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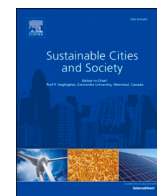
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Does climate policy exacerbate spatial development inequality? Quasi-experimental evidence from China

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ABSTRACT

This study aims to examine the causal relationship between climate policy and spatial development inequality within cities. To this end, we leverage the temporal and spatial variations in the implementation of the low-carbon city pilot initiative (LCCPI) to perform a staggered difference-in-difference (DID) estimation. Our estimated results demonstrate that the LCCPI is associated with an approximate 4.4 % reduction in the Gini coefficient for nighttime light intensity. Our findings are robust to alternative measures and different specifications. Further mechanism analyses reveal that the LCCPI operates by narrowing the green innovation gap and improving the factor allocation. Notably, we observe a more pronounced decrease in spatial development inequality in resource-dependent and high-marketization cities.

1. Introduction

Inequality related to gender, income, and development remains widespread across the world. Inequality undermines socio-economic stability and hampers poverty reduction, which can, in turn, foster crime, economic stagnation, and environmental degradation (Gabaix et al., 2016). In this context, mitigating inequality is a critical objective within the framework of the Sustainable Development Goals (SDGs).¹ Prior studies have devoted considerable attention to exploring strategies for curbing multidimensional inequality (Iammarino et al., 2019; Huang et al., 2020). For example, Derenoncourt and Montialoux (2021) demonstrate that the minimum wage policy in the United States can explain >20 % of the reduction in the racial income gap. Nevertheless, there is an insufficient understanding of how to effectively address spatial development inequality within cities.

Combating climate change is integral to achieving the SDGs as well.

While existing literature has investigated the relationship between climate policy and inequality from various perspectives, its effects on spatial development inequality remain largely unexplored. According to Stechemesser et al. (2024), climate policy refers to a comprehensive set of targeted strategies and regulatory frameworks explicitly designed to address climate change challenges, encompassing both mitigation and adaptation measures implemented at local, national, and international levels. In this study, our focus is on climate policy related to mitigation efforts initiated by the national government. Regarding legally binding climate policy, although carbon taxes may exacerbate inequality due to the income crowding-out effect on low-income households, the refunding of carbon tax revenues shows effectiveness in enhancing well-being and mitigating inequality (Budolfson et al., 2021; Rüb, 2024). From a regulatory perspective, the emissions trading system (ETS) employs market mechanisms to optimize resource allocation, thereby contributing to reductions in income and emissions inequality,

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¹ The SDGs are a set of 17 global goals established in 2015 to promote comprehensive social, economic, and environmental sustainability by 2030. These goals address a broad range of issues, including poverty, education, health, gender equality, clean energy, and climate action, aiming to foster equity, peace, and prosperity worldwide. Further details are available at <https://sdgs.un.org/goals>.

as documented in previous studies (Grainger & Ruangmas, 2018; Känzig, 2023; Bettarelli et al., 2024). Generally, despite robust evidence that government-implemented mitigation strategies, such as carbon taxes and ETS, play an essential role in alleviating inequality, there is little literature on whether and how climate policy based on the target responsible system influences inequality, particularly development inequality within cities.

This study represents the first attempt to assess the effects of the low-carbon city pilot initiative (LCCPI) on spatial development inequality within cities. Efficiency and equity are two critical dimensions for evaluating the effectiveness of climate policy (Fried, 2018; Picciano et al., 2023). Prior literature has investigated extensively the effects of the LCCPI on efficiency including innovation, productivity, and emissions abatement (Chen et al., 2022a; Pan et al., 2022; Wang et al., 2023; Sun et al., 2024). For instance, utilizing data from A-share listed enterprises, Chen et al. (2022a) reveal that the LCCPI significantly improves corporate performance in mitigating GHG emissions. Furthermore, Pan et al. (2022) demonstrate that the LCCPI contributes positively to high-quality development by promoting low-carbon innovation and boosting productivity. Nonetheless, it remains uncertain whether the LCCPI can alleviate inequality, particularly spatial development inequality, while simultaneously enhancing efficiency.

Our attention to China provides a unique opportunity to investigate the aforementioned issues. First, the LCCPI, a climate policy with China's characteristics, operates under the target responsibility system. Specifically, within the framework of the LCCPI, the central government mandates that provincial authorities establish GHG reduction targets for pilot cities (see Fig. 2). Driven by incentives for political promotion, local governments employ a range of measures to mitigate GHG emissions, including adjusting industrial structures and promoting green innovation. Second, China is confronted with the dual pressures of reducing emissions and addressing inequality. In detail, China, as the world's largest developing economy and leading carbon emitter, faces a considerable challenge in balancing emission reduction with economic growth (Lee et al., 2022). Furthermore, due to disparities in geographic location and resource endowments, spatial development inequality in China has been exacerbated. Third, in 2010, the Chinese government released the "Notification on Launching Pilot Initiatives in Low-Carbon Provinces, Regions, and Cities", which initiated three rounds of the low-carbon city pilot initiative.² Specifically, the launch of three rounds of the LCCPI occurred in the years 2010, 2012, and 2017, spanning six provinces, eighty municipalities, and one region. The spatial and temporal variations in policy implementation enable us to employ a staggered difference-in-difference (DID) method to obtain unbiased estimates.

We employ a staggered DID method to evaluate how the LCCPI affects spatial development inequality based on city-level data spanning from 2000 to 2020. First, our estimated results imply that the LCCPI leads to an approximate 4.4 % reduction in spatial development inequality. Importantly, our estimated results remain robust when performing a series of robustness checks. Second, mechanism analyses reveal that the green innovation gap and factor allocation are underlying channels through which the LCCPI influences spatial development inequality. Third, we also estimate the heterogeneous effects of the LCCPI on spatial development inequality across resource dependence and marketization levels. Specifically, we observe that spatial development inequality experiences a more significant decrease in resource-dependent cities compared to non-resource-dependent cities. Additionally, in high-marketization cities, the implementation of the LCCPI is associated with a 3.2 % reduction in spatial development inequality. However, such positive effects are not observed in low-marketization cities.

² Further details can be found at https://www.ndrc.gov.cn/xxgk/zcfb/tz/201008/t20100810_964674_ext.html (in Chinese).

This paper contributes to several strands of existing literature. First, we propose a potential solution for developing countries to assess spatial developmental inequality in a timely, efficient, and cost-effective manner. Given that county-level GDP data in China is notably missing, we calculate spatial development inequality within cities based on county-level nighttime light data derived from open-access, high-resolution satellite imagery. Specifically, we define spatial development inequality as the Gini coefficient for nighttime light intensity. The rationale lies in the strong correlation between nighttime light intensity and GDP, urbanization, and poverty (Jean et al., 2016; Jia et al., 2021). For instance, Jia et al. (2021) assess the economic growth at the town level by examining changes in nighttime light intensity.

Second, this study provides novel insights into inequality arising from climate policy. As emphasized by Jiang and Shi (2023), addressing development inequality within cities is crucial for achieving sustainable cities and societies. More specifically, coordinated development within cities can optimize the spatial allocation of factors, mitigate the spatial agglomeration of public goods, and thus contribute to sustainable economic growth. While existing literature has investigated the relationship between climate policy and inequality from various perspectives (e.g., income and emissions inequality) (Känzig, 2023; Bettarelli et al., 2024), its effects on spatial development inequality within cities remain largely unexplored.

Third, this study elucidates the mechanism by which climate policy influences spatial development inequality in developing countries, which is crucial for designing targeted interventions and enhancing policy effectiveness. In detail, previous literature provides insights into the micro-level mechanisms of how climate policy impacts inequality (Budolfson et al., 2021; Bettarelli et al., 2024; Rüb, 2024), whereas this study identifies the potential macro-level mechanisms, namely the green innovation gap and factor allocation.

The remainder of the paper is structured as follows. Section 2 presents the background and theoretical mechanisms. Section 3 is our estimation framework. Section 4 reports the empirical findings including baseline regressions, robustness tests, mechanism analyses, and heterogeneous effects. Section 5 is our conclusions and policy implications.

2. Background and theoretical mechanisms

2.1. Low-carbon city pilot initiative in China

As China underwent rapid industrialization and urbanization, carbon reduction stress has reached alarming levels (Lee et al., 2022). In 2007, China emerged as the top global emitter of carbon dioxide, with its contributions amounting to 30 % of the total global carbon emissions by 2020. Despite the sustained decrease in China's energy intensity from 2000 to 2020, it consistently surpasses both the corresponding global average and that of the European Union and the United States during the same timeframe (see Fig. 1). China's commitment to address climate change dates back to its ratification of the United Nations Framework Convention on Climate Change (UNFCCC) in 1992. In 2009, China proclaimed ambitious objectives at the Copenhagen Climate Conference, targeting a reduction of 40–45 % in carbon emissions per unit of GDP by 2020 relative to the levels of 2005.

In this context, the National Development and Reform Commission (NDRC) initiated three rounds of low-carbon city pilot initiatives in 2010, 2012, and 2017, involving 6 provinces, 80 cities, and 1 region. Fig. A1 in Appendix A illustrates the spatial distribution of the low-carbon city up to the year 2017. The LCCPI marks a pivotal step in China's commitment to green development. Specifically, to achieve industrial restructuring, environmental services enhancement, and innovation in low-carbon technologies, the initial LCCPI set up low-carbon industrial systems, promoted eco-friendly lifestyles with low carbon footprints, and enhanced systems for managing emission data. Regarding the second batch of pilots, the NDRC expanded the scope of

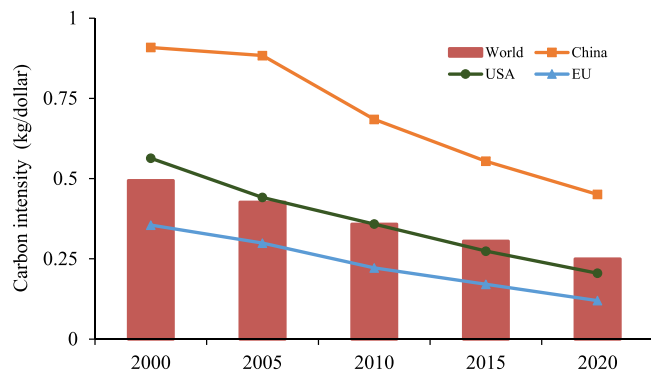


Fig. 1. Evolution of energy intensity from 2000 to 2020.

Notes: The figure shows the change in energy intensity for China, the World, the EU, and the USA from 2000 to 2020. Energy intensity is measured by CO₂ emissions per unit of GDP. Source: The World Bank (<https://www.worldbank.org/en/home>) and authors' calculations.

the LCCPI with the goal of constructing an eco-friendly China. With the positive outcomes of the initial two rounds of pilot initiatives, the third batch of pilot cities, emphasizing innovation, was launched in 2017. This signifies further investigation into low-carbon development within the policy context of the 13th Five-Year Plan for Controlling GHG Emissions and the National Climate Change Action Plan (2014–2020).

2.2. Theoretical mechanisms

The innovation gap and factor allocation are primary drivers of spatial development inequality. According to the classical growth theory, factor inputs (e.g., labor and capital) determine economic growth (Acemoglu, 2012). Neoclassical growth theory further incorporates total factor productivity (TFP) into the production function and emphasizes its fundamental role in driving long-term economic growth (Herrendorf et al., 2014). In contrast, endogenous growth theory internalizes TFP, associating its improvement with technological innovation (Peretto, 2018). Drawing on endogenous growth theory, previous studies have decomposed GDP to identify the key drivers of economic growth. For instance, according to estimates by Bosworth and Collins (2008), TFP accounts for approximately 20 %–30 % of China's economic growth since the implementation of the reform and opening-up policy. Similarly, Zhang et al. (2021) find that factor inputs and TFP contribute 63 % and 37 %, respectively, to economic growth in China. In general, factor inputs and innovation play an essential role in driving economic growth. That is, the development gap across regions can be attributed to the innovation gap and factor allocation.

The LCCPI can potentially mitigate the green innovation gap. As highlighted by induced innovation theory, technological progress is not an isolated event but a reflection of both internal and external conditions in an economic system, especially driven by shifts in demand and resource constraints (Bloom et al., 2016). The LCCPI aims to reduce GHG emissions by establishing a low-carbon industrial system and lifestyle, which could potentially stimulate green innovation (Sun et al., 2024). Given the regional heterogeneity in industrial and energy structures, LCCPI-induced green innovation is likely to vary across regions. In detail, under the LCCPI framework, developing regions face more transition pressure than developed regions as a result of the greater proportion of high-emission industries in the former. Consequently, within the same city, the LCCPI has a more pronounced impact on green innovation in developing counties than in developed counties. Notably, Xu et al. (2021) and Pan et al. (2022) demonstrate that innovation activities induced by climate policy are more pronounced in developing regions than in developed regions.

The LCCPI plays an essential role in improving factor allocation. As noted by Brandt et al. (2013) and Gopinath et al. (2017), cross-regional

factor allocation is closely linked to the ecological environment and industrial structure. Specifically, the growth of low-carbon industries can reduce GHG emissions, while simultaneously lowering the release of toxic pollutants, such as PM_{2.5} and SO₂, which serve as pull factors for population migration. According to Chen et al. (2022b), a 10 % decrease in PM_{2.5} corresponds to an increase in population of 2.7 per 100 inhabitants due to migration. Additionally, unlike high-emission industries, low-carbon industries are capital-intensive and feature extended value chains, which can attract more investment and high-skilled labor (Consoli et al., 2016). Therefore, in contrast to developed regions that have completed industrial upgrading, the LCCPI creates opportunities for developing regions to advance low-carbon industries. That is, within the same city, the LCCPI is expected to foster factor agglomeration in developing counties, driven by the increased share of low-carbon industries, which would mitigate spatial disparities in factor allocation relative to developed regions.

Drawing from the theoretical analysis outlined above (visualized in Fig. 2), we present three primary hypotheses:

H1. The LCCPI can alleviate spatial development inequality.

H2. The green innovation gap is one channel through which the LCCPI influences spatial development inequality.

H3. Factor allocation is another channel through which the LCCPI impacts spatial development inequality.

3. Estimation framework

3.1. Econometric specification

In this paper, the implementation of the LCCPI varies across years and cities, which allows us to employ a staggered DID method. Our basic DID specification, incorporating two-way fixed effects, is expressed as

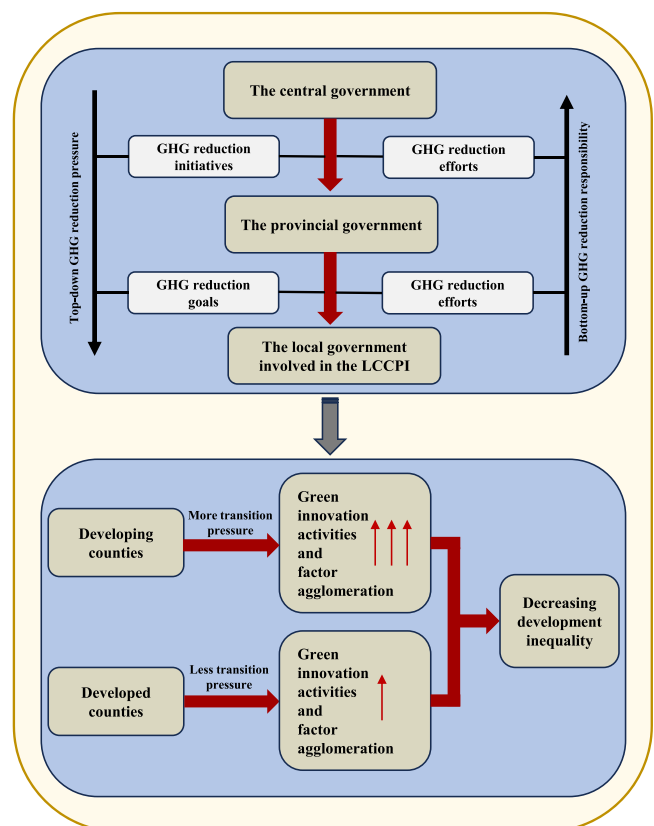


Fig. 2. The working mechanism of the LCCPI in China.

follows:

$$\log(SDI_{i,t}) = \alpha_0 + \alpha_1 Treat_i \times post_t + X_{i,t}\beta + \gamma_i + \mu_t + \varepsilon_{i,t} \quad (1)$$

Where the subscripts t and i represent the year and city, respectively. The outcome variable, $\log(SDI_{i,t})$, is the log-transformed Gini coefficient for nighttime light intensity. $Treat_i \times post_t$ equals 1 when city i was the LCCPI pilot in year t , and 0 otherwise. The key parameter of interest, α_1 , quantifies the causal relationship (interpreted as a percentage change) between the LCCPI and spatial development inequality. $X_{i,t}$ is a vector that includes fiscal expenditure, population density, financial development, fixed asset investment, and FDI, which are employed as control variables in this study. We incorporate $X_{i,t}$ into our model to account for the potential correlation between these socio-economic conditions and both the LCCPI and the dependent variable. Failing to account for these variables would lead to the omitted variable bias issue (Chen et al., 2022c). γ_i and μ_t denote city- and year-fixed effects, respectively. The former considers time-invariant characteristics that are specific to city i , while the latter controls for the annual common shocks faced by all cities.

Importantly, there is a prerequisite assumption for the validity of the DID method: both the treatment and the control groups should show the same time trend in the outcome variable before the LCCPI implementation. This condition, known as the parallel trend assumption, underpins the DID specification. Subsequently, we will assess this assumption through graphical and econometric tests. Finally, we also perform a series of robustness checks to assess the sensitivity of our baseline findings to alternative measures and different specifications.

3.2. Variable selection

Outcome variable. The outcome variable is the Gini coefficient for nighttime light intensity, used to quantify spatial development inequality at the city level. In line with the methodologies outlined by Alesina et al. (2016) and Lessmann and Seidel (2017), the Gini coefficients for nighttime light intensity and channel variables are calculated as follows:

$$Gini_{i,t} = \frac{1}{n_i} \left[n_i + 1 - 2 \frac{\sum_{j=1}^{n_i} (n_i + 1 - j) L_{j,t}}{\sum_{j=1}^{n_i} L_{j,t}} \right] \quad (2)$$

Where $Gini_{i,t}$ is the Gini coefficient of city i in year t . n_i represents the number of counties attributed to city i . $L_{j,t}$ denotes the county-level indicator, namely nighttime light intensity, the number of green patent applications, or the number of new firm registrations.

Channel variables. We identify two potential channels through which the LCCPI affects spatial development inequality: the green innovation gap and factor allocation. The green innovation gap is defined as the Gini coefficient for the number of green patent applications. Due to the unavailability of county-level data on employment and investment, we are unable to directly measure factor allocation at the city level. In this study, we define factor allocation as the Gini coefficient for new firm registrations. The underlying rationale is that enterprise registration activities can indirectly capture the spatial mobility of capital and labor.

Control variables. Based on prior studies associated with the LCCPI (Lee et al., 2022; Sun et al., 2024), the control variables used in this study include fiscal expenditure, population density, financial development, fixed asset investment, and FDI. Specifically, fiscal expenditure is defined as government budget expenditure per capita. Population density is expressed in people per square kilometer. Financial development refers to the ratio of outstanding loan balance to outstanding deposit balance at the end of the year. Fixed asset investment is fixed asset investment per capita. FDI represents foreign direct investment per capita.

3.3. Data sources and descriptive statistics

Raster-based data. Our primary data is the nighttime light intensity extracted from high-resolution satellite imagery. Particularly, the Operational Linescan System (OLS) of the United States Air Force Defense Meteorological Satellite Program (DMSP) provides consistent nighttime images of the Earth, taken between 20:00 and 21:30 local time. The annual composite measure is constructed by overlaying daily images collected throughout the year, with adjustments made for cloud cover and natural light sources. However, the DMSP records satellite imagery only from 1992 to 2013. After 2013, the data is sourced from the Visible Infrared Imaging Radiometer Suite (VIIRS). On the other hand, it is challenging to obtain time series data covering our sample period (i.e., 2000–2020) through integrating DMSP and VIIRS. In this case, Wu et al. (2021) developed an improved time-series DMSP-OLS-like dataset (1992–2022) for China, which is available on Harvard Dataverse.³ Then, we integrate the annual satellite images with county-level administrative boundaries and acquire the luminosity measurement at the county level from 2000 to 2020.

Firm registration data. The National Administration for Industry and Commerce of China (NAIC) maintains extensive and detailed records of new firm registrations. As emphasized by Kong et al. (2021), this dataset is highly representative, encompassing registration information for over 60 million enterprises in mainland China since 1949. The dataset is extensively utilized in previous empirical studies on entrepreneurship (Bu & Liao, 2022; Tian & Xu, 2022). Drawing on firm registration data by geographical location, we compile the annual number of new enterprise registrations at the county level.

Patent data. The data on patent applications is derived from the State Intellectual Property Office (SIPO) of China. The dataset reports extensive information associated with patent applications, such as application date, patent type, address of assignee, classification code, and more. According to the classification code, we further extract patents involving green technologies. Then, we aggregate these annual patent applications at the county level.

Yearbook data. We obtain socioeconomic variables from the China City Statistical Yearbook, covering the period from 2000 to 2020. The yearbook provides detailed city-level socioeconomic information on industrial structure, innovation, fiscal expenditure, population density, financial development, fixed asset investment, and FDI.

Fig. 3 depicts the distribution in the Gini coefficient for nighttime light intensity across years. Certainly, the kernel density curve for the year 2020 is shifted to the left in comparison to that for the year 2000. More specifically, there has been a notable reduction in spatial development inequality, decreasing from 0.632 in 2000 to 0.506 in 2020. However, the level of spatial development inequality in 2020 still exceeds the cautionary Gini coefficient threshold of 0.4. Moreover, Table 1 provides descriptive summary statistics for the dependent variable, channel variables, and control variables used in this study.

4. Empirical findings

4.1. Baseline estimates

We start by examining whether the LCCPI yields positive effects on alleviating spatial development inequality. Specifically, in columns (1) and (2) of Table 2, the dependent variable is the logarithm of the Gini coefficient of nighttime light intensity, which measures city-level spatial development inequality in China. We also incorporate city- and year-fixed effects in the two columns. The city-fixed effect absorbs city-level time-invariant characteristics, while the year-fixed effect controls for the annual common shocks faced by all cities. Furthermore, in

³ The dataset can be accessed at <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/GIYGJU>.

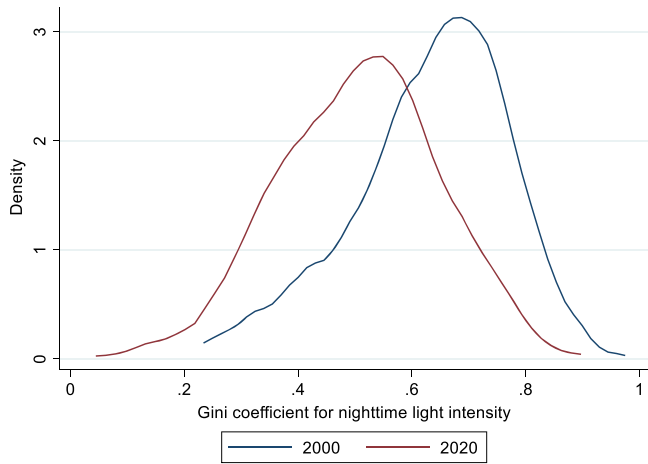


Fig. 3. The distribution in spatial development inequality across years.
Notes: The figure depicts the distribution of the Gini coefficient for nighttime light intensity in the years 2000 and 2020. Source: The Harvard Dataverse and authors' calculations.

Table 1
Summary statistics.

Variables	Observations	Mean	Min	Max
Ln (Gini coefficient for nighttime light intensity)	5624	−0.585	−2.449	−0.065
Ln (Gini coefficient for green innovation)	5624	−1.025	−3.519	−0.220
Ln (Gini coefficient for new firm registrations)	5624	−0.789	−2.754	−0.145
Ln (fiscal expenditure)	5624	8.068	2.197	11.603
Ln (population density)	5624	−3.448	−7.663	0.145
Ln (financial development)	5624	−0.400	−2.535	3.011
Ln (fixed asset investment)	5624	9.489	5.146	12.525
Ln (FDI)	5624	3.519	−3.934	7.990

Notes: All variables are measured in the logarithm. Monetary values are measured in constant 2020 RMB (Chinese currency).

Table 2
Estimated impacts of the LCCPI on spatial development inequality.

Variables	Ln (Gini coefficient for nighttime light intensity)	
	(1)	(2)
<i>Treat × Post</i>	−0.044*** (0.014)	−0.048*** (0.014)
Ln (population density)	−0.079* (0.041)	
Ln (financial development)	−0.043*** (0.014)	
Ln (fixed asset investment)	0.003 (0.010)	
Ln (FDI)	0.001 (0.003)	
Ln (fiscal expenditure)	0.003 (0.012)	
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	5624	5624
R ²	0.870	0.862

Notes: The dependent variable is the Gini coefficient for nighttime light intensity, assessing city-level spatial development inequality. Standard errors in parentheses are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

column (1) of Table 2, we also include a series of socioeconomic factors, such as fiscal expenditure, population density, financial development, fixed asset investment, and FDI. The specification accounts for potential correlations between these socioeconomic factors and both the LCCPI

and the outcome variable. Therefore, our preferred specification is column (1) of Table 2.

The estimated effects of the LCCPI on spatial development inequality are reported in Table 2. The coefficient of the *Treat × Post* in column (1) is −0.044 and is statistically significant at the 1 % level. More specifically, the LCCPI contributes to a 4.4 % reduction in the city-level spatial development inequality. Compared to previous studies (Campagnolo & Davide, 2019; Spinesi, 2022), which conclude that climate policy may exacerbate inequality despite reducing emissions, our findings confirm that the LCCPI is a potential win-win solution for developing countries to achieve a low-carbon transition.

Additionally, we observe that the estimated coefficient in column (2) is −0.048, which is slightly larger in magnitude than that in column (1). Meanwhile, there is no significant difference in the adjusted R² between the two columns. These findings collectively suggest that our estimated results are unbiased when using the LCCPI as a quasi-natural experiment.

4.2. Robustness checks

Parallel trend test. For the DID method to be effectively applied in policy evaluation, both the treatment and control groups need to satisfy the parallel trend hypothesis. Failure to satisfy this condition would result in biased estimated outcomes. As depicted in Fig. 4, there exists no notable disparity in the Gini coefficient for nighttime light intensity between the treatment and control cities before the LCCPI implementation. Hence, we can conclude that both the treatment and control groups satisfy the parallel trends hypothesis in this study. Moreover, we do not observe notable effects of the LCCPI on spatial development inequality during the first two years of its implementation. However, starting from the third year after its implementation, the parallel trend between the treatment and control groups is broken. This indicates that the decline in the Gini coefficient for treatment cities can be attributed to the implementation of the LCCPI and the pilot-induced effects exhibit lags.

Placebo test. We perform a placebo test using randomly generated virtual LCCPI events to examine whether the baseline estimates are driven by certain accidental factors. More specifically, in the actual

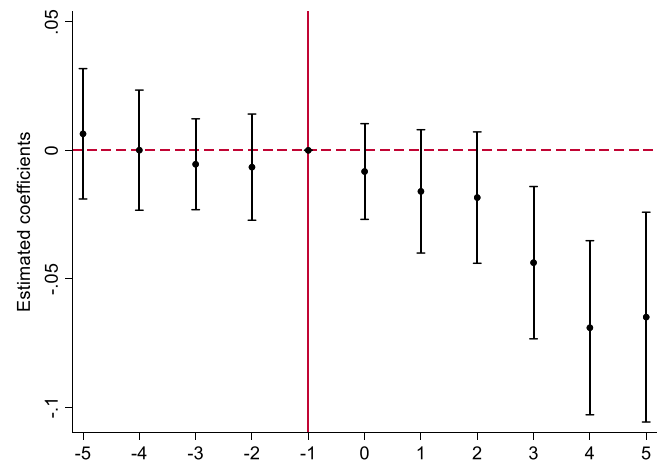


Fig. 4. Dynamic effects of the LCCPI.

Notes: The figure illustrates the dynamic effects of the LCCPI on spatial development inequality. The horizontal axis denotes the timeline of the LCCPI implementation, while the vertical axis displays estimated coefficients derived from the dynamic DID. The central blue long-dotted line delineates the event window of the LCCPI. The black solid circles depict the dynamic point estimates, accompanied by corresponding 95 % confidence intervals represented by black bars. Controls include fiscal expenditure, population density, financial development, investment, and FDI. Standard errors in the regression are clustered at the city level.

sample, there are a total of 121 cities in the treatment group. Accordingly, we randomly designate 121 cities from the entire sample as the false treatment group, with the remaining cities assigned to the false control group. We repeat the aforementioned steps 1000 times through Monte Carlo (MC) simulation and depict the distribution of the resulting coefficients and their corresponding p-values in Fig. 5. The absolute values of coefficients obtained from 1000 MC simulations consistently show a smaller magnitude compared to the estimate derived from actual data (−0.044). Furthermore, the distribution is centered around zero, and the majority of estimated p-values exceed 0.1. Therefore, no random factors appear to influence our baseline estimates.

Alternative measures on spatial development inequality. While the Gini coefficient is commonly utilized for assessing inequality, we also employ alternative measures to check the stability of the baseline estimates. Specifically, following Mayer et al. (2014) and Chancel (2022), we calculate the city-level Theil index for nighttime light intensity as an alternative measure of spatial development inequality. Furthermore, the relative mean deviation (RMD) is another method that is used to quantify inequality in previous studies (Blackorby & Donaldson, 1978; Kozminski & Baek, 2017). Appendix B provides detailed information on how to calculate the two indices. Importantly, the estimated results (shown in columns (1) and (2) of Table 3) reveal an 8.6 % decrease in the Theil index and a 5.2 % reduction in RMD due to the implementation of the LCCPI. This suggests the robustness of our baseline findings when substituting assessment methods for spatial development inequality. In summary, the LCCPI indeed contributes to the alleviation of spatial development inequality.

Predetermined variables. The section further examines whether our baseline estimates remain robust when considering the predetermined variables in the model. As discussed in the baseline section, the LCCPI is a potential quasi-natural experiment that is exogenous. However, it is noteworthy that pilot cities may not be chosen randomly by the NDRC but rather based on GDP and carbon emissions. To mitigate potential estimated bias, we follow prior literature and include the predetermined variables in column (3) of Table 3 (Lu et al., 2017; Chen et al., 2018; Li et al., 2024). In detail, we control for the interaction terms between the predetermined features and year-fixed effects. The results indicate that the estimated coefficient remains negative and statistically significant at the 1 % level, with a magnitude similar to the baseline estimates.

PSM-DID approach. To mitigate potential estimation bias, we re-assess the impact of the LCCPI on spatial development inequality

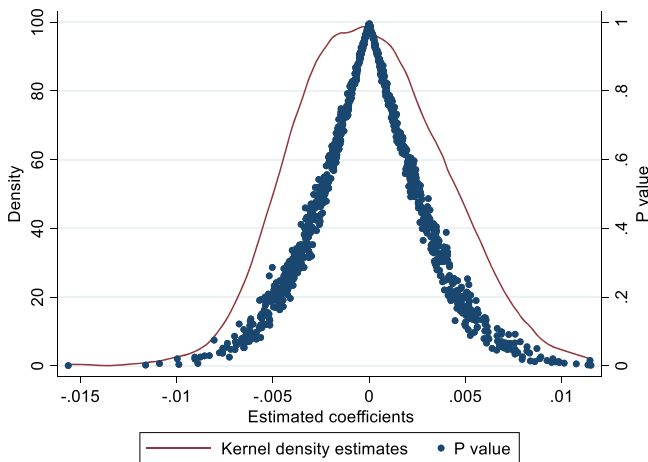


Fig. 5. Distribution of the estimated coefficients.

Notes: The figure illustrates the probability distribution of estimated coefficients from 1000 MC simulations. The dependent variable is the Gini coefficient for nighttime light intensity, assessing city-level spatial development inequality. Controls used in regressions include fiscal expenditure, population density, financial development, fixed asset investment, and FDI. Standard errors in parentheses are clustered at the city level.

Table 3

Robustness checks (alternative measures and predetermined variables).

Variables	(1) Ln (Theil index)	(2) Ln (RMD)	(3) Ln (Gini coefficient)
<i>Treat × Post</i>	−0.086*** (0.029)	−0.052*** (0.015)	−0.036*** (0.014)
Ln (population density)	−0.191** (0.077)	−0.094** (0.045)	−0.080** (0.040)
Ln (financial development)	−0.094*** (0.028)	−0.047*** (0.016)	−0.044*** (0.014)
Ln (fixed asset investment)	0.004 (0.021)	0.004 (0.012)	0.003 (0.010)
Ln (FDI)	0.001 (0.006)	0.002 (0.003)	−0.000 (0.003)
Ln (fiscal expenditure)	0.005 (0.025)	0.001 (0.014)	0.005 (0.012)
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5624	5624	5624
R ²	0.876	0.860	0.860

Notes: The dependent variable in column (1) represents the Theil index for nighttime light intensity, whereas the dependent variable in column (2) denotes the relative mean deviation (RMD) for nighttime light intensity. The dependent variable in column (3) is the Gini coefficient for nighttime light intensity. In column (3), we include two interaction terms between year-fixed effects and the predetermined variables (i.e., average carbon emission and GDP for 2000–2010). Standard errors in parentheses are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

using the PSM-DID approach, which integrates propensity score matching (PSM) with a staggered DID framework. Following prior studies (Cui et al., 2021; Wang et al., 2021), the PSM-DID estimation involves three main steps. First, we estimate propensity scores for both pilot and non-pilot cities employing a logit model. Second, given that the PSM method is designed for cross-sectional data, we adopt a year-by-year matching approach in this study. In this procedure, we exclude observations that fail to meet the common support assumption. Third, we use the annually matched samples to re-estimate the coefficient α_1 in Eq. (1).

To evaluate the sensitivity to different matching methods, Table 4

Table 4

Robustness checks (PSM-DID approach).

Variables	(1) Caliper matching	(2) Kernel matching	(3) Nearest neighbor matching
<i>Treat × Post</i>	−0.043*** (0.013)	−0.038*** (0.013)	−0.041*** (0.013)
Ln (population density)	−0.061 (0.038)	−0.059 (0.037)	−0.057 (0.037)
Ln (financial development)	−0.038*** (0.013)	−0.035*** (0.012)	−0.036*** (0.012)
Ln (fixed asset investment)	0.008 (0.010)	0.004 (0.010)	0.005 (0.010)
Ln (FDI)	0.001 (0.003)	0.002 (0.003)	0.002 (0.003)
Ln (fiscal expenditure)	−0.002 (0.011)	0.000 (0.011)	−0.001 (0.011)
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	5262	5175	5193
R ²	0.865	0.865	0.864

Notes: The dependent variable in columns (1) to (3) is the Gini coefficient for nighttime light intensity, assessing city-level spatial development inequality. Standard errors in parentheses are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

presents the regression outcomes based on caliper matching, kernel matching, and nearest-neighbor matching. As highlighted by Wang et al. (2021), the effectiveness of the PSM-DID estimation relies on matching quality. Accordingly, we first perform the balance test before discussing the estimation results. Given minimal differences in matching quality across matching methods, we present the balancing test results based solely on the caliper matching. As demonstrated in Fig. A2 in Appendix A, no significant difference is observed between the treatment and control groups after matching. Regarding the estimated results, the regression coefficients range from -0.038 to -0.043 across the different matching methods, which alleviates concerns about estimation bias.

Alternative samples. In this section, we further assess the sensitivity of estimated results to alternative samples. First, we examine whether the exclusion of direct-controlled municipality samples affects the regression results. Specifically, direct-controlled municipalities, operating under a distinctive administrative system, are situated in major economic centers, which may position them as preferred locations for the LCCPI. Additionally, compared to other cities, direct-controlled municipalities have access to a broader range of policy instruments to address internal development inequality. In this context, we re-estimated the causal relationship between the LCCPI and spatial development inequality using subsamples that exclude direct-controlled municipality samples. The estimated results presented in column (1) of Table 5 indicate that the regression coefficient is highly consistent with that of the baseline selection in both magnitude and significance.

Based on data availability, the time span of our sample is further extended to 2023. In the baseline section, the sample covers the period from 2000 to 2020 for two reasons. First, since the NDRC launched the first round of low-carbon city pilots in 2010, our sample provides a balanced representation of the periods before and after the policy intervention. Second, excluding samples after 2020 mitigates concerns that the COVID-19 shock influences the estimated results. To evaluate the robustness of the baseline estimates, we include the sample period from 2021 to 2023 in this analysis. As shown in column (2) of Table 5, the impact of the LCCPI on spatial development inequality remains statistically significant at the 1 % level.

Table 5
Robustness checks (alternative samples).

Variables	Subsamples without direct-controlled municipalities (1)	Extended samples (2000–2023) (2)
<i>Treat</i> × <i>Post</i>	−0.044*** (0.014)	−0.042*** (0.014)
Ln (population density)	−0.091* (0.047)	−0.080* (0.041)
Ln (financial development)	−0.043*** (0.014)	−0.045*** (0.014)
Ln (fixed asset investment)	0.001 (0.010)	0.003 (0.010)
Ln (FDI)	0.001 (0.003)	0.001 (0.003)
Ln (fiscal expenditure)	0.004 (0.012)	0.006 (0.012)
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	5540	6434
R ²	0.863	0.865

Notes: The dependent variable in columns (1) and (2) is the Gini coefficient for nighttime light intensity, assessing city-level spatial development inequality. Standard errors in parentheses are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3. Potential channels

We further investigate the mechanisms of how the LCCPI affects spatial development inequality. The first potential channel is the green innovation gap quantified by the Gini coefficient for the number of green patent applications. Given the unavailability of data on county-level employment and investment, we measure the second channel, factor allocation, using the Gini coefficient for new firm registrations. The rationale is that the spatial mobility of capital and labor can be indirectly captured through enterprise registration activities. More specifically, regions with higher levels of entrepreneurial activity tend to exhibit agglomeration effects in employment and investment. To validate the channel variable, we conduct a mediation effect test, estimating a 95 % confidence interval (CI) based on bootstrap methods with 500 replicate samples (Carpene & Zia, 2020). A bootstrap-based 95 % CI that excludes zero indicates a valid channel variable.

As highlighted earlier, innovation is a critical driver of productivity and long-term economic growth (Peretto, 2018). That is, narrowing the innovation gap can alleviate economic inequality across regions. While a substantial body of literature indicates that the LCCPI has the potential to facilitate green innovation (Pan et al., 2022; Zhu & Lee, 2022), its effectiveness in mitigating the innovation gap remains uncertain. To address this gap, we assess the impact of the LCCPI on the green innovation gap, with the corresponding regression outcomes reported in column (1) of Table 6. Our analysis reveals that the implementation of the LCCPI is associated with a 6.5 % reduction in the green innovation gap. Furthermore, the bootstrap-based 95 % CI excludes zero, indicating that the innovation gap is a valid channel variable, thereby confirming our hypothesis H2.

We then examine another potential channel influencing spatial development inequality, specifically factor allocation. Labor and capital, as essential factor inputs, have a direct and significant impact on regional economic output (Acemoglu, 2012). To a certain extent, the spatial distribution of factor inputs shapes regional development disparities. To the best of our knowledge, although numerous studies explore the causality between the LCCPI and employment or investment in China (Chen et al., 2022; Cao et al., 2023), it remains unclear whether the LCCPI simultaneously influences factor agglomeration. For this purpose, we investigate the causality between the LCCPI and factor allocation. As demonstrated in column (2) of Table 6, our findings

Table 6
Mechanisms of the LCCPI on spatial development inequality.

Variables	Ln (Green innovation gap) (1)	Ln (Factor allocation) (2)
<i>Treat</i> × <i>Post</i>	−0.065*** (0.019)	−0.039** (0.018)
Ln (population density)	−0.013 (0.012)	0.040 (0.038)
Ln (financial development)	−0.007 (0.005)	0.015 (0.018)
Ln (fixed asset investment)	0.004 (0.004)	−0.004 (0.012)
Ln (FDI)	0.002 (0.001)	0.006 (0.005)
Ln (fiscal expenditure)	0.008 (0.005)	−0.023 (0.015)
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	5624	5624
R ²	0.508	0.728
Mediation effect test	(−0.048, −0.026)	(−0.053, −0.030)

Notes: The dependent variable in column (1) is the Gini coefficient for the number of green patent applications assessing the green innovation gap. The dependent variable in column (2) is the Gini coefficient for new firm registrations, assessing factor allocation. The mediation effect test employs bootstrap methods with 500 replicate samples. Standard errors in parentheses are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

indicate that the implementation of the LCCPI can significantly improve spatial factor allocation. The mediation effect test further validates factor allocation as a channel variable, which is in line with our hypothesis H3.

4.4. Heterogeneity effects

In this section, we move to investigate the heterogeneous effects of the LCCPI on spatial development inequality across resource dependence and marketization levels.

First, we evaluate the heterogeneity impact of the LCCPI on spatial development inequality across resource dependence. As discussed earlier, we present compelling evidence that the LCCPI can significantly alleviate spatial development inequality. Compared to non-resource-dependent cities (NRDCs), resource-dependent cities (RDCs) confront more pronounced challenges in GHG abatement and economic transitions (Havranek et al., 2016). Therefore, RDCs are likely to be more sensitive to the LCCPI than NRDCs. More specifically, we hypothesize that the LCCPI is more effective in reducing spatial development inequality in RDCs. According to the National Sustainable Development Plan for Resource-based Cities (NSDP) released by the State Council, we further categorize the sample cities into RDCs and NRDCs.⁴ Table 7 displays the estimated impacts of the LCCPI on spatial development inequality across resource dependence. We observe a more pronounced reduction in spatial development inequality for RDCs following the LCCPI implementation compared to NRDCs.

Second, we compare the estimated effects of the LCCPI on spatial development inequality across marketization levels.⁵ As highlighted by previous literature, market mechanisms play an essential role in enhancing emission reduction efficiency (Fowlie et al., 2016; Beltrami et al., 2021). Compared to high-marketization cities, resource

Table 7

Estimated effects of the LCCPI on spatial development inequality across resource dependence.

Variables	(1) Resource-dependent cities	(2) Non-resource-dependent cities
<i>Treat × Post</i>	−0.060** (0.030)	−0.030* (0.016)
Ln (population density)	−0.103 (0.106)	−0.065* (0.038)
Ln (financial development)	−0.038* (0.022)	−0.047*** (0.016)
Ln (fixed asset investment)	−0.012 (0.015)	0.019 (0.012)
Ln (FDI)	0.000 (0.004)	0.000 (0.004)
Ln (fiscal expenditure)	−0.004 (0.012)	0.005 (0.019)
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	2065	3559
R ²	0.851	0.874

Notes: The dependent variable in both columns (1) and (2) is the Gini coefficient for nighttime light intensity, assessing city-level spatial development inequality. Standard errors in parentheses are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

⁴ Further information is available online at https://www.gov.cn/zwggk/201312/03/content_2540070.htm.

⁵ The dataset on the marketization index is derived from the China Market Index Database maintained by the Beijing National Economic Research Institute.

misallocation and market distortions are more pronounced in low-marketization cities, potentially undermining the effectiveness of the LCCPI. Therefore, we assume that the LCCPI has a more significant impact on spatial development inequality in high-marketization cities. To this end, we categorize sample cities into two groups: high-marketization cities and low-marketization cities. High-marketization cities are those that exceed the median in terms of marketization level, while the remaining cities are designated as low-marketization cities. Our estimated results (column (1) of Table 8) indicate that the implementation of the LCCPI is associated with a 3.2 % reduction in spatial development inequality in high-marketization cities. In contrast, no such positive effects are observed in low-marketization cities.

5. Conclusions and policy implications

Addressing climate change and mitigating inequality are two critical objectives within the framework of the SDGs. This study investigates the causal causality between the LCCPI and spatial development inequality in China, utilizing city-level data spanning from the years 2000 to 2020. The spatial and temporal variations in policy implementation enable us to use a staggered DID method to obtain unbiased estimates. We calculate city-level spatial development inequality based on county-level nighttime light intensity in China.

Our estimated results indicate that the LCCPI can significantly alleviate spatial development inequality in China. More specifically, the LCCPI contributes to a 4.4 % decline in the Gini coefficient for nighttime light intensity. We further find that the green innovation gap and factor allocation are the potential channels through which the LCCPI impacts spatial development inequality. Finally, our heterogeneity analyses reveal that there is a more significant decrease in spatial development inequality induced by the LCCPI for resource-dependent cities relative to non-resource-dependent cities. Moreover, for cities with a high level of marketization, the LCCPI leads to a 3.2 % reduction in spatial development inequality. In contrast, no such positive effects are observed in low-marketization cities.

This paper yields several policy implications as well. First, this study proposes a potential solution for developing countries to assess developmental inequality in a timely, efficient, and cost-effective manner. Specifically, identifying inequality is a fundamental prerequisite for

Table 8

Estimated effects of the LCCPI on spatial development inequality across marketization levels.

Variables	High-marketization cities (1)	Low-marketization cities (2)
<i>Treat × Post</i>	−0.032** (0.015)	−0.024 (0.023)
Ln (population density)	−0.113* (0.062)	−0.038 (0.031)
Ln (financial development)	−0.003 (0.013)	−0.041*** (0.014)
Ln (fixed asset investment)	−0.011 (0.010)	0.012 (0.012)
Ln (FDI)	0.001 (0.003)	0.003 (0.004)
Ln (fiscal expenditure)	−0.032 (0.022)	−0.005 (0.010)
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	2812	2812
R ²	0.915	0.869

Notes: The dependent variable in both columns (1) and (2) is the Gini coefficient for nighttime light intensity, assessing city-level spatial development inequality. High-marketization cities are those that exceed the median in terms of marketization level, while the remaining cities are designated as low-marketization cities. Standard errors in parentheses are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

effective policy intervention. However, this remains a significant challenge in developing countries, primarily due to the lack of accessible, reliable socioeconomic data. In this context, policymakers can leverage nighttime light data derived from open-access, high-resolution remote sensing imagery to assess development inequality within cities, providing essential insights for the design and implementation of pilot policies.

Second, efficiency and equity are two critical dimensions for evaluating the effectiveness of climate policy. In light of their economic vulnerability, developing countries may struggle to harmonize efficiency and equity in the design and implementation of climate policies. By contrast, this study highlights the effectiveness of LCCPI in mitigating developmental inequality, while existing literature establishes its role in reducing GHG emissions (Chen et al., 2022a; Sun et al., 2024). Therefore, developing nations can implement low-carbon city pilot initiatives for emissions reduction and coordinated development. In detail, policymakers can integrate the emissions reduction target for pilot cities into the political promotion evaluation system, which would ensure that local bureaucrats rigorously enforce climate policy.

Third, as highlighted by previous literature, market mechanisms play an essential role in enhancing the effectiveness of climate policy (Fowlie et al., 2016; Beltrami et al., 2021). Notably, our estimates indicate that the LCCPI can curb spatial development inequality in high-marketization cities rather than in low-marketization cities. Therefore, it is crucial for policymakers to cultivate a market-oriented environment, particularly in developing countries, where resource misallocation and market distortions are more prevalent. For example, policymakers can perform dynamic evaluations of the business environment in pilot cities and direct increased climate policy funding toward high-marketization cities.

Finally, we would like to highlight several limitations of our study and suggest potential avenues for future research. First, this study

focuses on the effectiveness of China's climate policy. Despite being the world's second-largest economy, China is still recognized as a developing country, which indicates our findings should be cautiously extended to developed countries. To enhance the external validity of our conclusions, future research could further investigate the causal relationship between climate policy and development inequality on a global scale. Second, in quantifying factor allocation (i.e., the second channel variable), we use new firm registrations as a proxy for labor and capital mobility. In this case, we are unable to examine the impact of the LCCPI on specific factor allocation. In light of this, it will be a potential direction to assess whether and how climate policy influences factor agglomeration in the future.

Ethic statement

Not applicable.

CRediT authorship contribution statement

Xiaoke Zhu: Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Weigang Liu:** Writing – review & editing, Software, Methodology, Data curation. **Jian Liu:** Writing – review & editing, Software, Methodology, Formal analysis.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgments

Not applicable.

Appendix

A. Additional figures

Figs. A1 and A2

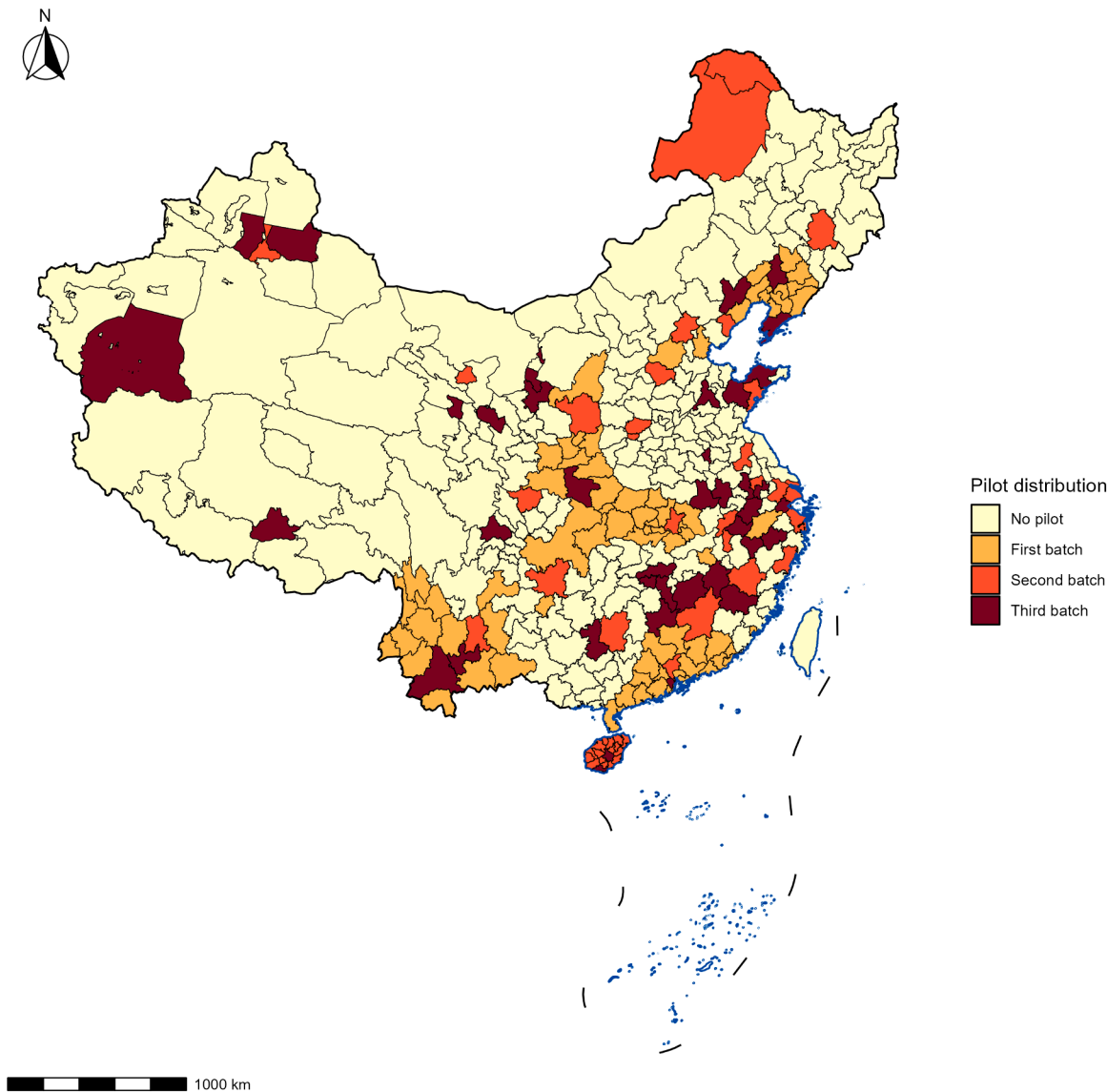


Fig. A1. The spatial distribution of pilot provinces and cities in China.
Notes: Three rounds of LCCPI were implemented in 2010, 2012, and 2017, respectively.

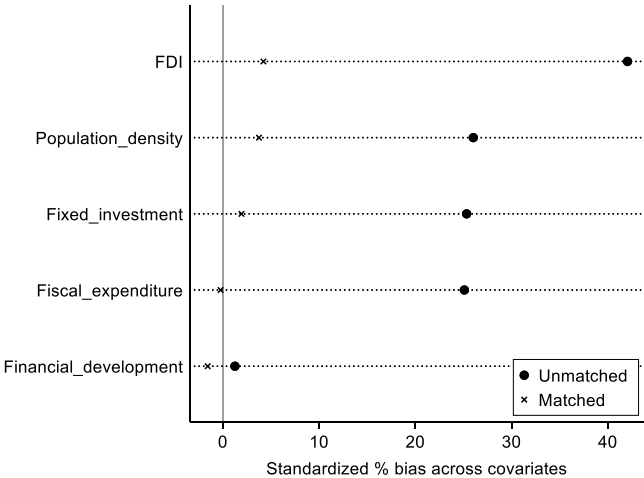


Fig. A2. Comparison of covariates before and after matching.
Notes: All covariates are log-transformed. Given minimal differences in matching quality across matching methods, we present the balancing test results based solely on caliper matching.

B. Additional model introduction

The city-level Theil index for nighttime light intensity can be computed as follows:

$$Theil_{i,t} = \frac{1}{n_i} \sum_{j=1}^{n_i} \left[\frac{L_{j,t}}{\bar{L}_{i,t}} \ln \left(\frac{L_{j,t}}{\bar{L}_{i,t}} \right) \right] \quad (B1)$$

Here n_i denotes the number of counties in city i . $L_{j,t}$ represents the nighttime light intensity of county j in year t , and $\bar{L}_{i,t}$ is the mean value of nighttime light intensity for city i in year t . Note that the Theil index values range from 0 to 1, with 0 denoting perfect equality and 1 indicating complete inequality.

The city-level relative mean deviation (RMD) can be calculated as follows:

$$RMD_{i,t} = \frac{\frac{1}{n_i} \sum_{j=1}^{n_i} |L_{j,t} - \bar{L}_{i,t}|}{\bar{L}_{i,t}} \quad (B2)$$

Where each term has the same interpretation as that in Eq. (B1).

Data availability

Data will be made available on request.

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