies in curbing building sector carbon emissions and underscores the need for additional efforts in tackling the rebound effects to realize building sector decarbonization.

**Keywords:** building-operation carbon emissions; low-carbon policy; urban management; heterogeneous effects; two-way fixed effects model



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## 1. Introduction

Anthropogenic carbon emissions are known as a leading cause of global climate change, severely challenging the goal of achieving sustainable development [1–4]. The building operations sector is becoming a main source of anthropogenic carbon emissions worldwide. For example, it is estimated that around 36% of the total carbon emissions globally come from the building sector, and this number is slightly higher in developed countries than in developing countries [5]. Given this background, a series of policies have been employed to curb the increasing trend of carbon emissions generated from the building operations sector. For example, in Europe, the Emission Trading Scheme (ETS) has been designed to mitigate carbon emissions from the building sector [6]. Similar ETS projects have also been adopted in several pilots in China, together with some other carbon emission regulations for the building sector [7]. Despite the wide application of these policies and instruments, rigorous evaluations of their effectiveness in mitigating carbon emissions are still sparse, hindering sustainable urban and environmental management.

Among the existing literature, mixed evidence on the impacts of policy measures on building sector emissions has been documented. On the one hand, a group of studies have shown that policy measures can effectively mitigate carbon emissions generated from the building operations sector [8,9]. On the other hand, another group of studies suggests that the adoption of policy measures or other instruments does not have significant emission-mitigation impacts and may even bring about emission-intensifying effects [10,11]. Such disparities may be explained by three reasons. First, there is a dualistic nature to certain types of policy measures affecting carbon emissions. For example, while improved energy efficiency may lead to energy savings and, subsequently, carbon emission reductions [12,13], it is also likely to induce additional energy use via the rebound effect, which have been widely documented in the Europe and elsewhere in the world [14,15]. Second, different sources of energy consumption may not respond in the same way to certain policy measures. For example, China's ETS is only applicable to carbon emissions generated from public and commercial buildings [16]. Therefore, it is less likely that the ETS could curb the increasing trend of carbon emissions from residential buildings at the current stage. Third, since the estimation results reflect the average treatment effects of policy measures, they can hardly capture the spatial heterogeneities underlying policy impacts on carbon emissions. For these reasons, a comprehensive understanding of how various types of policy measures affect carbon emissions generated from different sources of energy use for different cities during building operations holds significant value in paving the way toward building-sector decarbonization, motivating this study.

In this study, we ask four research questions: (1) how large are the impacts of low-carbon policy intensity on building sector carbon emissions?; (2) how do such impacts vary across cities?; (3) how do different types of policies affect building sector carbon emissions?; and (4) how do different types of policies affect carbon emissions from various end-use sources? For the analysis, we examine the impacts of the intensity of different emission-related policies on the carbon emissions generated from various sources of building operations, using a two-way fixed effects model on a 6-year panel dataset (2015–2020) for 286 Chinese cities.

We focus on China for two reasons. First, China, at present, is the largest carbon emitter in the world and has made an emission mitigation commitment to the world with its ambitious carbon emission mitigation plans [17,18]. Considering the carbon emissions and climate change are regional or even global issues, the findings drawn from this research are expected to also hold international implications. Second, as one of the largest developing countries in the world, China is experiencing rapid urbanization and soaring demand for buildings, particularly in the large cities with substantial migration inflows [19,20]. In this sense, our study would carry long-lasting policy and practical implications for the China's growing building sector.

The academic merit of this study is twofold. First, this study enriches the literature on building sector carbon emission control by quantifying the emission impacts of low-carbon policies. Previous studies have focused mainly on socioeconomic and technological impacts on building sector carbon emissions while neglecting the role of policy measures [21,22]. Second, the use of up-to-date policy intensity and building operation carbon emissions data for the analysis allows us to explore more details underlying the policy impacts on building sector carbon emissions. In particular, the policy intensity measures extracted from textual data used in this study can accurately capture variations in policy stringency, and the emissions data provide information on building types and end-use sources.

## 2. Materials and Methods

### 2.1. Empirical Model

A two-way fixed effects model is adopted to examine the impacts of the intensity of low-carbon policies on building sector carbon emissions. The two-way fixed effects model has the advantage of addressing the estimation biases brought by unobserved time-invariant confounding variables (e.g., topographic features, cultural factors) and time-

varying confounders that are applied to all samples (e.g., implementation of national-level standards and regulations), using city-and time-specific fixed effects terms. Specifically, a baseline model is specified as follows:

$$CE_{it} = \beta_0 + \beta_1 PI_{it} + \mathbf{X}_{it}\boldsymbol{\gamma} + \sigma_i + \mu_t + \varepsilon_{it} \quad (1)$$

where  $CE_{it}$  is the carbon emissions generated from the building-operations sector (in logarithm form) in city  $i$  at time  $t$ ;  $PI_{it}$  is the policy intensity for low-carbon policies implemented at national, provincial, and prefecture levels (in logarithm form) in city  $i$  at time  $t$ ;  $\mathbf{X}_{it}$  is a vector of control variables (in logarithm form), which are key drivers of energy consumption as suggested in previous empirical studies [23–25], including population, GDP per capita, GDP share of tertiary industry, temperature, wind speed, and precipitation, in city  $i$  at time  $t$ ;  $\beta_0$ ,  $\beta_1$ ,  $\boldsymbol{\gamma}$  are the coefficient or vector of coefficients to be estimated;  $\sigma_i$  and  $\mu_t$  are the city- and year-fixed effects terms; and  $\varepsilon_{it}$  is the error term.

Incorporating climatic variables into the regression analysis investigating the policy impacts on building sector carbon emissions is essential for several reasons. First, climatic factors, such as temperature, humidity, and precipitation, significantly influence energy demand patterns in buildings, particularly for heating and cooling requirements. By accounting for these variables, one can better isolate the effects of specific policies on carbon emissions, ensuring that the analysis accurately reflects the interplay between environmental conditions and energy consumption behaviors. Furthermore, the inclusion of climatic variables enhances the robustness of the model, allowing for a more comprehensive understanding of how external factors may exacerbate or mitigate the effectiveness of low-carbon policies.

Considering that various policies may have different impacts, in terms of the signs and magnitude of the effect on building sector carbon emissions, we further disaggregate the indicator of energy-related policy intensity to four specific policy measures in Equation (2):

$$CE_{it} = \beta_0 + \mathbf{PI}_{it}\boldsymbol{\tau} + \mathbf{X}_{it}\boldsymbol{\gamma} + \sigma_i + \mu_t + \varepsilon_{it} \quad (2)$$

where  $\mathbf{PI}_{it}$  is a vector of intensity measures for carbon reduction policies, energy conservation policies, capacity utilization policies, and technology policies in city  $i$  at time  $t$ ;  $\boldsymbol{\tau}$  is a vector of coefficients to be estimated; and all other notations are the same as defined in Equation (1).

To examine the heterogeneous effects underlying the policy–emission relationship, we estimate the regression model specified in Equation (3):

$$CE_{it} = \beta_0 + \beta_1 PI_{it} + \beta_2 PI_{it} \cdot D_i + \mathbf{X}_{it}\boldsymbol{\gamma} + \sigma_i + \mu_t + \varepsilon_{it} \quad (3)$$

where  $D_i$  is a binary dummy indicating whether city  $i$  is among the first half of the samples with a larger population size, a greater GDP per capita, or a higher temperature;  $\beta_2$  is the coefficient capturing the heterogeneous effects, and all other notations are the same as defined in Equation (1).

## 2.2. Data

A panel dataset for 286 Chinese cities has been developed for the period 2015–2020 from various public sources. A full list of variables, their definitions, and summary statistics are presented in Table 1, and the spatial distribution of sample cities is displayed in Figure 1a (since over 90% of the population resides in eastern China, socioeconomic data from statistical yearbooks is often missing for western Chinese cities). Specifically, the data on building-related carbon emissions from 2015 to 2020 are estimated and provided by Yu et al. (2024) [26]. This dataset contains the total carbon emissions generated from building operations and disaggregated carbon emissions for different building types (e.g., public and commercial buildings, urban residential buildings, and rural residential buildings) and end-use sources (e.g., appliances, lighting, cooling, cooking, heating) available on a yearly

basis at the city level. As shown in Figure 1b, carbon emissions from building operations are generally higher in northern Chinese cities and first- and second-tier cities than others. This may be explained by their greater energy consumption associated with winter heating and higher demand for socioeconomic activities.

Policy intensity data for low-carbon policies from 2007 to 2022 at the city level are calculated and offered by Dong et al. (2024) [27]. Specifically, natural language processing (NLP) techniques are applied to policy documents to develop policy intensity measures. The dataset contains aggregated policy intensity measures for low-carbon policies and disaggregated policy intensity measures for carbon reduction policies, energy conservation policies, capacity utilization policies, and technology policies. As shown in Figure 1c, the aggregated policy intensity for low-carbon policies tends to be higher in the eastern coastal region.

Finally, we collect socioeconomic and climate data from the China Urban Statistical Yearbooks and the National Centers for Environmental Information (NCEI) climate data online, respectively. Specifically, the data on population, GDP per capita, GDP share of tertiary industry, temperature, wind speed, and precipitation are used for the analysis.

**Table 1.** List of variables, variable definitions, and detailed statistics.

| Variable                         | Definition                                                                     | Obs  | Mean      | Std. Dev  |
|----------------------------------|--------------------------------------------------------------------------------|------|-----------|-----------|
| <i>Dependent Variables</i>       |                                                                                |      |           |           |
| TCE                              | Total carbon emissions from building operation ( $10^3$ tons)                  | 1716 | 6713.47   | 9123.20   |
| PCCE                             | Carbon emissions from public and commercial building operations ( $10^3$ tons) | 1716 | 2855.58   | 4640.28   |
| URCE                             | Carbon emissions from urban residential building operation ( $10^3$ tons)      | 1716 | 2630.85   | 4018.84   |
| RRCE                             | Carbon emissions from rural residential building operation ( $10^3$ tons)      | 1716 | 1227.05   | 1182.79   |
| ACE                              | Carbon emissions from appliances ( $10^3$ tons)                                | 1716 | 1482.89   | 2417.97   |
| LCE                              | Carbon emissions from lighting ( $10^3$ tons)                                  | 1716 | 751.65    | 897.63    |
| CCE                              | Carbon emissions from cooling ( $10^3$ tons)                                   | 1716 | 571.96    | 1036.11   |
| CWCE                             | Carbon emissions from cooking and water heating ( $10^3$ tons)                 | 1716 | 1203.48   | 1433.17   |
| DHCE                             | Carbon emissions from distributed heating ( $10^3$ tons)                       | 1716 | 1202.77   | 1627.34   |
| CHCE                             | Carbon emissions from central heating ( $10^3$ tons)                           | 1716 | 1501.12   | 3518.24   |
| <i>Policy Intensity Measures</i> |                                                                                |      |           |           |
| PIA                              | Total intensity for all low-carbon policies                                    | 1716 | 52.91     | 42.85     |
| PICR                             | Intensity for carbon reduction policies                                        | 1716 | 19.81     | 16.59     |
| PIEC                             | Intensity for energy conservation policies                                     | 1716 | 15.03     | 14.07     |
| PICU                             | Intensity for capacity utilization policies                                    | 1716 | 8.13      | 8.78      |
| PITEC                            | Intensity for technology policies                                              | 1716 | 9.95      | 12.32     |
| <i>Covariates</i>                |                                                                                |      |           |           |
| POP                              | Population within the city proper (million persons)                            | 1716 | 453.02    | 325.89    |
| GDPPC                            | Gross domestic product per capita (RMB)                                        | 1716 | 58,580.44 | 33,940.44 |
| T_SHR                            | GDP share of tertiary industry (%)                                             | 1716 | 45.65     | 8.90      |
| TEMP                             | Annual average temperature ( $^{\circ}\text{C}$ )                              | 1716 | 15.87     | 5.34      |
| WS                               | Annual average wind speed (m/s)                                                | 1716 | 4.92      | 0.98      |
| PREC                             | Annual total precipitation (mm)                                                | 1716 | 1156.13   | 589.90    |

Note: Obs refers to number of observations; std. dev refers to standard deviations.

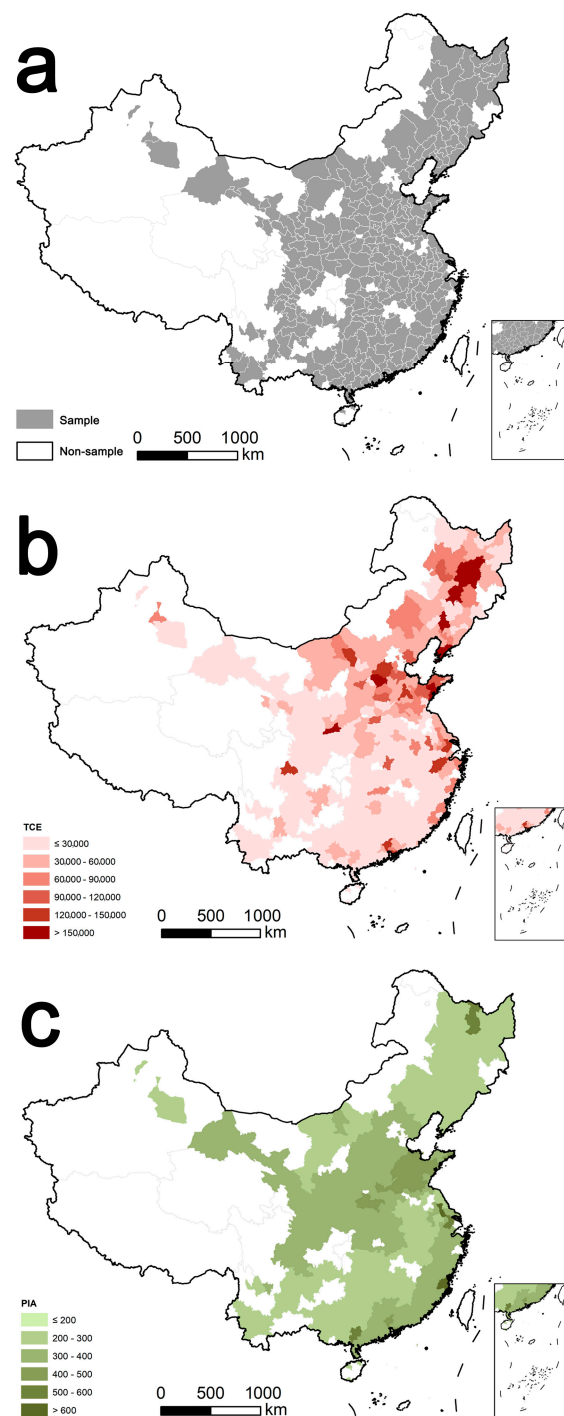


**Figure 1.** Spatial distribution of sample cities, building sector carbon emissions, and policy intensity for low-carbon policies. (a) Spatial distribution of sample cities; (b) building sector carbon emissions of sample cities; and (c) policy intensity for low-carbon policies of sample cities.

### 3. Results

#### 3.1. Baseline Results

This section attempts to answer the first research question. Specifically, the baseline model results show that the aggregated policy intensity for low-carbon policies fails to pose any significant impacts on carbon emissions generated from building operations (Table 2). As shown in column 1, the coefficient of interest is negative but not significant at the 10% or higher level. This may be understood in several ways. First, there are different types of low-carbon policies that may potentially have conflicting impacts on building-operation

carbon emissions. Second, residents in different cities may respond in different ways to low-carbon policies. Third, even within the same city, people's behavioral responses to low-carbon policies may vary across building types and end-use sources. Finally, there may be data limitation and policy design issues. For example, the document-based policy intensity data may not accurately capture the policy design features.

The results presented in column 2 confirm the first hypothesis. Among the four different types of policy measures, energy conservation policies tend to be negatively associated with building-operation carbon emissions, reflecting the effectiveness of this type of policy in promoting carbon neutrality in China's context. Specifically, a 1% increase in the intensity of energy conservation policies leads to a  $-0.005\%$  decrease in carbon emissions from building operations. In contrast, capacity utilization policies are positively associated with carbon emissions generated from building operations sector, with a coefficient of 0.010. This may be explained by the rebound effect, which refers to an increasing demand for energy associated with improved energy efficiency [28]. The remaining two types of policies, carbon reduction policies and technology policies, do not exhibit any significant impacts on building operation-related carbon emissions. Furthermore, to address potential multicollinearity problems, we calculate the variance inflation factor (VIF) value for each independent variable. As shown in the last column of Table 2, all estimated VIF values are substantially below the threshold of 10 [29,30], suggesting that the independent variables included in the regression model are not likely to be highly correlated with each other and cause estimation biases.

As for control variables, in both columns, the coefficients for population, GDP per capita, and wind speed are positive and statistically significant at the 5% or higher level, and the coefficient for precipitation is negative and statistically significant at the 1% level, following our expectations.

**Table 2.** Model results: baseline regression.

|                                  | LHS Variable: TCE     |                       |      |
|----------------------------------|-----------------------|-----------------------|------|
|                                  | (1)                   | (2)                   | VIF  |
| <i>Policy Intensity Measures</i> |                       |                       |      |
| PIA                              | −0.004<br>(0.005)     |                       |      |
| PICR                             |                       | 0.001<br>(0.004)      | 1.86 |
| PIEC                             |                       | −0.005 *<br>(0.003)   | 1.86 |
| PICU                             |                       | 0.010 ***<br>(0.003)  | 1.16 |
| PI TEC                           |                       | 0.004<br>(0.004)      | 1.89 |
| <i>Covariates</i>                |                       |                       |      |
| POP                              | 0.668 ***<br>(0.151)  | 0.657 ***<br>(0.148)  | 1.21 |
| GDPPC                            | 0.230 ***<br>(0.044)  | 0.236 ***<br>(0.043)  | 1.25 |
| T_SHR                            | 0.090<br>(0.062)      | 0.092<br>(0.062)      | 1.27 |
| TEMP                             | 0.038<br>(0.029)      | 0.040<br>(0.029)      | 1.83 |
| WS                               | 0.166 **<br>(0.068)   | 0.170 **<br>(0.068)   | 1.39 |
| PREC                             | −0.106 ***<br>(0.018) | −0.107 ***<br>(0.018) | 1.60 |
| City fixed effects               | YES                   | YES                   |      |
| Year fixed effects               | YES                   | YES                   |      |
| Constant                         | 0.418<br>(1.407)      | 0.404<br>(1.389)      |      |
| R <sup>2</sup>                   | 0.990                 | 0.990                 |      |
| Observations                     | 1716                  | 1716                  |      |

Note: \* 10% statistical significance; \*\* 5% statistical significance; \*\*\* 1% statistical significance; standard errors (in parentheses) are clustered at the city level.

### 3.2. Heterogeneous Effects

In this section, we investigate the spatial heterogeneities in the carbon emission effects of low-carbon policy intensity, answering the second research question. As demonstrated in Figure 2a,b, the estimated carbon emission impacts of policy intensity vary across space. Specifically, most cities in the northeast provinces (Heilongjiang, Jilin, and Liaoning) show positive coefficients, while most cities in the Guangxi, Henan, Jiangsu, Jiangxi, and Shandong provinces have negative coefficients (Figure 2c). This may be explained by the higher energy demand for winter heating and slow economic growth in the northeastern cities.

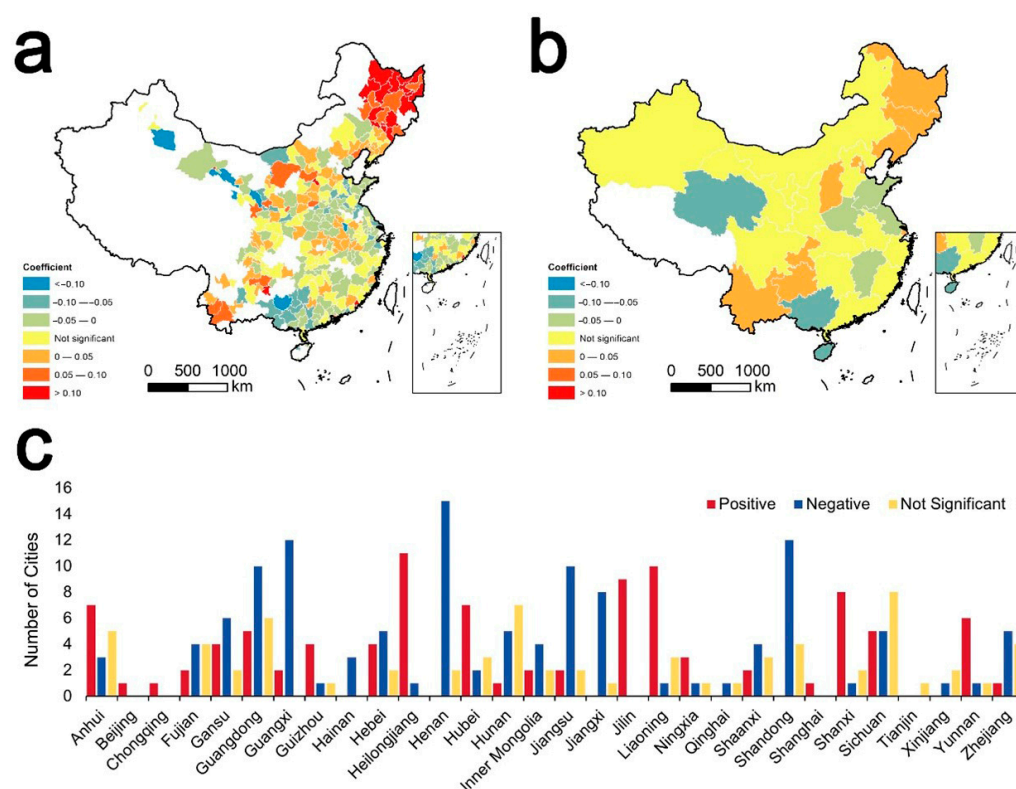


**Figure 2.** City- and province-specific estimates of policy intensity impacts on building sector carbon emissions. (a) City-specific estimates of the PIA impact on TCE; (b) province-specific estimates of the PIA impact on TCE; and (c) number of cities with positive, negative, and not significant coefficients within each province.

Then, we further investigate whether the spatial heterogeneity in the carbon emission impacts of policy intensity can be explained by socioeconomic and climate factors (Table 3). Among the three models displayed in columns 1 to 3, the coefficients for the interaction terms,  $PIA \times H\_GDPPC$  and  $H\_TEMP$ , are negative and significant at the 1% level, suggesting that low-carbon policies have greater emission-mitigation impacts in wealthier and warmer cities, with estimated elasticities of  $-0.016$  and  $-0.022$ , respectively. At one level, residents in wealthier and larger cities usually have a higher awareness of environmental problems [31,32]. At another level, energy demand for winter heating, a main source of building-operation carbon emissions, is inelastic to policy measures in cities with cold winters [33,34]. In addition, the coefficient for the interaction term,  $PIA \times H\_POP$ , is not significant at the 10% level, suggesting that the policy impacts on carbon emissions are indifferent across cities with various population sizes.

**Table 3.** Model results: heterogeneous effect.

|                                  | LHS Variable: TCE     |                       |                       |
|----------------------------------|-----------------------|-----------------------|-----------------------|
|                                  | (1)                   | (2)                   | (3)                   |
| <i>Policy Intensity Measures</i> |                       |                       |                       |
| PIA                              | −0.001<br>(0.006)     | 0.001<br>(0.006)      | 0.010<br>(0.007)      |
| <i>Interaction terms</i>         |                       |                       |                       |
| PIA × H_POP                      | −0.008<br>(0.006)     |                       |                       |
| PIA × H_GDPPC                    |                       | −0.016 ***<br>(0.006) |                       |
| PIA × H_TEMP                     |                       |                       | −0.022 ***<br>(0.006) |
| <i>Covariates</i>                |                       |                       |                       |
| POP                              | 0.659 ***<br>(0.149)  | 0.647 ***<br>(0.147)  | 0.623 ***<br>(0.142)  |
| GDPPC                            | 0.226 ***<br>(0.044)  | 0.240 ***<br>(0.044)  | 0.197 ***<br>(0.044)  |
| T_SHR                            | 0.087<br>(0.062)      | 0.109<br>(0.062)      | 0.063<br>(0.061)      |
| TEMP                             | 0.039<br>(0.029)      | 0.038<br>(0.029)      | 0.043<br>(0.029)      |
| WS                               | 0.166 **<br>(0.068)   | 0.174 **<br>(0.069)   | 0.142 **<br>(0.069)   |
| PREC                             | −0.106 ***<br>(0.018) | −0.098 ***<br>(0.018) | −0.103 ***<br>(0.018) |
| City fixed effects               | YES                   | YES                   | YES                   |
| Year fixed effects               | YES                   | YES                   | YES                   |
| Constant                         | 0.545<br>(1.403)      | 0.343<br>(1.376)      | 1.238<br>(1.358)      |
| R <sup>2</sup>                   | 0.990                 | 0.990                 | 0.990                 |
| Observations                     | 1716                  | 1716                  | 1716                  |

Note: \*\* 5% statistical significance; \*\*\* 1% statistical significance; standard errors (in parentheses) are clustered at the city level; H\_POP: binary dummy variable equals one if the city has a population size greater than the sample average; H\_GDPPC: binary dummy variable equals one if the city has a GDP per capita greater than the sample average; H\_TEMP: binary dummy variable equals one if the city has a higher temperature than the sample average.

### 3.3. Results for Different Building Types

To answer the third research question, we examine the emission effects of low-carbon policy intensity for different building types. Overall, the policy impacts on building-operation carbon emissions vary across building types (Table 4). Specifically, carbon emissions generated from public and commercial buildings are positively affected by the intensity of carbon reduction and capacity utilization policies, with a 1% increase in carbon reduction and capacity utilization policy intensity contributing to a 0.01% and a 0.009% increase in emissions from public and commercial buildings, respectively. In comparison, those generated from rural residential buildings are positively affected by the intensity of capacity utilization and technology policies, with estimated elasticity of 0.014 and 0.015, respectively. However, carbon emissions generated from urban residential buildings are not significantly impacted by low-carbon policies. These results suggest that China's low-carbon policies, in general, cannot mitigate carbon emissions from building operations and even result in a rebound effect, leading to increased carbon emissions.

**Table 4.** Model results: building type.

|                                  | LHS Variable: PCCE    | LHS Variable: URCE    | LHS Variable: RRCE    |
|----------------------------------|-----------------------|-----------------------|-----------------------|
|                                  | (1)                   | (2)                   | (3)                   |
| <i>Policy Intensity Measures</i> |                       |                       |                       |
| PICR                             | 0.010 *<br>(0.006)    | −0.000<br>(0.006)     | −0.003<br>(0.005)     |
| PIEC                             | −0.005<br>(0.004)     | −0.005<br>(0.004)     | −0.005<br>(0.004)     |
| PICU                             | 0.009 **<br>(0.004)   | 0.007<br>(0.005)      | 0.014 ***<br>(0.005)  |
| PITEC                            | 0.000<br>(0.005)      | 0.004<br>(0.005)      | 0.015 ***<br>(0.005)  |
| <i>Covariates</i>                |                       |                       |                       |
| POP                              | 0.829 ***<br>(0.200)  | 0.360 ***<br>(0.130)  | 0.448 ***<br>(0.137)  |
| GDPPC                            | 0.433 ***<br>(0.070)  | 0.187 ***<br>(0.050)  | 0.267<br>(0.038)      |
| T_SHR                            | 0.130<br>(0.100)      | 0.260 ***<br>(0.070)  | −0.178 **<br>(0.070)  |
| TEMP                             | 0.004<br>(0.042)      | 0.050<br>(0.043)      | 0.048 *<br>(0.027)    |
| WS                               | 0.233 ***<br>(0.086)  | 0.187 **<br>(0.082)   | 0.176 **<br>(0.088)   |
| PREC                             | −0.114 ***<br>(0.018) | −0.086 ***<br>(0.024) | −0.095 ***<br>(0.021) |
| City fixed effects               | YES                   | YES                   | YES                   |
| Year fixed effects               | YES                   | YES                   | YES                   |
| Constant                         | −4.184 **<br>(1.900)  | 1.459<br>(1.338)      | 3.677 ***<br>(1.334)  |
| R <sup>2</sup>                   | 0.983                 | 0.987                 | 0.985                 |
| Observations                     | 1716                  | 1716                  | 1716                  |

Note: \* 10% statistical significance; \*\* 5% statistical significance; \*\*\* 1% statistical significance; standard errors (in parentheses) are clustered at the city level.

### 3.4. Results for Different End-Uses

Finally, we answer the last research question by showing how the intensity of low-carbon policies affects carbon emissions generated from different end-use sources during building operations (Table 5). As shown in columns 1 and 2, energy conservation and capacity utilization policies serve as emission abators and intensifiers, respectively, for cooling, water heating, and distributed heating. This coincides with the results presented in Table 2, reflecting that energy conservation policies are a more favorable choice than capacity utilization in mitigating carbon emissions generated from cooling and heating during building operations. Additionally, the intensity of low-carbon technology policies is negatively associated with carbon emissions generated from central heating. This is probably because central heating is subsidized by the central government and will be influenced more by technological changes rather than residents' behavioral changes.

Furthermore, as shown in Table 6, energy conservation policies are found to be positively associated with carbon emissions generated from the use of appliances and cooking, and capacity utilization policies are positively associated with the use of appliances, lighting, and cooking. These results reflect that low-carbon policies tend to produce rebound effects relating to carbon emissions generated from end-use sources that are central to residents' daily lives.

**Table 5.** Model results: end-use sources (cooling and heating).

|                                  | LHS Variable:<br>CWCE | LHS Variable:<br>DHCE | LHS Variable:<br>CHCE |
|----------------------------------|-----------------------|-----------------------|-----------------------|
|                                  | (1)                   | (2)                   | (3)                   |
| <i>Policy Intensity Measures</i> |                       |                       |                       |
| PICR                             | 0.003<br>(0.006)      | 0.007<br>(0.006)      | −0.009<br>(0.019)     |
| PIEC                             | −0.015 ***<br>(0.005) | −0.012 **<br>(0.006)  | 0.011<br>(0.014)      |
| PICU                             | 0.020 ***<br>(0.006)  | 0.015 **<br>(0.007)   | 0.035<br>(0.025)      |
| PI TEC                           | 0.006<br>(0.006)      | 0.001<br>(0.005)      | −0.026 *<br>(0.016)   |
| <i>Covariates</i>                |                       |                       |                       |
| POP (log)                        | 0.703 ***<br>(0.179)  | 0.968 ***<br>(0.240)  | 0.694<br>(0.559)      |
| GDPPC (log)                      | 0.279 ***<br>(0.067)  | 0.409 ***<br>(0.094)  | −0.155<br>(0.145)     |
| T_SHR (log)                      | 0.021<br>(0.105)      | −0.087<br>(0.115)     | −0.048<br>(0.220)     |
| TEMP (log)                       | 0.073 *<br>(0.041)    | −0.120 ***<br>(0.043) | −0.225 ***<br>(0.086) |
| WS (log)                         | 0.042<br>(0.103)      | 0.188<br>(0.120)      | −0.345<br>(0.264)     |
| PREC (log)                       | −0.055 *<br>(0.028)   | −0.184 ***<br>(0.034) | 0.021<br>(0.083)      |
| City fixed effects               | YES                   | YES                   | YES                   |
| Year fixed effects               | YES                   | YES                   | YES                   |
| Constant                         | −2.039<br>(1.838)     | −5.153 **<br>(2.397)  | 0.710<br>(4.675)      |
| R <sup>2</sup>                   | 0.973                 | 0.996                 | 0.982                 |
| Observations                     | 1716                  | 1716                  | 1716                  |

Note: \* 10% statistical significance; \*\* 5% statistical significance; \*\*\* 1% statistical significance; standard errors (in parentheses) are clustered at the city level.

**Table 6.** Model results: end-use sources (others).

|                                  | LHS Variable:<br>ACE | LHS Variable:<br>LCE  | LHS Variable:<br>CCE |
|----------------------------------|----------------------|-----------------------|----------------------|
|                                  | (1)                  | (2)                   | (3)                  |
| <i>Policy Intensity Measures</i> |                      |                       |                      |
| PICR                             | −0.002<br>(0.008)    | −0.001<br>(0.003)     | −0.002<br>(0.005)    |
| PIEC                             | 0.016 **<br>(0.006)  | 0.000<br>(0.002)      | 0.009 **<br>(0.004)  |
| PICU                             | 0.013 **<br>(0.006)  | 0.006 ***<br>(0.002)  | 0.010 ***<br>(0.003) |
| PI TEC                           | −0.000<br>(0.006)    | 0.003<br>(0.002)      | 0.001<br>(0.004)     |
| <i>Covariates</i>                |                      |                       |                      |
| POP (log)                        | −0.053<br>(0.147)    | 0.467 ***<br>(0.096)  | 0.256 ***<br>(0.084) |
| GDPPC (log)                      | 0.273 ***<br>(0.068) | 0.124 ***<br>(0.027)  | 0.134 ***<br>(0.046) |
| T_SHR (log)                      | 0.234<br>(0.150)     | −0.063<br>(0.046)     | 0.056<br>(0.109)     |
| TEMP (log)                       | 0.014<br>(0.051)     | 0.029<br>(0.018)      | 0.013<br>(0.029)     |
| WS (log)                         | 0.239 *<br>(0.130)   | 0.155 ***<br>(0.044)  | 0.118 **<br>(0.058)  |
| PREC (log)                       | −0.040<br>(0.031)    | −0.037 ***<br>(0.012) | −0.049 **<br>(0.021) |
| City fixed effects               | YES                  | YES                   | YES                  |
| Year fixed effects               | YES                  | YES                   | YES                  |
| Constant                         | 3.061 *<br>(1.815)   | 1.242<br>(0.999)      | 1.944<br>(1.243)     |
| R <sup>2</sup>                   | 0.979                | 0.996                 | 0.993                |
| Observations                     | 1716                 | 1716                  | 1716                 |

Note: \* 10% statistical significance; \*\* 5% statistical significance; \*\*\* 1% statistical significance; standard errors (in parentheses) are clustered at the city level.

#### 4. Discussion

There are several important policy and urban management implications that can be drawn from the findings of this study. First, by comparing the effectiveness of different low-carbon policies in curbing building-related carbon emissions, we find that implementing energy conservation policies tends to mitigate carbon emissions generated from building operations, while capacity utilization policies are associated with rebound effects that drive up carbon emissions (Figure 3). Specifically, a 1% increase in energy conservation policy intensity would result in a 0.005%, a 0.015%, and a 0.012% decrease in total building-operation carbon emissions, carbon emissions from cooking and water heating, and carbon emissions from distributed heating, respectively, despite the fact that it could slightly increase carbon emissions from appliances and cooling. In contrast, a 1% increase in capacity utilization policy intensity tends to contribute to a 0.006% to 0.020% increase in carbon emissions from different building operations-related sources. This highlights the need to further promote energy conservation policies to curb the increasing trend of building sector carbon emissions and calls for additional efforts from policymakers to further consider rebound effects in the building sector when designing and refining capacity utilization policies. Addressing the rebound effect necessitates a multi-faceted approach that incorporates demand-side management strategies, such as incentivizing behavioral changes among occupants, which can mitigate the unintended consequences of increased capacity utilization. Policymakers should also explore the implementation of limits on energy consumption per capita in certain high-demand areas, ensuring that energy efficiency gains are not offset by increased usage.

In addition, it is also reflected in Figure 3 that the policy impacts on building-related carbon emissions can vary across building types and end-use sources. For example, the intensity of technology policies is positively associated with carbon emissions generated from rural residential buildings, but is negatively associated with those from central heating. This underscores the necessity for policy refinements targeting specific emission sources. Policymakers should invest in the research and development of targeted interventions that consider the unique characteristics of various building types, ensuring that policies are not only effective but also equitable across diverse populations. Furthermore, developing a framework for collaborative governance that involves stakeholders from local communities can enhance the effectiveness of these targeted interventions, ensuring they align with the needs and capacities of different populations.

Furthermore, the results of spatial heterogeneous effects show that the estimated carbon emission impacts vary largely across space. This reveals that context-specific low-carbon policies should be designed to adapt to local conditions. For example, low-carbon policies, which focus on regulating energy demand, fail to deliver any carbon emission mitigation in northeast Chinese cities, partly due to the inelastic heating demand during winter seasons. In this context, providing alternative clean energy for winter heating may be a potential solution that comes from the supply side. Furthermore, integrating building energy efficiency measures with broader urban planning strategies can enhance resilience against climate impacts, aligning with China's national commitments to reduce carbon emissions as outlined in its 14th Five-Year Plan and its long-term goals for carbon neutrality by 2060.

Finally, the findings of this study also have broader implications for China's national and international commitments to climate change mitigation. By adopting and refining effective low-carbon policies, China can not only meet its internal targets but also strengthen its role in global climate agreements, such as the Paris Agreement. This presents an opportunity for China to showcase its leadership in sustainable urban development and carbon management, potentially influencing other nations to adopt similar strategies.

|           |      | PICR   | PIEC      | PICU     | PITEC    |
|-----------|------|--------|-----------|----------|----------|
| (Table 2) | TCE  |        | −0.005*   | 0.010*** |          |
| (Table 4) | PCCE | 0.010* |           | 0.009**  |          |
|           | URCE |        |           |          |          |
|           | RRCE |        |           | 0.014*** | 0.015*** |
| (Table 5) | CWCE |        | −0.015*** | 0.020*** |          |
|           | DHCE |        | −0.012**  | 0.015**  |          |
|           | CHCE |        |           |          | −0.026*  |
| (Table 6) | ACE  |        | 0.016**   | 0.013**  |          |
|           | LCE  |        |           | 0.006*** |          |
|           | CCE  |        | 0.009**   | 0.010*** |          |

Not Significant
  Positive and Significant
  Negative and Significant

**Figure 3.** Summary of results. \* 10% statistical significance; \*\* 5% statistical significance; \*\*\* 1% statistical significance; PICR: intensity for carbon reduction policies; PIEC: intensity for energy conservation policies; PICE: intensity for capacity utilization policies; PITEC: intensity for technology policies; TCE: total carbon emissions from building operation; PCCE: carbon emissions from public and commercial building operations; URCE: carbon emissions from urban residential building operation; RRCE: carbon emissions from rural residential building operation; ACE: carbon emissions from appliances; LCE: carbon emissions from lighting; CCE: carbon emissions from cooling; CWCE: carbon emissions from cooking and water heating; DHCE: carbon emissions from distributed heating; CHCE: carbon emissions from central heating.

There are also two limitations of this study that are worth noting. First, the findings drawn from this study are only one piece of the puzzle for carbon emission control, since low-carbon policies could also influence carbon emissions generated from other sectors, such as transportation [35,36], construction [37,38], and manufacturing [39,40]. In addition, carbon policies could also bring about broader environmental impacts, such as air quality co-benefits and ecological diversity enhancement, which subsequently deliver positive socioeconomic and health outcomes [41–47], but have not been examined in the present study. Second, some empirical studies suggest that when environmental indicators are used as the dependent variable, there may be potential spatial interdependency problems [48,49].

Looking ahead, future research could explore the integration of low-carbon policies with renewable energy sources and smart grid technologies, assessing their combined effects on carbon emissions across different sectors. Moreover, longitudinal studies that track the long-term impacts of specific policies on urban carbon emissions will provide

valuable insights into their effectiveness over time. It would also be beneficial to investigate the social dimensions of policy implementation, such as public perception and acceptance, to ensure that low-carbon strategies are embraced by local communities. This multifaceted approach will enhance understanding of carbon emission dynamics and contribute to the development of more robust, adaptable policies.

## 5. Conclusions

This study has explored the impact of low-carbon policy intensity on building sector carbon emissions in 286 Chinese cities over a six-year period (2015–2020). Using a two-way fixed effects model, we have enhanced the current understanding of how different types of low-carbon policies affect carbon emissions from building operations.

Our findings show that, on average, the aggregated intensity of low-carbon policies does not significantly impact carbon emissions from building operations. This suggests that simply increasing the overall intensity of low-carbon policies may not be sufficient to achieve meaningful reductions in building-sector emissions.

The effectiveness of low-carbon policies varies significantly depending on the type of policy implemented. Specifically, we found that a 1% increase in the intensity of energy conservation policies resulted in a slight decrease in carbon emissions. This highlights the potential of targeted energy conservation measures to contribute to decarbonization efforts. Conversely, capacity utilization policies are associated with an increase in building-operation carbon emissions. This counterintuitive result suggests that such policies may bring rebound effects and require further adjustments and refinements.

This study also reveals that the relationship between policy intensity and carbon emissions varies across different building types and end-use sources. These variations underscore the importance of tailoring low-carbon policies to the specific characteristics and needs of different building categories.

Overall, this study provides a comprehensive assessment of the impacts of low-carbon policy intensity on building sector carbon emissions in Chinese cities. It offers valuable guidance for urban managers and policymakers striving to promote building sector decarbonization by shedding light on the variations in policy effectiveness. The insights gained from this research can contribute to the development of more effective and sustainable urban management practices, supporting global climate change mitigation.

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