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Decoupling Economic Growth from Carbon Emissions for Sustainable Development: An EKC Analysis of Regional Heterogeneity Across Five Chinese Urban Agglomerations

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Abstract

Decoupling economic growth from carbon emissions is central to the sustainable development of rapidly urbanizing economies, and urban agglomerations are the pivotal spatial units for delivering this transition under China's dual-carbon goals, yet systematic cross-agglomeration comparisons that could inform differentiated sustainability policy remain scarce. Using panel data for 107 prefecture-level cities in five agglomerations—the Yangtze River Delta (YRD), Beijing–Tianjin–Hebei (BTH), Pearl River Delta (PRD), Chengdu–Chongqing (CY), and the middle reaches of the Yangtze River (MRYR)—across five benchmark years spanning 2005–2023, we combined a two-way fixed-effects environmental Kuznets curve (EKC) model, the Tapio decoupling model, and cross-sectional quadrant analysis to examine the growth–emission relationship in shape, decoupling dynamics, and spatial structure. All five agglomerations traced an inverted-U trajectory, with turning-point per capita gross domestic product (GDP) rising in the order CY < PRD < BTH < MRYP < YRD. Once fixed effects and structural controls were added, most quadratic terms became insignificant and reversed sign after the secondary-industry share and carbon intensity entered; only the PRD and BTH retained a significant nonlinear form. The net income effect is therefore largely monotonic, with the inverted U carried by industrial upgrading and energy-efficiency gains. Tapio decoupling followed a non-monotonic “improve-then-regress” path, with expansive negative decoupling re-emerging across all agglomerations during 2020–2023. Spatially, high-value clustering persisted in the YRD, weakened in the BTH after 2020, and concentrated on single cores in Chengdu and Wuhan. We accordingly propose sustainability-oriented low-carbon pathways differentiated jointly by agglomeration and quadrant. By showing that decoupling is stage-dependent and reversible rather than an automatic by-product of income growth, our findings indicate that durable progress toward regional sustainability hinges on structural transformation and coordinated governance tailored to each agglomeration's stage of development.



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Keywords: sustainable development; low-carbon transition; environmental Kuznets curve; Tapio decoupling model; urban agglomeration; regional heterogeneity

1. Introduction

Urban agglomerations are key spatial carriers of regional collaborative emission reduction under China's dual-carbon goals. The 11th Five-Year Plan first incorporated urban agglomerations into national top-level design, and the 14th Five-Year Plan further defined

the macro layout of 19 national-level urban agglomerations, forming a tiered, functionally complementary spatial system [1]. Among these, the Yangtze River Delta (YRD), Beijing–Tianjin–Hebei (BTH), Pearl River Delta (PRD), Chengdu–Chongqing (CY), and middle reaches of the Yangtze River (MRYR) agglomerations together concentrate more than 40% of the national population and account for over 60% of total energy consumption, making them the regions where mitigation responsibilities are most concentrated within high-quality development [2]. Owing to a coal-dependent energy structure and uneven regional economic development, land-use and carbon-emission patterns across these five agglomerations show pronounced spatial heterogeneity, calling for context-specific mitigation pathways [3].

The Environmental Kuznets Curve (EKC) provides an inverted U-shaped framework for analyzing the carbon emission–economic growth relationship across spatial scales [4,5]. In developed economies in Europe and North America, a 1% increase in gross domestic product (GDP) corresponds to roughly a 0.062% decline in environmental pollution, and the decoupling of carbon emissions from economic growth is already pronounced [6]. By contrast, developing countries undergo compressed industrialization and urbanization, so emission peaks tend to be higher and arrive earlier in the development trajectory [7]. Existing EKC studies, however, concentrate largely on single-country or provincial scales, while systematic comparisons across urban agglomerations—and across prefecture-level cities within them—remain scarce.

This study addresses three core questions. First, do China’s five national-level urban agglomerations, taken together, exhibit an inverted U-shaped EKC between economic growth and carbon emissions? Second, do the EKC form and turning-point location differ significantly across agglomerations, and what stage-of-development features lie behind these differences? Third, how are prefecture-level cities distributed relative to the turning point of their respective agglomeration, and how does this distribution evolve over time?

Prefecture-level cities link national policy with local practice. They are the main arena for industrialization and urbanization, as well as the basic statistical unit for accounting energy consumption and carbon emissions [8]. Within an urban agglomeration, disparities in economic development and emissions across prefecture-level cities directly shape the region’s overall mitigation performance [9].

Using data from 107 prefecture-level cities across five urban agglomerations for five benchmark years from 2005 onward, this study proceeds along three lines.

First, we take five national-level urban agglomerations as the unit of analysis. This departs from prior work centered on the national or provincial scale and aligns more closely with the policy context of China’s new-type urbanization and regional collaborative governance.

Second, we triangulate panel environmental Kuznets curve (EKC) regression, the Tapio decoupling model, cross-sectional quadrant analysis, and a spatial Durbin model, characterizing the growth–emission relationship along four dimensions—long-term shape, annual decoupling status, a city’s relative position, and cross-city spatial spillovers—and offsetting the limited discriminating power of any single approach. This design also yields a key finding: once fixed effects and structural controls enter, the apparent inverted-U largely dissolves and the net income effect turns monotonic, indicating that the urban EKC is conditional on industrial structure and energy efficiency rather than an intrinsic income–emission law.

Third, we construct a quadrant plot centered on the panel EKC turning point to map each city’s relative position and dynamic trajectory within its agglomeration. This tool visually distinguishes differentiated city groups, including early-peaking cities, high-

emission catch-up cities, and low-emission emerging cities, and provides an empirical basis for tiered, differentiated collaborative mitigation pathways.

2. Materials and Methods

2.1. Literature Review

The relationship between regional economic development and carbon emissions has been examined across a range of spatial scales. At the provincial (macro) scale, Zhang et al. accounted for carbon emissions and carbon sinks using Chinese provincial panel data for 1997–2021 and found that an energy-dependent growth model correlates positively with carbon intensity, supporting the EKC hypothesis at the provincial level [10]. Using partial least squares regression, Yi et al. identified GDP and per capita GDP as the dominant contributors to provincial emissions, reflecting the driving effect of economic expansion [11]. At the meso scale of urban agglomerations, Wang and Shao showed for the Yangtze River Economic Belt that economic development level affects carbon emission efficiency more strongly than control variables such as urbanization level and industrial structure [12].

As key spatial units for regional low-carbon transition, urban agglomerations—together with their underlying mechanisms and policy pathways—have become a recent research focus. Methodologically, Zhang et al. combined a non-radial directional distance function with LightGBM and used SHapley Additive exPlanations (SHAP) for interpretable attribution, finding that the marginal cost of coordinated abatement is relatively high in the Yangtze River Delta, Pearl River Delta, and Chengdu–Chongqing agglomerations [13]. Applying the Tapio decoupling model to the Guanzhong Plain agglomeration over 2010–2019, Ma et al. found that regional classification strongly influences the degree of economy–emission decoupling [14]. On the spatial-governance side, Dai and Luo drew on 184 prefecture-level cities across 14 Chinese urban agglomerations to identify how spatial polycentricity shapes per capita emissions [15].

As a central market-based mitigation instrument, the spatial effects of carbon emissions trading scheme (ETS) pilots have attracted growing attention, though findings diverge. Using a propensity score matching difference-in-differences (PSM-DID) design for 283 prefecture-level cities over 2009–2019, Li et al. found that the pilots significantly reduced local emissions and generated positive spatial spillovers to neighboring cities [16]. Tian et al., studying 281 cities, likewise found that the pilots indirectly promoted green innovation in non-pilot cities through spillover effects [17]. In contrast, Xu et al. applied a spatial difference-in-differences approach to 278 cities and showed that, although the pilots stimulated local green innovation, they had negative effects on neighboring cities and a significantly negative total effect [18]; Yu and Luo similarly found that the pilots raised carbon intensity in surrounding areas [19]. This divergence stems largely from carbon leakage. Jiang et al. estimated that regional pilots cut emissions in regulated cities by about 6.1% and intensity by about 6.6%, yet raised emissions in neighboring cities by an average of 1.7% through production outsourcing [20]; Zhao et al. further documented substantial carbon transfer among pilot cities—for example, rising emissions in Tianjin were associated with spillovers from Beijing [21]. Cities are therefore not independent observational units: emission spillovers create spatial interdependence, and ignoring it biases the estimated coefficients of core variables such as economic scale, underscoring the need for spatial econometric methods.

Industrial transfer is an important source of this spatial dependence, and its net mitigation effect depends on which factors relocate and how they are received. From a factor-mobility perspective, Niu and Yang found that inflows of capital and technology aid abatement, whereas labor mobility has little effect [22]. Using PSM-DID for 274 cities, Zhao and Lee showed that national industrial-transfer demonstration zones can lower

emissions in receiving areas through scale, technology, structural, and market effects [23]. A multi-regional input–output accounting by Zhang et al. traced the movement of embodied carbon from northern China to affluent southern coastal regions [24]. Relatedly, Shen et al. reported that industrial co-agglomeration exerts significant, heterogeneous positive spatial spillovers on urban emissions [25]. Because high-carbon stages can relocate across regions, an apparent “high-income, low-emission” pattern may partly reflect this spatial shift rather than genuine decoupling—a confounder that must be treated cautiously when interpreting the income–emission relationship.

Given these cross-boundary spillovers, collaborative governance across urban agglomerations has emerged as a key policy pathway. Sun et al. constructed a spatial association network for coordinated pollution and carbon control and found a coordination gradient—Yangtze River Delta > Beijing–Tianjin–Hebei and surrounding areas > Fen–Wei Plain—dominated by within-agglomeration ties [26]. Liu and Cang identified three sets of factors—pressure, state, and individual—that constrain cooperation among local governments in the Yangtze River Delta [27]. Using multi-agent reinforcement learning, Zhao et al. showed that cooperative scenarios can lower peak emissions or bring forward the peaking year in Beijing–Tianjin–Hebei and the Yangtze River Delta [28]. Wang and Fang found that new-type urbanization raised the pollution–carbon coordination degree across the five major agglomerations from 0.65 to 0.90 [29].

As research has shifted from single agglomerations to cross-regional comparison, the spatiotemporal heterogeneity of carbon emissions has come into sharper focus. Using spatiotemporal geographically weighted regression, Wang et al. found a polycentric emission pattern in the Yangtze River Delta, Beijing–Tianjin–Hebei, and Central Plains agglomerations, but a monocentric structure in Chengdu–Chongqing and the Pearl River Delta [30]. Comparing the five major agglomerations across three dimensions—socioeconomic conditions, industrial structure, and energy-use patterns—Xu confirmed the nonlinear EKC pattern at the regional scale [31]. At a broader scale, Zioga et al. accounted for more than 1500 subnational regions worldwide and found that about 30% had decoupled growth from emissions, with faster decoupling in high-income, historically high-carbon regions and those with stronger climate policy; at current rates, however, most regions are unlikely to reach net zero before 2050 [32]. Their results provide an international benchmark for the feasibility and urgency of decoupling in agglomerations at different development stages.

The U.S. Regional Greenhouse Gas Initiative (RGGI), launched in 2009, was the country’s first multi-state, power-sector cap-and-invest program, covering more than ten states in the Northeast and Mid-Atlantic. In an econometric attribution study, Murray and Maniloff estimated that regional emissions would have been about 24% higher without RGGI—roughly half of the observed reduction—with the remainder attributable to the recession, falling natural-gas prices, and complementary policies [33]. Other scholars argue that the cap was non-binding for much of the period, so its actual impact may have been limited [34]. Over the same period, the program delivered net economic gains and employment growth alongside emission cuts [35], offering regional evidence that growth and mitigation can be compatible. This attribution debate highlights the importance of separating policy effects from market and macroeconomic factors in cross-regional assessment, echoing our own concern with coefficient bias arising from spatial spillovers and industrial transfer.

The applicability of the EKC hypothesis across regional scales continues to be tested, but its robustness and interpretation have drawn increasing scrutiny. Luo et al. and Armeanu et al. confirmed the regional applicability of the EKC using panel data for 31 Chinese provincial capitals and the 28 EU member states, respectively [36,37]. Majeed et al. identified asymmetric effects of natural resources, technological innovation,

and globalization on the ecological footprint of Belt and Road economies [38], and Xiong and Mo reported that the EKC is more pronounced in high-income countries [39]. Stern, however, argued long ago that the statistical basis of most EKC studies is fragile and that the inverted-U finding is sensitive to model specification [40]. Using Bayesian model averaging, Gravina and Lanzafame found that the curve is in fact inverted-N-shaped, with most emerging economies still on the segment where emissions rise with income [41]. Bias-corrected dynamic panel estimates for 147 countries by Guliyev and Seyfullayev showed that the inverted-U holds only for upper-middle-income countries, whereas low-income countries follow a U shape, and that foreign direct investment (FDI) aggravates emissions in lower-middle-income economies, supporting the pollution-haven hypothesis [42]. Wang et al. likewise found that trade protectionism worsens environmental outcomes in low-income countries through pollution transfer [43]. Taken together, this evidence indicates that the income–emission relationship depends heavily on scale, income grouping, and institutional capacity, and that the “improvement” observed in high-income regions may partly result from the cross-regional relocation of high-carbon production rather than genuine, income-driven abatement.

In sum, the literature has firmly established the central role of urban agglomerations in reconciling economic growth with ecological civilization, and has identified multiple channels of influence spanning carbon markets, spatial spillovers, industrial transfer, and collaborative governance. Systematic comparison across agglomerations, however, remains limited, and no comparative framework has yet been established that jointly accounts for the spatial dependence of emissions and industrial relocation while targeting agglomerations at different development stages. Addressing this gap, the present study extends EKC theory to the cross-regional urban-agglomeration scale. Controlling for spatial spillovers, we compare the emission characteristics and key drivers of agglomerations at different development stages and examine differentiated mitigation pathways, aiming to offer a reference for growth–environment coordination in countries in the early stages of industrialization [44].

2.2. Study Area

The study area comprises the five “optimization-and-upgrading” urban agglomerations identified in the 14th Five-Year Plan and the Long-Range Objectives Through 2035: the YRD, BTH, PRD, CY, and MRYS agglomerations. Following the boundaries defined in each agglomeration’s official development plan, we select 107 prefecture-level cities as the basic units of analysis (Figure 1; the detailed delimitation of the five agglomerations is reported in Appendix A.1, Table A1). In 2023, these five agglomerations together accounted for 55.5% of national GDP and 52.35% of the resident population, with per capita GDP about 1.09 times the national average, concentrating the spatial structure of urbanization and economic activity in China.

2.3. Methodological Framework

We combine a panel EKC model, the Tapio decoupling model, cross-sectional quadrant analysis, and a spatial panel econometric model to characterize the relationship between carbon emissions and economic growth in urban agglomerations. These four methods address, respectively, the long-term functional form, short-term incremental change, spatial distribution structure, and spatial dependence and spillover effects, together forming a complementary analytical framework.

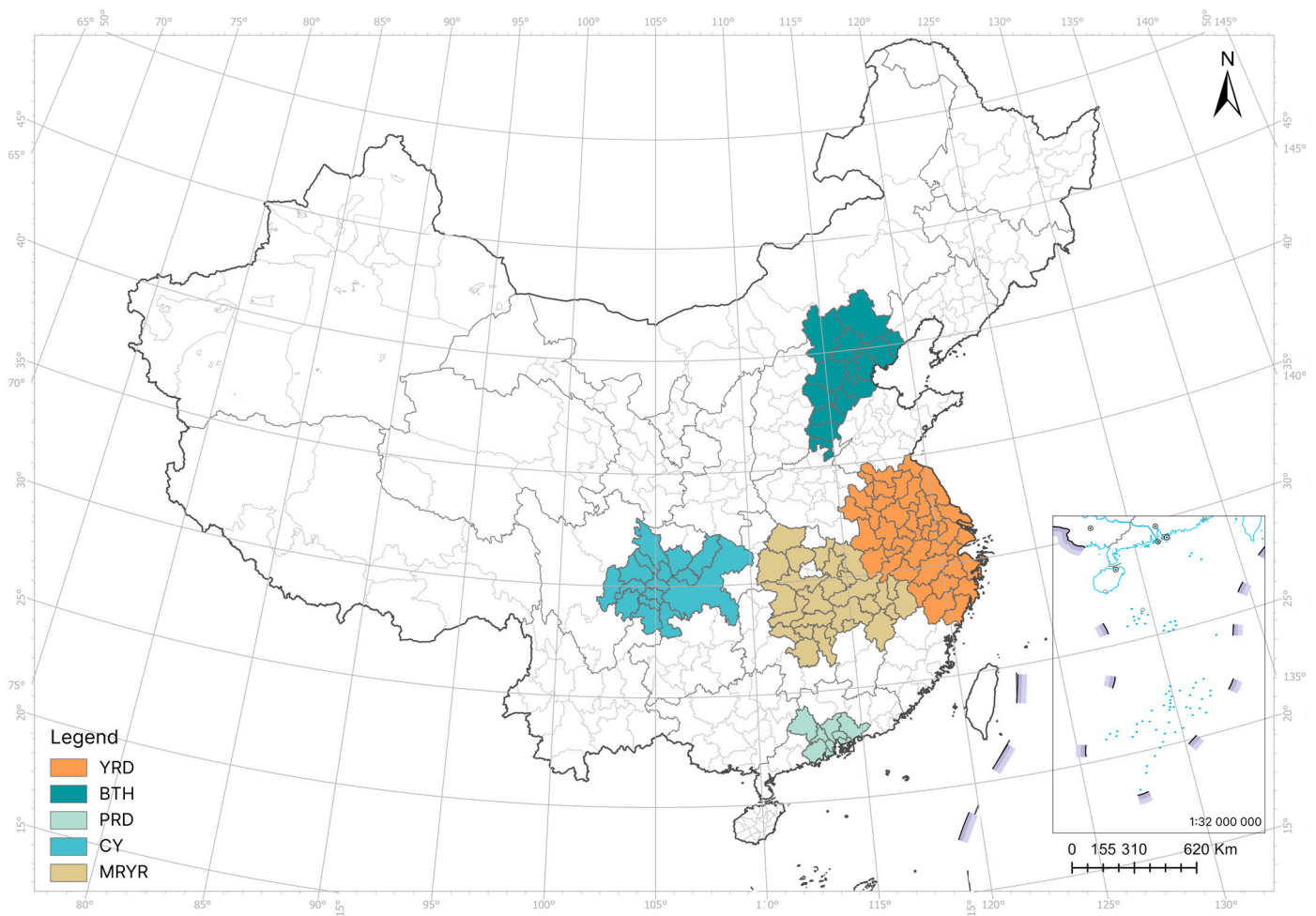


Figure 1. Study area.

2.3.1. Baseline Panel EKC Model

We specify a log-quadratic panel EKC:

$$\ln C_{it} = \alpha_0 + \beta_1 \ln G_{it} + \beta_2 (\ln G_{it})^2 + \gamma' X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where C_{it} and G_{it} denote per capita carbon emissions and per capita real GDP of city i in year t , X_{it} is a vector of control variables, μ_i and λ_t are city and year fixed effects; and ε_{it} is the error term. Per capita emissions, per capita GDP, and all non-percentage controls are log-transformed so that coefficients can be read as elasticities and heteroskedasticity is attenuated. The turning point on the inverted U is given by $\ln G^* = -\beta_1 / (2\beta_2)$. The adequacy of the quadratic specification is examined later through functional-form comparisons.

2.3.2. Tapio Decoupling Model

The Tapio decoupling elasticity is defined as

$$T = \frac{\Delta C / C}{\Delta G / G} \quad (2)$$

where ΔC and ΔG are the changes in carbon emissions and GDP between the end and base years. Based on T and the signs of ΔC and ΔG , the decoupling status is classified into eight categories (Table 1).

Table 1. Classification of Tapio decoupling states.

Decoupling State	ΔC	ΔG	Decoupling Index
Strong decoupling	≤ 0	> 0	$-\infty < T \leq 0$
Weak decoupling	> 0	> 0	$0 < T < 0.8$
Expansive negative decoupling	> 0	> 0	$1.2 \leq T < +\infty$
Strong negative decoupling	≥ 0	< 0	$-\infty < T \leq 0$
Weak negative decoupling	< 0	< 0	$0 < T < 0.8$
Recessive decoupling	< 0	< 0	$1.2 \leq T < +\infty$
Expansive coupling	> 0	> 0	$0.8 < T < 1.2$
Decline coupling	< 0	< 0	$0.8 < T < 1.2$

Note ΔC and ΔG are the changes in carbon emissions and GDP between endpoint years; T is the Tapio decoupling elasticity.

2.3.3. Cross-Sectional Quadrant Framework

To characterize the spatial distribution of cities around the EKC turning point and their dynamic evolution, we select five cross-sections—2005, 2010, 2015, 2020, and 2023—and partition each agglomeration into four quadrants using its panel EKC turning point (G^* , C^*) as the origin: Q1 ($G > G^*$, $C > C^*$) represents high-income, high-emission cities on the upward branch of the EKC; Q2 ($G < G^*$, $C > C^*$) low-income, high-emission cities, reflecting structural imbalance; Q3 ($G < G^*$, $C < C^*$) low-income, low-emission cities; and Q4 ($G > G^*$, $C < C^*$) high-income, low-emission cities, the most desirable configuration. Tracking each city's quadrant transitions across cross-sectional years reveals how its position relative to the agglomeration turning point evolves.

2.3.4. Spatial Panel Econometric Model

Because neighboring cities may influence one another in energy structure, industrial transfer, and pollution control, we further construct a spatial panel econometric model to test and quantify spatial spillover effects within a two-way fixed-effects framework. The spatial Durbin model (SDM) is specified as the general form:

$$Y_{it} = \rho \sum_{j=1}^N W_{ij} Y_{jt} + X_{it} \beta + \sum_{j=1}^N W_{ij} X_{jt} \theta + \mu_i + \gamma_t + \epsilon_{it} \quad (3)$$

where W is the spatial weight matrix, ρ is the spatial lag coefficient, X is the vector of explanatory variables, and θ captures the spatial spillover of explanatory variables from neighboring cities. The spatial weight matrix is a binary (0–1) matrix and is row-standardized.

2.4. Variables and Data Sources

The dependent variable is per capita carbon emissions, drawn from the Urban CO₂ Emissions Database released by the China City Greenhouse Gas Working Group (CCG), which provides direct and indirect emissions for prefecture-level administrative units under a uniform accounting framework covering industrial energy use, industrial processes, agriculture, services, urban and rural household consumption, and transportation [45]. The core explanatory variable is per capita real GDP, deflated to 2005 prices using the GDP deflator from the China Statistical Yearbook. Control variables span population and urbanization (resident population, population density, urbanization rate), industrial structure (share of secondary industry in value added), energy efficiency and ecology (carbon emissions per unit of GDP, green coverage ratio of built-up areas), and policy factors (fiscal support for science and technology, carbon-trading pilot dummy). All non-percentage variables are log-transformed. The definitions, units, and data sources of all variables are summarized in Table 2. The main abbreviations used throughout this study are listed in Table 3.

Table 2. Variable definitions, units, and data sources.

Variable	Symbol	Unit	Data Source	Missing-Value Treatment
Per capita carbon emissions (dependent variable)	C	t CO ₂ /person	China City Greenhouse Gas Working Group (CCG) urban CO ₂ emissions database (CHRED accounting framework)	For a few cities in certain benchmark years, filled by linear interpolation from adjacent benchmark years
Per capita real GDP (core explanatory variable)	G	CNY/person (constant 2005 prices)	China City Statistical Yearbook, China Statistical Yearbook, and provincial statistical yearbooks; deflated using the GDP deflator	None missing
Resident population	POP	10 ⁴ persons	Statistical yearbooks, population censuses, and sample surveys	Census and sample-survey years reconciled; a few missing years linearly interpolated
Population density	DEN	persons/km ²	Calculated from resident population and administrative area	Follows resident population
Urbanization rate	URB	%	Statistical yearbooks/statistical bulletins	A few missing years linearly interpolated
Share of secondary-industry value added	IND	%	Statistical yearbooks	None missing
Carbon emissions per unit of GDP	EI	t CO ₂ /10 ⁴ CNY	Calculated from CCG emissions and real GDP	Follows upstream variables
Green-space ratio of built-up area	GRN	%	China Urban Construction Statistical Yearbook	A few missing years linearly interpolated
Fiscal support for science and technology	TEC	% (S&T expenditure as a share of fiscal expenditure)	Statistical yearbooks/final fiscal accounts	A few missing years linearly interpolated

Note on missing values: The sample comprises five benchmark years—2005, 2010, 2015, 2020, and 2023. For a small number of cities, series are discontinuous in certain benchmark years owing to changes in statistical scope or data gaps; these were uniformly filled by linear interpolation from adjacent benchmark years. Interpolated observations account for a low share of the total and do not alter the overall distribution of any variable or the structure of between-group differences. All non-percentage variables are transformed by natural logarithm. GDP, gross domestic product; CHRED, China High Resolution Emission Database.

2.5. Descriptive Statistics and Preliminary Tests

2.5.1. Descriptive Statistics

The distributions of the main variables are reasonable during the sample period, with no extreme outliers (descriptive statistics for the pooled sample and the five sub-samples are reported in Appendix A.2, Tables A2–A7). Sub-sample differences are consistent with developmental-stage characteristics: the PRD ranks high on per capita GDP, urbanization rate, and fiscal support for science and technology; the BTH shows substantially higher carbon emissions per unit of GDP than the other agglomerations, in line with its heavy-industry base; and the CY ranks lower on per capita GDP, urbanization rate, and pilot coverage, reflecting its later industrialization stage. The cross-agglomeration variation in policy treatment provides the treated-versus-control comparisons needed for the sub-sample regressions reported below.

Table 3. List of main abbreviations.

Abbreviation	Full Term	Abbreviation	Full Term
EKC	Environmental Kuznets Curve	VIF	Variance Inflation Factor
CCG	China City Greenhouse Gas Working Group	LLC	Levin–Lin–Chu test
CHRED	China High Resolution Emission Database	LM	Lagrange Multiplier test
GDP	Gross Domestic Product	AIC/BIC	Akaike/Bayesian Information Criterion
FE	Fixed Effects	RESET	Regression Equation Specification Error Test
DID	Difference-in-Differences	2SLS	Two-Stage Least Squares
SDM	Spatial Durbin Model	Moran's I	Moran's Index
SAR	Spatial Autoregressive Model	AR(1)	First-order Autoregression
SEM	Spatial Error Model	R ²	Coefficient of Determination

Note: In this table, R² and adjusted R² are descriptive measures of explained cross-sectional variation—that is, the proportion of cross-city differences in per capita carbon emissions explained by the composite EKC specification. They are not indicators of causal identification or robustness, and their relatively low values do not weaken the conclusions of the main panel regression.

2.5.2. Collinearity Diagnostics

Pearson correlations (Appendix A.3, Figure A1) show that per capita emissions are strongly positively correlated with per capita GDP and the urbanization rate, and strongly negatively correlated with carbon emissions per unit of GDP, in directions consistent with theoretical expectations. Per capita GDP and the urbanization rate carry some risk of collinearity. Variance inflation factors (VIFs) confirm that all variables lie below the conventional threshold of 10, with urbanization rate (5.86) and ln per capita GDP (5.76) the highest but still within the acceptable range (Appendix A.3, Table A8).

2.5.3. Model Selection and Residual Diagnostics

The F-test, Lagrange multiplier (LM) test, and Hausman test consistently support a two-way fixed-effects model at the 1% level in both the pooled and the four sub-samples (Appendix A.4, Table A9). In the PRD, the LM test does not reject pooled ordinary least squares (OLS) ($p = 0.18$); however, because the sample is the population rather than a random draw and the Hausman test rejects random effects, we apply two-way fixed effects to the PRD as well for framework consistency.

The Modified Wald test for groupwise heteroskedasticity and the Wooldridge test for first-order serial correlation both reject the null at the 5% level in the pooled and sub-samples (Appendix A.5, Table A10). To correct for both heteroskedasticity and within-cluster serial correlation, all subsequent regressions use city-clustered robust standard errors. Levin–Lin–Chu (LLC) unit-root tests reject the null of a unit root at the 1% level for per capita emissions, per capita GDP, and urbanization rate in all samples, satisfying the stationarity requirement (Appendix A.6, Table A11).

2.5.4. DID Identification and Parallel Trends

We use treat $\times$ year interactions to assess pre-treatment comparability between treated and control cities (Appendix A.7, Table A12). Pre-trend coefficients are insignificant for the pooled sample ($p = 0.66$), the YRD ($p = 0.88$), and the MRYS ($p = 0.24$), supporting the parallel-trend assumption. For the BTH ($p = 0.06$), the pre-trend is marginally significant at the 10% level, and results should be interpreted with caution. The CY pre-trend is significant at the 1% level ($p < 0.001$), likely because pilot cities are concentrated in the Chengdu–Chongqing dual core and differ structurally from smaller control cities; we retain the CY difference-in-differences (DID) estimates for framework completeness but interpret them as correlational evidence. The PRD contains only two non-pilot cities, precluding a meaningful pre-trend test; the diagnostic is not reported for this sub-sample.

2.5.5. Endogeneity

The core explanatory variable and the dependent variable may be subject to endogeneity arising from reverse causality and omitted variables. We test for this systematically and conclude that no single instrument in these data satisfies both relevance and exclusion (Appendix A.8, Table A13). The main regression therefore relies on a two-way fixed-effects (FE) model with a quadratic EKC specification, and the instrumental-variable (IV) results are reported only as a transparent robustness check.

We first assess the validity of the commonly used one-period-lagged per capita GDP as an instrument. When current and one-period-lagged $\ln$ per capita GDP are entered together in the structural equation (two-way fixed effects, controlling for all covariates), the lagged term remains significantly positive ($\beta = 0.253$, $p = 0.018$) while the current term becomes insignificant ($\beta = 0.026$, $p = 0.87$). This indicates that lagged GDP has a direct effect on current emissions, violating the exclusion restriction. The lagged term is significant not because emissions are highly persistent—their AR(1) coefficient is only about 0.15—but because current and lagged per capita GDP are strongly autocorrelated; lagged GDP is thus “strong but invalid” as an instrument. We therefore do not use lagged GDP as an instrument.

We next construct geographic instruments that are correlated with economic growth but relatively exogenous—distance to the coastline, mean elevation, and slope—each interacted with a time trend, and estimate the model by two-stage least squares (2SLS). In the full sample, the first-stage F for the three geographic instruments jointly is 13.0, above the conventional threshold of 10; the Hansen J overidentification test does not reject instrument exogeneity ($p = 0.66$), and the Wu–Hausman test rejects exogeneity at the 1% level. However, the geographic instruments yield a negative coefficient on $\ln$ per capita GDP (about -0.50), opposite in sign to both the FE estimate and the lagged-GDP instrument. A specification-sensitivity analysis shows that, as the set of controls expands, the FE coefficient remains stably positive (0.27–0.63) and the lagged-GDP IV stays positive throughout, whereas the geographic IV stays near zero or negative—a systematic divergence between the two types of instruments. At the subsample level, only the full sample meets the strong-instrument condition; the first-stage F for the geographic instruments falls below 10 in the Yangtze River Delta, the middle reaches of the Yangtze River, Chengdu–Chongqing, Beijing–Tianjin–Hebei, and the Pearl River Delta, indicating a weak-instrument problem, so IV estimates for these subsamples are not reported.

This divergence originates in the nonlinearity of the income–emission relationship. In the specification without an energy-efficiency mediator, the full-sample quadratic EKC term is significantly negative, with an inverted-U turning point at about CNY 69,000 per capita for this specification (which omits the energy-efficiency mediator), broadly consistent with the composite-shape identification in Section 3.1.1 and with the Delta-method turning point of about CNY 67,200 reported in Section 3.2. Under this nonlinear structure, a linear IV compresses the heterogeneous slopes across income segments into a single coefficient, producing point estimates of indeterminate sign. On balance, the IV approach is not robust in these data, and no reliable causal conclusion can be drawn from its point estimates. The FE model with a quadratic EKC term both accommodates the nonlinearity and, through two-way fixed effects, absorbs time-invariant city heterogeneity and common shocks, making it the more robust primary specification. The empirical analysis below is based on FE + EKC, and the IV results above are reported transparently in the robustness section to convey the practical difficulty of identifying endogeneity.

On the basis of these tests, we settle on the following framework for the main regression. For both the full sample and each urban-agglomeration subsample, we use a two-way fixed-effects model with a quadratic EKC specification and city-level cluster-robust stan-

standard errors. For endogeneity, FE + EKC is the primary specification, with IV serving only as a transparent robustness reference. Where significant spatial dependence is present, at the full-sample level, we further estimate a spatial panel model to characterize spillover effects. The Chengdu–Chongqing DID coefficient is interpreted with caution, and for the Pearl River Delta we report only the FE results (the final modeling specification for each sample is summarized in Appendix A.9, Table A14).

3. Results

3.1. Baseline Regressions

3.1.1. The Composite Form of the Classical EKC

We first estimate the log-quadratic specification without control variables, capturing the composite relationship between economic development and carbon emissions that subsumes mediating mechanisms such as industrial upgrading, energy-efficiency improvement, and policy intensity. The linear term is significantly positive and the quadratic term significantly negative in all five agglomerations, producing the inverted U-shape predicted by the EKC hypothesis (Table 4). Ranked by turning-point per capita GDP from low to high, the order is CY, PRD, BTH, MRYR, and YRD (Figure 2). A higher turning-point GDP implies a longer interval over which emissions rise with growth and a higher economic threshold to cross before peaking.

Table 4. Log-quadratic EKC estimates for the five urban agglomerations.

Agglomeration	β_0 (Constant)	β_1 (Linear)	β_2 (Quadratic)	R ²	Adj. R ²	Turning-Point GDP (CNY)
YRD	−28.3982	5.1720	−0.2159	0.484	0.479	159,580
BTH	−46.7624	8.9473	−0.4056	0.314	0.294	61,754
PRD	−74.5166	14.2552	−0.6635	0.248	0.212	46,314
CY	−33.4531	6.5898	−0.3099	0.304	0.286	41,477
MRYR	−29.4155	5.6289	−0.2505	0.378	0.369	75,858

3.1.2. Net Marginal Effects from the Panel EKC

We next introduce structural control variables within the two-way fixed-effects framework to identify the net marginal effect of per capita GDP on per capita carbon emissions (Table 5). In the pooled sample, the linear term in $\ln$ per capita GDP is significantly positive while the quadratic term is close to zero and insignificant, indicating that after structural factors are controlled, the data do not support a nonlinear net effect of income on emissions. The coefficients on the secondary-industry share and $\ln$ carbon emissions per unit of GDP are significantly positive, consistent with prior findings on industrial-structure and energy-efficiency effects. The policy dummy is insignificant, suggesting that, conditional on economic growth, the average treatment effect of carbon-trading pilots is not pronounced.

The sub-sample results reveal heterogeneity in the net effect. In the PRD, the quadratic term is significantly negative, tracing an inverted U-shape; however, the implied turning point lies far above the maximum observed value, so within the sample period the PRD has not yet entered the descending branch—what we observe is only an attenuation of the marginal impact of growth on emissions. In the BTH, the quadratic term is significantly positive, producing a U-shape rather than an inverted U; a plausible explanation is the agglomeration’s deep heavy-industry base, with Beijing and Tianjin undergoing industrial relocation while parts of Hebei remain on the rising branch—the quadratic specification reads this combination as a U-shape, so the causal interpretation requires caution. In the YRD, MRYR, and CY, the quadratic term is insignificant and the linear term significantly positive, giving an approximately linear positive relationship.

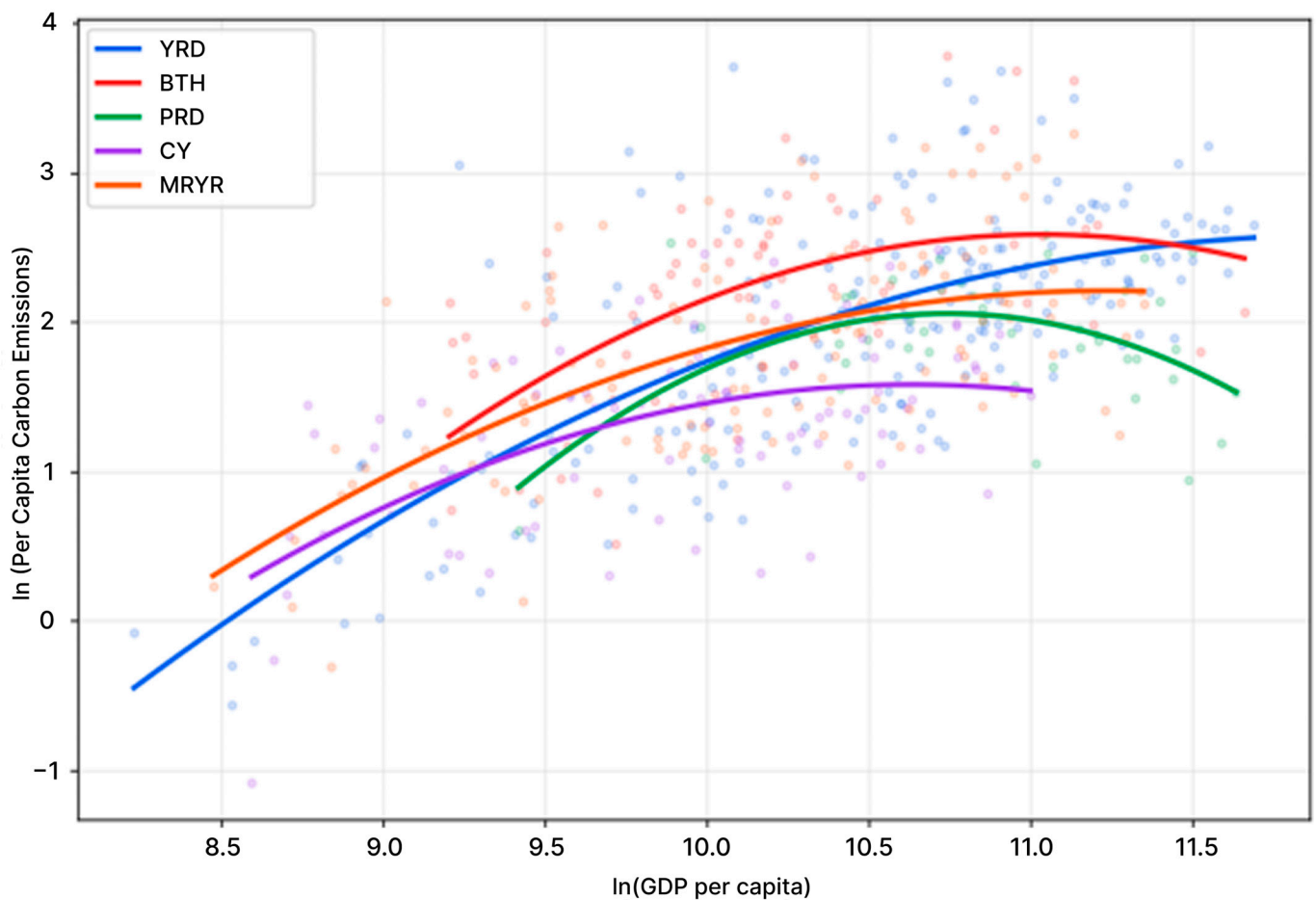


Figure 2. Log-quadratic EKC fits for the five urban agglomerations. Note: Each dot denotes a prefecture-level city in a given year (log per capita GDP vs. log per capita carbon emissions).

Table 5. Panel EKC baseline regressions.

Sample	N	ln GDP per Capita	(ln GDP per Capita) ²	Policy	R ² (Within)	Sample
Pooled	535	0.8063 *** (0.1603)	0.0011 (0.0078)	−0.0070 (0.0111)	0.4625	Pooled
YRD	205	0.5860 *** (0.1811)	0.0086 (0.0081)	0.0065 (0.0152)	0.4139	YRD
MRYR	135	0.9930 *** (0.2378)	−0.0058 (0.0124)	−0.0176 (0.0155)	0.4572	MRYR
CY	80	0.8503 *** (0.2814)	0.0040 (0.0151)	0.0018 (0.0255)	0.6868	CY
BTH	70	0.3976 (0.3016)	0.0291 ** (0.0139)	−0.0080 (0.0162)	0.6428	BTH
PRD	45	1.9471 *** (0.5351)	−0.0570 ** (0.0254)	—	0.1510	PRD

Notes: City-clustered robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$. Controls include ln resident population, ln population density, share of secondary industry, urbanization rate, ln carbon emissions per unit of GDP, green coverage ratio of built-up areas, and fiscal support for science and technology, with two-way city and year fixed effects. The PRD policy dummy is dropped automatically because of collinearity with the city/year fixed effects.

Comparing the two specifications, the five agglomerations exhibit inverted U-shaped long-term forms but, once industrial structure and energy efficiency are stripped out, the net effect of income alone is predominantly monotonically positive. The resolution difference between the two—the first reflects the empirical association between developmental stage

and emissions, the second the counterfactual net effect of income on emissions—points toward a diagnostic of where the EKC form originates.

3.1.3. Decomposing the Sources of the EKC

To identify which structural factors carry the inverted U-shape, we add controls stepwise: starting from specification (1) with only the core terms, we sequentially add population and urbanization (2), the secondary-industry share (3), ln carbon emissions per unit of GDP (4), and the remaining controls together with policy dummies (5), tracking the evolution of β_2 (Appendix A.10, Table A15).

Under specifications (1) and (2), β_2 remains significantly negative with stable magnitude across all five agglomerations, indicating that population and urbanization variables are not the key absorbers of the EKC form. Adding the secondary-industry share in specification (3) shrinks β_2 substantially: in the pooled sample its absolute value falls from 0.177 to 0.060, and the quadratic term loses significance simultaneously for the YRD, BTH, and PRD, indicating that industrial structure is the first-tier mediating mechanism. Further adding ln carbon emissions per unit of GDP in specification (4) reverses the sign of β_2 : in the pooled sample it moves from -0.060 to $+0.041$ and is significant at the 1% level, with parallel reversals in the YRD, MRYR, and BTH, indicating that energy-efficiency improvement is the decisive mechanism carrying the descending branch of the EKC. Specification (5), which adds the remaining controls, leaves the core estimates essentially unchanged.

This sequence shows that the inverted U-shape identified in Section 3.1.1 is in essence a composite expression of industrial upgrading and energy-efficiency improvement, not an autonomous effect of income. The policy implication is that, once the room for industrial restructuring narrows or the marginal cost of efficiency gains rises, further decoupling will depend increasingly on transformation of the energy mix itself.

3.2. Robustness Checks

Residual structure and standard errors. The Modified Wald test detects significant groupwise heteroskedasticity in the pooled and all sub-samples; for serial correlation, the null is rejected only in the YRD at the 1% level (Appendix A.11.1, Table A16). Comparing ordinary OLS, White heteroskedasticity-robust, and city-clustered standard errors, the linear ln per capita GDP term is significant and stable in direction across most samples, with clustered standard errors slightly larger, in line with the heteroskedasticity diagnostics (Appendix A.11.2, Table A17). The core conclusions are insensitive to the choice of inference method.

Functional-form comparison. We compare linear, quadratic, and cubic specifications using AIC, BIC, and within- R^2 (Appendix A.11.4, Table A22). For the pooled sample, YRD, MRYR, and CY, the linear specification dominates; adding the quadratic term yields no substantive improvement in information criteria, corroborating the insignificant quadratic terms in the panel EKC and indicating that these samples have yet to exhibit an identifiable nonlinear turning point over the observation window. In the BTH, AIC prefers the cubic and BIC the quadratic, suggesting a more complex nonlinear structure between growth and emissions. For the PRD, both AIC and BIC clearly favor the quadratic form, making it the sub-sample with the most robust evidence of an inverted U-shape. The Ramsey RESET test does not reject the null that the quadratic specification omits no further nonlinear terms (p between 0.14 and 0.79), indicating no serious functional-form misspecification.

Influential-observation diagnostics. Using standardized residuals $|e| > 3$ as a rule-of-thumb threshold, 10 influential points are identified in the pooled sample (1.87% of observations), drawn mainly from multiple-year observations of Ziyang and from several YRD and CY observations around 2010. Excluding these points moves the linear ln per

capita GDP coefficient within a narrow range while preserving the direction and significance structure, indicating that the baseline estimates are not driven by a few extreme observations (Appendix A.11.5, Table A23).

Cubic EKC and confidence intervals for the turning point. To test the robustness of the inverted-U turning point and quantify its uncertainty, we add two extensions to the two-way fixed-effects EKC model. First, we include a cubic term in ln per capita GDP to check for a more complex nonlinear structure. Except for Beijing–Tianjin–Hebei, the cubic coefficient is insignificant in the full sample and in the Yangtze River Delta, the middle reaches of the Yangtze River, Chengdu–Chongqing, and the Pearl River Delta, indicating that the quadratic specification adequately captures the income–emission relationship and that no N-shaped re-acceleration occurs within the sample period. For Beijing–Tianjin–Hebei, the cubic term is significantly negative (-0.638 , $p < 0.05$), consistent with the earlier Akaike information criterion (AIC) preference for the cubic form and suggesting a more complex shape; because of the small subsample size ($N = 70$) and high collinearity among the polynomial terms, however, we treat this result only as an indication of shape complexity. Second, we use the Delta method to compute the standard error and 95% confidence interval of the quadratic turning point [$\exp(\cdot)$], and we compare these with each sample's observed range of per capita GDP to distinguish “within-sample” from “out-of-sample” turning points.

The turning point for the middle reaches of the Yangtze River (about CNY 51,800) lies within the observed range, its quadratic term is significant at the 1% level, and its confidence interval is relatively narrow, making it the sample with the most robust evidence of an inverted U (Figure 3). The point estimates for Beijing–Tianjin–Hebei (about CNY 79,800), the Pearl River Delta (about CNY 62,400), and the full sample (about CNY 67,200) also fall within their observed ranges, but their confidence intervals are wide and the upper bounds approach or exceed the sample maximum; these should be read as “identifiable within the range but of limited precision.” By contrast, the turning points for the Yangtze River Delta (about CNY 215,600) and Chengdu–Chongqing (about CNY 81,200) both lie beyond the maximum observed per capita GDP in their respective samples, with insignificant quadratic terms and extremely wide confidence intervals (the upper bound of the Yangtze River Delta 95% CI exceeds CNY 5.9 million). This indicates that, within the observed range, the income–emission relationship in these two agglomerations remains essentially on a monotonically rising segment; the apparent “turning point” is an extrapolation into the out-of-sample region, is markedly less reliable, and should not be taken as evidence that these agglomerations are approaching their emission peak. This conclusion corroborates the finding in the cross-sectional analysis (Section 3.5.1) that the vertices for the Yangtze River Delta mostly fall outside the sample range, and it further cautions against reading too much into out-of-sample turning points for policy purposes.

3.3. Spatial Autocorrelation

3.3.1. Global and Local Spatial Autocorrelation

The global Moran's I indicates that the YRD index remains between 0.16 and 0.24 in all years with $p < 0.05$, exhibiting a stable and significant positive spatial correlation. The BTH, CY, and MRYS indices are negative or near zero and statistically insignificant in most years, suggesting that within-agglomeration emissions are broadly randomly distributed. The PRD shows some positive clustering in 2015 ($I = 0.294$), but overall significance is weak (Appendix A.11.3, Table A18).

Local Moran's I further characterizes within-agglomeration clustering across the five cross-sectional years (Figures 4–8, corresponding to 2005, 2010, 2015, 2020, and 2023, respectively; cluster membership is listed in Appendix A.11.3, Table A19). The YRD

displays the tightest spatial linkages: Shanghai and Suzhou consistently sit in the high–high cluster, joined repeatedly by Nantong, forming a contiguous high-emission belt around Lake Taihu; Huainan persistently shows a high–low pattern; and low–high clusters concentrate in cities ringing Shanghai such as Jiading and Huzhou. The BTH shows a dispersed pattern: from 2005 to 2015, Chengde lies persistently in the low–high cluster, reflecting its dependent position within a high-emission ring surrounding Beijing and Tianjin; from 2020 onward, no city falls into any significant cluster quadrant, and local autocorrelation weakens markedly—plausibly reflecting convergence in urban emissions under joint air-pollution control and energy-structure adjustment. The PRD shows diverse cluster types but a loose configuration: a high–high cluster appears only briefly in 2015 in Dongguan and Huizhou, consistent with deep economic integration and refined inter-city industrial division. The CY exhibits a single-pole pattern, with Chengdu entering the high–low cluster in four consecutive cross-sectional years from 2010 onward; Chongqing does not show a symmetric clustering pattern. The MRYR is dominated by low–high and low–low clusters: low–low clusters concentrate in Yingtan, Shangrao, and Fuzhou around Lake Poyang during 2005–2010 and disappear after 2015, while low–high clusters gradually shift toward Xianning, Huanggang, and Ezhou in southeastern Hubei, reflecting low-value satellite clustering around rising emissions in core cities such as Wuhan.

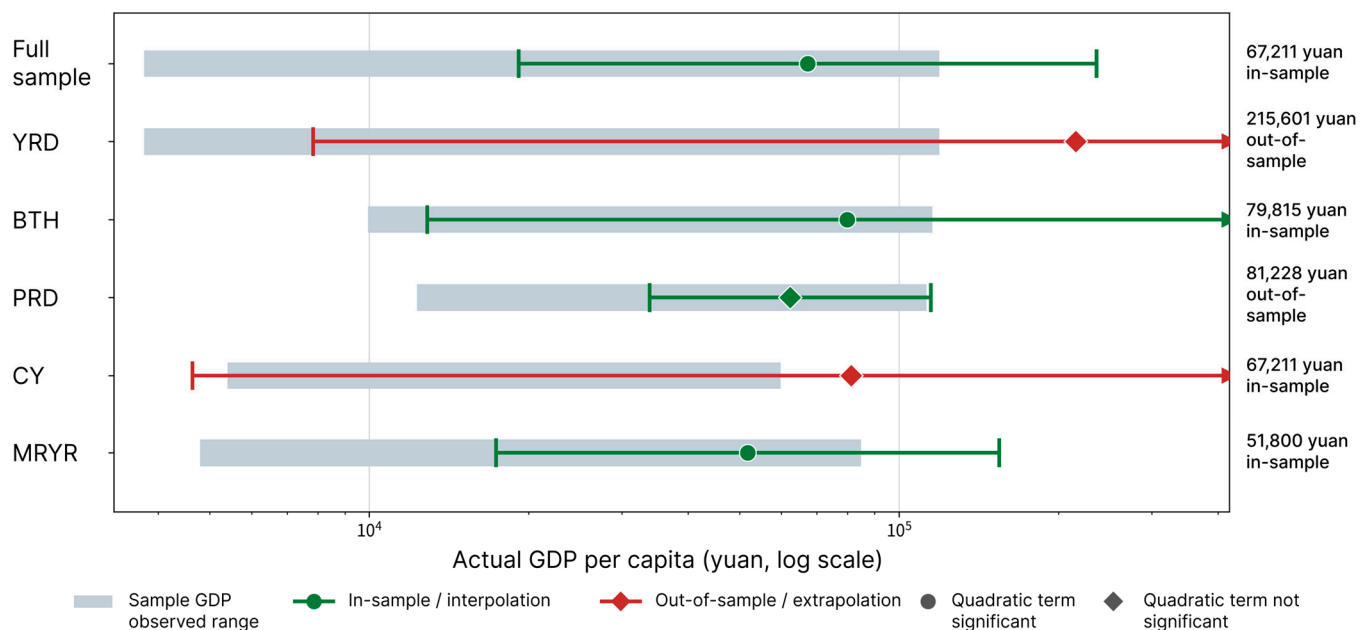


Figure 3. Comparison of the 95% confidence intervals of EKC turning points with the observed GDP ranges by urban agglomeration.

Taken together, the YRD is the only agglomeration with persistent high–high clustering; the BTH shows a marked weakening of local autocorrelation; the PRD shows weak and unstable clustering; the CY is dominated by Chengdu as a single pole; and the MRYR forms a pattern with Wuhan as an implicit core and southeastern Hubei as a low-value satellite belt.

3.3.2. Spatial Panel Model and Decomposition of Spillover Effects

To ensure stable estimation of the spatial parameters, the spatial model applies a stricter collinearity screen ($VIF < 3$), so the urbanization rate and the energy-efficiency variable are dropped. The local analysis above was conducted within each urban agglomeration; constrained by the sample size of individual agglomerations, stable spatial clustering

could not be identified except in the Yangtze River Delta. Treating the 107 cities as a whole, the global Moran's I is significantly positive in every period from 2005 to 2023 (ranging from 0.15 to 0.32, all $p < 0.05$), indicating robust positive spatial dependence in per capita carbon emissions at a larger spatial scale and providing a basis for estimating a spatial panel model.

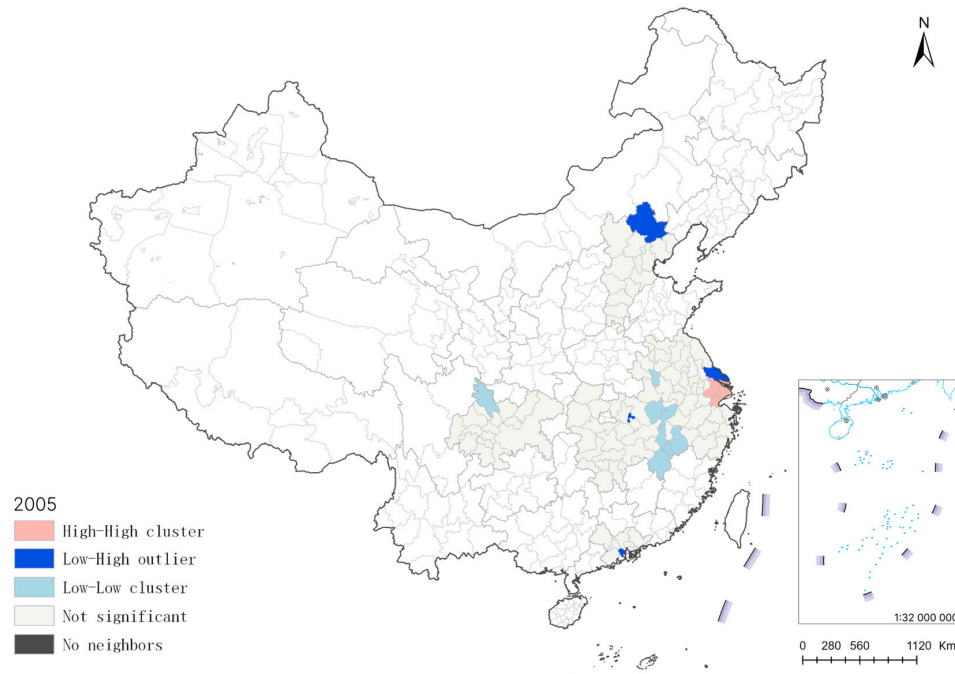


Figure 4. Analysis of Local Spatial Autocorrelation of Total Carbon Emissions in Five Major Urban Agglomerations in 2005.

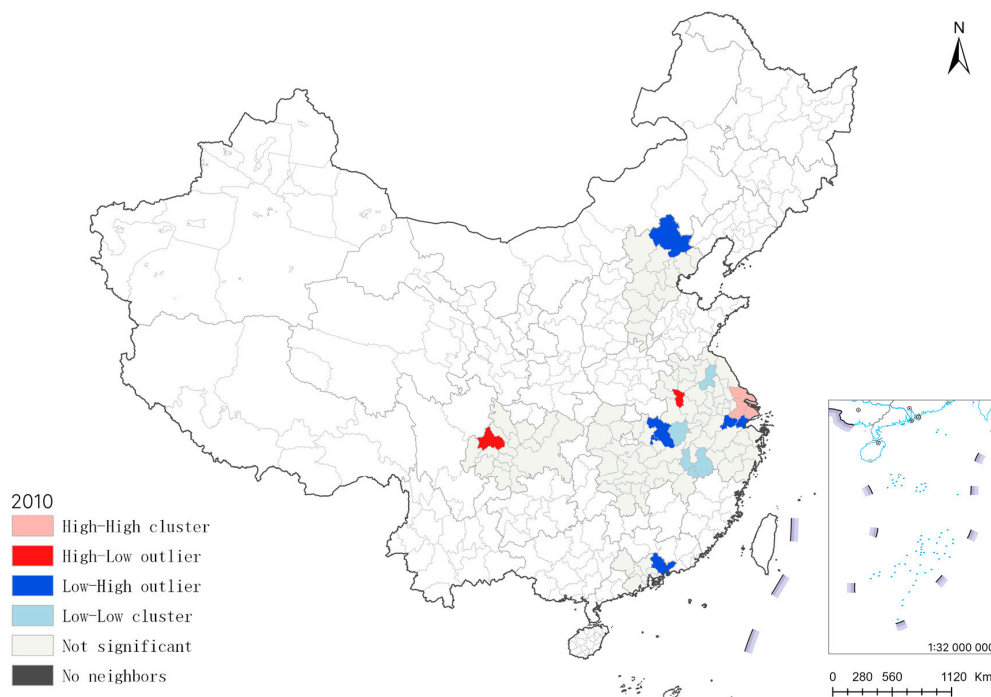


Figure 5. Analysis of Local Spatial Autocorrelation of Total Carbon Emissions in Five Major Urban Agglomerations in 2010.

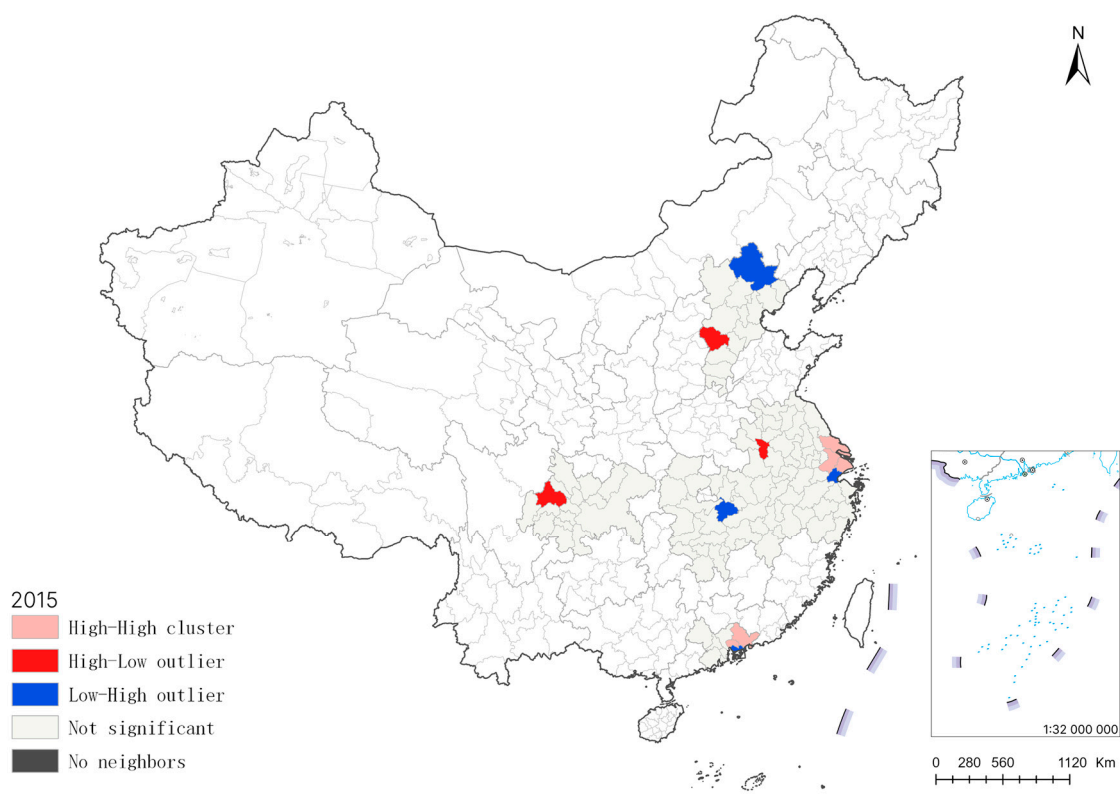


Figure 6. Analysis of Local Spatial Autocorrelation of Total Carbon Emissions in Five Major Urban Agglomerations in 2015.

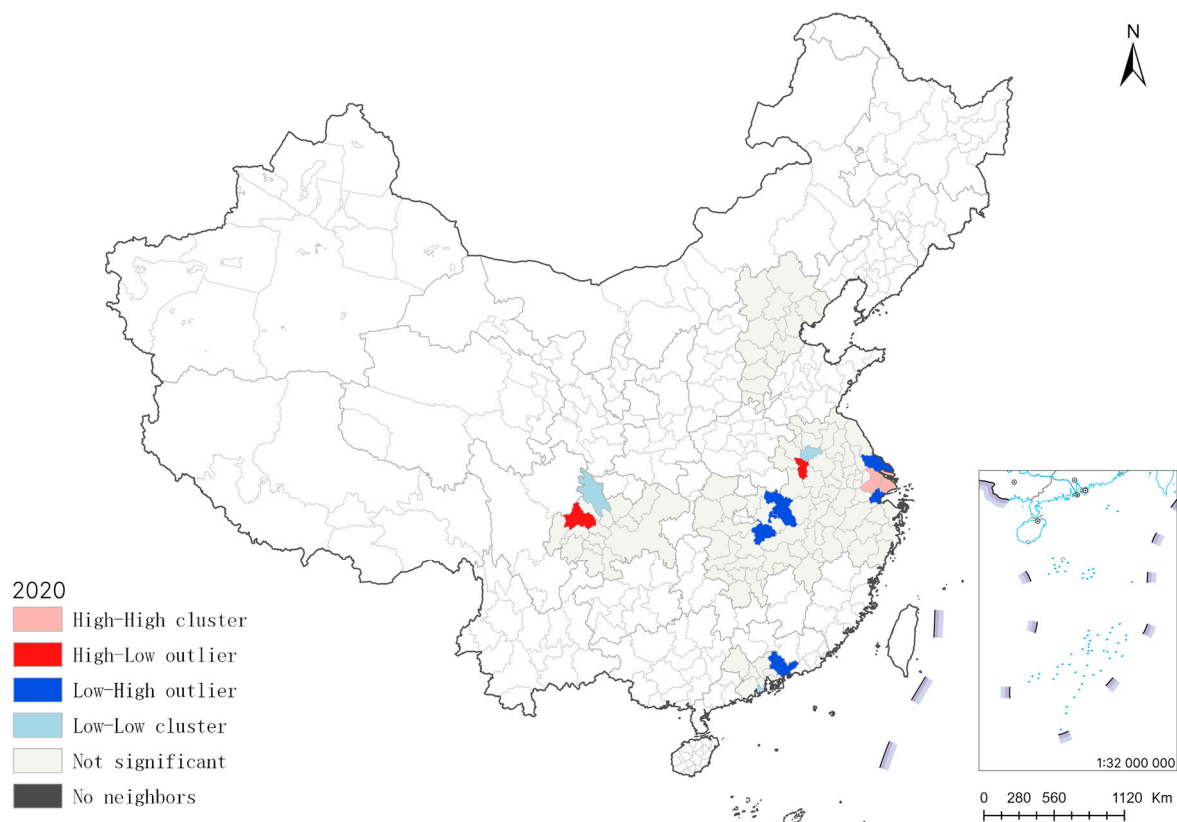


Figure 7. Analysis of Local Spatial Autocorrelation of Total Carbon Emissions in Five Major Urban Agglomerations in 2020.

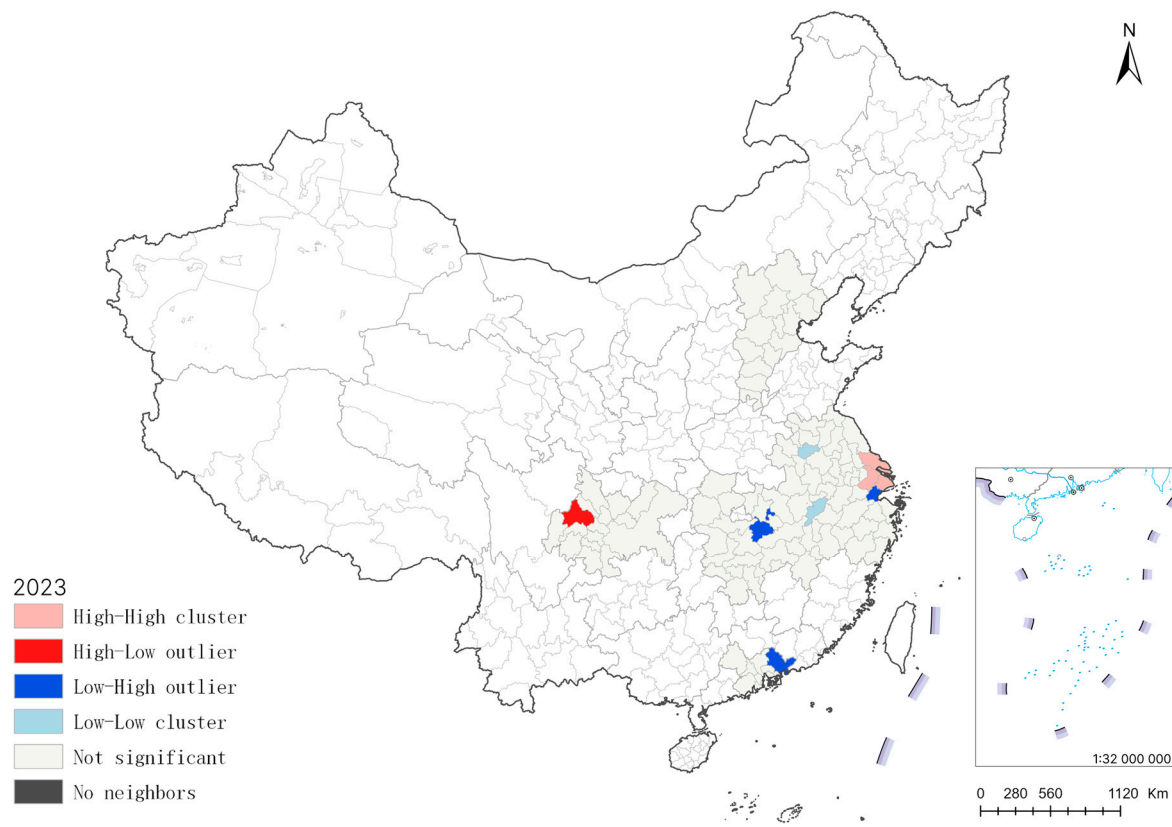


Figure 8. Analysis of Local Spatial Autocorrelation of Total Carbon Emissions in Five Major Urban Agglomerations in 2023.

LM tests based on the two-way fixed-effects residuals show that both LM-lag (14.83, $p < 0.001$) and LM-error (25.32, $p < 0.001$) are highly significant. Following Elhorst's procedure, we estimate the spatial Durbin model (SDM) and test downward. LR tests reject simplification of the SDM to a spatial autoregressive model (SAR) ($\chi^2(6) = 23.22$, $p < 0.001$) and to a spatial error model (SEM) ($\chi^2(6) = 13.18$, $p = 0.040$); the SDM is therefore selected as the preferred specification (Appendix A.11.3, Table A20).

The coefficient on ln per capita GDP is significantly positive in all models (0.310 in the SDM), consistent with the finding in Section 3.1.2 that the net income effect is monotonically positive after controlling for structural factors. The spatial lag coefficient ρ is 0.188 in the SAR and 0.232 in the SDM, both significant at the 1% level, confirming significant positive spatial linkage in per capita emissions among neighboring cities.

Because coefficients in spatial models cannot be interpreted directly as marginal effects, we further decompose the SDM into direct, indirect (spillover), and total effects (Figure 9; Appendix A.11.3, Table A21). The direct effect of ln per capita GDP is 0.299 ($p < 0.01$), meaning that local economic growth significantly raises local per capita emissions; its indirect effect (−0.215) and total effect (0.084) are both insignificant, indicating that the influence of income on emissions is mainly local, with little cross-city spillover. The share of secondary industry has a significantly positive direct effect (1.825) and a significantly negative indirect effect (−1.196, $p < 0.05$), suggesting that, under regional industrial division of labor, local industrial expansion raises a city's own emissions while possibly accompanying a relative contraction of the corresponding industry in neighboring cities. Population density has significantly negative direct (−2.780) and indirect (−3.638) effects, with a total effect of −6.418 ($p < 0.01$), reflecting that intensive population and economic activity is associated with lower per capita emissions both locally and in neighboring areas. All effects of the

carbon-trading pilots are insignificant, consistent with the modest average treatment effect of the policy found in the baseline regression.

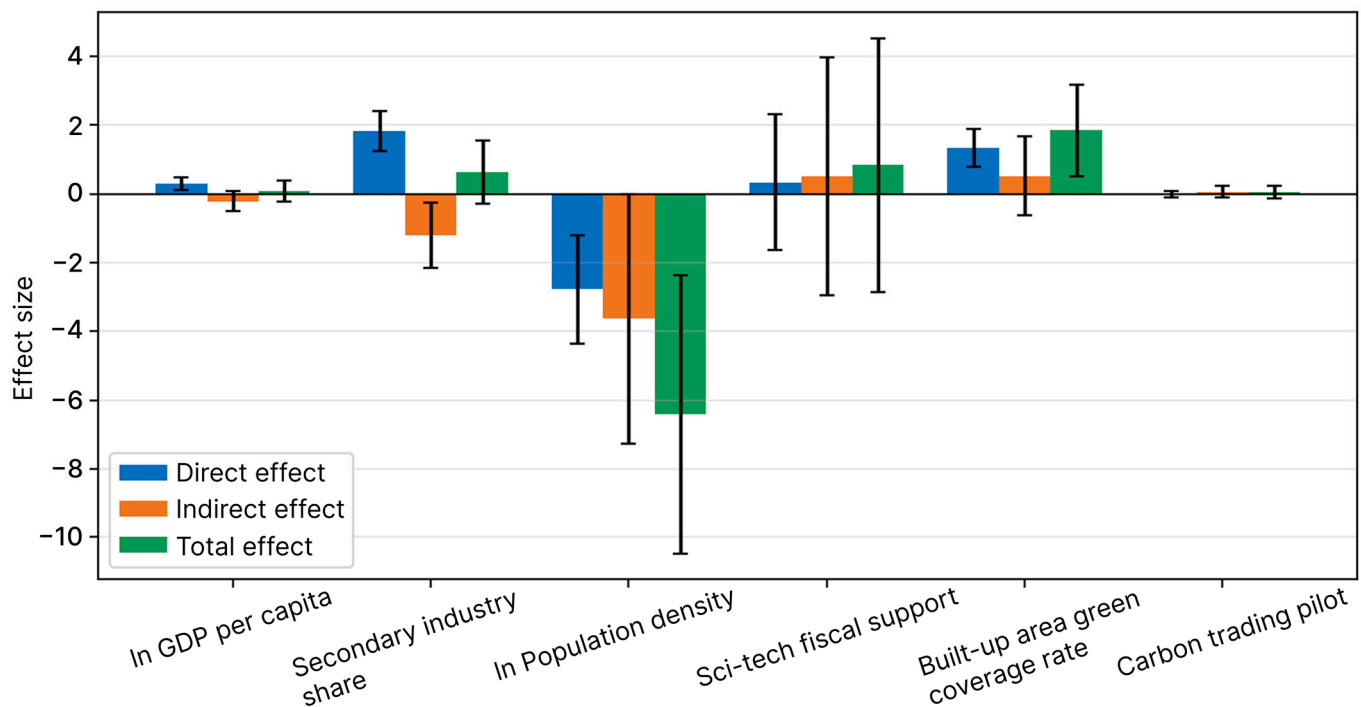


Figure 9. Decomposition of spatial Durbin model effects.

The presence of spatial spillover effects shows that carbon mitigation across urban agglomerations is distinctly regionally interlinked: the mitigation performance of any single city is affected by its neighbors. This provides empirical support for pursuing coordinated mitigation with the urban agglomeration as the unit and for avoiding the mere relocation of industry and emissions within the region.

3.4. Tapio Decoupling Analysis

3.4.1. Whole-Period Decoupling

Computing the whole-period decoupling elasticity with 2005 and 2023 as endpoints, of the 107 cities, 71 are in weak decoupling, 8 in strong decoupling, 19 in expansive negative decoupling, and 9 in expansive coupling (Appendix A.12, Table A24). By agglomeration, the MRYR has the highest weak-decoupling share (89%), with the CY close behind (88%), and no CY city reaching strong decoupling; the PRD has the highest strong-decoupling share (22%), consistent with its earlier completion of industrial upgrading; and the BTH has a relatively high share of expansive negative decoupling (29%), reflecting a clear emissions rebound in some industrial cities in Hebei.

The eight cities reaching strong decoupling are Huaibei, Shanghai, Hangzhou, and Jiaxing in the YRD; Beijing in the BTH; Guangzhou and Jiangmen in the PRD; and Wuhan in the MRYR—most of them either core cities or sub-core cities that completed transition relatively early. Expansive negative decoupling concentrates in mid-sized cities dominated by traditional energy and raw-material industries.

3.4.2. Sub-Period Trajectories

Dividing the sample into four sub-periods reveals a trajectory of steady improvement followed by partial reversal (Appendix A.12, Tables A25–A28).

During 2005–2010, of 107 cities 46 were in weak decoupling and 17 in strong decoupling, jointly accounting for about 59% of all cities; 30 were in expansive negative decoupling,

pling, reflecting the widespread co-movement of emissions and growth during the rapid expansion of heavy and chemical industry. Decoupling accelerated during 2010–2015, with the number of strong-decoupling cities rising from 17 to 40, aligning with the binding-target window of national energy-saving and emission-reduction policies. During 2015–2020, strong-decoupling cities edged down from 40 to 36 while expansive negative decoupling rose to 22, with regional divergence intensifying. The CY reached its sample-period peak in decoupling share (94%); the YRD's strong-decoupling base broadened from core Jiangsu–Zhejiang cities to Anhui cities such as Hefei and Huaibei; the PRD's strong-decoupling share fell to 33%, with Shenzhen, Guangzhou, and Foshan shifting into expansive coupling or expansive negative decoupling and entering a phase of fading mitigation dividends and renewed investment-driven emissions; and the BTH decoupling share dropped to 29%. During 2020–2023, decoupling reversed markedly, with expansive negative decoupling jumping to 61 cities. All nine PRD cities exited decoupling (seven in expansive negative decoupling, two in expansive coupling), making the PRD the agglomeration with the most pronounced reversal; 81% of CY cities, 63% of MRYR cities, 51% of YRD cities, and 43% of BTH cities moved into expansive negative decoupling or expansive coupling.

The widespread reversal in the fourth sub-period reflects two factors. First, the investment-driven recovery following the pandemic shock fueled an emission rebound. Second, the room for efficiency gains and structural change achievable through low-cost pathways has narrowed, so further decoupling now depends on deeper transformation of the energy mix. The reversal suggests that the decoupling gains accumulated earlier are stage-dependent rather than permanent.

3.5. Cross-Sectional Quadrant Analysis

3.5.1. Cross-Sectional EKC Fits

We estimate the EKC separately for each of the five annual cross-sectional samples of the prefecture-level cities within each urban agglomeration, yielding 25 independent cross-sectional regressions (Appendix A.13, Table A29). Most agglomerations show a relatively high cross-sectional explained variation (descriptive R^2) early in the sample period—0.557 for the Yangtze River Delta and 0.547 for the middle reaches of the Yangtze River in 2005, with quadratic terms significantly negative at the 5% level—so the inverted-U pattern is relatively clear. This R^2 measures the proportion of that year's cross-city differences in per capita carbon emissions explained by the specification; it is a descriptive goodness-of-fit measure and should not be interpreted as a Pearson linear correlation or as a measure of causal strength. It generally declines over time, falling by 2023 to 0.154 for the Yangtze River Delta, 0.056 for Chengdu–Chongqing, and 0.124 for the middle reaches of the Yangtze River, with the significance of the quadratic term weakening in parallel; in some years, the fitted curve is closer to linear within the observed range, and the data are more dispersed. This change indicates that, in the early stages of agglomeration development, horizontal differences in economic level are the dominant factor explaining cross-city divergence in carbon emissions. As overall economic levels within an agglomeration rise and inter-city gaps converge, per capita GDP alone explains less of the cross-sectional variation, and the relevant drivers gradually shift toward dimensions such as industrial structure, energy structure, and mitigation policy.

Turning-point GDP at the apex differs across agglomerations (Appendix A.13, Table A30). The YRD shows the highest apex economic level, with turning-point GDP exceeding CNY 80,000 in most years and reaching about CNY 197,000 in 2010; the 2005, 2010, and 2023 turning points lie outside the observed range, indicating that most cities have yet to reach the model-implied peak. The BTH apex is only about CNY 8141 in 2005, outside the sample, but settles in the CNY 46,000–56,000 range from 2010 onward and

falls within the observed range. The PRD, CY, and MRYR apices generally lie inside the observed range across years, and turning-point GDP rises steadily over time, with the model-implied emissions peak shifting back as the economy develops.

3.5.2. Quadrant Transition Paths

Using each year's cross-sectional EKC apex as the origin to define the four quadrants and tracking each city's quadrant membership and transitions, we observe a “coastal-transformation, inland-stability” pattern, with substantial within-agglomeration heterogeneity (the distribution of cities across quadrants is summarized in Appendix A.13, Table A31, and the city-level quadrant assignments by agglomeration are reported in Appendix A.14, Tables A32–A36).

The YRD is the most stable: of 41 cities, 28 retain their quadrant assignment, 24 of which remain in Q3, while four coal- and ore-based cities in central Anhui—Huaibei, Huainan, Ma'anshan, and Tongling—remain in Q2. Of the 13 cities that move, most shift from Q3 to Q2. Shanghai briefly enters Q4 in 2020 but returns to Q3 in 2023.

The BTH shows high mobility, with all 14 cities transitioning at some point. The most striking evolution is the large-scale movement from Q1 (high-carbon) in 2005 to Q3: four cities—Shijiazhuang, Zhangjiakou, Xingtai, and Anyang—move from Q1 to Q3, and four cities—Langfang, Baoding, Cangzhou, and Hengshui—move from Q4 to Q3, reflecting a region-wide decline in carbon intensity relative to economic level in Hebei following joint air-pollution control and overcapacity-reduction policies. Beijing and Tianjin move from Q1 into and stabilize in Q4, while Tangshan remains in Q1 throughout, illustrating divergent transition paths between core cities and heavy-industry cities.

The PRD shows the deepest transformation. Shenzhen remains in Q4 throughout; Zhuhai remains in Q1 throughout; Guangzhou and Foshan move from Q1 into Q4, where they stabilize. The PRD is the only agglomeration dominated by decoupled cities, consistent with its early completion of industrial upgrading and high share of services and high-tech manufacturing.

The CY and MRYR are both dominated by central- and western-region prefecture-level cities at developing stages, though their evolutionary emphases differ. Of 16 CY cities, 6 remain persistently in Q3, with transitions mainly small upward moves from Q3 to Q2; Chongqing moves from Q3 up to Q1, where it stabilizes, while Chengdu remains in Q4 throughout, producing a “dual-core leader, peripheral climbing” pattern. Of 27 MRYR cities, 10 remain stably in Q3, with transitions dispersed; Wuhan, Changsha, and Nanchang lie in or move toward Q4, forming a low-emission high ground within the region. Most peripheral cities in both agglomerations remain in the Q3 climbing phase.

3.6. Cross-Validation of EKC Quadrants and Tapio Decoupling

Cross-tabulating Tapio decoupling states with EKC quadrants offers a further test of decoupling robustness. Theoretically, cities on the lower-right branch of the EKC (Q4) should predominantly be in strong or weak decoupling; cities on the lower-left branch (Q3) may be in weak decoupling or expansive negative decoupling; and cities on the upper-left (Q2) and upper-right (Q1) branches are more likely to be in expansive negative decoupling or expansive coupling.

The whole-period cross-tabulation supports these correspondences. Of the eight strong-decoupling cities, Shanghai, Hangzhou, Wuhan, and Guangzhou all lie in Q4 at the end of the sample, consistent with the assessment that they have crossed the fitted peak and entered the descending branch. Of the 19 expansive-negative-decoupling cities, a substantial share remain in Q2 in 2023 (e.g., Tongling, Huainan, Ma'anshan, Chizhou, Zhoushan) or Q1 (e.g., Dongguan), in line with the expansive-negative-decoupling assess-

ment. Sub-period comparisons show similar systematic correspondences: the surge of strong-decoupling CY cities during 2015–2020 aligns with the upward shift of the cross-sectional EKC apex in that period; the complete exit of PRD cities from decoupling during 2020–2023 corresponds to small backward shifts from Q4 toward Q1 or Q3 in the quadrant analysis. The cross-validation indicates that the mitigation trajectory of the five agglomerations is not a monotonic “peak-then-decline” path but a complex one with episodic reversals, shaped jointly by economic cycles, the pace of industrial transition, and external shocks.

3.7. Discussion of Errors and Uncertainty

This section briefly and collectively discusses the stages that may introduce error—data sources, the interpretation of statistical indicators, and the consistency of the different EKC definitions. We note at the outset that the items below mainly affect the precision of the estimates and the rigor of their expression; they do not alter this study’s core qualitative conclusions—that the EKC shape is carried primarily by industrial structure and energy efficiency, that decoupling exhibits a non-monotonic regression, and that the spatial structure differs across regions.

3.7.1. Reliability and Potential Error of the Emissions Database

Per capita carbon emissions are taken from the CCG urban CO₂ emissions database, based on the China High Resolution Emission Database (CHRED) accounting framework. Such top-down gridded-sectoral accounting databases carry three types of uncertainty at the prefecture level. First, the downscaling assumptions used to derive prefecture-level energy balance sheets and activity data may introduce systematic bias. Second, cross-regional electricity imports and exports, embodied carbon, and adjustments to the accounting scope are not fully comparable across years. Third, a few cities show changes in statistical scope in certain benchmark years. To mitigate these effects, we use a time series drawn from a single database and a single accounting scope; city fixed effects absorb time-invariant accounting differences across cities, year fixed effects absorb nationwide scope adjustments and common shocks, and an influential-point exclusion test in the robustness section confirms that the estimates are not driven by a few extreme observations. On balance, database error mainly takes the form of uncertainty in level values and has limited effect on the main conclusions, which rely on within-group variation and on the sign-significance structure of the coefficients.

3.7.2. Interpretation and Applicable Limits of the Statistical Indicators

(1) The meaning of the p -value. The p -value is the probability of observing the current or a more extreme result under the null hypothesis (no effect, or no statistically significant difference); it is not “the probability that the effect is real.” We interpret coefficient significance accordingly: when a reported coefficient is significant at the 1% or 5% level, this means only that the null of “no effect” is rejected at that level.

(2) Distinguishing simple correlation from curve fitting. A simple Pearson linear correlation coefficient captures only the strength of the linear association between two variables, conventionally using $|r| > 0.7$ as an empirical threshold for a strong correlation. On this basis, we use the term “strong correlation” only for approximately linear relationships such as that between city size and GDP growth. The EKC relationship is itself nonlinear, and its fit quality should not be judged by a simple linear correlation but by multivariate goodness-of-fit measures such as the coefficient of determination (R^2). In a strict curve-fitting context, the threshold for an “excellent” R^2 (e.g., above 0.9) is far higher than the strong-correlation threshold for linear correlation.

(3) Positioning of cross-sectional goodness-of-fit and renaming of the indicator. The R^2 (including adjusted R^2) reported in Figure 10 and Section 3.5.1 measures the proportion of

cross-city differences in per capita carbon emissions explained by the corresponding specification; it is a descriptive goodness-of-fit measure, not an indicator of causal identification or robustness. Because the cross-sectional R^2 is low in some years and some agglomerations, the corresponding fitted curve (blue) is closer to linear than to a pronounced quadratic form within the observed range, the data are more dispersed, and the fit to the quadratic form is limited. To avoid misreading, we have relabeled “goodness-of-fit/ R^2 ” in the relevant figures and tables uniformly as “cross-sectional explained variation (descriptive R^2),” and we make clear that a low R^2 indicates a declining explanatory power of per capita GDP alone for cross-sectional differences (with the relevant drivers shifting toward the industrial, energy, and policy dimensions). It should not be interpreted as a Pearson linear relationship or as a measure of causal strength, nor does it weaken the conclusions of the main panel regression.

(4) Basis for shape and robustness. Our conclusions on the inverted-U shape and the robustness of the turning point do not rest on the cross-sectional R^2 , but on multiple lines of evidence: two-way fixed-effects panel regression, stepwise removal of control variables, comparison of functional forms (Akaike/Bayesian information criteria, AIC/BIC; regression equation specification error test, RESET), the cubic-term test, and Delta-method confidence intervals for the turning point. For turning points whose confidence intervals are too wide and fall outside the observed range (the Yangtze River Delta and Chengdu–Chongqing), we have explicitly labeled them as out-of-sample extrapolations of limited reliability and have not used them to infer emission peaking. In this sense, the robustness of the main conclusions comes from the panel identification strategy and multi-method cross-validation rather than from any single correlation or fit measure; accordingly, we have renamed the original goodness-of-fit indicator “cross-sectional explained variation” to distinguish it from the robustness evidence.

(5) Applicable limits of the EKC functional form. The inverted-U EKC is a reduced-form descriptive tool, not a universal law applicable to all large urban agglomerations. Population and economic expansion generally push up total emissions, and the downturn in emissions depends largely on the implementation of effective public policy, whose stringency in turn varies with the administrative cycle and each region’s development stage (developed or less developed). This means that the applicability of the same EKC specification is itself heterogeneous across agglomerations and periods—which corroborates our finding that, once structural factors are removed, the net income effect is predominantly monotonically positive and the inverted U is carried mainly by industry and energy efficiency. We therefore position the EKC as a stage-specific, conditional descriptive and diagnostic tool rather than a prediction that any given agglomeration will necessarily peak.

We use both a panel EKC and year-by-year cross-sectional EKCs. The two differ in definition and answer different questions, and must be distinguished to remove any apparent inconsistency. After controlling for two-way city and year fixed effects, the panel EKC identifies the net effect of income changes on emissions “for the same city over time,” characterizing within-city temporal change (within variation). The year-by-year cross-sectional EKC, by contrast, identifies how income differences “across cities in a given year” explain differences in emissions, characterizing cross-city variation (between variation). The apparent discrepancy between them—the quadratic term is mostly insignificant in the panel specification, whereas the early cross-sections show a relatively clear inverted U—is not a contradiction but reflects the separation of two kinds of information: differences in development stage across cities, and each city’s own evolution over time. The cross-sectional inverted U arises mainly from the gradient of development stages across cities and weakens as within-agglomeration gaps converge; the monotonically positive net effect in the panel captures the marginal effect of income on a city’s own emissions

once structural factors are removed. For clarity, we confine the cross-sectional results to characterizing “cross-city differences” and the panel results to characterizing “within-city temporal change,” treating the two as cross-validating rather than substituting for each other. This distinction in definition does not alter the main conclusions in Section 5.

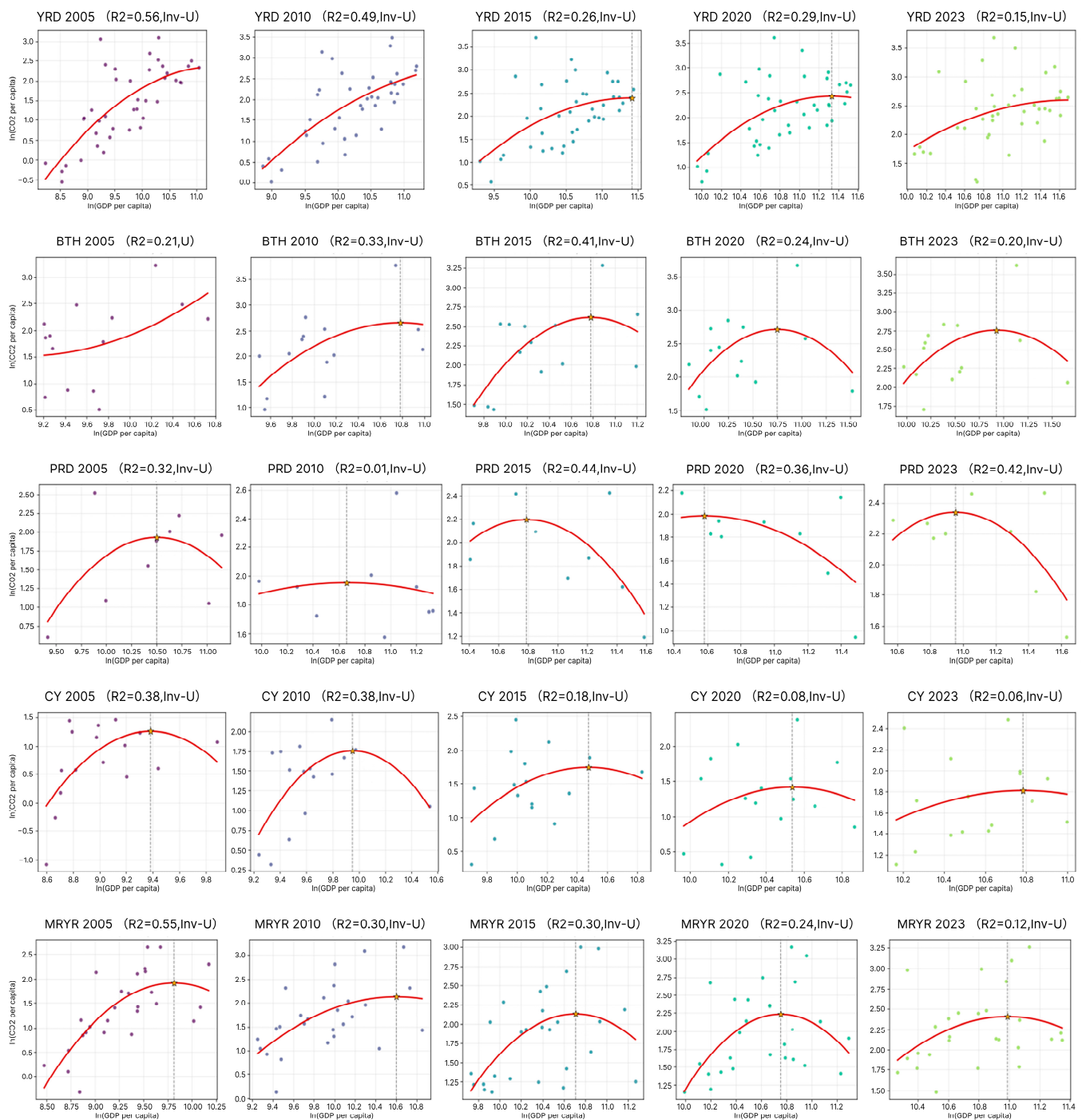


Figure 10. Cross-sectional log-quadratic EKC fits for the five urban agglomerations. Notes: The vertical axis is ln per capita carbon emissions and the horizontal axis is ln per capita GDP. Each dot represents the ln per capita GDP and ln per capita carbon emissions of a prefecture-level city in a given year; the red line denotes the cross-sectional log-quadratic EKC fit for each agglomeration in that year; and the dashed line indicates the estimated turning point.

In sum, across Sections 3.7.1 and 3.7.2, database error, the limited cross-sectional fit, and the joint use of different EKC definitions mainly affect the precision of the estimates

and the boundaries of their expression. We have controlled for these through a unified accounting scope, two-way fixed effects, multi-method cross-validation, and the repositioning of indicators; these factors do not affect the direction or the substance of this study's core conclusions.

4. Discussion

4.1. Main Findings

First, the classical EKC holds broadly across the five agglomerations, but turning points are stratified. Ranked by turning-point per capita GDP from low to high, the order is CY, PRD, BTH, MRYR, and YRD, reflecting differences in industrial structure, energy mix, and developmental stage.

Second, the net effect of income itself is predominantly monotonically positive, and the inverted U-shape is carried by structural mechanisms. After two-way fixed effects and control variables are introduced, the quadratic term loses significance in most samples; only the PRD and BTH retain a significant nonlinear form. Stepwise inclusion of controls shows that the shrinkage of β_2 occurs after adding the secondary-industry share, and the sign reversal occurs after adding carbon emissions per unit of GDP. The observed mitigation patterns are therefore carried mainly by industrial restructuring and energy-efficiency improvement, not by an autonomous effect of income growth.

Third, Tapio decoupling follows a non-monotonic trajectory of steady improvement followed by partial reversal. The period 2010–2015 saw a concentrated emergence of strong-decoupling cities, aligning with the binding-target window of national energy-saving and emission-reduction policies. During 2020–2023, all five agglomerations experienced an expansive-negative-decoupling rebound: the PRD exited decoupling entirely, while 81% of CY cities, 63% of MRYR cities, 51% of YRD cities, and 43% of BTH cities moved into expansive negative decoupling or expansive coupling, suggesting that mitigation gains achieved through low-cost pathways are stage-dependent.

Fourth, the spatial structure of emissions exhibits a “coastal-transformation, inland-stability” regional pattern. The YRD shows persistent high–high clustering and clear spatial lock-in; local spatial autocorrelation in the BTH weakens markedly from 2020 onward, reflecting urban emission convergence driven by collaborative governance; the PRD shows weak and unstable spatial clustering; the CY is dominated by Chengdu as a single pole; and the MRYR forms a pattern with Wuhan as an implicit core and southeastern Hubei as a low-value satellite belt.

4.2. Mechanisms

The “industry–efficiency” dual mediation of the EKC. The shrinkage and ultimate sign reversal of β_2 following the sequential inclusion of the secondary-industry share and carbon emissions per unit of GDP is consistent with the literature view that the EKC is driven jointly by structural and technical effects. Once the model controls for the secondary-industry share, the portion previously read as a “nonlinear effect of income” is absorbed into a “linear effect of structural change”; adding carbon emissions per unit of GDP then reverses the sign of the quadratic term, implying that energy-efficiency improvement is the deeper mechanism carrying the descending branch of the inverted U.

A dual cyclical and structural explanation for the decoupling reversal. The rebound into expansive negative decoupling over 2020–2023 can be understood along two dimensions. Cyclically, investment-driven growth following the pandemic shock produced a temporary expansion in infrastructure and energy-intensive manufacturing, so the short-term rebound in carbon emissions has the character of demand recovery. Structurally, the low-cost abatement achieved earlier through such measures as phasing out obsolete

capacity and promoting energy-saving technologies has narrowed, and further reductions must rely on a deeper transformation of the energy structure—renewable energy substitution, power-system retrofitting, and industrial-process decarbonization, whose marginal costs are markedly higher than those of earlier mitigation measures. Notably, the reversal is unevenly distributed across agglomerations: the Pearl River Delta is at a stage of “fading mitigation dividends and a new round of rising investment-driven emissions”; Chengdu–Chongqing is linked to the recent relocation of manufacturing and the reception of energy-intensive industries; and Beijing–Tianjin–Hebei shows the smallest reversal, consistent with the region’s relatively early establishment of a joint air-pollution prevention and control mechanism and its continued industrial relief. These judgments—concerning the post-pandemic investment-driven recovery, manufacturing relocation, and deep transformation of the energy structure—are mechanistic, forward-looking interpretations of the empirical results. They lie beyond what this study’s evidence can directly test and should be understood as an extended policy reading of the findings.

Pathways shaping spatial heterogeneity. The YRD’s persistent high–high clustering aligns with its Shanghai-centered, contiguous industrialization along the Suzhou–Wuxi–Changzhou–Nantong–Jiaxing–Huzhou corridor. The weakening of local autocorrelation in the BTH reflects emission convergence under collaborative governance and is a clear case of policy-driven change in spatial structure. The low clustering in the PRD is linked to refined industrial division among cities. The single-pole pattern around Chengdu in the CY and the implicit Wuhan core in the MRYS both reflect a common feature of central- and western-region agglomerations: large developmental gaps between core and peripheral cities and limited spatial linkages between them.

Differences in emission and pollution levels across regions. Beyond differences in shape and mechanism, we need to establish whether the emission levels themselves differ across regions. Descriptive statistics and the baseline results jointly show that the five major agglomerations do differ systematically in emission levels, and that this difference is driven mainly by industrial structure and development stage rather than by economic scale alone. Beijing–Tianjin–Hebei has significantly higher carbon emissions per unit of GDP than the other agglomerations, consistent with its heavy-industry base in steel, energy, and raw materials, and cities such as Tangshan have long sat in the high-carbon Q1 quadrant. In the Yangtze River Delta, the contiguous industrialization spanning Shanghai, Suzhou–Wuxi–Changzhou, and Nantong forms a persistent high–high cluster of high values, with clear spatial lock-in of emission levels. The Pearl River Delta, having completed industrial upgrading earlier and with a higher share of services and high-tech manufacturing, has a relatively lower overall emission intensity. Chengdu–Chongqing and the middle reaches of the Yangtze River consist mainly of developing prefecture-level cities in central and western China; their peripheral cities have generally low emission levels but are still on an upward climb, while internally, they show a concentration of high values around single poles or latent cores in Chengdu and Wuhan. This structural difference in emission levels across regions provides direct grounds for the “agglomeration $\times$ quadrant” differentiated—rather than one-size-fits-all—mitigation pathways developed later.

4.3. Region-Specific Low-Carbon Strategies

Building on the cross-tabulation of EKC quadrants and Tapio decoupling states, we propose differentiated strategies along an agglomeration $\times$ quadrant matrix.

YRD—deepening structural transition. Peripheral cities stable in Q3 should raise energy-efficiency standards and tighten industrial-entry thresholds in parallel with industrialization, avoiding replication of the early coastal high-carbon trajectory. For central Anhui resource-based cities stable in Q2, efficiency improvement alone cannot reverse

the pattern; these cities should be incorporated into a regional framework for industrial relocation and the cultivation of alternative industries. Core cities (Shanghai, Hangzhou, Nanjing, Suzhou) should take the lead in green-technology diffusion and standard setting within the agglomeration.

BTH—deepening collaborative governance. For Beijing and Tianjin, now in Q4, the priority should shift from emissions reduction to consolidation, with particular attention to preventing the expansive-negative-decoupling rebound observed during 2020–2023. For Tangshan, which remains in Q1, the deep decarbonization of the steel industry should be included as a national-level pilot for low-carbon transition in key sectors. For other Hebei cities that have moved from Q1 or Q4 down to Q3, the current low-carbon profile reflects the passive effect of industrial relocation rather than active transformation; its long-term sustainability is uncertain, and these cities will need strict emission thresholds when absorbing industry relocated from Beijing and Tianjin.

PRD—managing the rebound. For Shenzhen, Guangzhou, and Foshan, the expansive-negative-decoupling rebound demonstrates that mitigation gains in early-peaking cities are not irreversible; the next phase should focus on further coal phase-out in the energy mix and the cleaner generation of electricity. For Zhuhai, which remains in Q1, the coexistence of high economic level and high emissions points to a specific industrial-structure issue that calls for a targeted upgrading pathway. For the more volatile cities of Dongguan, Huizhou, Zhongshan, Jiangmen, and Zhaoqing, the Greater Bay Area integration framework should drive industrial repositioning and coordinated emissions management.

CY and MRYR—dual-core leadership with peripheral climbing. For the dual cores of Chongqing, Chengdu, Wuhan, Changsha, and Nanchang, the priority is to address the single-pole mitigation risk reflected in Chengdu's persistent high–low pattern in the spatial autocorrelation analysis, with metropolitan-area integration used to distribute mitigation pressure to surrounding cities. For peripheral cities in Q3, the path to peak emissions should follow a green-industrialization model that skips some high-carbon stages when absorbing relocated industry and moves directly into low- and medium-carbon industries. A few resource-based industrial cities (e.g., Ezhou, Xinyu) will need tailored transition plans.

4.4. Research Limitations and the Boundary of Extended Policy Interpretation

This study has several limitations, and the scope of its conclusions should be treated with corresponding caution. First, the sample covers only five benchmark years—2005, 2010, 2015, 2020, and 2023—so the temporal resolution is coarse. It cannot capture year-to-year fluctuations between benchmark years or the immediate response to short-term policy shocks, and the period-by-period characterization of Tapio decoupling is therefore sensitive to the choice of endpoint years. Second, although spatial spillovers have been characterized through global and local Moran's *I* and the spatial Durbin model, the sample size of individual agglomerations makes it difficult to identify stable spatial clustering within any agglomeration other than the Yangtze River Delta; moreover, the spatial weights use only a row-standardized 0–1 adjacency matrix, without a systematic comparison of alternative weights such as economic or transport distance, so spatial spillovers are not yet fully controlled for. Third, the EKC turning points for some agglomerations (the Yangtze River Delta and Chengdu–Chongqing) fall outside the observed range of per capita GDP and have very wide confidence intervals; these turning points are out-of-sample extrapolations and should not be used to infer a peaking date. Fourth, constrained by the database and the statistical scope, the emission level values carry the uncertainty noted above.

The boundary between the study's conclusions and its policy interpretation warrants particular emphasis. The conclusions directly supported by our evidence are limited to the following: the inverted-U profile of the five agglomerations in long-term shape and

the gradient of their turning points; the predominantly monotonically positive net income effect once structural factors are removed; the non-monotonic “improvement-then-reversal” path of decoupling; and the regional differentiation of spatial structure. By contrast, the statements in this paper concerning “post-pandemic investment-driven recovery fueling an emissions rebound,” “the relocation of manufacturing to inland regions,” “next-stage abatement depending on a deep transformation of the energy structure,” and “rising marginal abatement costs” are mechanistic, forward-looking interpretations of these empirical results. They lie beyond what our evidence can directly test and should be understood as an extended policy reading of the conclusions rather than causal findings rigorously identified from our data. These interpretations are offered as directional references for policymaking; their empirical verification awaits future research using higher-frequency data, longer samples, and targeted identification strategies.

5. Conclusions

Drawing on 107 prefecture-level cities across five Chinese urban agglomerations over 2005–2023, this study combined a two-way fixed-effects EKC model, the Tapio decoupling model, and cross-sectional quadrant analysis to identify the form, mechanisms, and spatial structure of the growth–emission relationship.

In terms of functional form, all five agglomerations trace an inverted U under the log-quadratic specification, but this shape is not an autonomous income effect. Once two-way fixed effects and structural controls are introduced, the quadratic term loses significance in most samples—only the PRD (inverted-U) and BTH (U-shaped) retain a significant nonlinear form—so the long-run relationship is predominantly monotonically positive at the net-income level. The stepwise decomposition confirms a dual mediation: β_2 contracts after the secondary-industry share enters and reverses sign after carbon intensity is added, indicating that the observed inverted U is carried by industrial restructuring and energy-efficiency improvement.

In terms of dynamics, Tapio decoupling follows a non-monotonic path of steady improvement followed by partial reversal. The concentrated emergence of strong decoupling during 2010–2015 coincides with the binding-target window of national energy-saving policy, whereas the widespread return to expansive negative decoupling during 2020–2023 suggests that low-cost mitigation options have been largely exhausted and that further decoupling will hinge on deeper transformation of the energy mix.

In terms of spatial structure, the agglomerations diverge sharply. The YRD is the only one with persistent high–high clustering and clear spatial lock-in; the BTH is highly mobile, with large-scale movement from the high-carbon quadrant toward low-income, low-emission positions under collaborative governance; the PRD is dominated by high-income, low-emission cities yet shows the most pronounced recent rebound; and the CY and MRYR display a “dual-core leadership with peripheral climbing” gradient anchored on Chengdu and Wuhan. On this basis, we propose low-carbon strategies differentiated along an agglomeration $\times$ quadrant matrix: the YRD should deepen structural transition while guarding against path lock-in in resource-based cities; the BTH should advance deep decarbonization of heavy-industry cities within its joint-governance framework; the PRD should manage the decoupling rebound in its core cities through energy-mix cleanup; and the CY and MRYR should use green industrialization to help peripheral cities bypass high-carbon stages while distributing single-core mitigation pressure across their metropolitan areas.

Overall, decoupling in these agglomerations is not a self-executing consequence of income growth but a stage-dependent outcome shaped jointly by industrial restructuring, efficiency gains, and external shocks; the 2020–2023 reversal signals that the road

to peak emissions will continue to face external shocks and rising marginal abatement costs, making region-specific strategies and collaborative governance a practical necessity. These conclusions are bounded by a coarse five-benchmark-year resolution and by turning-point estimates that fall outside the observed income range for the YRD and CY. Future work using higher-frequency and longer panels, together with stronger identification (e.g., credible instruments or quasi-experimental designs), is needed to date the peaks and to test the forward-looking mechanisms—post-pandemic investment rebound, manufacturing relocation, and energy-structure transformation—that the present evidence can only interpret directionally.

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Institutional Review Board Statement: Not applicable.

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Data Availability Statement: The original data presented in the study are openly available in the China City Greenhouse Gas Working Group (CCG) database at <https://lca.cityghg.com/> (for carbon-emissions data), and in the China City Statistical Yearbooks and provincial yearbooks via the China National Knowledge Infrastructure (CNKI) at <https://www.cnki.net/> and the National Bureau of Statistics of China at <https://www.stats.gov.cn/> (for socioeconomic data). Processed datasets and replication code are available from the corresponding author upon reasonable request.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A.1 Study Area

Table A1. Delimitation of the five urban agglomerations.

Agglomeration	Constituent Cities	Count	Source Plan	Date of Release
YRD	Nanjing, Wuxi, Xuzhou, Changzhou, Suzhou, Nantong, Lianyungang, Huai’an, Yancheng, Yangzhou, Zhenjiang, Taizhou (Jiangsu), Suqian, Hefei, Huaibei, Bozhou, Suzhou (Anhui), Bengbu, Fuyang, Huainan, Chuzhou, Lu’an, Ma’anshan, Wuhu, Xuancheng, Tongling, Chizhou, Anqing, Huangshan, Shanghai, Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Quzhou, Zhoushan, Taizhou (Zhejiang), Lishui	41	Yangtze River Delta Urban Agglomeration Development Plan	May 2016
BTH	Beijing, Tianjin, Shijiazhuang, Chengde, Zhangjiakou, Qinhuangdao, Tangshan, Langfang, Baoding, Cangzhou, Hengshui, Xingtai, Handan, Anyang	14	Outline of the Beijing–Tianjin–Hebei Coordinated Development Plan	April 2015

Table A1. *Cont.*

Agglomeration	Constituent Cities	Count	Source Plan	Date of Release
PRD	Guangzhou, Shenzhen, Foshan, Dongguan, Zhongshan, Huizhou, Zhuhai, Jiangmen, Zhaoqing	9	Outline Development Plan for the Guangdong–Hong Kong–Macao Greater Bay Area	February 2019
CY	Chongqing, Chengdu, Zigong, Luzhou, Deyang, Mianyang, Suining, Neijiang, Leshan, Nanchong, Meishan, Yibin, Guang'an, Dazhou, Ya'an, Ziyang	16	Chengdu–Chongqing Urban Agglomeration Development Plan	April 2016
MRYR	Wuhan, Xiangyang, Jingmen, Yichang, Jingzhou, Xiaogan, Ezhou, Huanggang, Huangshi, Xianning, Changsha, Changde, Yueyang, Yiyang, Loudi, Xiangtan, Hengyang, Zhuzhou, Nanchang, Jiujiang, Jingdezhen, Shangrao, Yingtian, Fuzhou (Jiangxi), Pingxiang, Xinyu, Yichun	27	Middle Reaches of the Yangtze River Urban Agglomeration Development Plan	2 April 2015

*Appendix A.2 Descriptive Statistics***Table A2.** Descriptive statistics for the pooled sample.

Variable	N	Mean	SD	Min	Median	Max
ln per capita carbon emissions	535.00	1.8606	0.7507	−1.0878	1.9348	3.7879
ln per capita GDP	535.00	10.3214	0.7023	8.2324	10.3990	11.6877
ln resident population	535.00	6.1240	0.6727	4.2603	6.1298	8.0737
ln population density	535.00	1.8277	0.1153	1.4884	1.8378	2.2077
Secondary-industry share	535.00	45.7333	8.9593	14.9100	46.1200	72.7400
Urbanization rate	535.00	0.5635	0.1772	0.1141	0.5632	1.0000
ln carbon emissions per unit of GDP	535.00	0.4201	0.7329	−1.8070	0.3672	3.0289
Green coverage ratio of built-up areas	535.00	37.4496	7.0495	7.2200	38.2000	54.8000
Fiscal support for science and technology	535.00	0.0256	0.0218	0.0008	0.0199	0.1743
Policy dummy (treat × post)	535.00	0.2972	0.4575	0.0000	0.0000	1.0000
Pilot city (treat)	535.00	0.4673	0.4994	0.0000	0.0000	1.0000
Policy timing (post)	535.00	0.2972	0.4575	0.0000	0.0000	1.0000

Notes: N = 535 (107 cities × 5 periods). The “ln” prefix indicates the natural logarithm; percentage variables retain their original scale.

Table A3. Descriptive statistics for the YRD sub-sample.

Variable	N	Mean	SD	Min	Median	Max
ln per capita carbon emissions	205.00	1.9807	0.8170	−0.5655	2.1251	3.7146
ln per capita GDP	205.00	10.4744	0.7250	8.2324	10.6010	11.6877
ln resident population	205.00	6.0829	0.6708	4.2603	6.1358	7.8193
ln population density	205.00	1.8489	0.1041	1.5702	1.8656	2.1132
Secondary-industry share	205.00	46.3147	8.3731	23.9700	46.3300	72.7400
Urbanization rate	205.00	0.5871	0.1612	0.1219	0.6108	0.8946
ln carbon emissions per unit of GDP	205.00	0.3894	0.6929	−0.9006	0.2729	3.0289
Green coverage ratio of built-up areas	205.00	37.5395	7.0972	7.2200	38.3500	54.8000
Fiscal support for science and technology	205.00	0.0330	0.0240	0.0008	0.0270	0.1743
Policy dummy (treat × post)	205.00	0.2195	0.4149	0.0000	0.0000	1.0000
Pilot city (treat)	205.00	0.4390	0.4975	0.0000	0.0000	1.0000
Policy timing (post)	205.00	0.2195	0.4149	0.0000	0.0000	1.0000

Table A4. Descriptive statistics for the BTH sub-sample.

Variable	N	Mean	SD	Min	Median	Max
ln per capita carbon emissions	70.0000	2.1832	0.6489	0.5126	2.2081	3.7879
ln per capita GDP	70.0000	10.2012	0.5565	9.2050	10.1652	11.6582
ln resident population	70.0000	6.5305	0.5357	5.6630	6.5693	7.6913
ln population density	70.0000	1.8188	0.1295	1.4884	1.8465	1.9735

Table A4. *Cont.*

Variable	N	Mean	SD	Min	Median	Max
Secondary-industry share	70.0000	42.5120	10.8879	14.9100	44.6400	61.5200
Urbanization rate	70.0000	0.5271	0.1858	0.1690	0.5409	0.8783
ln carbon emissions per unit of GDP	70.0000	0.8632	0.6571	−1.0051	0.8949	2.2049
Green coverage ratio of built-up areas	70.0000	37.8534	6.1620	21.0400	38.4900	49.8000
Fiscal support for science and technology	70.0000	0.0158	0.0146	0.0030	0.0116	0.0658
Policy dummy (treat × post)	70.0000	0.2429	0.4319	0.0000	0.0000	1.0000
Pilot city (treat)	70.0000	0.3571	0.4826	0.0000	0.0000	1.0000
Policy timing (post)	70.0000	0.2429	0.4319	0.0000	0.0000	1.0000

Table A5. Descriptive statistics for the PRD sub-sample.

Variable	N	Mean	SD	Min	Median	Max
ln per capita carbon emissions	45.0000	1.8887	0.4318	0.6062	1.9243	2.5854
ln per capita GDP	45.0000	10.8623	0.4947	9.4186	10.8915	11.6327
ln resident population	45.0000	6.3809	0.6633	4.9528	6.3107	7.5405
ln population density	45.0000	1.9624	0.1462	1.7068	1.9904	2.2077
Secondary-industry share	45.0000	48.3662	9.6713	25.1700	50.5600	62.6800
Urbanization rate	45.0000	0.7951	0.1701	0.3899	0.8696	1.0000
ln carbon emissions per unit of GDP	45.0000	−0.0412	0.6823	−1.8070	0.0157	1.8589
Green coverage ratio of built-up areas	45.0000	38.4472	7.3509	10.6000	39.2100	54.5000
Fiscal support for science and technology	45.0000	0.0469	0.0236	0.0122	0.0407	0.1013
Policy dummy (treat × post)	45.0000	0.8000	0.4045	0.0000	1.0000	1.0000
Pilot city (treat)	45.0000	1.0000	0.0000	1.0000	1.0000	1.0000
Policy timing (post)	45.0000	0.8000	0.4045	0.0000	1.0000	1.0000

Table A6. Descriptive statistics for the CY sub-sample.

Variable	N	Mean	SD	Min	Median	Max
ln per capita carbon emissions	80.0000	1.3106	0.6339	−1.0878	1.4212	2.4877
ln per capita GDP	80.0000	9.9407	0.6321	8.5958	10.0527	10.9977
ln resident population	80.0000	6.0780	0.7156	4.9621	5.8832	8.0737
ln population density	80.0000	1.7879	0.0955	1.5159	1.7929	1.9890
Secondary-industry share	80.0000	45.1121	9.3746	28.3400	45.4250	60.7800
Urbanization rate	80.0000	0.4621	0.1246	0.1980	0.4576	0.8050
ln carbon emissions per unit of GDP	80.0000	0.2246	0.7306	−1.2837	0.2661	1.8841
Green coverage ratio of built-up areas	80.0000	34.2458	7.3002	14.2900	35.4600	47.6890
Fiscal support for science and technology	80.0000	0.0110	0.0096	0.0020	0.0088	0.0583
Policy dummy (treat × post)	80.0000	0.0750	0.2651	0.0000	0.0000	1.0000
Pilot city (treat)	80.0000	0.1250	0.3328	0.0000	0.0000	1.0000
Policy timing (post)	80.0000	0.0750	0.2651	0.0000	0.0000	1.0000

Table A7. Descriptive statistics for the MRYR sub-sample.

Variable	N	Mean	SD	Min	Median	Max
ln per capita carbon emissions	135.00	1.8276	0.6755	−0.3088	1.8483	3.2625
ln per capita GDP	135.00	10.1966	0.6678	8.4762	10.2974	11.3474
ln resident population	135.00	5.9171	0.6074	4.6444	6.0225	7.2280
ln population density	135.00	1.7789	0.0726	1.6510	1.7672	1.9991
Secondary-industry share	135.00	46.0110	7.8105	28.5600	45.5300	63.9000
Urbanization rate	135.00	0.5292	0.1491	0.1141	0.5440	0.8479
ln carbon emissions per unit of GDP	135.00	0.5065	0.7170	−1.0831	0.4406	2.4092
Green coverage ratio of built-up areas	135.00	38.6697	6.6773	14.2500	38.8900	53.9660
Fiscal support for science and technology	135.00	0.0213	0.0154	0.0023	0.0178	0.0822
Policy dummy (treat × post)	135.00	0.4074	0.4932	0.0000	0.0000	1.0000

Table A7. Cont.

Variable	N	Mean	SD	Min	Median	Max
Pilot city (treat)	135.00	0.5926	0.4932	0.0000	1.0000	1.0000
Policy timing (post)	135.00	0.4074	0.4932	0.0000	0.0000	1.0000

Appendix A.3 Collinearity and Multicollinearity Diagnostics

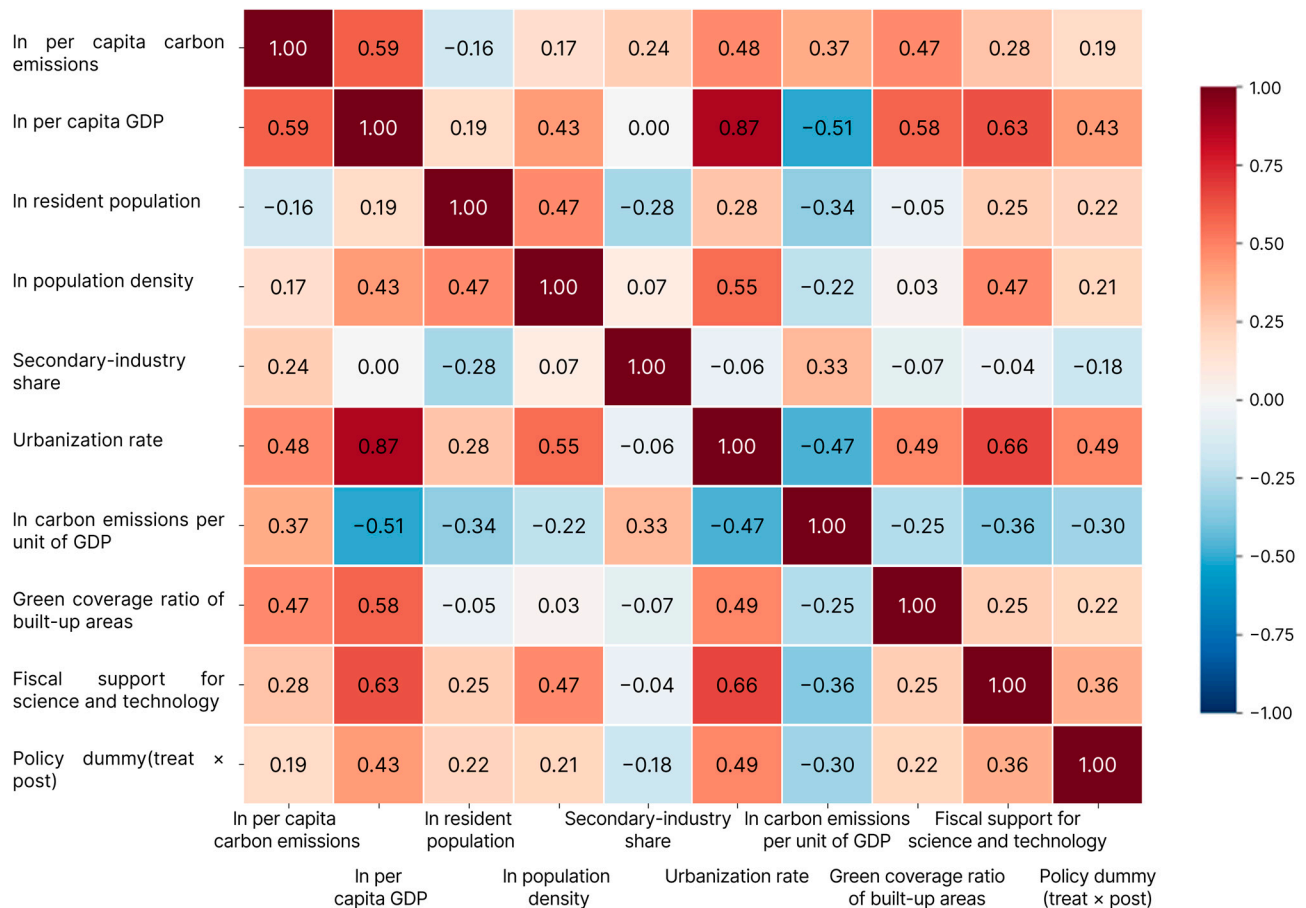


Figure A1. Correlation-coefficient heat map.

Table A8. Variance inflation factor (VIF) diagnostics.

Variable	VIF	1/VIF	Assessment
ln per capita GDP	5.7560	0.1740	Acceptable
ln resident population	1.5760	0.6340	Acceptable
ln population density	2.0590	0.4860	Acceptable
Secondary-industry share	1.3410	0.7460	Acceptable
Urbanization rate	5.8610	0.1710	Acceptable
ln carbon emissions per unit of GDP	1.6690	0.5990	Acceptable
Green coverage ratio of built-up areas	1.7260	0.5790	Acceptable
Fiscal support for science and technology	1.9140	0.5230	Acceptable
Policy dummy (treat × post)	1.3850	0.7220	Acceptable

Appendix A.4 Model Selection Tests

Table A9. Model selection: F-test, LM test, and Hausman test.

Sample	F-Test (FE vs. Pooled)		LM Test (RE vs. Pooled)		Hausman (FE vs. RE)		Preferred Model
	F-Stat	p-Value	LM-Stat	p-Value	H-Stat	p-Value	
Pooled	12.187	0.0000 ***	73.946	0.0000 ***	13,939.351	0.0000 ***	FE
YRD	9.210	0.0000 ***	20.879	0.0000 ***	59.269	0.0000 ***	FE
MRYR	12.898	0.0000 ***	38.252	0.0000 ***	37.708	0.0000 ***	FE
CY	28.333	0.0000 ***	19.006	0.0000 ***	60.341	0.0000 ***	FE
BTH	18.077	0.0000 ***	11.204	0.0008 ***	98.098	0.0000 ***	FE
PRD	3.150	0.0119 **	1.813	0.1781	55.331	0.0000 ***	FE

Notes: *** $p < 0.01$, ** $p < 0.05$. All three tests jointly support a two-way fixed-effects model.

Appendix A.5 Heteroskedasticity and Serial Correlation Diagnostics

Table A10. Modified Wald test for groupwise heteroskedasticity and Wooldridge test for first-order serial correlation.

Sample	Modified Wald			Wooldridge		
	W-Stat	p-Value	Conclusion	F-Stat	p-Value	Conclusion
Pooled	27,626.18	0.0000 ***	Heteroskedasticity present	32.858	0.0000 ***	Serial correlation present
YRD	27,544.25	0.0000 ***	Heteroskedasticity present	14.508	0.0005 ***	Serial correlation present
MRYR	225.46	0.0000 ***	Heteroskedasticity present	16.367	0.0004 ***	Serial correlation present
CY	170.64	0.0000 ***	Heteroskedasticity present	4.908	0.0426 **	Serial correlation present
BTH	5677.87	0.0000 ***	Heteroskedasticity present	17.052	0.0012 ***	Serial correlation present
PRD	68.55	0.0000 ***	Heteroskedasticity present	12.090	0.0084 ***	Serial correlation present

Notes: *** $p < 0.01$, ** $p < 0.05$.

Appendix A.6 Stationarity Tests

Table A11. LLC unit-root tests for key variables.

Sample	Variable	Adjusted t-Statistic	p-Value	Conclusion
Pooled	ln per capita carbon emissions	−15.448	0.0000 ***	Stationary
	ln per capita GDP	−28.149	0.0000 ***	Stationary
	Urbanization rate	−18.697	0.0000 ***	Stationary
YRD	ln per capita carbon emissions	−9.546	0.0000 ***	Stationary
	ln per capita GDP	−18.460	0.0000 ***	Stationary
	Urbanization rate	−14.728	0.0000 ***	Stationary
MRYR	ln per capita carbon emissions	−6.816	0.0000 ***	Stationary
	ln per capita GDP	−15.183	0.0000 ***	Stationary
	Urbanization rate	−10.469	0.0000 ***	Stationary
CY	ln per capita carbon emissions	−13.097	0.0000 ***	Stationary
	ln per capita GDP	−12.384	0.0000 ***	Stationary
	Urbanization rate	−4.537	0.0000 ***	Stationary

Table A11. Cont.

Sample	Variable	Adjusted t-Statistic	p-Value	Conclusion
BTH	ln per capita carbon emissions	−6.508	0.0000 ***	Stationary
	ln per capita GDP	−9.527	0.0000 ***	Stationary
	Urbanization rate	−7.500	0.0000 ***	Stationary
PRD	ln per capita carbon emissions	−9.709	0.0000 ***	Stationary
	ln per capita GDP	−6.914	0.0000 ***	Stationary
	Urbanization rate	−5.762	0.0000 ***	Stationary

Notes: *** $p < 0.01$.

Appendix A.7 Parallel Trends Test

Table A12. Parallel-trends test for the DID identification assumption.

Sample	Treat $\times$ Year Coefficient	Approx. SE	p-Value	N	Conclusion
Pooled	−0.00107	—	0.6624	376	Parallel trends supported
YRD	0.00046	—	0.8844	160	Parallel trends supported
MRYR	−0.00230	—	0.2360	80	Parallel trends supported
CY	−0.01828 ***	—	0.0001	74	Parallel trends violated (interpret DID with caution)
BTH	0.00279 *	—	0.0571	53	Marginally supported at the 10% level
PRD	—	—	—	9	Insufficient sample (test infeasible)

Notes: *** $p < 0.01$, * $p < 0.1$.

Appendix A.8 Endogeneity Treatment

Table A13. Endogeneity diagnostics for the core regressor (ln per capita real GDP).

Sample	Baseline FE			Lagged FE			IV-2SLS			IV Diagnostics		
	ln_GDP	Policy	N	ln_GDP	Policy	N	ln_GDP	Policy	N	WH p-Value	First-Stage F	Partial R ²
Pooled	0.8295 ***	−0.0068	535	0.3443 ***	0.0187	428	1.1599 ***	0.0135	428	0.0000	768.21	0.7626
YRD	0.7565 ***	0.0066	205	0.2557 ***	−0.0233	164	1.1464 ***	0.0317 *	164	0.0000	252.12	0.6725
MRYR	0.8733 ***	−0.0188	135	0.2496 **	−0.0558	108	1.1717 ***	−0.0145	108	0.0000	208.42	0.7849
CY	0.9332 ***	0.0017	80	0.1302	−0.4707 ***	64	1.2039 ***	0.1800	64	0.2904	202.43	0.8005
BTH	0.9895 ***	−0.0079	70	0.0539	0.0750	56	1.1078 ***	−0.0435	56	0.0008	136.85	0.8015
PRD	—	—	—	−0.0057	2.7310	36	2.2948 *	−26.6291 *	36	0.0097	2.08	0.0710

Notes: WH = Wu–Hausman test. The PRD first-stage F of 2.08 indicates a weak instrument; only the FE results are interpreted for this sub-sample. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix A.9 Modeling Decision Summary

Table A14. Final modeling specification by sample.

Sample	Model	Standard Errors	DID Credibility	Endogeneity Treatment	Overall Recommendation
Pooled	Two-way FE	City-clustered robust SE	Parallel trends supported	IV-2SLS (WH $p = 0.000$, $F = 768$)	Main regression with IV robustness check
YRD	Two-way FE	City-clustered robust SE	Parallel trends supported	IV-2SLS (WH $p = 0.000$, $F = 252$)	Main regression with IV robustness check
MRYR	Two-way FE	City-clustered robust SE	Parallel trends supported	IV-2SLS (WH $p = 0.000$, $F = 208$)	Main regression with IV robustness check
CY	Two-way FE	City-clustered robust SE	Parallel trends not satisfied	FE sufficient (WH $p = 0.29$)	Interpret DID coefficient with caution
BTH	Two-way FE	City-clustered robust SE	Marginally supported ($p = 0.06$)	IV-2SLS (WH $p = 0.001$, $F = 137$)	Supplement with event-study plot
PRD	Two-way FE	City-clustered robust SE	Insufficient sample to test	Weak IV ($F = 2.08$); IV not used	Report FE results only

Appendix A.10 Stepwise Decomposition of the EKC

Table A15. Panel EKC regressions with stepwise inclusion of control variables.

Sample	Specification	N	ln GDP per Capita	(ln GDP per Capita) ²	R ² (Within)	Linear-Term Change	Quadratic-Term Change
Pooled	(1) Core EKC terms only	535	4.0153 *** (0.7398)	−0.1774 *** (0.0383)	0.571		
	(2) + Population and urbanization	535	3.9073 *** (0.9072)	−0.1737 *** (0.0447)	0.592		
	(3) + Secondary-industry share	535	1.3474 *** (0.3288)	−0.0596 *** (0.0196)	0.247	From 4.015 to −0.012	From −0.177 to 0.039
	(4) + Energy efficiency	535	−0.0293 (0.0940)	0.0405 *** (0.0052)	0.324		
	(5) + Other controls and policy	535	−0.0120 (0.0846)	0.0390 *** (0.0046)	0.326		
YED	(1) Core EKC terms only	205	3.8751 *** (0.9520)	−0.1586 *** (0.0490)	0.708		
	(2) + Population and urbanization	205	3.9238 *** (1.0545)	−0.1638 *** (0.0541)	0.719		
	(3) + Secondary-industry share	205	0.7758 * (0.3989)	−0.0227 (0.0230)	0.406	From 3.875 to −0.013	From −0.159 to 0.036
	(4) + Energy efficiency	205	−0.1097 (0.1468)	0.0422 *** (0.0085)	0.318		
	(5) + Other controls and policy	205	−0.0132 (0.1053)	0.0361 *** (0.0062)	0.309		
MRYR	(1) Core EKC terms only	135	5.9136 *** (1.4406)	−0.2766 *** (0.0730)	0.582		
	(2) + Population and urbanization	135	6.9185 *** (1.9812)	−0.3189 *** (0.0990)	0.612		
	(3) + Secondary-industry share	135	3.5756 * (1.8908)	−0.1762 * (0.0991)	0.204	From 5.914 to 0.282	From −0.277 to 0.025
	(4) + Energy efficiency	135	0.3794 ** (0.1495)	0.0206 ** (0.0085)	0.284		
	(5) + Other controls and policy	135	0.2821 * (0.1642)	0.0252 *** (0.0094)	0.271		
CY	(1) Core EKC terms only	80	4.5260 ** (2.0602)	−0.1951 * (0.1048)	0.504		
	(2) + Population and urbanization	80	4.9156 (3.4474)	−0.2154 (0.1660)	0.503		
	(3) + Secondary-industry share	80	1.4379 (1.0277)	−0.0607 (0.0597)	0.502	From 4.526 to 0.662	From −0.195 to 0.013
	(4) + Energy efficiency	80	0.6998 *** (0.1997)	0.0106 (0.0128)	0.626		
	(5) + Other controls and policy	80	0.6624 *** (0.1786)	0.0127 (0.0113)	0.654		
BTH	(1) Core EKC terms only	70	7.1046 ** (2.7409)	−0.3105 ** (0.1335)	0.566		
	(2) + Population and urbanization	70	6.6379 * (3.3746)	−0.2884 * (0.1561)	0.549		
	(3) + Secondary-industry share	70	1.1662 (1.6509)	−0.0297 (0.0911)	0.540	From 7.105 to −0.515	From −0.311 to 0.073
	(4) + Energy efficiency	70	−0.4768 *** (0.1488)	0.0713 *** (0.0073)	0.638		
	(5) + Other controls and policy	70	−0.5152 ** (0.2041)	0.0730 *** (0.0096)	0.625		
PRD	(1) Core EKC terms only	45	12.4352 ** (4.7053)	−0.5766 ** (0.2197)	0.297		
	(2) + Population and urbanization	45	16.3053 ** (7.1245)	−0.7543 ** (0.3248)	0.224		
	(3) + Secondary-industry share	45	3.1018 (5.1875)	−0.1507 (0.2423)	−0.031	From 12.435 to 1.947	From −0.577 to −0.057
	(4) + Energy efficiency	45	−0.3481 (0.7386)	0.0488 (0.0369)	−0.283		
	(5) + Other controls and policy	45	1.9471 *** (0.5351)	−0.0570 ** (0.0254)	n/a		

Notes: City-clustered robust standard errors in parentheses. “Energy efficiency” denotes ln carbon emissions per unit of GDP. “Other controls” includes the green coverage ratio of built-up areas and fiscal support for science and technology. All specifications include two-way city and year fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix A.11 Robustness Checks

Appendix A.11.1 Residual Diagnostics for the Baseline Model

Table A16. Residual diagnostics after including the EKC quadratic term and all controls.

Sample	Modified Wald	<i>p</i> -Value	Heteroskedasticity	Wooldridge F	<i>p</i> -Value	Serial Correlation
Pooled	43,707.98	0.0000	Present	0.067	0.7969	Absent
YRD	4788.99	0.0000	Present	8.814	0.0050	Present
MRYR	1471.92	0.0000	Present	1.001	0.3262	Absent
CY	9393.65	0.0000	Present	0.516	0.4837	Absent
BTH	2787.80	0.0000	Present	2.250	0.1575	Absent
PRD	226.97	0.0000	Present	0.640	0.4467	Absent

Notes: After the EKC quadratic term and the full set of controls are included, serial correlation is largely absorbed in most sub-samples, but groupwise heteroskedasticity remains pervasive.

Appendix A.11.2 Comparison of Standard-Error Estimators

Table A17. Comparison of ordinary, heteroskedasticity-robust, and city-clustered standard errors.

Sample	Linear Term: Ordinary SE	Linear Term: HC Robust SE	Linear Term: City-Clustered SE	Quadratic Term: Ordinary SE	Quadratic Term: HC Robust SE	Quadratic Term: City-Clustered SE
Pooled	0.8063 *** (0.117)	0.8063 *** (0.118)	0.8063 *** (0.160)	0.001 (0.006)	0.001 (0.006)	0.001 (0.008)
YRD	0.5860 *** (0.168)	0.5860 *** (0.152)	0.5860 *** (0.181)	0.009 (0.008)	0.009 (0.007)	0.009 (0.008)
MRYR	0.9930 *** (0.175)	0.9930 *** (0.188)	0.9930 *** (0.238)	−0.006 (0.008)	−0.006 (0.010)	−0.006 (0.012)
CY	0.8503 *** (0.313)	0.8503 *** (0.221)	0.8503 *** (0.281)	0.004 (0.015)	0.004 (0.012)	0.004 (0.015)
BTH	0.398 (0.337)	0.398 (0.258)	0.398 (0.302)	0.029 * (0.017)	0.029 ** (0.013)	0.029 ** (0.014)
PRD	1.947 ** (0.880)	1.947 *** (0.676)	1.947 *** (0.535)	−0.057 (0.041)	−0.057 * (0.032)	−0.057 ** (0.025)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix A.11.3 Spatial Autocorrelation

Table A18. Global Moran's I for total carbon emissions by agglomeration and year.

Agglomeration	Year	Moran's I	Expected I	Variance	z-Score	<i>p</i> -Value
YRD	2005	0.197392	−0.025	0.005636	2.962326	0.003053
	2010	0.245858	−0.025	0.007102	3.214139	0.001308
	2015	0.160507	−0.025	0.006771	2.254494	0.024165
	2020	0.211111	−0.025	0.007492	2.727897	0.006374
	2023	0.218177	−0.025	0.007725	2.766734	0.005662
BTH	2005	−0.154342	−0.076923	0.03558	−0.410436	0.681486
	2010	−0.064246	−0.076923	0.025006	0.080165	0.936106
	2015	−0.128432	−0.076923	0.036637	−0.269106	0.787848
	2020	−0.056802	−0.076923	0.025802	0.125267	0.900312
	2023	−0.09954	−0.076923	0.029652	−0.131344	0.895503
PRD	2005	−0.264646	−0.125	0.056757	−0.586166	0.557764
	2010	0.038176	−0.125	0.062715	0.651588	0.514667
	2015	0.294443	−0.125	0.061923	1.685573	0.091878
	2020	0.209916	−0.125	0.057539	1.396228	0.162646
	2023	0.162848	−0.125	0.061274	1.162852	0.24489
CY	2005	−0.147001	−0.066667	0.006407	−1.003637	0.315554
	2010	−0.093467	−0.066667	0.003401	−0.459587	0.645813
	2015	−0.125345	−0.066667	0.008018	−0.655289	0.512282
	2020	−0.112467	−0.066667	0.003898	−0.733562	0.463216
	2023	−0.112467	−0.066667	0.003898	−0.733562	0.463216
MRYR	2005	−0.010865	−0.038462	0.008174	0.305238	0.760185
	2010	0.037616	−0.038462	0.009047	0.799831	0.423809
	2015	−0.129405	−0.038462	0.009202	−0.948072	0.343093
	2020	−0.100864	−0.038462	0.013608	−0.534949	0.592685
	2023	−0.085701	−0.038462	0.013088	−0.412915	0.679669

Table A19. Local Moran's I cluster membership for total carbon emissions.

Agglomeration	Year	High–High Cluster	High–Low Cluster	Low–High Cluster	Low–Low Cluster
YRD	2005	Shanghai, Jiaxing, Suzhou	—	Nantong	Huainan, Anqing, Chizhou
	2010	Shanghai, Nantong, Suzhou	Huainan	Huzhou, Jiaxing	Huai'an, Anqing
	2015	Shanghai, Nantong, Suzhou	Huainan	Jiaxing	—
	2020	Shanghai, Suzhou	Huainan	Nantong, Jiaxing	Bengbu
	2023	Shanghai, Nantong, Suzhou	—	Jiaxing	Bengbu, Chizhou
BTH	2005	—	—	Zhongshan	—
	2010	—	—	Huizhou	—
	2015	Dongguan, Huizhou	—	Shenzhen	—
	2020	—	—	Huizhou	Zhuhai
	2023	—	—	Huizhou	—
PRD	2005	—	—	Chengde	—
	2010	—	—	Chengde	—
	2015	—	Shijiazhuang	Chengde	—
	2020	—	—	—	—
	2023	—	—	—	—
CY	2005	—	—	—	Mianyang
	2010	—	Chengdu	—	—
	2015	—	Chengdu	—	—
	2020	—	Chengdu	—	Mianyang
	2023	—	Chengdu	—	—
MRYR	2005	—	—	Ezhou	Yingtian, Shangrao, Fuzhou (Jiangxi)
	2010	—	—	Huanggang, Ezhou	Shangrao, Yingtian
	2015	—	—	Xianning	—
	2020	—	—	Huanggang, Xianning, Ezhou	—
	2023	—	—	Xianning, Ezhou	—

Table A20. Baseline and spatial panel model estimation results (two-way fixed effects).

Variable	Pooled OLS	Two-Way FE	SAR	SEM	SDM
ln per capita GDP	0.5752 *** (0.0585)	0.2855 *** (0.0866)	0.2458 *** (0.0760)	0.3074 *** (0.0830)	0.3098 *** (0.0959)
Share of secondary industry	2.1284 *** (0.2807)	1.3447 *** (0.2945)	1.3898 *** (0.2565)	1.6105 *** (0.2858)	1.8847 *** (0.3090)
ln population density	−0.3452 (0.2539)	−2.8043 *** (0.8919)	−2.3846 *** (0.7837)	−2.3591 *** (0.7827)	−2.5991 *** (0.8140)
Fiscal support for science and technology	−2.2911 (1.5291)	0.5288 (1.0617)	0.1743 (0.9282)	0.4189 (0.9689)	0.3173 (1.0092)
Green-space ratio of built-up area	2.0820 *** (0.4487)	1.4337 *** (0.3217)	1.4568 *** (0.2799)	1.3826 *** (0.2772)	1.3046 *** (0.2817)
Carbon-trading pilot	−0.0012 (0.0608)	−0.0132 (0.0466)	−0.0058 (0.0406)	−0.0153 (0.0412)	−0.0090 (0.0415)
W × ln per capita GDP					−0.2453 * (0.1289)
W × share of secondary industry					−1.4009 *** (0.4210)
W × ln population density					−2.3325 (1.5461)
W × fiscal support for science and technology					0.3309 (1.4686)
W × green-space ratio of built-up area					0.1165 (0.4854)
W × carbon-trading pilot					0.0490 (0.0679)
ρ (spatial lag coefficient)			0.1880 *** (0.0498)		0.2316 *** (0.0531)
λ (spatial error coefficient)				0.2690 *** (0.0528)	
Log-likelihood			39.49	44.51	51.1
City/year fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors in parentheses; *** $p < 0.01$, * $p < 0.1$. LR tests: SDM vs. SAR $\chi^2(6) = 23.22$ ($p = 0.0007$); SDM vs. SEM $\chi^2(6) = 13.18$ ($p = 0.040$). Both reject simplification, so the SDM is selected.

Table A21. Direct, indirect (spillover), and total effects of the spatial Durbin model (SDM).

Variable	Direct Effect	Indirect Effect	Total Effect
ln per capita GDP	0.2991 *** (0.0948)	−0.2152 (0.1489)	0.0839 (0.1536)
Share of secondary industry	1.8253 *** (0.3024)	−1.1957 ** (0.4845)	0.6296 (0.4687)
ln population density	−2.7799 *** (0.8034)	−3.6379 ** (1.8492)	−6.4178 *** (2.0711)
Fiscal support for science and technology	0.3422 (1.0119)	0.5013 (1.7664)	0.8435 (1.8829)
Green-space ratio of built-up area	1.3304 *** (0.2849)	0.5189 (0.5862)	1.8493 *** (0.6821)
Carbon-trading pilot	−0.0061 (0.0409)	0.0582 (0.0842)	0.0521 (0.0919)

Notes: Standard errors computed from 2000 parameter simulations; *** $p < 0.01$, ** $p < 0.05$.

Appendix A.11.4 Functional-Form Comparison

Table A22. Comparison of linear, quadratic, and cubic functional forms.

Sample	Specification	R ² (Within)	AIC	BIC	Preferred
Pooled	Linear	0.4636	−1739.16	−1221.01	★
	Quadratic	0.4625	−1737.21	−1214.78	
	Cubic	0.4692	−1736.43	−1209.71	
YED	Linear	0.4124	−671.58	−488.81	★
	Quadratic	0.4139	−671.02	−484.94	
	Cubic	0.4509	−671.10	−481.69	
MRYS	Linear	0.4456	−588.14	−469.03	★
	Quadratic	0.4572	−586.83	−464.81	
	Cubic	0.4589	−584.88	−459.95	
CY	Linear	0.6921	−331.05	−259.59	★
	Quadratic	0.6868	−329.16	−255.32	
	Cubic	0.6955	−329.65	−253.42	
BTH	Linear	0.6292	−294.57	−231.61	
	Quadratic	0.6428	−297.61	−232.40	★ (BIC)
	Cubic	0.6750	−298.77	−231.31	★ (AIC)
PRD	Linear	−0.0339	−159.72	−118.16	
	Quadratic	0.1510	−161.40	−118.04	★
	Cubic	0.1575	−159.65	−114.48	

Notes: ★ marks the specification preferred by AIC and/or BIC. Lower information-criterion values are preferred.

Appendix A.11.5 Influential Observations

Table A23. Identification of influential observations and comparison of coefficients before and after exclusion.

Sample	Original N	Original ln per Capita GDP	Original (ln per Capita GDP) ²	Observations Removed	ln per Capita GDP After Removal	(ln per Capita GDP) ² After Removal
Pooled	535	0.8063	0.0011	10	0.9039	−0.0035
YRD	205	0.5860	0.0086	2	0.6084	0.0083
MRYS	135	0.9930	−0.0058	1	0.8734	0.0011
CY	80	0.8503	0.0040	1	0.8075	0.0083
BTH	70	0.3976	0.0291	1	0.3910	0.0302
PRD	45	1.9471	−0.0570	0	1.9471	−0.0570

Notes: Influential observations are identified using a standardized-residual threshold of $|e| > 3$.

Appendix A.12 Tapio Decoupling Analysis

Table A24. Distribution of decoupling states across agglomerations, 2005–2023 (whole period).

Agglomeration	Strong Decoupling	Weak Decoupling	Expansive Coupling	Expansive Negative Decoupling	Strong Negative Decoupling	Weak Negative Decoupling	Recessive Coupling	Recessive Decoupling
YRD	4	23	5	9	0	0	0	0
BTH	1	7	2	4	0	0	0	0
PRD	2	3	1	3	0	0	0	0
CY	0	14	1	1	0	0	0	0
MRYR	1	24	0	2	0	0	0	0

Table A25. Distribution of decoupling states, 2005–2010.

Agglomeration	Strong Decoupling	Weak Decoupling	Expansive Coupling	Expansive Negative Decoupling	Strong Negative Decoupling	Weak Negative Decoupling	Recessive Coupling	Recessive Decoupling
YRD	3	19	6	13	0	0	0	0
BTH	3	5	1	5	0	0	0	0
PRD	4	0	2	3	0	0	0	0
CY	1	7	3	5	0	0	0	0
MRYR	6	15	2	4	0	0	0	0

Table A26. Distribution of decoupling states, 2010–2015.

Agglomeration	Strong Decoupling	Weak Decoupling	Expansive Coupling	Expansive Negative Decoupling	Strong Negative Decoupling	Weak Negative Decoupling	Recessive Coupling	Recessive Decoupling
YRD	9	17	3	9	0	0	2	1
BTH	6	4	0	4	0	0	0	0
PRD	5	0	1	2	1	0	0	0
CY	7	6	1	2	0	0	0	0
MRYR	13	6	2	6	0	0	0	0

Table A27. Distribution of decoupling states, 2015–2020.

Agglomeration	Strong Decoupling	Weak Decoupling	Expansive Coupling	Expansive Negative Decoupling	Strong Negative Decoupling	Weak Negative Decoupling	Recessive Coupling	Recessive Decoupling
YRD	15	12	6	7	1	0	0	0
BTH	3	1	0	8	0	1	0	1
PRD	3	0	0	1	1	0	2	2
CY	9	6	0	0	0	0	0	1
MRYR	6	10	2	6	3	0	0	0

Table A28. Distribution of decoupling states, 2020–2023.

Agglomeration	Strong Decoupling	Weak Decoupling	Expansive Coupling	Expansive Negative Decoupling	Strong Negative Decoupling	Weak Negative Decoupling	Recessive Coupling	Recessive Decoupling
YRD	9	9	1	21	1	0	0	0
BTH	3	5	1	5	0	0	0	0
PRD	0	0	2	7	0	0	0	0
CY	0	3	2	11	0	0	0	0
MRYR	3	5	2	17	0	0	0	0

Appendix A.13 Cross-Sectional Quadrant Analysis

Table A29. Log-quadratic EKC fits on cross-sectional data, by agglomeration and year.

Agglomeration	Year	β_0 (Constant)	β_1 (Linear)	β_2 (Quadratic)	R ²	Adj. R ²
YRD	2005	−35.449	6.663 *	−0.2936	0.557	0.534
	2010	−30.312	5.434	−0.2229	0.491	0.464
	2015	−37.568	6.999	−0.3065	0.256	0.217
	2020	−85.593	15.533	−0.6853	0.292	0.254
	2023	−38.714	7.061	−0.3017	0.154	0.109
BTH	2005	33.876	−7.188	0.3991	0.214	0.071
	2010	−85.288	16.311	−0.7563	0.332	0.211
	2015	−111.583	21.189	−0.9829	0.408	0.301
	2020	−123.591	23.496	−1.0927	0.237	0.099
	2023	−88.869	16.769	−0.7673	0.197	0.051
PRD	2005	−102.714	19.927	−0.9487	0.316	0.088
	2010	−17.533	3.656	−0.1715	0.01	−0.319
	2015	−145.341	27.349	−1.2674	0.438	0.25
	2020	−76.317	14.796	−0.6990	0.356	0.142
	2023	−146.284	27.137	−1.2387	0.417	0.223
CY	2005	−185.26	39.757 *	−2.1185 *	0.38	0.285
	2010	−203.574	41.267 **	−2.0735 **	0.377	0.281
	2015	−144.036	27.836	−1.3288	0.184	0.059
	2020	−185.438	35.462	−1.6826	0.077	−0.065
	2023	−82.741	15.680	−0.7270	0.056	−0.089
MRYR	2005	−112.796	23.372 **	−1.1905 **	0.547	0.509
	2010	−71.181	13.829	−0.6522	0.3	0.242
	2015	−115.693	22.002 **	−1.0272 *	0.298	0.24
	2020	−209.893	39.446 **	−1.8338 **	0.245	0.182
	2023	−121.517	22.556	−1.0264	0.124	0.051

Notes: Significance levels for β_1 and β_2 : ** $p < 0.05$, * $p < 0.1$.**Table A30.** Apex (turning point) of the cross-sectional EKC fits.

Agglomeration	Year	Apex ln(GDP)	Apex per Capita Real GDP (CNY)	Apex per Capita Emissions (t)	Apex Within Sample?
YRD	2005	11.346	84,618	10.48	No
	2010	12.189	196,534	16.52	No
	2015	11.419	91,053	10.96	Yes
	2020	11.333	83,562	11.34	Yes
	2023	11.701	120,660	13.41	No
BTH	2005	9.005	8141	4.54	No
	2010	10.783	48,213	14.23	Yes
	2015	10.779	47,991	13.62	Yes
	2020	10.751	46,680	15.1	Yes
	2023	10.928	55,703	15.76	Yes
PRD	2005	10.502	36,401	6.86	Yes
	2010	10.66	42,621	7.05	Yes
	2015	10.789	48,503	8.99	Yes
	2020	10.584	39,487	7.26	Yes
	2023	10.954	57,167	10.38	Yes
CY	2005	9.383	11,884	3.52	Yes
	2010	9.951	20,978	5.79	Yes
	2015	10.474	35,385	5.71	Yes
	2020	10.538	37,725	4.11	Yes
	2023	10.785	48,270	6.11	Yes

Table A30. Cont.

Agglomeration	Year	Apex ln(GDP)	Apex per Capita Real GDP (CNY)	Apex per Capita Emissions (t)	Apex Within Sample?
MRYR	2005	9.816	18,327	6.78	Yes
	2010	10.602	40,206	8.36	Yes
	2015	10.71	44,796	8.39	Yes
	2020	10.755	46,869	9.31	Yes
	2023	10.988	59,145	11.06	Yes

Table A31. Distribution of cities across the four EKC quadrants.

Agglomeration	Year	Q1	Q2	Q3	Q4
YRD	2005	0	8	33	0
	2010	0	4	37	0
	2015	1	14	26	0
	2020	4	10	26	1
	2023	0	14	27	0
BTH	2005	10	0	0	4
	2010	0	2	10	2
	2015	2	0	11	1
	2020	1	3	8	2
	2023	1	2	9	2
PRD	2005	3	1	4	1
	2010	2	1	2	4
	2015	1	1	2	5
	2020	1	1	0	7
	2023	2	0	4	3
CY	2005	0	3	11	2
	2010	1	2	12	1
	2015	1	4	10	1
	2020	2	4	7	3
	2023	1	5	8	2
MRYR	2005	1	6	18	2
	2010	2	4	20	1
	2015	3	5	16	3
	2020	3	6	10	8
	2023	2	6	13	6

Appendix A.14 City-Level Quadrant Assignments

Table A32. Quadrant assignment of YRD cities by cross-sectional year.

Agglomeration	City	2005	2010	2015	2020	2023
YRD	Nanjing	Q3	Q3	Q3	Q1	Q2
	Wuxi	Q3	Q3	Q2	Q1	Q2
	Xuzhou	Q3	Q3	Q3	Q3	Q3
	Changzhou	Q2	Q3	Q2	Q1	Q2
	Suzhou	Q2	Q3	Q1	Q1	Q2
	Nantong	Q3	Q3	Q3	Q3	Q3
	Lianyungang	Q3	Q3	Q3	Q3	Q3
	Huai'an	Q3	Q3	Q3	Q3	Q3

Table A32. Cont.

Agglomeration	City	2005	2010	2015	2020	2023
YRD	Yancheng	Q3	Q3	Q3	Q3	Q3
	Yangzhou	Q3	Q3	Q3	Q3	Q3
	Zhenjiang	Q2	Q3	Q2	Q2	Q2
	Taizhou (Jiangsu)	Q3	Q3	Q3	Q3	Q3
	Suqian	Q3	Q3	Q3	Q3	Q3
	Hefei	Q3	Q3	Q3	Q3	Q3
	Huaibei	Q2	Q2	Q2	Q2	Q2
	Bozhou	Q3	Q3	Q3	Q3	Q3
	Suzhou (Anhui)	Q3	Q3	Q3	Q3	Q3
	Bengbu	Q3	Q3	Q3	Q3	Q3
	Fuyang	Q3	Q3	Q3	Q3	Q3
	Huainan	Q2	Q2	Q2	Q2	Q2
	Chuzhou	Q3	Q3	Q3	Q3	Q3
	Lu'an	Q3	Q3	Q3	Q3	Q3
	Ma'anshan	Q2	Q2	Q2	Q2	Q2
	Wuhu	Q3	Q3	Q2	Q2	Q2
	Xuancheng	Q3	Q3	Q3	Q2	Q3
	Tongling	Q2	Q2	Q2	Q2	Q2
	Chizhou	Q3	Q3	Q2	Q2	Q2
	Anqing	Q3	Q3	Q3	Q3	Q3
	Huangshan	Q3	Q3	Q3	Q3	Q3
	Shanghai	Q2	Q3	Q2	Q4	Q3
	Hangzhou	Q3	Q3	Q3	Q3	Q3
	Ningbo	Q3	Q3	Q2	Q3	Q3
	Wenzhou	Q3	Q3	Q3	Q3	Q3
	Jiaxing	Q3	Q3	Q3	Q3	Q3
	Huzhou	Q3	Q3	Q2	Q3	Q2
	Shaoxing	Q3	Q3	Q3	Q3	Q3
	Jinhua	Q3	Q3	Q3	Q3	Q3
	Quzhou	Q3	Q3	Q2	Q2	Q2
	Zhoushan	Q3	Q3	Q2	Q2	Q2
	Taizhou (Zhejiang)	Q3	Q3	Q3	Q3	Q3
	Lishui	Q3	Q3	Q3	Q3	Q3

Table A33. Quadrant assignment of BTH cities by cross-sectional year.

Agglomeration	City	2005	2010	2015	2020	2023
BTH	Beijing	Q1	Q4	Q4	Q4	Q4
	Tianjin	Q1	Q4	Q1	Q4	Q4
	Shijiazhuang	Q1	Q3	Q3	Q3	Q3
	Chengde	Q1	Q3	Q3	Q2	Q2
	Zhangjiakou	Q1	Q3	Q3	Q3	Q3
	Qinhuangdao	Q1	Q3	Q3	Q2	Q2
	Tangshan	Q1	Q2	Q1	Q1	Q1

Table A33. Cont.

Agglomeration	City	2005	2010	2015	2020	2023
BTH	Langfang	Q4	Q3	Q3	Q3	Q3
	Baoding	Q4	Q3	Q3	Q3	Q3
	Cangzhou	Q4	Q3	Q3	Q3	Q3
	Hengshui	Q4	Q3	Q3	Q3	Q3
	Xingtai	Q1	Q3	Q3	Q3	Q3
	Handan	Q1	Q2	Q3	Q2	Q3
	Anyang	Q1	Q3	Q3	Q3	Q3

Table A34. Quadrant assignment of PRD cities by cross-sectional year.

Agglomeration	City	2005	2010	2015	2020	2023
PRD	Guangzhou	Q1	Q4	Q4	Q4	Q4
	Shenzhen	Q4	Q4	Q4	Q4	Q4
	Foshan	Q1	Q4	Q4	Q4	Q4
	Dongguan	Q3	Q1	Q4	Q4	Q1
	Zhongshan	Q3	Q4	Q4	Q4	Q3
	Huizhou	Q3	Q3	Q2	Q4	Q3
	Zhuhai	Q1	Q1	Q1	Q1	Q1
	Jiangmen	Q2	Q3	Q3	Q4	Q3
	Zhaoqing	Q3	Q2	Q3	Q2	Q3

Table A35. Quadrant assignment of CY cities by cross-sectional year.

Agglomeration	City	2005	2010	2015	2020	2023
CY	Chongqing	Q3	Q1	Q1	Q1	Q1
	Chengdu	Q4	Q4	Q4	Q4	Q4
	Zigong	Q3	Q3	Q3	Q3	Q3
	Luzhou	Q3	Q3	Q3	Q3	Q3
	Deyang	Q4	Q3	Q3	Q4	Q4
	Mianyang	Q3	Q3	Q3	Q4	Q2
	Suining	Q3	Q3	Q3	Q3	Q3
	Neijiang	Q2	Q2	Q2	Q2	Q2
	Leshan	Q2	Q2	Q2	Q1	Q2
	Nanchong	Q3	Q3	Q3	Q3	Q3
	Meishan	Q2	Q3	Q3	Q3	Q3
	Yibin	Q3	Q3	Q2	Q2	Q2
	Guang'an	Q3	Q3	Q2	Q2	Q2
	Dazhou	Q3	Q3	Q3	Q2	Q3
	Ya'an	Q3	Q3	Q3	Q3	Q3
	Ziyang	Q3	Q3	Q3	Q3	Q3

Table A36. Quadrant assignment of MRYR cities by cross-sectional year.

Agglomeration	City	2005	2010	2015	2020	2023
MRYR	Wuhan	Q1	Q1	Q1	Q4	Q4
	Xiangyang	Q3	Q3	Q3	Q4	Q4
	Jingmen	Q3	Q3	Q3	Q2	Q2
	Yichang	Q3	Q3	Q4	Q4	Q4
	Jingzhou	Q3	Q3	Q3	Q3	Q3
	Xiaogan	Q3	Q3	Q3	Q3	Q3
	Ezhou	Q2	Q2	Q1	Q1	Q1
	Huanggang	Q3	Q3	Q3	Q3	Q3
	Huangshi	Q2	Q2	Q2	Q2	Q2
	Xianning	Q3	Q3	Q3	Q3	Q3
	Changsha	Q4	Q4	Q4	Q4	Q4
	Changde	Q3	Q3	Q3	Q3	Q3
	Yueyang	Q3	Q3	Q3	Q4	Q3
	Yiyang	Q3	Q3	Q3	Q3	Q3
	Loudi	Q2	Q2	Q2	Q2	Q2
	Xiangtan	Q2	Q3	Q2	Q1	Q2
	Hengyang	Q3	Q3	Q3	Q3	Q3
	Zhuzhou	Q3	Q3	Q3	Q4	Q3
	Nanchang	Q4	Q3	Q4	Q4	Q4
	Jiujiang	Q3	Q3	Q3	Q2	Q2
	Jingdezhen	Q3	Q3	Q2	Q2	Q2
	Shangrao	Q3	Q3	Q3	Q3	Q3
	Yingtian	Q3	Q3	Q3	Q4	Q4
	Fuzhou (Jiangxi)	Q3	Q3	Q3	Q3	Q3
	Pingxiang	Q2	Q2	Q2	Q2	Q3
	Xinyu	Q2	Q1	Q1	Q1	Q1
	Yichun	Q3	Q3	Q3	Q3	Q3

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