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Green Knowledge Recombination and Urban Carbon Intensity: University–Industry Collaboration and the Conditioning Role of Regional Green Innovation Efficiency

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Abstract

Green innovation is commonly assessed through patent counts or aggregate efficiency measures, while the recombination structure of regional technological knowledge remains underexplored. This study examines whether university–industry collaboration is associated with greater recombination distance and diversity and whether these dimensions are related to urban carbon intensity. Using a balanced panel of 212 Chinese cities from 2003 to 2021, we construct IPC-based indicators of recombination distance and diversity and estimate the proposed relationships using three-stage least squares, supplemented by alternative estimators, indicator specifications, and heterogeneity tests. University–industry collaboration is positively associated with both recombination dimensions, although the first-stage evidence is statistically modest. Greater recombination distance and diversity are negatively associated with subsequent urban carbon intensity in the baseline and conventional robustness specifications. Regional green innovation efficiency consistently strengthens the collaboration–distance relationship, whereas its moderating effect on recombination diversity is weaker and sensitive to the efficiency specification. The

negative recombination–carbon-intensity association is more pronounced among cities with high initial carbon intensity and remains evident under both mean- and median-based initial-period classifications. Dynamic specifications and exclusion-restriction sensitivity tests yield less stable estimates after accounting for carbon-intensity persistence and allowing FiscalRD to enter the outcome equation directly. The findings are therefore interpreted as conditional associations consistent with the proposed pathway rather than as definitive causal effects. Overall, the results suggest that the structure, rather than only the volume, of green innovation is associated with low-carbon transition, although the strength of this relationship depends on model specification, regional conditions, and instrument strength.

Keywords

Carbon intensity; Green knowledge recombination; University–industry collaboration; Regional innovation systems; Green innovation efficiency

Highlights

- University–industry collaboration shows modest positive associations with recombination distance and diversity.
- Baseline and conventional robustness estimates show negative associations between both recombination dimensions and urban carbon intensity.
- Regional green innovation efficiency robustly strengthens the collaboration–distance relationship.
- The recombination–carbon-intensity association is stronger in cities with high initial carbon intensity.

1 Introduction

Reducing carbon intensity requires more than expanding the stock of green technologies; it also depends on how regions combine and deploy technological knowledge. China provides a particularly relevant setting because its low-carbon

transition must proceed alongside continued industrial upgrading and economic development. Existing studies have linked green patents, green total factor productivity, environmental regulation, and technological spillovers to regional carbon performance (Chen et al., 2023; Ke et al., 2023; K. Liu et al., 2023). These indicators capture the volume or efficiency of green innovation, but reveal less about the internal composition of regional technological knowledge. A city may generate many green patents while remaining dependent on a narrow technological trajectory, whereas another may combine knowledge across several technological domains to develop broader low-carbon solutions.

This study focuses on two dimensions of green knowledge recombination. Recombination distance captures the technological separation between the knowledge fields combined within a regional green knowledge base, while recombination diversity captures the breadth and distribution of those combinations. Distant recombination may facilitate departures from established high-carbon technological paths, and diverse recombination may support the integration of complementary solutions in energy efficiency, cleaner production, and environmental management (Lin et al., 2023; X. Liu et al., 2024). Both dimensions may also raise search, coordination, and integration costs; whether they are associated with lower carbon intensity therefore remains an empirical question.

Regional innovation systems shape the ability to generate and absorb such combinations (Mao et al., 2023). Evolutionary economic geography emphasizes that technological change is embedded in inherited regional capabilities and development paths (Boschma & Martin, 2007), while the Triple Helix framework highlights the complementary roles of universities, firms, and public institutions (Etzkowitz & Zhou, 2017). Universities can broaden firms' technological search, firms provide production problems and application settings, and regional institutional conditions affect whether collaboration can be translated into usable technological combinations. Although previous research has examined collaboration intensity, knowledge transfer, and

innovation output (Cowan & Zinovyeva, 2013; Rybnicek & Königsgruber, 2019; J. A. Zhang et al., 2024; Zhao et al., 2024), the effect of university–industry collaboration on the structure of green knowledge recombination remains less well understood.

We examine this relationship using panel data for 212 Chinese cities from 2003 to 2021. IPC-based indicators are constructed to measure recombination distance and diversity, and linked equations are estimated to assess whether university–industry collaboration is associated with these recombination structures and whether the structures are, in turn, associated with urban carbon intensity. We also examine whether regional green innovation efficiency conditions the collaboration–recombination relationship and whether the recombination–carbon-intensity association differs between cities with high and low initial carbon intensity.

This study makes three contributions. First, it extends the measurement of green innovation beyond patent volume and aggregate efficiency by distinguishing the technological distance and diversity of regional knowledge combinations. Second, it develops a temporally ordered empirical framework linking university–industry collaboration, green knowledge recombination, and subsequent carbon intensity, while avoiding the assumption that collaboration has a direct environmental effect. Third, it identifies regional green innovation efficiency and initial carbon-intensity level as conditions under which these relationships vary. The contribution lies primarily in the structural measurement of regional green knowledge bases and the identification of their empirical boundary conditions, rather than in establishing definitive causal mediation.

2 Literature review

2.1 Green technology and carbon intensity

Carbon intensity measures the carbon emissions generated per unit of economic output and provides an indication of whether economic growth is becoming less carbon dependent. At the city level, variation in carbon intensity reflects differences in industrial composition, energy systems, technological capability, and economic development (C. He et al., 2022; Ke et al., 2023). The STIRPAT framework groups these determinants into population, affluence, and technology, and has therefore been widely applied to analyses of regional environmental performance (Dietz & Rosa, 1997).

Green technology can reduce carbon intensity by improving energy efficiency, facilitating cleaner energy use, and supporting carbon capture and resource reutilization (Haider & Mishra, 2021; Leung et al., 2014; T. Yang et al., 2023). It may also increase the economic output generated from a given resource base through improvements in green total factor productivity and industrial upgrading (Sohag et al., 2019). Empirical studies consequently tend to measure green innovation through patent counts, innovation efficiency, or green productivity (Chen et al., 2023; Ye et al., 2020).

These measures capture innovation scale and performance but not the organization of technological knowledge. Regions with similar patent output may differ substantially in the distance and diversity of the fields they combine. Because technological change is conditioned by inherited regional capabilities and development paths (Boschma & Martin, 2007), the key question is whether recombination structure explains variation in carbon intensity beyond conventional measures of innovation quantity and efficiency.

2.2 Triple Helix collaboration and regional innovation systems

Regional innovation systems emphasize that technological change emerges from interactions among firms, knowledge-producing institutions, and public organizations rather than from isolated actors (Cooke, 2010; Pino & Ortega, 2018). The Triple Helix framework formalizes this interaction by distinguishing the knowledge-producing role of universities, the application and commercialization role of firms, and the institutional and coordinating role of government (Etzkowitz & Zhou, 2017; Strand & Leydesdorff, 2013). This framework is especially relevant to green innovation, which often combines scientific knowledge, industrial application, and institutional support.

University–industry collaboration can provide firms with access to scientific fields beyond their established technological routines, while universities gain access to practical production problems and application environments. Previous studies have examined how such collaboration affects innovation capability, cooperation intensity, technological output, and collaborative strategy (Doblinger et al., 2019; Z. Yang et al., 2021). Regional institutional conditions may further affect whether these exchanges result in sustained innovation by reducing information barriers and coordination costs.

The literature nevertheless focuses mainly on the amount of collaboration, knowledge transfer, and resulting innovation output. Less attention has been paid to whether university–industry interaction changes the technological composition of the regional knowledge base. The environmental contribution of collaboration may therefore depend not only on whether it produces additional green patents, but also on whether it enables combinations across more distant and more diverse technological fields.

2.3 Green knowledge recombination and carbon intensity

Knowledge recombination refers to the creation of new technological possibilities through novel combinations of existing knowledge elements (Arthur, 2007; Schumpeter & Swedberg, 2021; Weitzman, 1998). Green innovation may be particularly dependent on recombination because environmental problems cut across energy, production, materials, transport, information technology, and pollution-control systems (Barbieri et al., 2020). Studies have consequently examined whether green technologies draw on broader or more novel knowledge combinations than non-green technologies and whether academic inventors contribute to regional green diversification (Ghisetti et al., 2015; Orsatti et al., 2024).

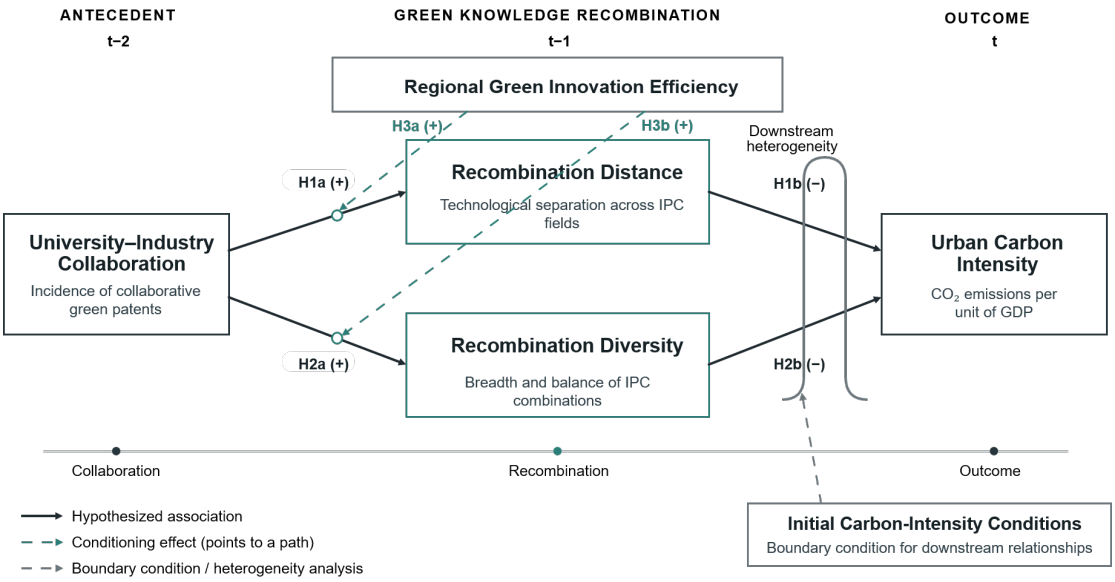
Two dimensions are central to the present analysis. Recombination distance captures how far apart the combined technological fields are within the IPC hierarchy. Greater distance may introduce knowledge that supports technological path renewal, but may also increase uncertainty and integration costs. Recombination diversity captures the richness and distribution of technological combinations. Greater diversity may facilitate complementary low-carbon solutions, but may become difficult to coordinate where regional absorptive capacity is limited.

Existing studies have linked green recombination to innovation and technological diversification, but have rarely examined the complete empirical sequence from university–industry collaboration to recombination structure and then to city-level carbon intensity. The present study tests this sequence by treating distance and diversity as distinct dimensions of regional green knowledge bases.

3 Hypotheses

Figure 1 summarizes the proposed framework. University–industry collaboration is expected to influence recombination distance and diversity, which are in turn

associated with subsequent carbon intensity. Regional green innovation efficiency is introduced as a conditioning factor on the collaboration–recombination relationship. The following hypotheses distinguish these pathways.



Baseline framework represents a temporally ordered indirect pathway; arrows denote expected associations rather than definitive causal effects.

Fig. 1. Research framework

3.1 University–industry collaboration and green recombination distance

Universities provide firms with access to scientific and technological knowledge beyond their established production routines (Trajtenberg et al., 1997). This function is especially relevant in emission-intensive industries, where incremental improvements within existing technological paths may be insufficient for substantial low-carbon transformation. University‐industry collaboration can broaden firms' technological search and facilitate the translation of distant scientific knowledge into production settings, thereby reducing some of the uncertainty associated with cross-domain recombination (Ahuja & Katila, 2004; Tsouri et al., 2022).

Greater recombination distance may connect established industrial capabilities with technological fields that support cleaner production and energy-system

transformation. It may therefore widen the range of low-carbon options available to regional firms. Because distant knowledge also creates integration and coordination costs, the expected environmental benefit should be understood as an average relationship within the observed sample rather than as an unlimited gain from increasing distance.

H1a. University–industry collaboration is positively associated with green technology recombination distance.

H1b. Green technology recombination distance is negatively associated with urban carbon intensity.

3.2 University–industry collaboration and green recombination diversity

Firms commonly develop specialized knowledge around established production and market requirements, whereas universities draw on broader scientific and disciplinary domains (Rosenberg & Nelson, 1994; Trajtenberg et al., 1997). Collaboration can therefore connect specialized industrial knowledge with a wider range of technological fields (Nan et al., 2018; Wirsich et al., 2016). This breadth is relevant to carbon-intensity reduction because energy efficiency, materials innovation, cleaner production, digital control, and environmental treatment often function as complementary rather than isolated solutions.

Diverse recombination may improve the capacity of a regional knowledge base to address complex environmental problems, although excessive diversity can increase coordination costs where absorptive and integrative capabilities are weak. As with distance, the empirical expectation concerns the average relationship observed across cities.

H2a. University–industry collaboration is positively associated with green technology recombination diversity.

H2b. Green technology recombination diversity is negatively associated with urban carbon intensity.

3.3 The moderating role of regional green innovation efficiency

Green innovation involves environmental externalities, uncertain returns, and long development cycles, while university–industry projects may face divergent objectives, information asymmetry, and opportunistic behaviour (De Marchi, 2012; Z. Yang et al., 2021). The extent to which collaboration produces meaningful technological recombination therefore depends partly on the regional capacity to convert knowledge and resources into innovation outputs.

Regional green innovation efficiency captures this capacity. It is treated as an outcome-based indicator of the regional innovation environment rather than a direct measure of government capability or policy quality. Higher efficiency should help partners identify complementary expertise, coordinate research, and translate heterogeneous knowledge into patentable green technologies. Accordingly, the positive association between collaboration and recombination is expected to strengthen as regional green innovation efficiency increases.

H3a. Regional green innovation efficiency positively moderates the relationship between university–industry collaboration and green technology recombination distance.

H3b. Regional green innovation efficiency positively moderates the relationship between university–industry collaboration and green technology recombination diversity.

4 Methodology

4.1 Data collection and processing

The empirical analysis uses a balanced panel of 212 Chinese cities from 2003 to 2021, comprising 208 prefecture-level cities and four municipalities directly under the central government. Hong Kong, Macao, Taiwan, and prefecture-level administrative units in Tibet are excluded because of incomplete data coverage. Cities with no recorded green patent applications for six consecutive years or with more than 25% missing observations for any control variable are also excluded. Limited gaps in the retained socioeconomic series are filled using linear interpolation. These screening criteria are necessary because the construction of the recombination indicators requires sustained and observable green patenting activity, whereas extensive interpolation would increase measurement uncertainty. The resulting sample therefore represents cities with relatively active and consistently recorded green innovation systems, and the findings should not be generalized directly to all Chinese cities.

The sample begins in 2003 because city-level fiscal expenditure on science and technology becomes consistently available from that year. It ends in 2021 to reduce right-censoring in the patent data. The analysis retains green invention patents that were eventually granted but assigns them to their application year, which more closely approximates the timing of knowledge creation than the grant year (Albino et al., 2014). Because the examination and authorization of invention patents commonly require several years, applications filed near the end of the observation period may not yet have completed the examination process and would consequently be underrepresented if more recent years were included (Huang et al., 2022).

Patent data are obtained from the IncoPat database. Green patents are identified using the Cooperative Patent Classification tagging scheme, including Y02B, Y02C, Y02D, Y02E, Y02P, Y02T, Y02W, and Y04S (Angelucci et al., 2018). Only granted patents are retained because they have undergone substantive examination and are less likely than unexamined applications to represent inventions of limited technological

value (Messeni Petruzzelli et al., 2011). Patents filed solely by individuals are excluded because the analysis focuses on organizational innovation and university–industry collaboration. University–industry collaborative patents are identified when at least one firm and at least one university or research organization are jointly listed as applicants. Supplementary Table S1 reports the technological categories included in the green patent sample. Because several green-technology categories contain relatively few observations at the city-year level, the baseline analysis pools all categories rather than estimating category-specific recombination patterns.

Annual city-level CO_2 emissions are obtained from the China Emission Accounts and Datasets database (CEADs). The CEADs estimates are matched to the city-year panel and used together with reported city-level GDP to calculate carbon intensity. Socioeconomic data, including GDP, registered population, average employee income, fiscal expenditure on science and technology, the number of enterprises above designated size, and the number of higher-education institutions, are collected from the China City Statistical Yearbook and the China Regional Economic Statistical Yearbook. Variables are matched consistently by city and year, and city names and administrative codes are harmonized across different yearbook editions to account for changes in administrative naming and statistical reporting.

The complete balanced panel contains 4,028 city-year observations. Because university–industry collaboration is lagged by two years and the recombination indicators and control variables are lagged by one year in the empirical models, the baseline estimation sample contains 3,604 observations covering 212 cities from 2005 to 2021.

4.2 Indicator construction and validation

This section defines the variables used to measure carbon intensity, university–industry collaboration, green knowledge recombination, regional green innovation efficiency, and the relevant controls.

4.2.1 Dependent and independent variables

The dependent variable is carbon intensity, measured as city-level carbon dioxide emissions divided by regional GDP:

$$CI_{it} = \frac{\mathrm{CO}_{2,\mathrm{it}}}{GDP_{it}} \tag{1}$$

where CI_{it} denotes the carbon intensity of city i in year t; $\mathrm{CO}_{2,\mathrm{it}}$ denotes the total carbon dioxide emissions of city i in year t; and GDP_{it} denotes the regional GDP of city i in year t. A lower value of CI_{it} indicates that a city generates less carbon dioxide emissions per unit of economic output, reflecting better low-carbon economic performance.

The main explanatory variable is the incidence of university–industry collaboration in green technology. It is measured as the share of green patents jointly owned by universities or research organizations and firms in the total number of green patents:

$$UniversityIndustry_{it} = \frac{CoGreenPatent_{it}}{GreenPatent_{it}} \tag{2}$$

where $UniversityIndustry_{it}$ denotes the incidence of university – industry collaboration in green innovation in city $i$and year t; $CoGreenPatent_{it}$ denotes the number of green patents jointly applied for by firms and universities or research organizations; and $GreenPatent_{it}$ denotes the total number of green patents in the corresponding city-year. The indicator ranges from zero to one, with a higher value representing a larger collaborative share of the city's green patenting activity.

For city-years with no green patent applications, $UniversityIndustry_{it}$ is mathematically undefined. In the baseline coding, these observations are assigned a value of zero to indicate that no patent-based university–industry collaboration is observable in the corresponding city-year. This operational treatment may not fully distinguish the absence of green patenting activity from the absence of collaboration among active green innovators and is therefore acknowledged as a measurement limitation. To reduce simultaneity concerns and preserve the temporal ordering of the proposed pathway, $UniversityIndustry$ is lagged by two years when explaining subsequent green knowledge recombination.

4.2.2 Mechanism variables

The mechanism variables of this paper are recombination distance and diversity of regional green technology. Green knowledge recombination is measured through technology-code combinations observed in green patents. Specifically, for each green patent, four-digit IPC codes are used to construct unordered IPC-code pairs, and all IPC pairs observed in city i up to and including year t are used to describe the accumulated structure of the city's green knowledge base. The first four-digit IPC codes are used because four-digit IPC codes are sufficient to describe the key technological features of patents while avoiding excessive fragmentation at more detailed classification levels (Jiancheng Guan & Liu, 2015).

Recombination distance is measured using a hierarchical Hamming-distance approach. The Hamming-distance approach can capture differences between IPC pairs at different hierarchical levels without relying on subjective semantic interpretation of technology categories, thereby reducing measurement subjectivity (Caviggioli, 2016). For a given IPC pair p, the distance score d_p is determined by the highest IPC hierarchy at which the two codes differ. Differences at the section level indicate the greatest

technological distance, followed by differences at the class level and then at the subclass level. The distance score is defined as follows:

$$d_{\mathrm{p}} = wsecIsec, p + wclassIclass, p + wsubIsub, p \tag{3}$$

where $I_{sec,p} = 1$if the two IPC codes in pair $p$differ at the section level and 0 otherwise; $I_{class,p} = 1$if they share the same section but differ at the class level and 0 otherwise; and $I_{sub,p} = 1$if they share the same section and class but differ at the subclass level and 0 otherwise. w_{sec}, w_{class}, and w_{sub}denote the weights assigned to section-, class-, and subclass-level differences, respectively. In the baseline specification, they are set to 9, 4, and 1.

The recombination distance of city i in year t is then calculated as the average distance of all accumulated four-digit IPC pairs:

$$Distance_{it} = \frac{1}{P_{it}} \sum_{p=1}^{P_{it}} d_p \tag{4}$$

where $Distance_{it}$ denotes the average recombination distance of green technology in city i up to and including year t; P_{it} denotes the total number of accumulated four-digit IPC pairs in city i up to and including year t; and d_p denotes the hierarchical distance score of IPC pair p. In the baseline specification, w_{sec}, w_{class}, and w_{sub} are set to 9, 4, and 1, respectively. This weighting structure reflects the hierarchical nature of the IPC system: a section-level difference represents a broader technological boundary than a class-level or subclass-level difference. The 9–4–1 setting therefore gives greater weight to more distant cross-section recombination while still allowing within-section technological differences to contribute to the distance measure.

Because the numerical weighting scheme may affect the distance measure, the baseline 9–4–1 specification is compared with a 3–2–1 alternative. The latter reduces the relative gap between section-, class-, and subclass-level differences.

Re-estimating the models with this alternative indicator assesses whether the findings depend on the baseline weighting choice.

Recombination diversity is measured using the Simpson diversity index. This index captures not only the richness of technological combinations but also the balance of their distribution across different IPC-pair types (Leydesdorff, 2015). It is defined as follows:

$$Diversity_{it} = 1 - \sum_{r=1}^{R_{it}} \left(\frac{n_{rit}}{P_{it}}\right)^2 \quad (5)$$

where $Diversity_{it}$ denotes the recombination diversity of green technology in city i up to and including year t; R_{it} denotes the number of distinct IPC-pair types; n_{rit} denotes the number of occurrences of IPC-pair type r; and P_{it} denotes the total number of accumulated IPC pairs. A higher value of $Diversity_{it}$ indicates that the city's green knowledge base combines a broader and more balanced set of technological fields.

To validate the diversity indicator, this study also uses the Margalef diversity index as an alternative measure in robustness tests. While the Simpson index reflects both richness and balance, the Margalef index places greater emphasis on the number of distinct recombination types. Consistent results across these two measures would indicate that the estimated relationship is not dependent on a single diversity formula.

4.2.3 Regional green innovation efficiency

The conditioning variable, regional green innovation efficiency, is estimated using a variable-returns-to-scale super-SBM model (Li et al., 2022). It captures the observed efficiency with which regional inputs are transformed into green innovation outputs and is not interpreted as a direct measure of government capability, institutional quality, or policy effectiveness. The variable is defined as follows:

$$GreenInnovationEfficiency_{it} = \rho_{it}^{SBM} = SuperSBM(X_{it}, Y_{it}) \quad (6)$$

where $GreenInnovationEfficiency_{it}$ denotes the regional green innovation efficiency of city i in year t; ρ_{it}^{SBM} denotes the corresponding super-SBM efficiency score; X_{it} denotes the vector of green innovation inputs; and Y_{it} denotes the vector of green innovation outputs. The input set represents the regional industrial application base, knowledge-production capacity, public R&D support, and economic resource base, while the outputs capture overall and university–industry collaborative green innovation.

The super-SBM model is estimated under variable returns to scale. No undesirable outputs are included, and efficiency scores above one indicate that an efficient decision-making unit remains super-efficient relative to the reference frontier formed by the remaining units.

The selection of inputs follows endogenous growth theory, which emphasizes the role of innovation actors, knowledge institutions, and capital input in technological progress (Romer, 1987). Enterprises above designated size capture the industrial application base of green innovation; institutions of higher education capture the local knowledge-production base; fiscal-scientific expenditures capture public R&D support; and regional GDP captures the overall economic resource base. The outputs are selected to reflect both general green innovation output and university–industry collaborative green innovation output. The specific input and output indicators used to measure regional green innovation efficiency are summarized in Table 1.

Table 1. Inputs and outputs used to measure regional green innovation efficiency

Inputs/ outputs	Variables
Inputs	Enterprises above Designated Size
	Institutions of higher education
	Fiscal-scientific expenditures
	Regional GDP
Outputs	Number of green patents
	Number of collaboration green patent

4.2.4 Control variables

The control variables are selected based on the STIRPAT framework, which explains human impacts on the environment through three dimensions: population, affluence, and technology. This framework is suitable for modelling carbon intensity because carbon emissions per unit of output are closely related to demographic scale, economic conditions, and technological capability.

For the technology dimension, the baseline models control for both the total number of green patents and the number of university–industry collaborative green patents. $GreenPatent$captures the overall scale of regional green innovation, whereas $CoGreenPatent$captures the absolute scale of collaborative green patenting. Their simultaneous inclusion allows $UniversityIndustry$to represent the relative incidence of collaboration after accounting for differences in both total and collaborative patent output. Because $CoGreenPatent$ also constitutes the numerator of $UniversityIndustry$, the collaboration coefficient should be interpreted as a conditional association rather than as an unrestricted measure of the total contribution of collaborative patenting. Fiscal expenditure on science and technology is included in the recombination equation because public R&D resources may influence the formation of regional green knowledge recombination (JianCheng Guan & Yam, 2015). As explained in Section 4.3, $FiscalRD$is used as a first-stage variable under the maintained exclusion restriction rather than as a general control in the baseline carbon-intensity equation.

For the affluence dimension, this study includes average employee income and the 2003-based producer price index. Average employee income reflects local income and development conditions (Dong & Zhao, 2017), while the producer price index captures price-level changes that may affect industrial production and carbon-intensity performance (Y. He & Lin, 2018). For the population dimension, registered population

is included to control for the effect of city size and demographic pressure on carbon intensity (Martínez-Zarzoso et al., 2007).

All control variables are lagged by one year in the empirical models to reduce simultaneity concerns and to allow time for socioeconomic and technological factors to affect carbon-intensity outcomes. Table 2 summarizes the variables used in this study.

Table 2. Variables

Variable types	Name	Meaning
Dependent variable	*CI*	Carbon intensity of GDP
Independent variable	*UniversityIndustry*	Incidence rate of university–industry collaboration in green technology
Mechanism variable	*Distance*	Average recombination distance of four-digit IPC pairs
	Diversity	Diversity of four-digit IPC-pair combinations
Conditioning variable	*GreenInnovationEfficiency*	Regional green innovation input–output efficiency
Control variable	*GreenPatent*	Number of green patents
	Income	Average employee income
	PPI	Producer price index, with 2003 as the base year
	Pop	Registered population
	CoGreenPatent	Number of collaboration green patent
First-stage variable	*FiscalRD*	Fiscal-scientific expenditures, used in the first-stage recombination equation

4.3 Baseline simultaneous-equation models

Equations (7)–(10) specify the proposed collaboration–recombination–carbon-intensity pathway. Equations (7) and (8) form the recombination-distance system, while Equations (9) and (10) form the recombination-diversity system. Because recombination distance and diversity are modelled both as outcomes of university–industry collaboration and as explanatory variables for carbon intensity, the linked equations are estimated jointly using three-stage least squares (3SLS). This approach accounts for correlations among the disturbances across equations and may improve estimation efficiency relative to estimating each equation separately (Wang et al., 2022; Zellner & Theil, 1992; Y.-J. Zhang & Du, 2025).

$$CI_{it} = \alpha_0 + \alpha_1 Distance_{i,t-1} + \alpha_2 X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it} \tag{7}$$

$$Distance_{i,t-1} = \beta_0 + \beta_1 UniversityIndustry_{i,t-2} + \beta_2 FiscalRD_{i,t-2} + \beta_3 X_{i,t-2} + \mu_i + \lambda_t + \nu_{it} \tag{8}$$

$$CI_{it} = \theta_0 + \theta_1 Diversity_{i,t-1} + \theta_2 X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it} \tag{9}$$

$$Diversity_{i,t-1} = \delta_0 + \delta_1 UniversityIndustry_{i,t-2} + \delta_2 FiscalRD_{i,t-2} + \delta_3 X_{i,t-2} + \mu_i + \lambda_t + \omega_{it} \tag{10}$$

where CI_{it} denotes the carbon intensity of city i in year t; $Distance_{i,t-1}$ and $Diversity_{i,t-1}$ denote the one-year-lagged recombination distance and recombination diversity of the city's green knowledge base; $UniversityIndustry_{i,t-2}$ denotes the two-year-lagged incidence rate of university–industry collaboration in green technology; $FiscalRD_{i,t-2}$ denotes fiscal-scientific expenditures used in the first-stage recombination equation; X denotes the vector of control variables; μ_i denotes city fixed effects; λ_t denotes year fixed effects; and ε_{it}, ν_{it}, and ω_{it} are error terms.

The lag structure reflects the temporal ordering of the proposed pathway. University‐industry collaboration is measured two years before the carbon-intensity outcome because collaboration is expected to precede the formation and subsequent

application of recombined green knowledge. Recombination distance and diversity are measured one year before carbon intensity to allow time for technological combinations to influence production processes, energy use, and environmental performance. The control variables are lagged correspondingly to reduce simultaneity concerns.

Identification of the carbon-intensity equations relies on excluding $UniversityIndustry$ and $FiscalRD$ from the baseline outcome equations. The maintained assumption is that, conditional on green patenting activity, socioeconomic controls, city fixed effects, and year fixed effects, these variables are associated with subsequent carbon intensity primarily through the structure of green knowledge recombination. This restriction may be contestable because university–industry collaboration and public science expenditure could also affect carbon intensity through direct technology-transfer, investment, or implementation channels.

The exclusion restrictions are therefore examined using two augmented specifications. The first adds lagged $UniversityIndustry$ directly to the carbon-intensity equation, leaving $FiscalRD$ as the excluded instrument for the recombination variable. The second adds $FiscalRD$ directly to the carbon-intensity equation, leaving $UniversityIndustry$ as the excluded instrument. The two variables are not included jointly because doing so would leave no excluded instrument for the recombination variable under the baseline instrument set. These specifications are interpreted as sensitivity analyses rather than equally strong alternative identification strategies, because the strength of the remaining instrument varies across models.

The 3SLS framework does not by itself establish causal mediation. The estimated coefficients are therefore interpreted as conditional associations within a temporally ordered system rather than as definitive causal indirect effects.

4.4 Conditioning role of regional green innovation efficiency

To test H3, this study introduces mean-centered interaction terms between university – industry collaboration and regional green innovation efficiency into the simultaneous-equation models. The conditioning effect is specified on the relationship between university – industry collaboration and green knowledge recombination because the theoretical framework assumes that a more efficient regional innovation system facilitates the conversion of collaborative knowledge into more distant and more diverse technological combinations.

$UniversityIndustry$ and $GreenInnovationEfficiency$ are mean-centered before constructing their interaction term to reduce multicollinearity and facilitate the interpretation of the component coefficients. Equations (11) and (12) examine the conditioning effect on recombination distance, while Equations (13) and (14) examine the corresponding effect on recombination diversity.

$$CI_{it} = \alpha_0 + \alpha_1 Distance_{i,t-1} + \alpha_2 X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it} \tag{11}$$

$$\begin{aligned} Distance_{i,t-1} = {} & \beta_0 + \beta_1 UniversityIndustry_{i,t-2} \\ & + \beta_2 GreenInnovationEfficiency_{i,t-2} \\ & + \beta_3 \big(UniversityIndustry_{i,t-2} \\ & \times GreenInnovationEfficiency_{i,t-2}\big) + \beta_4 FiscalRD_{i,t-2} \\ & + \beta_5 X_{i,t-2} + \mu_i + \lambda_t + \nu_{it} \end{aligned} \tag{12}$$

$$CI_{it} = \theta_0 + \theta_1 Diversity_{i,t-1} + \theta_2 X_{i,t-1} + \mu_i + \lambda_t + \varepsilon_{it} \tag{13}$$

$$\begin{aligned} Diversity_{i,t-1} = {} & \delta_0 + \delta_1 UniversityIndustry_{i,t-2} \\ & + \delta_2 GreenInnovationEfficiency_{i,t-2} \\ & + \delta_3 \big(UniversityIndustry_{i,t-2} \\ & \times GreenInnovationEfficiency_{i,t-2}\big) + \delta_4 FiscalRD_{i,t-2} \\ & + \delta_5 X_{i,t-2} + \mu_i + \lambda_t + \omega_{it} \end{aligned} \tag{14}$$

where $GreenInnovationEfficiency_{i,t-2}$ denotes the two-year-lagged local policy and resource environment proxy, measured by green innovation input–output efficiency; $UniversityIndustry_{i,t-2} \times GreenInnovationEfficiency_{i,t-2}$ denotes the interaction term between university–industry collaboration and the local policy and resource environment proxy. Other variables are defined as in Section 4.3.

A significantly positive interaction coefficient indicates that regional green innovation efficiency strengthens the positive association between university–industry collaboration and green knowledge recombination. In other words, collaboration is more strongly associated with recombination distance or diversity where regional innovation inputs are more efficiently transformed into green innovation outputs.

4.5 Robustness and sensitivity analyses

4.5.1 Alternative estimators and indicator construction

To assess the sensitivity of the baseline findings, the simultaneous-equation models are re-estimated using robust two-stage least squares and two-stage generalized method of moments. Alternative recombination measures are also considered: the baseline 9–4–1 IPC weighting for Distance is replaced by a less differentiated 3–2–1 scheme, while the Simpson index for Diversity is replaced by the Margalef index. In addition, five-year rolling-window indicators are constructed to reduce potential dependence on cumulative patent stocks. The corresponding estimates are reported in Supplementary Tables S2–S4.

4.5.2 Cross-sectional dependence and dynamic persistence

Cross-sectional dependence is assessed using Pesaran's CD test, and covariance sensitivity is examined using Driscoll–Kraay and city-clustered standard errors. To assess temporal persistence, the carbon-intensity equation is augmented with lagged carbon intensity and estimated using dynamic fixed-effects, instrumental-variable, and two-step system GMM specifications. The latter use collapsed instrument sets and are evaluated using Hansen and Arellano–Bond diagnostic tests. Results are reported in Supplementary Tables S5 and S6.

4.5.3 Robustness of the conditioning effect

The conditioning analysis is repeated using two alternative measures of regional green innovation efficiency: one excludes regional GDP from the input set, and the other excludes collaborative green patents from the output set. These specifications reduce potential mechanical overlap with variables used elsewhere in the models. Results are reported in Supplementary Table S7.

4.6 Heterogeneity by initial carbon-intensity conditions

The heterogeneity analysis examines whether the recombination–carbon-intensity relationship varies according to cities' initial carbon-intensity conditions. Cities are classified using their average carbon intensity during the initial period of 2003–2005. A city is defined as high-carbon-intensity if its initial-period average exceeds the corresponding sample mean; otherwise, it is classified as low-carbon-intensity. This predetermined classification avoids assigning cities on the basis of carbon-intensity outcomes observed later in the sample period.

To assess sensitivity to the cutoff, the analysis is repeated using the median of initial-period carbon intensity. Group-specific slopes are estimated within a common interaction framework, and Wald tests are used to determine whether the relevant coefficients differ statistically between the two groups. The city classification is predetermined and remains fixed throughout the estimation period.

5 Results

5.1 Descriptive Statistics

Figure 2 shows a general decline in urban carbon intensity between 2003 and 2021, accompanied by persistent spatial variation. Relatively high values are observed in parts of northern and western China, whereas lower values are more common in several eastern and southeastern cities. These descriptive patterns motivate the subsequent econometric analysis but do not by themselves identify their underlying industrial, economic, or technological causes.

Table 3 reports descriptive statistics for the complete balanced panel before the lag structure is applied; the baseline regressions use 3,604 city-year observations. The mean value of carbon intensity is 2.495, with a standard deviation of 2.460, indicating substantial variation in carbon-emission performance across cities and years. The mean value of $UniversityIndustry$ is 0.028, suggesting that university–industry collaborative green patents account for a relatively small share of total green patenting activity on average. Its maximum value of 1.000 indicates that, in some city-years, all recorded green patents involved university–industry collaboration. The mean values of recombination distance and diversity are 4.947 and 0.759, respectively, revealing considerable heterogeneity in both the technological distance and the breadth of green knowledge recombination across Chinese cities.

Green patenting activity is also highly uneven across the sample. The average number of green patents is 135.995, whereas the standard deviation is 606.613 and the maximum reaches 16,134. The corresponding number of collaborative green patents displays a similarly skewed distribution. These patterns indicate substantial cross-city heterogeneity in the scale and collaborative structure of regional green innovation and motivate the inclusion of city and year fixed effects in the subsequent empirical analysis.

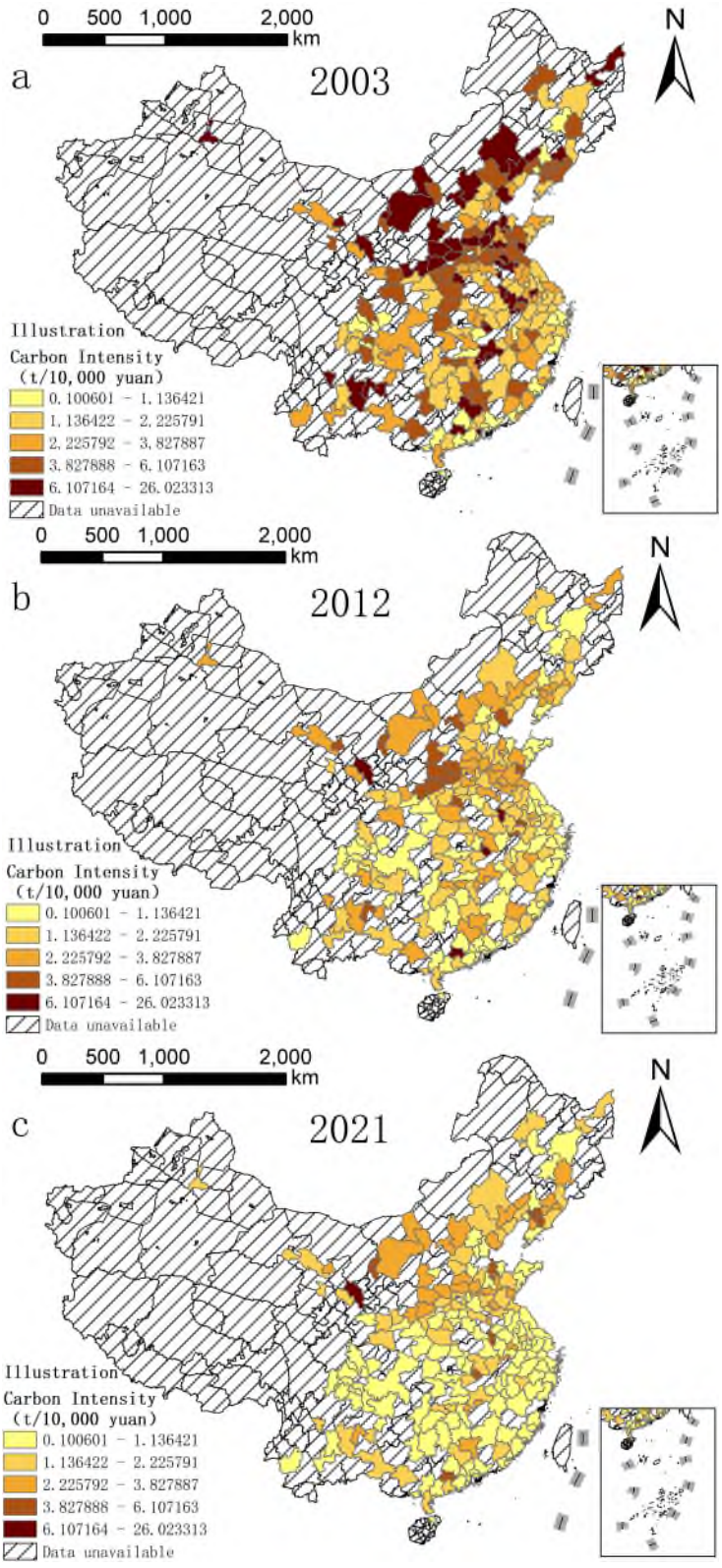


Fig. 2 Spatial distribution of urban carbon intensity in 2003, 2012, and 2021

Table 3 Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max

CI	4028	2.495	2.460	0.045	26.023
UniversityIndustry	4028	0.028	0.084	0.000	1.000
Distance	4028	4.947	2.314	0.000	9.000
Diversity	4028	0.759	0.371	0.000	0.998
GreenInnovationEfficiency	4028	0.757	0.149	0.201	1.134
FiscalRD	4028	10.247	35.527	0.000	554.982
GreenPatent	4028	135.995	606.613	0.000	16134.000
CogreenPatent	4028	4.672	26.342	0.000	682.000
Income	4028	4.507	2.704	0.633	20.150
PPI	4028	129.569	20.851	89.520	236.136
Pop	4028	487.951	330.563	41.600	3416.000

5.2 Specification tests

Table 4 reports the identification and endogeneity diagnostics for the baseline simultaneous-equation models. The Kleibergen–Paap LM statistics reject underidentification in both systems. The Anderson–Rubin, Kleibergen K, and conditional likelihood ratio tests provide weak-instrument-robust inference for the endogenous recombination coefficients under the maintained instrument set. However, the first-stage partial F statistic is 7.17 for the Distance specification and 14.95 for the Diversity specification. Instrument strength is therefore more satisfactory for Diversity, whereas the Distance specification remains potentially vulnerable to weak-instrument bias.

Taken together, the diagnostics support the relevance of the selected instruments, particularly in the Diversity specification, but they do not establish the substantive validity of the exclusion restrictions. The Distance estimates are interpreted with additional caution because their first-stage statistic is below the conventional reference value of 10.

Table 4 Specification tests

	Distance as	*Diversity* as

	mechanism variable	mechanism variable
Under-identification test		
Kleibergen-Paap LM	23.054***	20.747***
Weak-identification-robust test		
Anderson-Rubin	13.27***	13.27***
Kleibergen K	4.34**	6.44**
Moreira CLR	8.42***	10.36***
Over-identification test		
Sargan	1.759	0.742
Hansen J	1.562	0.703
Durbin-Wu-Hausman test		
Durbin	7.091***	8.233***
Wu-Hausman	6.642**	7.714***
First-stage partial F	7.17	14.95

Note: ***, ** and * indicates significance at the 1%, 5%, 10% level. The same applies hereafter.

5.3 Baseline effects of university–industry collaboration

Table 5 presents the baseline 3SLS estimates for the proposed collaboration – recombination – carbon-intensity pathway. The upper panel reports the associations between university – industry collaboration and the two dimensions of green knowledge recombination, corresponding to H1a and H2a, while the lower panel reports the associations between recombination structure and subsequent carbon intensity, corresponding to H1b and H2b.

$UniversityIndustry$ is positively associated with $Distance$(0.484, $p < 0.10$) and $Diversity$ (0.064, $p < 0.10$). Because $UniversityIndustry$ranges from zero to one, a one-percentage-point increase in the collaboration incidence rate corresponds to increases of 0.00484 in recombination distance and 0.00064 in recombination diversity, respectively. These estimates provide modest, rather than strong, support for H1a and H2a.

$Distance$ (-0.373, $p < 0.05$) and $Diversity$ (-2.373, $p < 0.01$) are both negatively associated with subsequent carbon intensity. These findings support H1b and H2b and suggest that the structure of green knowledge recombination contains explanatory information beyond the volume of green innovation alone. Taken together, the estimates are consistent with the proposed empirical sequence, but they do not constitute a formal test of causal mediation.

Table 5 Baseline models testing H1a–H2b

	(1)	(2)
	3SLS	3SLS
Dependent variables: recombination equation	*Distance*	*Diversity*
UniversityIndustry	0.484*	0.064*
	(1.72)	(1.87)
cons	1.657**	0.122
	(2.36)	(1.46)
Dependent variables: carbon-intensity equation	*CI*	*CI*
Distance	-0.373**	
	(-2.33)	
Diversity		-2.373***
		(-2.77)
cons	6.722***	6.394***
	(13.34)	(15.65)
Controls	Yes	Yes
Year fixed effects	Yes	Yes
City fixed effects	Yes	Yes
R^2	0.7968	0.8266
N	3604	3604

5.4 Conditioning role of regional green innovation efficiency

Table 6 reports the baseline estimates for the conditioning role of regional green innovation efficiency. The interaction coefficients are positive for both recombination dimensions, but the evidence is stronger for $Distance$ (10.043, $p < 0.01$) than for $Diversity$ (0.755, $p < 0.10$). The results therefore provide strong support for H3a and limited support for H3b. Because $UniversityIndustry$ and $GreenInnovationEfficiency$ are mean-centred before constructing the interaction term, the coefficient of $UniversityIndustry$ represents its association with recombination when $GreenInnovationEfficiency$ is at its sample mean. The insignificant main effect of $UniversityIndustry$ does not imply an absence of association at other efficiency levels. Section 5.5.4 examines the sensitivity of these interaction effects to alternative measures of regional green innovation efficiency.

Table 6 Conditioning role of regional green innovation efficiency

	(3)	(4)
	3SLS	3SLS
Dependent variables: recombination equation	*Distance*	*Diversity*
UniversityIndustry	-0.541	-0.028
	(-1.21)	(-0.53)
*Universityindustry*GreenInnovationEfficiency*	10.043***	0.755*
	(2.79)	(1.76)
GreenInnovationEfficiency	6.484***	0.804***
	(8.10)	(8.43)
cons	-4.812***	-0.681***
	(-4.54)	(-5.38)
Dependent variables: carbon-intensity equation	*CI*	*CI*
Distance	-0.183***	
	(-3.28)	
Diversity		-1.586***

		(-3.68)
cons	6.406***	6.297***
	(16.92)	(16.91)
Controls	Yes	Yes
Year fixed effects	Yes	Yes
City fixed effects	Yes	Yes
R^2	0.8500	0.8488
N	3604	3604

5.5 Robustness and sensitivity analyses

This section evaluates the sensitivity of the baseline findings to alternative estimators and indicators, cross-sectional dependence, dynamic persistence, alternative efficiency measures, and the maintained exclusion restrictions.

5.5.1 Alternative estimators and indicator construction

Supplementary Tables S2–S4 show that the principal coefficient patterns are retained under alternative estimators, IPC weighting schemes, diversity measures, and five-year rolling-window indicators. UniversityIndustry remains positively associated with recombination, while Distance and Diversity remain negatively associated with subsequent carbon intensity. The rolling-window results also reduce concern that the baseline findings are driven solely by the cumulative construction of the recombination indicators, although instrument strength remains weaker for Distance.

5.5.2 Cross-sectional dependence and covariance sensitivity

Supplementary Table S5 shows evidence of cross-sectional dependence in the Distance-based carbon-intensity equation but not in the Diversity-based equation. The recombination coefficients remain negative under alternative covariance estimators,

although their statistical significance varies. The baseline relationships should therefore be interpreted cautiously with respect to statistical precision.

5.5.3 Dynamic persistence

Supplementary Table S6 shows that carbon intensity is highly persistent. Once this persistence is included, the Distance and Diversity coefficients become insignificant in the dynamic fixed-effects and instrumental-variable models. System GMM estimates either fail the AR(2) diagnostic or become unstable under deeper lag restrictions. These results do not confirm an immediate causal effect and support interpreting the baseline estimates as medium-term associations.

5.5.4 Robustness of the conditioning effect

Supplementary Table S7 shows that the positive conditioning effect of regional green innovation efficiency on recombination distance remains robust across alternative efficiency measures. By contrast, the corresponding interaction for diversity is less stable. The results therefore provide stronger support for H3a than for H3b.

5.5.5 Sensitivity of the exclusion restrictions

Supplementary Table S8 shows that the negative recombination coefficients remain significant when UniversityIndustry is allowed to enter the carbon-intensity equation directly. They become insignificant when FiscalRD is included directly, but the remaining instruments are weak. The baseline interpretation therefore remains sensitive to the exclusion restriction imposed on FiscalRD.

5.6 Heterogeneity by initial carbon intensity

Supplementary Table S9 reports the heterogeneity estimates based on cities' average carbon intensity during the initial period of 2003–2005. The mean of initial-period carbon intensity is used as the baseline cutoff, while the corresponding median provides an alternative classification. The interaction-based specification estimates the high- and low-initial-carbon slopes within a common model and uses Wald tests to evaluate whether the coefficients differ statistically across the two groups.

Panel A reports the relationship between university–industry collaboration and green knowledge recombination. The group-specific coefficients should be interpreted together with the formal equality tests rather than on the basis of within-group significance alone. The results indicate that the principal heterogeneity does not arise in the initial collaboration–recombination relationship, because the high–low coefficient differences are not statistically significant under either cutoff.

Panel B reports the relationship between green knowledge recombination and subsequent carbon intensity. Under both mean- and median-based initial-period classifications, the coefficients of Distance and Diversity are more negative among cities with high initial carbon intensity, and the Wald tests reject equality of the high- and low-initial-carbon coefficients. The consistency of this pattern across the two predetermined cutoffs reduces concern that the finding is driven by an arbitrary classification threshold. The heterogeneity evidence therefore indicates that the principal difference lies in the recombination–carbon-intensity relationship rather than in the collaboration–recombination relationship.

6 Discussion and policy implications

The analyses yield three main patterns. University–industry collaboration is modestly associated with greater recombination distance and diversity, and both

dimensions are negatively associated with subsequent carbon intensity in the baseline and conventional robustness models. Regional green innovation efficiency robustly conditions the collaboration–distance relationship, whereas the diversity interaction is weaker. These associations are stronger in cities with high initial carbon intensity, but the dynamic and covariance-sensitivity results limit causal interpretation.

6.1 Theoretical implications

The first implication concerns the relationship between regional technological evolution and environmental performance. Evolutionary economic geography emphasizes path dependence, inherited knowledge bases, and the creation of new technological trajectories, whereas environmental economic geography focuses on the spatial differentiation of environmental outcomes and transition processes (Bridge, 2008; Patchell & Hayter, 2013). The present findings connect these perspectives by showing that urban carbon intensity is associated not only with the scale of green innovation, but also with the structure through which technological knowledge is combined. Green knowledge recombination therefore provides a concrete analytical link between changes in regional technological capabilities and differences in environmental performance (Lin et al., 2023; Sovacool et al., 2024).

The results also refine the interpretation of university–industry collaboration within regional innovation systems. Previous research has emphasized both its benefits and its organizational costs. Collaboration can broaden access to scientific knowledge, accelerate technological application, and support knowledge transfer, but it can also create divergent objectives, coordination difficulties, and unequal control over resources (Cooke, 2010; Hou et al., 2019; Xu et al., 2023). The present analysis suggests that collaboration should not be evaluated only by the number of patents or projects it produces. One of its potential contributions lies in changing the technological composition of the regional knowledge base. Universities and research organizations

may broaden firms' search beyond established production routines, while firms provide the application settings through which scientific knowledge can be converted into technologically relevant combinations. The marginal significance of the baseline first-stage coefficients, however, indicates that this relationship is not uniformly strong across cities.

Recombination distance and diversity capture different aspects of this structural transformation. The negative coefficient of recombination distance is consistent with the argument that knowledge drawn from technologically separated fields can support departures from established high-carbon paths. Such recombination may connect existing industrial capabilities with new approaches to energy use, production processes, materials, or environmental management. Recombination diversity, by contrast, reflects the breadth and distribution of technological combinations and may facilitate the integration of complementary low-carbon solutions. This extends existing research linking green innovation to energy efficiency and cleaner production by showing that the internal organization of the knowledge base may also matter (Haider & Mishra, 2021; Khan et al., 2022; Lin et al., 2023; T. Yang et al., 2023).

These relationships should not be interpreted as implying that greater distance or diversity is always beneficial. Technologically distant knowledge can be difficult to absorb and translate into production, while a highly diverse knowledge base may increase search and coordination costs. The supplementary nonlinearity tests (Supplementary Table S10) do not identify a robust nonlinear relationship between either recombination dimension and carbon intensity, but this absence of statistical nonlinearity does not imply that integration costs are irrelevant. Rather, the estimated coefficients describe average relationships within the observed sample. The practical value of recombination is likely to depend on regional absorptive capacity, engineering capability, and the ability to coordinate heterogeneous actors.

Regional green innovation efficiency robustly strengthens the collaboration–distance relationship, suggesting that efficient regional innovation systems help actors

search across, translate, and integrate distant technological fields (Sovacool et al., 2024; Zhao et al., 2024). The weaker and less consistent interaction for recombination diversity indicates that the breadth and balance of technological combinations may depend on additional organizational or sectoral conditions not fully captured by an aggregate input–output efficiency measure. Because the efficiency measure reflects the joint performance of firms, universities, public resources, markets, and the wider economic base, it should be interpreted as an outcome-based regional condition rather than as a direct measure of government capability or an independent government effect.

6.2 Heterogeneity and boundary conditions

The heterogeneity analysis indicates that initial carbon intensity conditions the downstream recombination–carbon-intensity relationship rather than the upstream collaboration–recombination relationship. This pattern is stable across mean- and median-based initial-period cutoffs.

A plausible explanation is that cities with high initial carbon intensity have greater scope for applying new technological combinations to energy-intensive production systems and industrial upgrading. Cities with lower initial carbon intensity may already have relatively cleaner production systems or more mature low-carbon technologies, leaving less room for additional reductions through technological recombination alone (Ke et al., 2023; Xing et al., 2024).

The dynamic estimates provide an additional boundary condition. Carbon intensity displays strong temporal persistence, and the recombination coefficients become statistically insignificant when lagged carbon intensity is introduced into dynamic fixed-effects and instrumental-variable models. The system GMM estimates either fail the second-order serial-correlation diagnostic or produce unstable coefficients under deeper lag restrictions. The baseline findings should therefore be understood as medium-term associations consistent with the proposed regional innovation pathway,

765 rather than as definitive evidence of an immediate causal effect. Persistent industrial
766 structure, energy systems, and accumulated capital stock may dominate short-run
767 changes in urban carbon intensity (Herman et al., 2025; Sovacool et al., 2024).

768 The exclusion-restriction tests provide a further boundary condition. The
769 recombination coefficients remain negative and significant when a direct
770 UniversityIndustry pathway is introduced, but become insignificant when FiscalRD is
771 allowed to enter the carbon-intensity equation directly. Because the latter specifications
772 rely on weak remaining instruments, they cannot be treated as decisive evidence against
773 the baseline estimates. Nevertheless, they show that the interpretation of the
774 recombination pathway remains dependent on the maintained exclusion restriction for
775 fiscal R&D expenditure.

776 The covariance-sensitivity analysis leads to a similar qualification. The
777 recombination coefficients remain negative under both Driscoll–Kraay and city-
778 clustered inference, but statistical significance varies across covariance estimators. In
779 addition, the supplementary analyses (Supplementary Table S11) reveal no systematic
780 differences in the recombination–carbon-intensity relationship across broad
781 geographical regions or administrative categories. Taken together, these results suggest
782 that carbon-intensity level is a more informative boundary condition in the present
783 sample than regional location or administrative status, although stronger identification
784 strategies are needed before drawing firm causal conclusions.

785 6.3 Policy implications

786 First, university–industry policy should focus on the technological content and
787 application relevance of collaboration rather than on the number of partnerships or
788 patents alone. Collaborative programmes can be organized around clearly identified
789 regional decarbonization problems, with universities contributing scientific and cross-
790 disciplinary expertise and firms providing production knowledge and implementation

settings (Sovacool et al., 2024). In high-carbon-intensity cities, such collaboration may be particularly valuable when it broadens technological search beyond established industrial routines. However, support for distant recombination should be matched with local absorptive and engineering capabilities rather than treated as an objective in itself (Herman et al., 2025; Sovacool et al., 2024).

Second, regional policy should strengthen the mechanisms through which collaborative knowledge is converted into usable technological combinations. Intermediary organizations, applied research centres, pilot-testing facilities, technology-transfer services, and long-term collaborative research arrangements can reduce information barriers and coordination costs (Kerstens & Langley, 2025; Sun et al., 2025). The stronger and more robust conditioning effect found for recombination distance suggests that these supporting arrangements are especially important when collaboration crosses technological boundaries. Public support should therefore consider whether projects facilitate knowledge integration, testing, adaptation, and deployment, rather than relying primarily on patent or project counts.

Third, low-carbon innovation policy may be differentiated according to cities' initial carbon-intensity conditions (Ma et al., 2025). Cities with high initial carbon intensity may place greater emphasis on collaboration that supports technological path renewal and the integration of knowledge relevant to industrial decarbonization. Cities with lower initial carbon intensity may obtain greater value from improving the application, diffusion, and integration quality of their existing technological portfolios (Ke et al., 2023; Xing et al., 2024). This distinction should not be converted into a rigid policy classification, because the initial-period mean and median are sample-specific analytical cutoffs rather than universal policy thresholds.

Finally, innovation evaluation should distinguish between the scale and structure of green technological activity. Patent counts remain useful indicators of innovation output, but they do not show whether regional actors are combining knowledge across technological fields or building complementary technological portfolios (X. Liu et al.,

2024). Recombination distance and diversity can therefore serve as supplementary diagnostic indicators. They should, however, be interpreted together with evidence on absorptive capacity, implementation, industrial relevance, and environmental performance, rather than being used as stand-alone policy targets.

7 Conclusion

This study examines how university–industry collaboration is related to the structure of green knowledge recombination and how this structure is associated with urban carbon intensity. Drawing on evolutionary economic geography, environmental economic geography, and the Triple Helix framework, it shifts attention from the volume of green innovation to the technological composition of regional knowledge bases. Using a balanced panel of 212 Chinese cities from 2003 to 2021, the study constructs IPC-based measures of recombination distance and diversity and estimates the proposed relationships within a simultaneous-equation framework.

The results provide modest evidence that university–industry collaboration is positively associated with both recombination distance and diversity. In the baseline 3SLS models and conventional robustness specifications, greater recombination distance and diversity are associated with lower subsequent carbon intensity. Regional green innovation efficiency consistently strengthens the collaboration–distance relationship, whereas its conditioning effect on recombination diversity is weaker and sensitive to the efficiency specification. The negative recombination–carbon-intensity association is also more pronounced among cities with high initial carbon intensity under both mean- and median-based classifications. This heterogeneity arises mainly in the downstream recombination–carbon-intensity relationship rather than in the upstream collaboration–recombination relationship.

These findings support evaluating green innovation not only by output volume but also by recombination structure. University–industry programmes should therefore

emphasize problem-oriented knowledge integration and adapt support to cities' initial carbon-intensity conditions, while treating recombination distance and diversity as diagnostic rather than stand-alone policy targets.

Several limitations qualify these conclusions. First, patent classifications capture codified technological combinations but do not fully represent non-patented innovation, informal knowledge exchange, implementation quality, or commercial application. Coding $UniversityIndustry$ as zero in city-years without green patent applications may also fail to distinguish the absence of patenting activity from the absence of collaboration among active green innovators. Second, the distance measure depends on the hierarchical structure and weighting of IPC codes. Although alternative weighting schemes and diversity measures produce broadly consistent results, future research could validate these indicators using patent citations, technology networks, or semantic measures of technological similarity. Third, the simultaneous-equation design, lagged variables, and fixed effects reduce but do not eliminate endogeneity concerns. The recombination coefficients become statistically insignificant once carbon-intensity persistence is modelled explicitly, and their statistical precision is sensitive to the treatment of cross-sectional dependence. The interpretation of the recombination pathway also depends on the exclusion restriction imposed on $FiscalRD$; when $FiscalRD$enters the carbon-intensity equation directly, the recombination coefficients become insignificant, although the remaining instruments are weak. The findings should therefore be interpreted as medium-term conditional associations rather than definitive causal effects.

The measurement of carbon intensity may also be sensitive to the price basis used for city-level GDP, and future work could assess robustness using constant-price GDP measures and harmonized city-level deflators. In addition, regional green innovation efficiency is an outcome-based measure jointly shaped by firms, universities, public resources, markets, and the wider economic base. Its patent-based outputs partly overlap with the variables used to measure collaboration and innovation activity.

Finally, the sample primarily represents cities with sustained and observable green patenting activity, limiting direct generalization to cities with weak or intermittent innovation systems.

Overall, the study shows that the recombination structure of green technological knowledge complements conventional measures of innovation quantity. By distinguishing technological distance from diversity and identifying the conditions under which their relationships with carbon intensity vary, the analysis provides a more differentiated account of how regional innovation systems are associated with low-carbon transition.

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Ethical Approval

This article does not contain any studies with human participants performed by any of the authors.

Informed Consent

Not applicable.

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