

The “environment-economy” asymmetric effect of land conservation and intensive use policies: evidence from quasi-natural experiments at the county level in China

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ONLINE APPENDIX

Appendix A. Literature review

The finite nature of land supply necessitates its efficient and intensive use. Consequently, scholars have primarily concentrated their research on the core concept of land intensification. Broadly speaking, the scientific organization of land market supply is referred to as economical and intensive land usage – including its categories, quantity, and timing – through land reserves, supply planning, and layout optimization, thereby fully tapping the potential of existing land resources (Xie *et al.*, 2018). Narrowly defined, it centers on “enhancing output per unit area” – achieving efficient land resource allocation through optimized utilization methods (Abe *et al.*, 2020), thus establishing a foundational conceptual framework for subsequent research.

Existing research primarily explores two dimensions: “evaluation methods” and “effect analysis.” First, in the field of land intensification evaluation, scholars predominantly employ indicator-based approaches to construct evaluation systems. Methods including principal component analysis (Zhu and Cao, 2011) and entropy-based approaches (Qu *et al.*, 2022) are utilized to quantitatively assess the urban land intensification.

Second, regarding the analysis of land intensification effects, existing research primarily examines environmental and economic impacts, though conclusions remain inconclusive. Concerning environmental effects, some studies suggest that land intensification exacerbates environmental pressures. For instance, Zhao *et al.* (2017) indicate that urban land intensification worsens environmental issues in cities; Chen *et al.* (2021) confirmed that urban land intensification is a primary factor in ecological degradation. Conversely, other studies emphasize its environmental benefits. Xie *et al.* (2018) found that industrial land

intensification can mitigate pollution, while Shang *et al.* (2022) demonstrated that intensive land use effectively curbs urban carbon emissions. Ma *et al.* (2023) further found that intensive land management can regulate the growth rate of GDP-specific carbon emissions. From an economic perspective, intensive land use can promote economic development. It facilitates the centralized layout of rural industrial land, enhancing economic benefits and output efficiency through economies of scale and agglomeration (Gao *et al.*, 2021). However, some scholars contend that generating economic benefits should not be the primary objective of land use planning (Kim, 2011). Land intensification may negatively impact regional economic growth by restricting the expansion of resource-intensive and polluting industries.

Despite extensive exploration of land intensive utilization in existing research, three key shortcomings remain. First, prior studies frequently depend on indicator-based methodologies to assess land conservation and intensive exploitation, which may bring endogeneity concerns and potentially skew research results. Second, current analyses predominantly focus on the urban level, neglecting the county scale. Given that counties serve as critical units for policy implementation, studying their land intensive utilization effects holds significant practical importance. Third, existing studies often consider only the singular effect of land conservation use, overlooking the coexistence of economic and environmental impacts. The conflicting conclusions regarding environmental versus economic effects further underscore the necessity for systematic evaluation. These shortcomings form the research entry point of this paper.

Appendix B. Synergistic effects of factor policies and LCIUP

The preceding discussion revealed how industrial transformation costs and potential influence the effects of LCIUP based on county-level industrial characteristics. However, achieving industrial transformation and upgrading relies not only on internal foundations but also on complementary external policies to form synergistic forces. Clearly, land-intensive policies alone cannot drive industrial transformation and upgrading. Policy support for the three core factors – technology, capital, and labor – may serve as key exogenous drivers to activate industrial upgrading, thereby offsetting the negative impacts of land-constraint policies. Therefore, this section examines the synergistic effects between external policies and LCIUP by constructing an “LCIUP $\times$ factor policy” interaction term, exploring effective pathways to overcome county-level industrial upgrading challenges.

At the technological factor level, technological innovation policy (*Tech_Policy*) serves as the proxy variable. The establishment of China’s “Comprehensive Innovation and Reform Pilot Zones” is regarded as a quasi-natural experiment. The assignment rule for this policy variable is: 1 for counties located in cities approved as pilot zones in the year of designation and thereafter; 0 otherwise. This policy primarily aims to enhance independent innovation capabilities by providing institutional safeguards for technological innovation through systemic reforms. Data is derived from approved documents released by the State Council and provincial governments pertaining to reform pilot zones.

At the capital factor level, green finance policy (*GF_Policy*) serves as the proxy variable. The establishment of “Green Finance Reform Pilot Zones” is treated as a quasi-natural experiment. The dummy variable assignment rule is: pilot regions are assigned a value of 1

for 2017 and subsequent years; all other regions and years prior to 2017 are assigned a value of 0. This policy channels financial resources toward green industries and environmental projects, providing capital support for industrial transformation. Data sources include the People's Bank of China's pilot list and policy documents.

At the labor factor level, the talent introduction policy (*Talent_Policy*) is employed as the proxy variable. It compiles talent recruitment policies enacted by the county's city government in the given year, including core provisions such as housing subsidies, talent incentives, preferential education for children, and tax breaks. The policy is assigned a value of 1 for the year of implementation and subsequent years, and 0 otherwise. This policy data originates from policy texts compiled from provincial and municipal government websites.

This study examines the synergistic effects of three categories of factor-related policies with LCIUP, focusing on the significance and sign of the interaction term coefficients between "LCIUP $\times$ factor policies." The regression results are presented in Table A1.

Table A1. Synergistic effects of LCIUP and factor policies

Variables	(1) <i>Ind_trans</i>	(2) <i>Ind_trans</i>	(3) <i>Ind_trans</i>
<i>LCIUP</i> $\times$ <i>Tech_Policy</i>	-0.0140 (0.0529)		
<i>LCIUP</i> $\times$ <i>GF_Policy</i>		-0.1417 (0.0710)	
<i>LCIUP</i> $\times$ <i>Talent_Policy</i>			-0.0182 (0.0236)
Controls	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	31264	31264	31264

Source: The table was created by the author.

In column (1), the regression coefficient for the interaction term between technological innovation policies and LCIUP is not significant. This indicates that technological innovation policies have failed to form synergistic effects with LCIUP to promote industrial transformation and upgrading. This may stem from the fact that land constraints imposed by LCIUP already compress corporate profit margins. The additional R&D investment required by technology further increases operational pressure, leaving enterprises unable to simultaneously manage transformation and production, thus preventing synergistic effects from materializing.

Column (2) of Table A1 indicates that the interaction coefficient between green finance policies and LCIUP is significantly positive. This indicates that green finance policies constitute an effective factor policy capable of synergizing with LCIUP to drive industrial transformation and upgrading. The tools provided by green financial reform and innovation pilot zones, offer financial subsidies to industrial enterprises preparing for transformation and facilitate financing for entities developing green services, thereby aiding industrial upgrading.

In column (3) of Table A1, the interaction term between talent recruitment policies and LCIUP does not achieve statistical significance. The talent recruitment policies cannot supplement LCIUP to activate industrial upgrading effects. A likely reason is that existing talent recruitment policies primarily target “high-level scientific research talent,” while counties lack the retention conditions – such as high-end industrial positions and quality public services – to keep such talent. Even when talent is recruited through policies like housing subsidies, retention challenges often arise, hindering the synergistic effect between talent policies and LCIUP.

Therefore, green finance policies exhibit synergistic effects with LCIUP, while technology and labor-related policies prove ineffective. This outcome stems not from inherent policy strengths or weaknesses, but from the factor constraints inherent in county-level industrial upgrading. Capital scarcity represents the core bottleneck hindering counties from breaking through “secondary industry lock-in” and cultivating the tertiary sector at this stage. Green finance’s targeted empowerment precisely addresses this gap.

Appendix C. Cost-benefit analysis

From an environmental economics perspective, cost-benefit analysis provides a quantitative tool for evaluating policy effectiveness (Li *et al.*, 2020; Feng *et al.*, 2023). This study constructs a dual-dimensional “environment-economy” accounting framework for LCIUP to further examine its net social benefits. Enterprise relocation may generate spillover effects in LCIUP. This paper calculates net effects based on regression results excluding spillover effects. Specifically, after controlling for spillover effects, LCIUP reduces PM2.5 concentrations in demonstration counties by approximately 1.5 per cent on average compared to non-demonstration counties, while lowering per capita GDP by 4.24 per cent.

According to research by Barwick *et al.* (2018), a 10 $\mu\text{g}/\text{m}^3$ reduction in China’s PM2.5 levels saves approximately \$9.2 billion in health expenditures. The 1.5 per cent reduction in PM2.5 concentrations following policy implementation resulted in average annual health expenditure savings of \$595 million during the study period. Concurrently, the policy’s economic costs are significant: based on the estimated 4.24 per cent decline in per capita GDP, average annual economic losses amounted to approximately \$128 million during the

study period. Thus, the marginal environmental benefit of LCIUP was approximately 4.65 times its economic cost.

To conduct further robustness analysis, this study focused on the five-year short-term window (2017–2021) following the implementation of the third batch of policies, quantifying health cost savings and economic losses during this phase. During the study period, average annual health cost savings amounted to \$467 million, while average annual economic losses reached \$211 million. Health cost savings were 2.21 times the economic losses – though lower than the full study period ratio, this figure remains significantly greater than 1, indicating the policy still achieved net social benefits in the short term.

Further incorporating regional heterogeneity, this study divided the sample into eastern, central, and western regions to separately calculate the cost-benefit relationship for each area. The eastern region recorded average annual health benefits of \$652 million and average annual economic losses of \$158 million, with marginal environmental benefits reaching 4.13 times the economic costs. The western region achieved average annual health benefits of \$598 million and average annual economic losses of \$113 million, yielding a marginal benefit-to-cost ratio of 5.29 times. The central region recorded annual health benefits of \$365 million and annual economic losses of \$122 million, with a final marginal benefit-to-cost ratio of 3 times. Although lower than the eastern and western regions, it still achieved a positive net benefit. These results further validate the conclusion that LCIUP delivers net social benefits.

Appendix D. Robustness tests

D.1. SA Estimator

The SA estimator proposed by Sun and Abraham (2021) captures the dynamic treatment effects and heterogeneity in Multi-period DID, thereby enhancing the precision of policy impact estimates. This paper further employs the SA estimator to examine the effects of LCIUP on the mean PM2.5 concentration and per capita GDP, with its dynamic treatment effects shown in Figure A1. Prior to policy implementation, estimated coefficients fluctuate around zero with confidence intervals encompassing zero. This indicates no significant pre-policy trend differences in mean PM2.5 concentrations or per capita GDP between treatment and control groups, satisfying the parallel trends assumption of DID. After policy implementation, the estimated coefficients gradually shifted toward negative significance. This indicates that the LCIUP significantly impacted both the mean PM2.5 concentration and per capita GDP, with this effect exhibiting dynamic variations across different time periods following policy implementation.

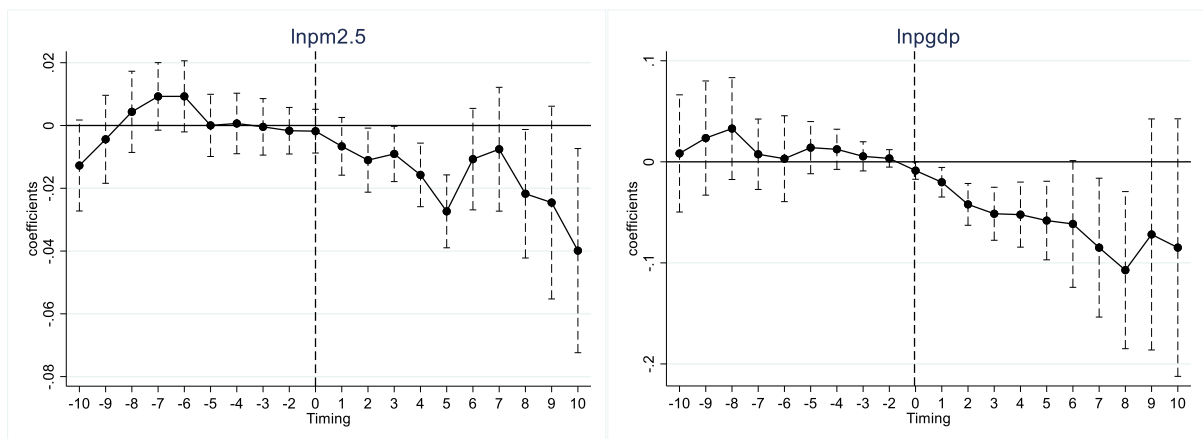


Figure A1. Dynamic effects based on SA estimators.

Source: The figure was created by the author.

D.2. Examination of other policies interference

To avoid the potential bias caused by other policies influencing the explained variables during the sample period, this study identifies and controls for four policies that may affect PM2.5 concentration and per capita GDP. These include the county-to-district reform policy, the low-carbon city pilot policy, the e-commerce demonstration county policy, and the national new urbanization pilot policy. Dummy variables for these policies are introduced into the regression model to account for their impact on the estimated results.

First, we examine the county-to-district reform policy. After China's reform and opening-up, two intensive adjustment periods for this policy occurred: 1998–2000 and 2014–2016. This policy can impact both the economy and the environment at the county level. On the one hand, upgrading a county to an urban district facilitates resource optimization, improves administrative efficiency, and accelerates local economic development. On the other hand, urban district construction may accelerate urbanization, potentially affecting the surrounding rural and ecological environment. We treated this policy as a control variable in regression analysis. The empirical results are presented in columns (1) and (5) of Table A2, where the regression coefficients are both statistically significant, indicating that the county-to-district reform policy does not affect the empirical results of this study.

Second, we consider the low-carbon city pilot policy. This policy strictly limits carbon emissions in the pilot areas to promote green technological innovation and industrial restructuring. We constructed policy dummy variables as control variables based on the counties involved in the three batches of low-carbon pilot cities and conducted regression analysis. The empirical results are presented in columns (2) and (6) of Table A2. The

regression coefficient for LCIUP was found to be largely consistent with the benchmark regression results.

Third, we examine the e-commerce demonstration county policy. By the end of 2021, China had selected 1,672 counties for the e-commerce demonstration county program. While this policy enhances economic vitality, it may also have environmental impacts. This study regresses the dummy variable for the e-commerce model county policy as a control variable, with results presented in columns (3) and (7) of Table A2. The findings indicate that even after controlling for the e-commerce demonstration county policy, the LCIUP still significantly reduces both PM2.5 concentrations and per capita GDP in demonstration counties. Therefore, the e-commerce model county policy does not substantially affect the regression results.

Finally, we consider the national new urbanization pilot policy. In 2015 and 2016, China implemented the national new urbanization pilot policy in three phases to promote urban-rural integration and achieve sustainable economic and social development. The empirical results are shown in columns (4) and (8) of Table A2. After controlling for this policy, the LCIUP still significantly reduces both PM2.5 concentrations and per capita GDP in the demonstration counties.

Overall, the estimated results after controlling for these policy interferences are similar to the baseline regression results, implying that the formulation and implementation of other major policies related to the environment or economy during the same period did not significantly affect the conclusions of this study.

Table A2. Excluding other policy interferences

Variables	<i>lnpm2.5</i>				<i>lnpgdp</i>			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CS_ATT	-0.0120 (0.0044)	-0.0121 (0.0044)	-0.0119 (0.0044)	-0.0122 (0.0044)	-0.0525 (0.0146)	-0.0520 (0.0146)	-0.0518 (0.0146)	-0.0519 (0.0146)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31264	31264	31264	31264	31264	31264	31264	31264

Source: The table was created by the author.

Table A3. Robustness tests

Variables	Replacing the dependent variables		Propensity score matching		Robustness to potential spillover effects		Controlling for the impact of the COVID-19 pandemic	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>lngdp</i>	<i>lnpm2.5_sum</i>	<i>lnpgdp</i>	<i>lnpm2.5</i>	<i>lnpgdp</i>	<i>lnpm2.5</i>	<i>lnpgdp</i>	<i>lnpm2.5</i>
CS_ATT	-0.0115 (0.0046)	-0.0646 (0.0124)	-0.0117 (0.0044)	-0.0521 (0.0146)	-0.0150 (0.0049)	-0.0424 (0.0164)	-0.0093 (0.0042)	-0.0395 (0.0125)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31264	31264	31224	31224	17328	17328	27356	27356

Source: The table was created by the author.

D.3. Replacing the dependent variables

This paper replaces the main dependent variables with the total PM2.5 concentration and total GDP, respectively. The results are shown in columns (1) and (2) of Table A3. The estimated coefficient for LCIUP is significantly negative, indicating that the core conclusion of this paper is robust.

D.4. Propensity score matching

This research utilizes propensity score matching to construct a comparable control group, while integrating the CSDID method to address endogeneity stemming from sample self-selection bias. The matching method utilizes 1:1 nearest neighbor matching with a caliper set at 0.05. Control variables based on baseline regression are matched as covariates, ultimately creating a singular control group that is balanced with the treatment group on features. Balance tests show that the absolute values of post-matching biases are all below 3 per cent, and all P-values are insignificant. This study further plotted a standardized deviation plot (Figure A2), revealing scattered outcomes before matching that converged around zero post-matching. After re-estimating the sample, the regression results are presented in columns (3) and (4) of Table A3. The coefficients for LCIUP are close to the benchmark regression results, demonstrating that the fundamental conclusions of this investigation are resilient.

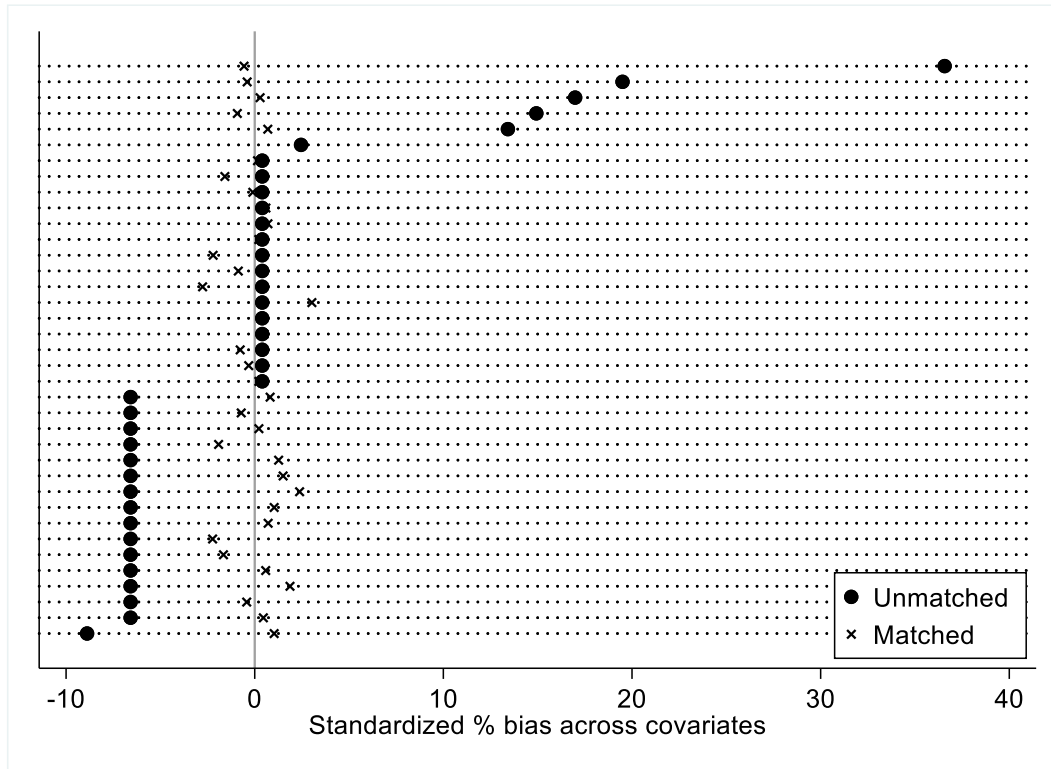


Figure A2. Standardized deviation plot.

Source: Figure created by the author.

D.5. Robustness to potential spillover effects

To verify the robustness of our main results to potential spillover effects, we replicate our main analysis with a geographic buffer sample in which we exclude from our analysis all control counties that are adjacent to treated counties. This reduces the risk that our estimates are biased by firm relocation to nearby untreated areas. The results in columns (5) and (6) of Table A3 indicate that our main findings are robust to this restriction, suggesting that spillovers to adjacent counties are unlikely to be driving our main results. It should be acknowledged that spillovers to non-adjacent control counties cannot be fully ruled out, though they are less likely given the distance decay in firm relocation patterns.

D.6. Controlling for the impact of the COVID-19 pandemic

To eliminate potential interference from the COVID-19 pandemic on the findings, data from 2020 and 2021 were excluded. The regression results are presented in columns (7) and (8) of Table A3. It can be observed that the coefficients for LCIUP align with those of the benchmark regression, demonstrating the robustness of the core conclusions presented in this paper.

Table A4 provides detailed descriptions of all variables used in this paper, including definitions, units, and sources.

Table A4. Variables and datasets in the empirical analysis

Type of variables	Name	Measurement	Unit	Source
Explained variables	<i>lnpm2.5</i>	Natural logarithm of the mean PM2.5 concentration by government fiscal concentration.	μg/m ³	Atmospheric Composition Analysis Group, Washington University in St. Louis
	<i>lnpgdp</i>	Natural logarithm of the ratio of GDP to resident population.	CNY per person	China County Statistical Yearbook
Explanatory variable	LCIUP	Whether the county has implemented land conservation and intensive use policies.	-	Manually curated by the authors
Control variables	<i>Indensity</i>	The natural logarithm of the year-end total population divided by the land area of the administrative region.	People per square meter	China County Statistical Yearbook
	<i>lngov</i>	The natural logarithm of local government general budget revenue as a percentage of regional GDP.	Ratio	
	<i>lnfinde</i>	The natural logarithm of the year-end outstanding balance of all loans extended by financial institutions relative to regional GDP.	Ratio	
	<i>lnedu</i>	Natural logarithm of the ratio of the number of students enrolled in regular secondary schools to the total population at year-end.	Ratio	
	<i>lnhum</i>		%	
	<i>lnitem</i>	Sum the daily time series data for these three indicators and calculate their average to obtain the county-level annual average data, then take the natural logarithm.	°C	
	<i>lnwind</i>		Meters per second	

	<i>Incropland</i>	Generated from remote sensing raster data with 30-meter resolution, taking the natural logarithm.	Hectare	Remote sensing data
	<i>Interrain</i>	Extracted using ArcGIS software, taking the natural logarithm.	-	China 30-meter DEM (ASTER DEMv3) Data
Mechanism variables	<i>lnlsa</i>	The supply volume of all land types, taking the natural logarithm.	Hectare	China Land Market Network
	<i>lnisa</i>	Calculate the supply area of land designated for industrial use by taking the natural logarithm.		
	<i>lnlsa</i>	Calculate the supply area of land designated for commercial and service use by taking the natural logarithm.		
	<i>lnrsa</i>	Calculate the supply area of land designated for residential use by taking the natural logarithm.		
	<i>lnenter</i>	Count the number of enterprises entering each county, then take the natural logarithm.	Unit	China Industrial and Commercial Database
	<i>lnexit</i>	Calculate the number of enterprises that have exited the county, then take the natural logarithm.	Unit	
	<i>lnexist</i>	Count the number of all existing enterprises in the county and take the natural logarithm.	Unit	
	<i>lnpollution</i>	Count the number of enterprises entering the seven polluting industries and take the natural logarithm.	Unit	
	<i>lnnopollution</i>	Count the number of enterprises entering 12 non-polluting industries and take the natural logarithm.	Unit	
	<i>Ind1</i>	The share of primary industry value added in GDP	Ratio	China County Statistical Yearbook
	<i>Ind2</i>	The share of secondary industry value added in GDP.	Ratio	
	<i>Ind3</i>	The share of the tertiary industry's value added in GDP.	Ratio	
	<i>Ind_trans</i>	The ratio of the value added of the tertiary industry to that of the secondary industry.	Ratio	

Source: The table was created by the author.

Table A5 reports the means and standard deviations of the dependent variables and firm characteristics for the treatment and control groups. Significant differences exist between the treatment and control groups for most variables, providing a foundation for our study.

Table A5. Descriptive statistics of variables

Variables	Control group			Treatment group			T-test
	N	Mean	SD	N	Mean	SD	T-value
<i>lnpm2.5</i>	25136	3.645	0.458	6128	3.752	0.370	-0.108
<i>lnpgdp</i>	25136	10.08	0.833	6128	10.39	0.829	-0.308
<i>Indensity</i>	25136	-4.127	1.341	6128	-3.686	1.054	-0.441
<i>lngov</i>	25136	-3.018	0.537	6128	-2.948	0.504	-0.070
<i>lnfinde</i>	25136	-0.643	0.586	6128	-0.629	0.558	-0.014
<i>lnedu</i>	25136	6.199	0.325	6128	6.170	0.315	0.028
<i>lnhum</i>	25136	-4.932	0.410	6128	-4.865	0.372	-0.066
<i>lnitem</i>	25136	5.656	0.0191	6128	5.660	0.0163	-0.003
<i>lnwind</i>	25136	1.568	0.210	6128	1.598	0.198	-0.030
<i>lncropland</i>	25136	10.24	1.005	6128	10.40	0.852	-0.160
<i>lnterrains</i>	25136	-0.788	1.727	6128	-1.307	1.621	0.520
<i>lnlsa</i>	22824	4.215	1.564	5702	4.692	1.323	-0.47
<i>lnenter</i>	25136	7.561	0.991	6128	7.901	0.891	-0.339

Source: The table was created by the author.

Table A6 summarizes the results of all robustness tests conducted in this paper, all of which confirm the robustness of the core findings.

Table A6. Summary table of robustness tests

Types	Methods	Test results	Significance of tests
Replace the dependent variable	Replace the average PM2.5 concentration with the total PM2.5 concentration, and replace per capita GDP with total GDP.	All passed the significance test.	Eliminate result bias caused by dependent variable measurement methods
Preference Score Matching	Employ 1:1 propensity score matching (calibration = 0.05) to construct a comparable control group based on controlled variables.	All passed the significance test.	Mitigate endogeneity issues caused by sample self-selection bias
Demonstrate robustness to spillovers	Excluding all control counties adjacent to treated counties	All passed the significance test.	Spillovers to adjacent counties are unlikely to be driving our main results.
SA Estimator Test	Plot dynamic effect diagrams using the Sun & Abraham (2021) SA estimator.	Prior to policy implementation, the coefficient fluctuated around zero (with a confidence interval containing zero). After implementation, it became significantly negative and exhibited reasonable dynamic variation.	Verify the parallel trend hypothesis holds true, while supporting the temporal rationality and heterogeneity of policy impacts.
Eliminate other policy interference	Incorporate the policy variables for county-to-district conversion, low-carbon city pilot programs, e-commerce demonstration counties, and new urbanization pilot initiatives as control variables.	All passed the significance test.	Eliminating the confounding effects of other relevant policies during the same period demonstrates that the core effect is independently generated by the LCIUP policy.
Eliminate the impact of the COVID-19	Exclude data from 2020-2021	All passed the significance test.	Mitigate the impact of exogenous shocks during exceptional periods

pandemic

Source: The table was created by the author.

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