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Does Policy Synergy Improve Ecological Resilience? Evidence from Smart City and Low-Carbon Pilots in China

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Abstract

Pilot policies are key determinants of urban ecological resilience, while the corresponding results are inconsistent. Moreover, existing research on the synergistic effects of policies on ecological resilience remains insufficient. Thus, this study selects low-carbon pilot policies and smart city pilot policies to explore the possible channels through which they affect ecological resilience. Consequently, using the sample data of China's prefecture-level cities during the period of 2005–2022, we employ a multi-period difference-in-differences approach and two-step regression to examine the relationship between dual pilot policies and ecological resilience. We find that dual pilot policies have a significant positive impact on ecological resilience, and the conclusion is still held after a series of robustness tests. We also find that regional and population size heterogeneity effects exist. Furthermore, the sequences of pilots significantly influence ecological resilience, where the sequence of implementing low-carbon pilot programs earlier than smart city pilot programs has a greater impact on ecological resilience. Finally, the dual pilot policies enhance ecological resilience through channels of technological innovation and industrial structure upgrading. Overall, this study reveals the relationship between policies and ecological resilience, providing policy insights for building resilient cities.

Keywords: dual pilot policies; ecological resilience; multi-period difference-in-differences



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1. Introduction

Recently, environmental issues brought by climate risks have had a significant impact on sustainable development [1,2], which has become a topic of global concern, e.g., [3–5]. In addition, sustainable development is closely associated with ecological resilience (ER), which implies the capacity to mitigate crises, achieve timely recovery, safeguard regional ecological security, and sustain development when subjected to disturbances and long-term pressures [6]. In addition, with the advancement of industrialization and technological progress, our society is entering the era of Industry 4.0, serving as a fundamental building block for smart cities, and further contributing to sustainable development. In light of this, countries around the world are actively formulating carbon reduction policies and smart city development strategies to enhance ER.

To our best knowledge, the determinants of ER have become hotspots, with particular focus on policy drivers. Nowadays, an increasing number of results of the synergistic effect of pilot policies on ER are generated. In detail, the prior studies are mainly focused on two aspects, namely the choice of dual pilot policies and the examination of the effects of policies. On the one hand, dual pilot policies typically involve synergies between environmental regulatory policies, synergies between energy policies, synergies between financial

policies and innovation policies, synergies between environmental policies and innovation policies [7,8], and so on. On the other hand, the synergistic effects are associated with green total factor productivity [9–11], green innovation [12,13], energy efficiency [14,15], greenhouse gas emissions [16–20], and environmental performance [21,22].

However, there is no consensus on the effectiveness of synergy. Most studies found that policy synergy is beneficial to environmental performance, while several scholars argued that different policies may become duplicate incentives and may amplify resource misallocation and market distortions [23]. Secondly, previous studies have mainly focused on environmental consequences from a static perspective, whilst resilience constructs a dynamic evaluation framework. To be the first research that examines the impact of environmental policy synergies on urban ER, ref. [24] overlooks the synergistic effects between environmental policies and innovation policies.

To fill these two research gaps, we treat low-carbon city pilots (LCPPs) and smart city pilots (SCPPs) as a quasi-natural experiment and construct a multi-period difference-in-differences, DID, model to estimate the impact of dual pilot policies on ER using the sample data of 295 cities during the period 2005–2022. We find that the dual pilot policies have significantly improved ER, and this conclusion is still held after using a series of robustness tests. The positive effect is more pronounced for cities in western regions and with a population exceeding one million. We also find that the sequence of pilot policies has a significant impact on ER, where implementing LCPP followed by SCPP has a greater impact on improving ER. Finally, we conduct the mechanism analysis and find that dual pilot policies enhance ER through innovation and structure upgrading.

The focus on Chinese contexts in this study stems from two considerations: on the one hand, as the largest carbon emitter in the world, China pledges to commit to achieving its dual carbon goals. Meanwhile, China is undergoing the shift from the pursuit of economic growth to the pursuit of high-quality growth, which further proposes requirements for carbon reduction. On the other hand, China's government has conducted a series of pilots, such as LCPP, SCPP, big data pilot zones, broadband China, and so on, to actualize sustainable development. Notably, LCPP and SCPP are representative of environmental policies and innovation policies, respectively. Thus, whether have any synergistic effects of LCPP and SCPP on ER, is deserves further exploration.

The contributions are as follows. First, we expand the increasing literature examining the environmental impacts of policies. Most existing research has focused on the effects of single-pilot policies [25,26], while the corresponding results are inconsistent. For instance, [27,28] argued that the smart city pilot policy (SCPP) affects ER positively. However, ref. [29] conclude that SCPP significantly enhances social resilience, while the smart city has no effect on ER. They argued that the construction process of smart cities may neglect the long-term ecological benefits due to the early stage of pilots. Furthermore, studies on the effects of synergistic policies remain relatively scarce, while none of research explores the combined impact of LCPP and SCPP on ER, and the possible channels through which dual pilot polices affect ER. Second, we expand the literature on the determinants of a city's ER. Prior studies focus on factors such as economic development [30], digital finance [31,32], technology innovation and industrial structure [33], while paying less attention to the influence of dual pilot polices. In addition, we extend the sample in assessing ER, while most existing research typically uses provincial-level data or city-level data of a specific region [34].

The study is organized as follows. Section 2 introduces the institutional background and proposes our hypothesis. In Section 3, we present the methodology, research design and data source. In Section 4, we analyze the empirical results, and Section 5 is the discussion and conclusions.

2. Policy Background and Hypotheses

In this section, we focus on the policy background and theoretical analysis, and further propose the hypotheses. Specifically, we briefly summarize the conception, contents, and goals of the dual pilot policies in Section 2.1, which further indicate the possibility of generating synergistic effects on ER. In Section 2.2, we further analyze the theoretical basis and propose the tested hypotheses.

2.1. Policy Background

To actively address climate risks, China is progressively strengthening environmental policies aimed at achieving a low-carbon transition. Among them, LCPP, as a representative regulatory measure, is exploring the pathways for low-carbon development [35]. The National Development and Reform Commission (NDRC) launched three rounds of LCPP in 2010, 2012, and 2017, including a total of 77 pilot cities. Overall, LCPP is a bottom-up policy, indicating that the pilot cities are encouraged to actively explore innovative experiences.

Meanwhile, constructing smart cities is becoming increasingly important to enhance environmental sustainability [36], referring to a new mode that leverages information technology to advance planning, construction, management, and services of urban areas, characterized by Industry 4.0 [37]. Ministry of Housing and Urban Rural Development launched SCPP in 2012, 2013, and 2014, marking the nationwide expansion. Although some issues, such as data protection and digital divide, exist in the process of smart cities [38,39], most studies have found that smart cities enhance the level of ER [40,41].

Since then, many cities have become dual pilots, namely, low-carbon city pilots and smart city pilots. Actually, the dual pilot policies differ in goals, pilots, and timelines as they closely reinforce policies. For example, LCPP emphasizes achieving carbon emission reductions and environmental improvements through energy and industrial restructuring, while SCPP enhances operational and management efficiency by applying information technology. Thus, the dual pilot policies are conducive to transforming cities into low-carbon and green development, thereby having a synergistic effect on enhancing ER.

2.2. Research Hypotheses

In this section, we analyze the mechanism through two possible channels, namely, innovation and structure upgrading.

First, the dual pilot policies enhance the level of ER by improving innovation. SCPP relies on new digital technology to promote the city's intelligence [42], improving the intensity and efficiency of environmental regulation [43]. Meanwhile, regulation provided by LCPP directly controls carbon emissions; thus, high regulatory efficiency spurs low-carbon technological innovation [44]. On the other hand, LCPP encourages changing production and consumption to a low-carbon mode. Additionally, SCPP changes the combination form of resources by using the new technology, promotes the connection and interoperability of data and knowledge, and further provides a source of power for urban technological innovation [45].

Second, the dual pilot policies improve ER by fostering industrial structure upgrading. Under the background of LCPP, pilot cities adjust their industrial structure to low-carbon development through a series of measures of regulations [46]. SCPP accordingly upgrades the industrial structure in two ways. On the one hand, the emerging industries such as information, software, design, and business services are developed [47], leading to the restructuring of the economic structure. On the other hand, the new technology penetrates into traditional industries to form intelligent industries, improving the operating efficiency greatly and further realizing the transformation of traditional industries. Thus, the dual pilot policies have a synergistic effect on industrial structure upgrading.

Thus, three hypotheses are proposed.

H1: *Dual pilot policies promote the level of ecological resilience.*

H2: *Dual pilot policies improve the level of ecological resilience via technological innovation.*

H3: *Dual pilot policies improve the level of ecological resilience by industrial structure upgrading.*

3. Methodology and Data

3.1. Model Specification

The DID method is an econometric approach for estimating causal effects, treating public policy as a natural experiment. To assess the net impact of a policy, the sample is divided into two groups: the treatment group (exposed to the policy) and the control group (unexposed to the policy). Further, we perform a first-difference between the two groups to eliminate individual heterogeneity that does not change over time, then a second difference on the two groups' change values is performed to eliminate increments that change over time.

Based on this, we use a DID approach by treating dual pilot policies as a quasi-natural experiment to explore the synergistic effects of dual pilot policies on ER. Due to the fact that LCPP and SCPP are implemented in batches, a multi-period DID model is established to evaluate the net effects of policies, and the specification is as follows:

$$ER_{i,t} = \beta_0 + \beta_1 carbonsmart_{i,t} + \beta Controls + p_i + u_t + \varepsilon_{it} \quad (1)$$

where $ER_{i,t}$ is the ecological resilience of city i in year t , and $carbonsmart_{i,t}$ is the dummy variable, representing whether city i is exposed to policies in year t . The coefficient of this variable is our research object, indicating the net effect of synergistic policies on ER. *Controls* are a series of city-level control variables. p_i , u_t , and ε_{it} represent city-fixed effects, time-fixed effects, and random error terms, respectively.

The two-step regression approach is further conducted to validate the possible channels of the dual pilot policies affecting ER. The equations are as follows:

$$Med_{i,t} = \alpha_0 + \alpha_1 carbonsmart_{i,t} + \alpha Controls + p_i + u_t + \varepsilon_{it} \quad (2)$$

$$ER_{i,t} = \lambda_0 + \lambda_1 carbonsmart_{i,t} + \lambda_2 Med_{i,t} + \lambda Controls + p_i + u_t + \varepsilon_{it} \quad (3)$$

where $Med_{i,t}$ is the mechanism variable, including technological innovation (TI) and industrial structure upgrading (IS).

3.2. Variables Definition

3.2.1. Dependent Variable

The dependent variable is ER, which is measured based on three dimensions: resistance, adaptability, and recovery, and the basic indicators of ER are shown in Table 1 (Resistance refers to the capacity to maintain its original structure and function when facing external pressures, which is closely associated with its natural resources. Adaptability refers to the ability to continue functioning after an external disturbance occurs, which is negatively affected by pollution or emissions. Recovery refers to an ecosystem's ability to recover to its original state or achieve a higher level after severe damage, which is positively associated with governance measures). Due to the positive and negative effects of different indicators on ER, we standardized the indicators and used the entropy weight approach to calculate ER.

Table 1. The evaluation system of ER.

Dimensions	Indicators	Units	Directions
Resistance	Water resources per capita	Cubic meter/person	Positive
	Green coverage rate of built-up areas	%	Positive
	per capita greenery area of park	Hectares/10,000 person	Positive
	Per capita built-up area	Square meters/10,000 person	Positive
Adaptability	Per capita wastewater discharge	Tons/person	Negative
	Per capita industrial sulfur dioxide emissions	Tons/person	Negative
	Per capita industrial smoke and dust emissions	Tons/person	Negative
	Per capita industrial nitrogen oxide emissions	Tons/person	Negative
	Annual average concentration of inhalable fine particulate matter	Micrograms/cubic meter	Negative
Recovery	Industrial sulfur dioxide removal capacity	Tons	Positive
	Industrial smoke and dust removal capacity	Tons	Positive
	Non-hazardous treatment rate of domestic waste	%	Positive
	Comprehensive utilization rate of industrial solid waste	%	Positive
	Centralized treatment rate of sewage treatment plant	%	Positive

3.2.2. Independent Variable

The core independent variable is a dummy variable, defined as LCPP multiplied by SCPP. If city i is exposed to policies in year t , we then define it as 1, and 0 otherwise.

3.2.3. Control Variables

Several control variables are added into the model referring to the previous studies, namely economic development ($lncgdp$), the degree of openness ($open$), the density of population ($lnpd$), urbanization (urb), and human capital (hc). Table 2 summarizes all of the definitions.

Table 2. The definition of the variables.

Variables	Definition
ER	The scores calculated by entropy weight approach according to Table 1
DID	Dummy variable, equal to 1 if a city becomes a dual pilot city, otherwise 0
$lncgdp$	Natural logarithm of per capita GDP
$open$	The actual foreign investment divided by GDP
$lnpd$	Population divided by land area
urb	Natural logarithm of the total collection of thousands of books in public libraries
hc	Natural logarithm of the number of students in college

3.3. Data

We select a sample from the China Annual Urban Statistical Yearbook, sourced from the National Bureau of Statistics, during the period from 2005 to 2022. We exclude the sample data with substantial missing elements, and supplement the data with partially missing elements using the linear interpolation method (linear interpolation is a commonly used method in data processing (Chen et al., 2024; Liao et al., 2025) [48,49], capable of preserving the distribution characteristics of original data and the relationships between variables while minimizing information loss and sample bias), forming an unbalanced

panel data for 295 cities. All variables are winsorized at a 1% level except for the dummy variable. Table 3 summarizes the descriptive statistics.

Table 3. The descriptive statistics of variables.

Variables	Obs	Mean	SD	Min	P25	Median	P75	Max
<i>ER</i>	5095	0.3122	0.0162	0.1237	0.310	0.3148	0.318	0.3313
<i>DID</i>	5095	0.0775	0.2675	0.0000	0.000	0.0000	0.000	1.0000
<i>lncgdp</i>	5095	10.4726	0.7472	8.6216	9.985	10.5253	11.001	12.0075
<i>open</i>	5095	0.1107	0.1609	−0.0611	0.015	0.0497	0.129	0.8075
<i>lnpd</i>	5095	0.4226	0.2976	0.0160	0.179	0.3590	0.638	1.3850
<i>urb</i>	5095	7.2530	1.0165	5.0626	6.553	7.1148	7.787	10.2826
<i>hc</i>	5095	10.4629	1.3713	6.8926	9.617	10.4516	11.285	13.6221

4. Empirical Analysis

4.1. Baseline Regression

The results of baseline regression examining the effect of dual pilot policies on ER are shown in Table 4. Column (1) and column (3) control city- and year-fixed effects, while column (2) only controls city-fixed effects. In addition, we incorporate several control variables in column (2) and column (3). As shown in each column, the coefficient of *DID* is significantly positive, and all of the estimated coefficients are 0.0017, indicating that the implementation of dual pilot policies improves the city's ER by 0.17%. Thus, the regression results are consistent with our hypothesis.

According to the coefficients of other control variables, the coefficients indicate that a city's economic level and economic openness are significantly positively correlated with ER, while urban population density and human capital level are negatively correlated with ER. The coefficient for urbanization level is not significant.

Table 4. The results of baseline regression.

Variables	(1)	(2)	(3)
<i>DID</i>	0.0017 *** (4.8892)	0.0017 *** (4.6592)	0.0017 *** (4.8111)
<i>lncgdp</i>		0.0042 *** (20.6399)	0.0019 *** (4.7878)
<i>open</i>		0.0066 *** (5.9932)	0.0070 *** (6.2275)
<i>lnpd</i>		−0.0041 ** (−2.4538)	−0.0054 *** (−3.2160)
<i>urb</i>		0.0005 *** (2.6035)	0.0003 (1.4531)
<i>hc</i>		−0.0003 (−1.4913)	−0.0008 *** (−3.2990)
<i>Constant</i>	0.3121 *** (4470.5955)	0.2690 *** (151.0558)	0.3000 *** (63.4135)
<i>City</i>	Yes	Yes	Yes
<i>Year</i>	Yes	No	Yes
<i>Observations</i>	5095	5095	5095
<i>R-squared</i>	0.9252	0.9253	0.9266

Note: The values in parentheses are *t*-test values; **, and *** indicate significance levels of 5%, and 1%, respectively.

4.2. Parallel Trend Test

Regressing a multi-period DID model involves stringent assumptions, which means that the treatment group (with LCPP and SCPP cities) and the control group (without LCPP

and SCPP cities) have a common trend before the policy shock. Thus, an event study is conducted referring to [50].

Figure 1 is the testing results of the parallel trend, displaying the estimated coefficients and their 95% confidence intervals. It is observed that the coefficients are close to zero and statistically insignificant for at least nine years before implementing the dual pilot policies, indicating that the difference between the two groups is not significant. Furthermore, following the implementation of policies, the correlation coefficient exhibited an expanding trend, reaching statistical significance in the third year. The findings show that the test was passed, indicating that the dual pilot policy has indeed enhanced the city's ER.

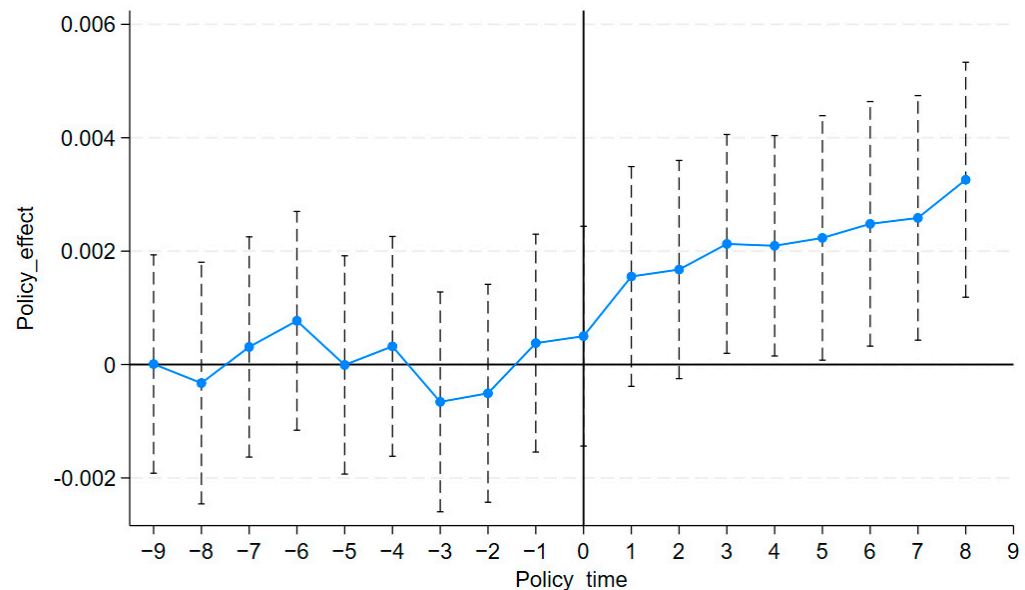


Figure 1. The parallel trend test. Note: The horizontal axis is Policy_time, referring to the year conducting the dual pilot policies; negative signs indicate years prior to becoming dual pilots, while positive signs indicate years after becoming dual pilots. The vertical axis is Policy_effect, reflecting the estimated dummy variable coefficients for each period before and after the dual pilots. The dashed line represents the 95% confidence interval, reflecting whether an estimated coefficient is significant. If the interval includes zero, the coefficient is not significant; otherwise, it is significant.

4.3. Robustness Tests

We further examine whether the conclusions are robust by four approaches and present the results in Table 5. We regress the baseline model by Propensity Score Matching (PSM) estimation to address sampling bias in pilot policies, and the results are displayed in Column (1). It can be seen that the positive coefficient of DID is slightly less than the baseline results of 0.0017, supporting that dual pilot policies increase ER. We also lag all independent variables by one year to regress the model, as shown in column (2). The results indicate that the conclusion is held. In Addition, column (3) is the result of the original sample data. The positive coefficient shows that the conclusion is not affected by extreme outliers. Finally, we conducted the regression with sample exclusion during the period from 2005 to 2006, with the results presented in column (4), indicating that the positive causal relationship is not influenced by sample restriction. In summary, all of the above robustness tests indicate that the estimated results are robust.

Table 5. The baseline results.

Variables	(1)	(2)	(3)	(4)
DID	0.0016 *** (3.4495)	0.0019 *** (5.2618)	0.0024 *** (4.2980)	0.0018 *** (4.8714)
lncgdp	−0.0019 ** (−2.4624)	0.0017 *** (4.3987)	0.0021 *** (3.4595)	0.0017 *** (4.2349)
open	0.0134 *** (6.4220)	0.0069 *** (5.9370)	0.0086 *** (5.4226)	0.0067 *** (5.6912)
lnpd	0.0006 (0.1350)	−0.0047 *** (−2.5865)	−0.0083 *** (−4.3132)	−0.0041 ** (−2.3942)
urb	0.0007 * (1.9329)	0.0004 * (1.7832)	0.0005 (1.4680)	0.0003 (1.4816)
hc	−0.0005 (−0.8833)	−0.0008 *** (−3.2617)	−0.0012 *** (−3.7656)	−0.0007 *** (−2.6865)
Constant	0.3300 *** (33.2406)	0.3010 *** (61.7188)	0.3022 *** (41.5593)	0.3002 *** (59.5897)
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	1314	4811	5095	4532
R-squared	0.9526	0.9311	0.8401	0.9373

Note: All models are controlled for city and year fixed effects. t-statistics are in parentheses, and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.4. The Impact of Policy Sequence on ER

As proved above, dual pilot policies improve the city's ER. We further introduce two dummy variables to examine the impact of policy sequence on ER, with the results reported in Table 6. Specifically, DID1 is measured as whether pilot city *i* implements SCPP earlier than LCPP. In other words, DID1 is set to 1 if pilot city *i* becomes the smart city before implementing LCPP, and is otherwise 0. Similarly, DID2 is defined as whether pilot city *i* implements LCPP earlier than SCPP.

Table 6. Effects of pilot policy sequences.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
DID1	0.0014 ** (2.1117)	0.0011 * (1.7334)	0.0011 * (1.6562)			
DID2				0.0021 *** (4.2125)	0.0019 *** (3.8140)	0.0022 *** (4.6053)
lncgdp		0.0020 *** (5.1216)	0.0019 *** (4.7573)		0.0018 *** (4.7221)	0.0017 *** (4.2937)
open		0.0065 *** (5.8018)	0.0064 *** (5.4671)		0.0068 *** (6.0513)	0.0067 *** (5.7683)
lnpd		−0.0055 *** (−3.2486)	−0.0048 *** (−2.6448)		−0.0055 *** (−3.3066)	−0.0048 *** (−2.6613)
urb		0.0003 (1.4035)	0.0004 * (1.7528)		0.0003 (1.3089)	0.0003 * (1.6468)
hc		−0.0009 *** (−3.6236)	−0.0009 *** (−3.6081)		−0.0008 *** (−3.4030)	−0.0008 *** (−3.3590)
Constant	0.3122 *** (4804.3371)	0.2998 *** (63.2237)	0.3007 *** (61.4858)	0.3121 *** (4644.6744)	0.3009 *** (63.4308)	0.3020 *** (61.7822)
City	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5095	5095	4811	5095	5095	4811
R-squared	0.9248	0.9263	0.9307	0.9251	0.9265	0.9310

Note: All models are controlled for city- and year-fixed effects; In column (1) and column (4), the regression models are estimated without control variables; The results in column (2) and column (5) incorporate control variables; In column (3) and column (6), all independent variables are lagged by one year; t-statistics are in parentheses, and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The coefficient for DID1 is significantly positive in columns (1) to (3), and the coefficient for DID2 is also significantly positive in columns (4) to (6). Moreover, the coefficients of DID2 are greater than those of DID1, indicating that implementing LCPP earlier than SCPP has a more significant impact on improving ER. The conclusion is plausible in that LCPP is a comprehensive environmental regulation policy, implementing decarbonization plans, targets, and solutions, which further provides for becoming smart cities.

4.5. Heterogeneity Analysis

The combined effect of dual pilot policies on ER may vary depending on the geographical location, population size, and other factors. Thus, we further explored the heterogeneous impact of dual pilot policies, and the results are shown in Table 7.

Table 7. Results of heterogeneity.

Variables	(1)	(2)	(3)	(4)	(5)
<i>DID</i>	0.0009 *	−0.0019 ***	0.0046 ***	0.0092 ***	0.0013 ***
	(1.7245)	(−3.1135)	(6.4694)	(3.8365)	(3.4813)
<i>lncgdp</i>	0.0015 **	−0.0018 ***	0.0046 ***	0.0004	0.0021 ***
	(2.5129)	(−3.1629)	(5.0238)	(0.1442)	(5.3869)
<i>open</i>	0.0084 ***	0.0012	−0.0146 ***	0.0014	0.0065 ***
	(7.1304)	(0.5788)	(−3.0357)	(0.1082)	(5.7740)
<i>lnpd</i>	0.0036	0.0001	−0.0262 ***	0.0385 **	−0.0053 ***
	(1.3090)	(0.0511)	(−4.3713)	(2.3273)	(−3.1585)
<i>urb</i>	0.0012 ***	−0.0001	0.0010 **	0.0039 **	0.0002
	(4.0736)	(−0.1871)	(2.1191)	(2.2110)	(0.7508)
<i>hc</i>	−0.0019 ***	0.0008 **	−0.0023 ***	−0.0021	−0.0009 ***
	(−4.5049)	(2.3464)	(−4.6212)	(−1.3563)	(−3.9240)
<i>Constant</i>	0.3053 ***	0.3251 ***	0.2823 ***	0.2784 ***	0.3007 ***
	(39.9857)	(48.2192)	(25.9072)	(8.3344)	(62.9954)
City	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
Observations	1797	1799	1499	201	4893
R-squared	0.8713	0.6211	0.9572	0.9739	0.9131

Note: All models are controlled for city- and year-fixed effects; t-statistics are in parentheses, and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

First, we group the sample into three regions by geographical location, and re-estimate the results, which are shown in columns (1) to (3). The dual pilot policies have a significant positive impact on the ER of the eastern and western regions, except for the central region. One possible explanation is that the eastern region has a strong foundation, such as digital infrastructure and green innovation level, which is beneficial for improving ER. The western region is rich in hydropower and solar energy, providing a good foundation for developing clean energy and further enhancing the level of ER. In contrast, the central region has a high proportion of heavy industry, coupled with the lagging cultivation of green alternative industries, weakening a city's resilience to external shocks.

Second, we categorize the sample into small and medium-sized cities and large cities based on whether the permanent resident population exceeds one million, and the regression results are presented in columns (4) and (5). The significant positive coefficients indicate that dual pilot policies improve ER of the two types of cities, while the effect is greater in small and medium-sized cities. Small and medium-sized cities usually have more potential for development; for example, SCPP improves the efficiency of resource allocation through new digital technologies, making up for the lack of infrastructure in small and medium-sized cities and improving ER more quickly. Moreover, small and

medium-sized cities face less pressure in industrial transformation and are more likely to achieve low-carbon development through green technological innovation.

4.6. Possible Channels

We also analyze the channels by which dual pilot policies influence ER to employ a two-step regression. We can see that the coefficient of DID is positive and statistically significant in column (1) of Table 8, and that of TI is also significantly positive in column (2), which indicates that the implementation of dual pilot policies improves technological innovation, resulting in enhanced ER.

Similarly, the statistically significant coefficients of DID and IS are positive in columns (3) and (4), which validates our hypothesis that dual pilot policies improve ER through industrial structure upgrading.

Table 8. The results of the affected mechanism.

Variables	(1)	(2)	(3)	(4)
<i>TI</i>		0.0002 * (1.7528)		
<i>IS</i>				0.0001 * (1.6550)
<i>DID</i>	0.0745 * (1.9125)	0.0017 *** (4.7619)	0.1683 ** (2.0243)	0.0020 *** (5.3922)
<i>Incgdp</i>	1.0779 *** (25.4014)	0.0016 *** (3.8914)	1.7246 *** (17.2561)	0.0014 *** (2.9491)
<i>open</i>	−0.0855 (−0.6940)	0.0070 *** (6.2461)	−1.3307 *** (−4.4677)	0.0077 *** (5.7856)
<i>lnpd</i>	0.4858 *** (2.6629)	−0.0055 *** (−3.2817)	0.4677 (0.9264)	−0.0035 (−1.5477)
<i>urb</i>	0.2557 *** (11.3256)	0.0002 (1.1512)	0.2445 *** (4.8999)	0.0001 (0.5651)
<i>hc</i>	−0.0912 *** (−3.5369)	−0.0008 *** (−3.2059)	0.0431 (0.7353)	−0.0007 *** (−2.6521)
<i>Constant</i>	−2.5508 *** (−4.9369)	0.3006 *** (63.3912)	17.8714 *** (14.6466)	0.3013 *** (54.0008)
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	5095	5095	4243	4243
R-squared	0.9236	0.9266	0.8843	0.9350

Note: All models are controlled for city- and year-fixed effects; the TI mechanism variable is defined as the natural logarithm of science expenditure, and IS mechanism variable is defined by the following formula: $\text{the proportion of primary industry} \times 0.2 + \text{the proportion of secondary industry} \times 0.5 + \text{the proportion of tertiary industry} \times 0.3$. Move the variable forward by three periods when performing regression; t-statistics are in parentheses, and *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5. Discussion and Conclusions

In this section, we would like to summarize the estimation results and findings and briefly discuss the policy implications and possible limitations.

As previously mentioned, the existing literature has extensively studied the environmental impacts of pilot policies. However, research on the synergistic effects of policies on ER remains lacking, let alone the specific mechanisms through which they influence environmental restoration. Thus, we use a multi-period DID method to analyze the effect of dual pilot policies on ER with an unbalanced panel data of cities from 2005 to 2022.

We find the following main conclusions. First, dual pilot policies significantly enhance the level of ER, which is held after several robustness checks. Secondly, the sequence of pilots has an important significance on ER; in other words, the policy sequence of

implementing LCPP earlier than SCPP has a greater impact on ER. Thirdly, the effect of dual pilot policies on ER varies considering location and population size. Specifically, a positive effect exists in the eastern region and western region, while there exists a negative impact in the central region. In addition, the effect has a greater influence on ER in small and medium-sized cities than in large-scale cities. Finally, we find that technological innovation and industrial structure upgrading are important channels through which dual pilot policies affect ER. As shown, our results are consistent with the three hypotheses proposed in Section 2.2.

The conclusions offer significant policy implications. Firstly, pilot policies are an important factor affecting ER, and the sequence of pilots can have different impacts on ER. Therefore, when implementing pilot policies, attention should be paid to the combined effects of different policies to maximize their impact on ER. Secondly, the heterogeneous effect of pilot policies on ER exists; thus, we should implement differentiated pilot policies. For example, implementing dual pilot policies may inhibit the level of ER in the central region. For this region, we should fully mobilize the infrastructure and industrial supporting resources, make good use of new technology to adjust the industrial structure, and thus promote the level of ER. Finally, we must vigorously promote technological innovation and industrial upgrading. However, global climate risks are contagious and have spillover effects, particularly during periods of frequent foreign trade activities. Therefore, emphasizing the importance of innovation and industrial upgrading on a global scale is crucial for sustainability.

However, we examine the synergistic effects of pilot policies on ER by using a dummy variable, that is, the DID variable, and have yet to consider the influence of the frequency of pilot policies. Future studies should focus on this issue.

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Abbreviations

The following abbreviations are used in this manuscript:

ER	Ecological resilience
LCPP	Low-carbon pilot policy
SCPP	Smart city pilot policy
DID	Difference-in-differences
NDRC	National Development and Reform Commission

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