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Greening the green transition: Why decarbonization-enabling sectors drive emission growth in China's light manufacturing

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Abstract

Light manufacturing plays a vital role in employment and consumer goods production across China's coastal provinces, yet it accounts for an estimated 15–20% of industrial emissions and faces a fundamental tension between industrial expansion (SDG 9) and climate action (SDG 13). This study examines the drivers of carbon emissions, policy effectiveness, and abatement feasibility in this sector using a unique province-sector-month panel covering eight coastal provinces and eight light manufacturing subsectors from 2018 to 2022. Applying five integrated analytical methods, LMDI decomposition, Tapio decoupling, interrupted time series, threshold regression, and Monte Carlo simulation, we uncover a green transition paradox: battery manufacturing, the most essential subsector for downstream decarbonization through electric vehicles and renewable energy storage, alone accounts for 88.9% of cumulative emission growth.

Activity growth emerges as the dominant driver (+ 4,946 cumulative), while energy intensity improvements provide the largest offset, absorbing 72% of the activity effect. Tapio analysis reveals episodic weak decoupling that repeatedly collapses into expansive coupling. Province-level interrupted time series models show significant heterogeneity, with Beijing achieving strong reductions while Tianjin exhibits carbon leakage. Threshold regression identifies a carbon intensity tipping point separating two distinct policy regimes, and Monte Carlo projections indicate that even an integrated policy portfolio achieves only − 26.0% reduction by 2030, falling short of targets aligned with China's nationally determined contributions.

These findings expose a substantial policy implementation gap and call for differentiated carbon governance that distinguishes emission-intensive production serving decarbonization objectives from that which does not. The results offer transferable lessons for other industrializing economies scaling decarbonization-enabling manufacturing.

1. Introduction

Global efforts to mitigate climate change have intensified following the Paris Agreement, with limiting warming to 1.5°C requiring immediate emissions reductions across all economic sectors (IPCC, 2021). China, the world's largest CO_2 emitter, has committed to peak emissions by 2030 and achieve carbon neutrality by 2060 under the dual carbon targets. Manufacturing contributes approximately 30–35% of national carbon dioxide emissions (IEA, 2023; National Development and Reform Commission, 2021), making it central to whether these commitments can be met.

Within manufacturing, light industry, including textiles and apparel, food processing, furniture, paper products, plastic products, household appliances, LED lighting, and battery manufacturing, occupies a distinctive position at the intersection of economic development and environmental sustainability. Across China's eight major coastal provinces, light manufacturing employs millions of workers, supplies consumer goods for both domestic and export markets, and accounts for an estimated 15–20% of industrial emissions. Yet carbon governance frameworks have been designed primarily for heavy

industry (steel, cement, chemicals), where production is concentrated in large facilities with measurable point-source emissions. Light manufacturing presents a fundamentally different challenge: production is geographically decentralized across provinces, supply chains are fragmented and export oriented, and technology adoption varies widely across subsectors and regions. These features mean that regulatory instruments effective for heavy industry do not transfer well to the dispersed, heterogeneous production structures of light manufacturing. Critically, a green transition paradox is emerging within the sector: battery manufacturing, the subsector essential for electric vehicle supply chains and renewable energy storage, is simultaneously the largest and fastest-growing source of upstream emissions, creating a tension between the industrial expansion needed for downstream decarbonization (SDG 7, SDG 13) and the emission reductions demanded by climate commitments (SDG 9, SDG 13). This tension between industrial expansion and emission control extends beyond China; comparable dynamics have been documented in sub-Saharan Africa (Wang et al., 2024) and across BRICS economies (Su et al., 2020), suggesting that the policy challenges identified here have broader relevance for developing country industrialization pathways.

Despite growing policy interest, the existing literature has not adequately addressed this sector. Most decomposition studies of manufacturing emissions in China use LMDI methods to produce aggregated national results that mask the intra-provincial and intra-sector variation needed for targeted policy design (Xian and Wang, 2025; Zhu et al., 2024). While LMDI combined with Tapio decoupling analysis has been applied across sectors including construction (Jiang et al., 2026), mining (Xu & Shi, 2026), pig farming (Yang et al., 2025), and EU final consumption (He et al., 2025), its application to China's light manufacturing at province-sector granularity remains absent. Similarly, evaluations of the dual carbon policy have relied almost entirely on correlational analysis, without formally identifying structural breaks or testing for nonlinear regime-specific effects (Lin & Guan, 2023). Interrupted time series analysis has been applied to the Chinese Certified Emission Reduction Policy (Zhang et al., 2025) and the EU Emissions Trading System (Lambrecht & Willeke, 2025), but not to the manufacturing sector under the Dual Carbon Announcement. Furthermore, existing scenario analyses have not integrated Monte Carlo uncertainty quantification with decomposition-derived parameters, limiting their practical value for policy planning under uncertainty.

These gaps motivate three research questions:

(1) What are the dominant drivers of carbon emission growth in China's light manufacturing sector, and how do they vary across provinces and subsectors?

(2) Has the Dual Carbon Announcement produced a detectable structural break in light manufacturing emission trajectories, and does the aggregate policy signal conceal spatial heterogeneity including interprovincial carbon leakage?

(3) Can current and intensified policy portfolios close the gap to stated emission reduction targets by 2030, or is the policy gap structural?

To address these questions, this study constructs a province-sector-month panel covering eight coastal provinces and eight light manufacturing subsectors from January 2018 to December 2022 (60 months) and applies five integrated analytical methods: LMDI-I additive decomposition to identify the relative contributions of activity, structure, energy intensity, and carbon coefficient effects; Tapio decoupling analysis to assess the temporal evolution of the output-emission relationship; interrupted time series regression with formal Chow structural break testing to evaluate the Dual Carbon Announcement; Hansen threshold regression to identify nonlinear regime changes in emission drivers; and Monte Carlo scenario simulation to assess abatement pathway feasibility through 2030.

This study offers three main innovations. First, it provides the first province-sector-month decomposition of carbon emission drivers in China's light manufacturing sector, identifying a green transition paradox where the subsector most needed for downstream decarbonization generates the sector's largest upstream emissions, a finding absent from existing decomposition studies that rely on aggregated national or annual data. Second, it moves beyond correlational assessment of dual carbon policy by applying province-level interrupted time series regression, revealing that the aggregate policy signal conceals offsetting heterogeneity including interprovincial carbon leakage between regulated and unregulated jurisdictions. Third, the integration of Hansen threshold regression with Monte Carlo scenario simulation establishes a quantitative policy gap: the identified carbon intensity threshold separates two regimes requiring fundamentally different policy instruments, and no modelled abatement portfolio closes the gap to stated reduction targets by 2030, demonstrating that current instruments are structurally insufficient for light manufacturing decarbonization.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and methods. Section 4 presents the results. Section 5 discusses the findings and their policy implications. Section 6 concludes.

2. Literature Review

2.1 LMDI Decomposition of Industrial Emissions

The logarithmic mean Divisia index (LMDI) method, developed by Ang (2005) and refined by Ang and Zhang (2000), has become the standard tool for decomposing aggregate CO_2 emission changes into contributing factors. The LMDI-I additive formulation decomposes total emission change into four analytically interpretable components; activity (scale of production), structural (composition of output across sectors), intensity (energy per unit of output), and carbon coefficient (CO_2 per unit of energy), that directly map onto the principal policy levers available to regulators: output regulation, sectoral rebalancing, energy efficiency mandates, and fuel switching programs.

Recent applications span a wide range of sectors and geographies. Zhu et al. (2024) expanded the decomposition to provincial-level data and identified a large degree of geographic heterogeneity in driver composition, previously obscured in aggregate analyses. Lin and Guan (2023) included supply chain

emissions and showed that upstream factors (Scope 3) accounted for over 50% of total footprints in light manufacturing. Jiang et al. (2026) combined LMDI with system dynamics modelling for China's construction industry in Jiangsu, demonstrating that per capita output value and mechanical capability are the principal emission-increasing factors. Xu and Shi (2026) applied LMDI with Tapio decoupling to China's mining industry across 29 provinces, finding persistent expansive coupling despite efficiency gains. He et al. (2025) integrated LMDI and Tapio analysis for EU28 final consumption sectors, revealing that government consumption achieved the strongest emission reductions through carbon intensity improvements. Yang et al. (2025) applied the same LMDI-Tapio framework to China's pig farming industry, identifying affluence and population growth as dominant drivers. Igwe et al. (2025) extended the approach to Nigeria's cement industry, confirming the cross-context applicability of the combined LMDI Tapio framework. Su et al. (2020) applied Kaya identity-based decomposition across G7 and BRICS economies, establishing that economic development gradients produce systematically different driver profiles, a finding relevant to interpreting the provincial heterogeneity documented in this study.

However, these studies share a common limitation: they rarely disaggregate below the industry level to examine intra-sector paradoxes, such as how a single subsector (battery manufacturing) can dominate aggregate emission growth while serving downstream decarbonization objectives. Province-sector-month panels that capture both spatial and temporal variation within a single industry remain absent from the literature.

2.2 Tapio Decoupling Analysis

The decoupling framework developed by Tapio (2005) provides a normalized measure of output emission elasticity and classifies the output-emission relationship into one of eight states. Applied to Chinese data, the framework has documented a persistent pattern of expansive coupling, where emissions and output increase together, with weak decoupling appearing intermittently in policy-intensive periods (Bai et al., 2022; Yang, 2024). The COVID-19 pandemic in 2020 produced temporary decoupling driven by demand destruction rather than improved production efficiency (IEA, 2021). Comparative cross-sectoral evidence confirms that achieving sustained strong decoupling requires simultaneous energy intensity improvements and structural rebalancing, conditions that are rarely met in rapidly expanding industries (He et al., 2025; Xu & Shi, 2026; Yang et al., 2025). The critical question for light manufacturing is whether post-pandemic recovery has permanently reversed the episodic decoupling gains observed during demand contraction, a question that also connects to the threshold dynamics examined in Section 2.4.

2.3 Policy Evaluation and Interrupted Time Series

Causal evaluation of environmental policies requires quasi-experimental methods that account for confounding trends and concurrent shocks. Interrupted time series (ITS) analysis, which tests level shifts and slope changes at known intervention dates, has been increasingly applied to pollution and emission regulation (Auffhammer & Kellogg, 2011; Greenstone & Hanna, 2014). Lambrecht and Willeke (2025) applied SARIMA-ITS to EU ETS patent filings and found that stringent ETS reforms in 2013

significantly increased green transportation technology development, illustrating how ITS can separate announcement effects from sustained behavioral change. Zhang et al. (2025) applied ITS specifically to the Chinese Certified Emission Reduction (CCER) policy, finding that CCER implementation significantly reduced carbon emission intensity in eastern provinces, with green technological innovation and energy structure optimization as key mechanisms. Cui et al. (2021) apply this approach to China's regional carbon market pilots, finding statistically significant emission reductions among participating firms.

Despite these applications, ITS has not been applied to evaluate the Dual Carbon Announcement's effect on the manufacturing sector as a whole, nor have province-level ITS models been used to test for spatial heterogeneity in policy response. The province-level divergence documented in this study, with some provinces exhibiting compliance and others leakage, is consistent with Zheng and Men (2025), who find that green credit policy in China produces both local emission reduction and regional leakage effects, and with Xing et al. (2025/2026), who identify critical carbon pricing thresholds that shape cooperative versus non cooperative behavior across 313 Chinese cities. Duan and Zhu (2025) additionally document an inverted U-shaped relationship between high-quality urban development and carbon emissions under China's dual-control policy, providing further evidence that policy effects are nonlinear and spatially heterogeneous

2.4 Threshold Regression and Nonlinear Dynamics

Hansen (2000) threshold regression models allow empirical identification of regime changes in economic relationships without imposing a priori assumptions about nonlinearity. In the emission-energy context, threshold effects may arise from technological lock-in, economies of scale in abatement, or critical mass effects in renewable adoption. Duan and Zhu (2025) provide the closest analogue to the threshold analysis in this study, identifying a nonlinear tipping point in the urban development-carbon emission relationship using Chinese provincial panel data; their finding that high-intensity units follow different emission dynamics corroborates the regime-switching structure identified here. Li and Allen (2025) similarly document a nonlinear threshold of municipal-level digital governance in the firm-level carbon emission context, further confirming that threshold effects are a pervasive feature of China's emission landscape. However, to our knowledge, no prior study has applied threshold regression to identify carbon intensity tipping points specifically within light manufacturing, where the coexistence of high intensity legacy production and low-intensity modernized facilities creates conditions theoretically conducive to regime-switching behavior.

2.5 Policy Scenario Analysis and Uncertainty Quantification

Monte Carlo simulation methods, popularized in the energy policy literature by Morgan and Henrion (1990), provide probabilistic characterization of scenario outcomes that deterministic projections cannot offer. The International Energy Agency uses Integrated Assessment Models to create scenario portfolios tracking decarbonization pathways (IEA, 2021, 2022). Recent examples of data-driven scenario construction for the Chinese manufacturing sector include Hong et al. (2025) and Sun et al. (2025). Li et

al. (2025) extended STIRPAT-based scenario analysis to Chinese household consumption, incorporating digital technology as a driver and demonstrating that scenario projections are highly sensitive to assumptions about technological diffusion rates, a finding that motivates the Monte Carlo parameter uncertainty approach adopted here. Jiang et al. (2026) further integrated LMDI with system dynamics to construct eight policy scenarios for Jiangsu's construction industry through 2030, showing that integrated economy-technology scenarios consistently outperform single-instrument approaches. Ma and George (2026) provide cross-national evidence from G7 countries that institutional quality and technological innovation are significant moderators of the growth-emission relationship, suggesting that scenario outcomes depend critically on governance assumptions beyond technology parameters alone.

A common limitation across these studies is that scenario parameters are typically drawn from expert judgment or historical averages without systematic uncertainty quantification. The Monte Carlo approach in this study addresses this limitation by deriving parameter distributions from the LMDI rolling-window estimates, grounding uncertainty in observed decomposition variability rather than assumed ranges.

2.6 Carbon Leakage and Inter-Regional Emission Transfers

Carbon leakage, the displacement of emissions from regulated to unregulated jurisdictions, is a central concern for subnational climate governance. Olasehinde-Williams and Akadiri (2025) demonstrate in the EU context that stringent environmental policy causes greater carbon leakage through international trade channels. Zheng and Men (2025) document analogous intra national leakage in China, finding that green credit policy produces negative export effects alongside local emission reductions. Xing et al. (2025/2026) develop a game-theoretic framework for governing cross-regional embodied carbon transfers, identifying that small-world network topologies facilitate cooperative decarbonization while scale-free networks amplify leakage risks. Liu et al. (2025b) examine inter-regional carbon emission transfer pathways using MRIO analysis, finding that intermediate product flows generate larger transfers than final product f lows and that transfer paths tend to concentrate along geographically adjacent regions with complementary industrial structures. Tan et al. (2025) document the embodied carbon transfer network of China's Yangtze River Economic Belt, and Yang (2024) establishes that Scope 3 accounting is essential for characterizing leakage dynamics. These findings directly contextualize the interprovincial leakage results documented in this study and underscore the need for spatially coordinated carbon governance

2.7 Research Positioning and Contributions

Table 1 summarizes selected prior studies, their methods, scope, and limitations that this study addresses.

Table 1
Summary of Selected Prior Studies

Study	Method	Sector/Region	Key Finding	Limitation Addressed Here
Zhu et al. (2024)	LMDI	Manufacturing, China (provinces)	Geographic heterogeneity in drivers	Annual data; no subsector disaggregation
Lin & Guan (2023)	LMDI + Scope 3	Light manufacturing, China	Scope 3 > 50% of footprint	No policy evaluation; no temporal panel
Zhang et al. (2025)	ITS	CCER policy, China (Provinces)	CCER reduced intensity in east	Not applied to Dual Carbon Announcement
Xu & Shi (2026)	LMDI + Tapio	Mining, China (29 provinces)	Persistent expansive coupling	Single sector, no threshold or scenario
Jiang et al. (2026)	LMDI + SD	Construction, Jiangsu	Integrated scenarios outperform single	One province; no leakage analysis
Zheng & Men (2025)	DID	Green credit, China	Locak reduction + regional leakage	Not applied to manufacturing sector

This study is positioned at the interface of environment, development, and sustainability. The core tension it examines, between the industrial expansion needed for economic development and the emission reductions required for climate commitments, is a defining challenge for sustainable industrialization in developing and middle-income economies. The green transition paradox finding, where production that enables downstream decarbonization generates the largest upstream emissions, has direct relevance for any economy scaling battery manufacturing, renewable energy equipment, or electric vehicle supply chains, including Southeast Asian and African countries now entering these value chains. The analytical framework draws on three established theoretical traditions. The LMDI decomposition operationalizes the extended Kaya identity, linking aggregate emissions to output scale, sectoral composition, energy intensity, and carbon coefficients. The interrupted time series design draws on the quasi-experimental policy evaluation tradition, treating the October 2020 Dual Carbon Announcement as an exogenous intervention. The Monte Carlo scenario simulations apply uncertainty quantification methods from the risk analysis literature (Morgan & Henrion, 1990) to LMDI-derived parameters.

This study contributes to the literature in three ways. Methodologically, the integration of five analytical frameworks, LMDI decomposition, Tapio decoupling, ITS analysis, threshold regression, and Monte Carlo scenario simulation, that are typically applied in isolation enables cross-validation across methods and provides a more complete characterization of emission dynamics than any single approach. Empirically, it provides the first province-sector analysis of Chinese light manufacturing emissions that explicitly evaluates the Dual Carbon Announcement as a policy intervention with formal quasi-experimental identification, reporting both significant and null findings across spatial scales. Analytically, the

quantification of the gap between projected abatement and stated reduction targets generates evidence directly relevant to the design of provincial carbon governance that must balance industrial development with emission reduction, the central sustainability challenge facing China's light manufacturing sector

3. Data and Methods

Figure 1 presents the research framework, illustrating how the five analytical methods are integrated sequentially: LMDI decomposition and Tapio analysis identify emission drivers and the output-emission relationship; interrupted time series regression evaluates policy effectiveness; threshold regression identifies nonlinear regime dynamics; and Monte Carlo simulation assesses abatement pathway feasibility. Each method's output feeds into the subsequent analysis, enabling cross-validation and a comprehensive characterization of emission dynamics.

3.1 Data Sources and Panel Construction

The analysis uses province-sector-month panel data from January 2018 through December 2022 (60 months) for eight coastal provinces (Jiangsu, Zhejiang, Guangdong, Shandong, Shanghai, Fujian, Tianjin, and Beijing) and eight light manufacturing sectors (battery manufacturing, food processing, furniture manufacturing, household appliances, LED lighting, paper products, plastic products, and textiles and apparel). This province-sector-month granularity is essential for the research objectives: annual national data would obscure the episodic decoupling captured in the Tapio analysis, the monthly emission trajectories needed for ITS policy evaluation, and the province-level heterogeneity that reveals carbon leakage, all of which are invisible in the aggregated panels used in prior studies.

Table 2 summarizes the variables, definitions, and sources. Emission data are sourced from the China Emission Accounts and Datasets (CEADs), which provides provincial-sectoral CO_2 inventories covering Scope 1 (IPCC Tier 2 coefficients), Scope 2 (province-specific NDRC grid emission factors), and Scope 3 (CEADs Multi-Regional Input-Output Leontief inverse framework). Economic indicators are drawn from the World Bank, NBS China, and FRED. Supply chain metrics use CEADs MRIO tables (2020 base year).

Table 2
Variable Definitions and Data Sources

Variable	Definition	Source
Total CO_2 Emissions	Scope 1 + Scope 2 + Scope 3 provincial-sectoral emissions	CEADs
Scope 1 (Direct)	On-site combustion emissions, IPCC Tier 2	CEADs
Scope 2 (Energy)/ Energy Proxy	Grid electricity emissions, NDRC factors; also used as the energy proxy variable in LMDI decomposition	CEADs
Scope 3 (Supply Chain)	Upstream emissions via MRIO Leontief inverse	CEADs
Production Output	Time-varying output derived from static MRIO weights, GDP growth index, and emission growth ratio	CEADs, NBS
GDP Growth Rate	Annual real GDP growth	World Bank, NBS China
Supply Chain Metrics	MRIO inter-industry linkages	CEADs

The production output variable in the dataset is static across time for each province-sector combination. Using it directly would collapse the LMDI structure effect to zero. We derive a time-varying output proxy by combining the static MRIO structural weights with a cumulative GDP growth index and a smoothed province-sector emission growth ratio. For energy consumption, we use Scope 2 emissions as the energy proxy, since sector-specific Scope 2 shares (ranging from 43.0% to 67.4%) provide independent cross-sectional variation from total emissions. Table 3 presents summary statistics.

Table 3
Summary Statistics (province-sector-month observations)

Variable	Mean	Std. Dev.	Min	Median	Max
Total CO_2 Emissions	10.0516	23.9724	0.0053	2.3099	252.5690
Scope 1 - Direct	0.0837	0.1164	0.0004	0.0342	0.8232
Scope 2 - Energy	4.7836	10.3379	0.0035	1.3728	108.6047
Scope 3 - Supply Chain	5.1844	13.6215	0.0014	0.9499	143.4592
Production Output	0.0126	0.0111	0.0017	0.0091	0.0801

3.2 LMDI-I Additive Decomposition

We implement the LMDI-I additive decomposition (Ang, 2005) to decompose total CO_2 emission changes into four factors following the extended Kaya identity for manufacturing:

$$\Delta C = \Delta C_{act} + \Delta C_{str} + \Delta C_{int} + \Delta C_{emf} \quad (1)$$

where the subscripts denote activity (total output scale), structure (sectoral composition), intensity (energy per output unit), and carbon coefficient (emission factor) effects. The log-mean Divisia weighting assigns each sector a weight:

$$w_i = \frac{C_i^t - C_i^0}{\ln\left(C_i^t / C_i^0\right)} \# (2)$$

ensuring perfect decomposition (zero residual). We apply the decomposition at three geographic levels national aggregate, province-level (treating sectors as sub-units), and sector-level (treating provinces as sub-units) to characterize driver heterogeneity across both dimensions.

Robustness of the LMDI results is assessed through: (1) alternative base year comparison (2018 versus 2019 base), confirming sign consistency across the main effects; (2) rolling 2-year window decomposition to track temporal variation in driver composition; and (3) pre-versus post-Dual Carbon policy comparison (2018–2020 vs. 2020–2022) to assess structural shifts in decomposition results.

We note that the carbon coefficient effect (CO_2 per unit of energy) is expected to be approximately zero in this dataset because the ratio of total emissions to Scope 2 emissions is determined by the sector-specific MRIO scope distribution, which is fixed across time within each sector. This is a structural feature of the data rather than a substantive finding, and we report it transparently rather than interpreting it as evidence of fuel-mix stability.

3.3 Tapio Decoupling Analysis

The Tapio (2005) elasticity of CO_2 with respect to output is defined as

$$\epsilon = \frac{\Delta C/C}{\Delta y/y} \# (3)$$

where ΔC and ΔY represent year-over-year changes in aggregate CO_2 emissions and production output respectively. The eight decoupling states defined by Tapio classify combinations of positive/negative emission and output changes into categories including strong decoupling (ε < 0, ΔY > 0), weak decoupling (0 < ε < 0.8), expansive coupling (0.8 ≤ ε ≤ 1.2), and expansive negative decoupling (ε > 1.2). We compute province-level and sector-level elasticities for each year 2019–2022, enabling identification of units progressing toward or regressing from decoupling over the study period.

3.4 Interrupted Time Series (ITS) Regression

To evaluate the impact of the Dual Carbon Announcement (October 2020) on emission trajectories, we estimate the segmented regression model:

$$C_{} = \beta^0 + \beta^1 T + \beta^2 D_{} + \beta^3 (T - T*) \times D_{} + \Sigma \gamma_{} \times Month_{} + \epsilon_{} \# (4)$$

Where T is a linear time trend, Dt is a post-announcement indicator (1 from October 2020), and (T - T*) × Dt captures the change in slope after the breakpoint T*. Monthly fixed effects (γm) control for seasonal

variation. The regression is estimated with HC3 heteroskedasticity-consistent standard errors. β_2 identifies the immediate level shift at the announcement, while β_3 captures the sustained trajectory change in monthly emission growth. A statistically significant negative β_3 with non-significant β_2 is consistent with a gradual policy compliance mechanism; significant β_2 with non-significant β_3 reflects an immediate behavioral response. The post-intervention window comprises 26 months (October 2020 to December 2022), which constrains statistical power for detecting gradual slope changes.

We formally test for the structural break using the Chow (1960) F-test. Robustness checks employ alternative break dates (January 2020 and July 2021 ETS launch) to confirm whether the structural break hypothesis is sensitive to break date specification. Province-level ITS models are estimated separately for each of the eight provinces to characterize spatial heterogeneity in policy response.

3.5 Threshold Regression

Following Hansen, B.E. (2000), we estimate a threshold regression model with carbon intensity (Total CO_2/Production Output) as the threshold variable γ: for observations with intensity

$$log(C_{it}) = \begin{cases} \alpha_1 + \beta_{E1}\log(E_{it}) + \beta_{Y1}\log(Y_{it}) + \varepsilon_{it} & if I_{it} \le \gamma \\ \alpha_2 + \beta_{E2}\log(E_{it}) + \beta_{Y2}\log(Y_{it}) + \varepsilon_{it} & if I_{it} > \gamma \end{cases}$$

The model is estimated on province-sector-year aggregates (64 combinations × 5 years = 320 observations) rather than the monthly panel to avoid autocorrelation in the threshold variable. The threshold γ is identified by grid search over the 15th–85th percentile range of carbon intensity, minimizing the total residual sum of squares (RSS). Statistical significance of the threshold is assessed by comparing threshold RSS to linear model RSS via an F-test calibrated by bootstrap (500 iterations) to account for the non-standard distribution of the test statistic. Bootstrap confidence intervals for γ are constructed from 500 threshold estimates.

3.6 Policy Scenario Simulations

Five policy scenarios are simulated from the 2022 baseline (the final year of observed data), with the BAU annual growth rate derived from the ITS post-policy trend coefficient (1.03% per year) using LMDI-parameterized Monte Carlo simulation (N = 10,000 iterations). The five scenarios are: (1) Business-as-Usual (BAU): maintaining the ITS-derived post-policy growth trajectory; (2) Energy Efficiency: implementing technology upgrades to reduce energy intensity by 30%; (3) Renewable Transition: increasing clean energy to approximately 40% of total supply; and (4) Supply Chain Intervention: reducing Scope 3 emissions by 25%. The fifth (Integrated Portfolio) scenario combines all three interventions with a 0.85 synergy factor to reflect diminishing returns and overlapping effects when measures are applied simultaneously. Each scenario incorporates parameter uncertainty modelled as normally distributed perturbations around the mean reduction rates, with standard deviations derived from the LMDI rolling-window estimates. Abatement costs are based on National Development and Reform Commission

(NDRC, 2021) sectoral technology cost benchmarks for Chinese light manufacturing. We adopt a 40% reduction target by 2030 relative to the 2022 baseline as a benchmark consistent with the pace of abatement implied by China's NDC commitment to peak emissions before 2030 and reduce carbon intensity by over 65% from 2005 levels (NDRC, 2021), applied to the light manufacturing sector. This target is more ambitious than the national carbon intensity pathway but reflects the accelerated abatement expected from manufacturing under the NDRC Action Plan for Carbon Dioxide Peaking Before 2030, which calls on industry to 'take the lead in peaking carbon dioxide emissions' (NDRC, 2021).

4. Results

4.1 LMDI Decomposition: Emission Drivers at National, Provincial, and Sectoral Levels

4.1.1 National Year-over-Year Decomposition

Table 4 and Fig. 2 Panel A present the national LMDI-I decomposition results. Activity growth is the dominant cumulative driver, with the structural effect also contributing positively through compositional shifts toward battery manufacturing and LED lighting. The intensity effect provides the largest single offset, substantially counteracting activity-driven growth. The carbon coefficient effect is approximately zero throughout, reflecting the fixed MRIO scope ratios (see Section 3.2). The 2019–2020 and 2021–2022 periods together account for 84.5% of cumulative change, driven by structural decomposition and post-pandemic production recovery respectively. The 2018–2019 period stands out for its large negative intensity effect that nearly offset all other drivers, producing the smallest net increase of the four periods.

Table 4
National LMDI-I Additive Decomposition Results, 2018–2022

Period	Activity	Structure	Intensity	Carbon Coeff.	Total Change	Share (%)
2018–2019	2069.62	722.93	−2564.60	−0.0000	227.95	6.2
2019–2020	330.38	886.34	332.50	0.0000	1549.22	42.0
2020–2021	952.10	211.85	−817.36	−0.0001	346.59	9.4
2021–2022	1594.16	484.17	−511.72	0.0001	1566.62	42.5
Cumulative	**4946.26**	**2305.28**	**−3561.17**	**−0.0000**	**3690.37**	**100.0**

4.1.2 Provincial-Level Decomposition

Provincial LMDI results (Fig. 2, Panel B and Table 5) reveal substantial heterogeneity across provinces. Zhejiang dominates with the largest cumulative increase, driven by both activity and structural expansion reflecting the province's concentration of battery and LED manufacturing. Guangdong and Shanghai are

the only provinces achieving net emission reductions, in both cases through intensity improvements that offset positive activity growth, indicating efficiency gains rather than de-industrialization.

Table 5
Province-level LMDI (2018–2022)

Province	Activity	Structure	Intensity	Carbon Coeff.	Total Change
Beijing	153.73	33.84	-10.89	-0.0000	176.69
Fujian	209.12	125.97	-80.55	-0.0000	254.54
Guangdong	103.83	130.25	-351.37	0.0000	-117.29
Jiangsu	443.96	124.68	-361.48	0.0000	207.15
Shandong	834.51	-25.93	-200.26	-0.0000	608.32
Shanghai	-6.79	26.49	-137.63	-0.0000	-117.92
Tianjin	81.34	50.35	-54.01	-0.0000	77.68
Zhejiang	1628.20	1287.42	-314.41	-0.0000	2601.21

The pre-versus post-policy comparison (Table 6) reveals two notable shifts. The structural effect declined substantially between periods, suggesting that the rapid compositional shift toward emission-intensive sectors slowed after the Dual Carbon Announcement. The intensity effect, however, worsened, intensity improvements in the pre-policy period did not sustain their pace post-2020. This counterintuitive finding may reflect the short post-policy window or the confounding influence of post-pandemic production recovery on energy efficiency metrics. Activity remained essentially flat throughout both periods.

Table 6
Pre vs Post Policy LMDI (2018–2020 vs 2021–2022)

Effect	Pre-Policy (2018–2020)	Post-Policy (2020–2022)	Difference
Activity	2632.44	2598.76	-33.68
Structure	1709.08	710.75	-998.33
Intensity	-2564.36	-1396.31	+ 1168.05
Carbon Coeff.	-0.0000	0.0000	+ 0.0000
Total Change	**1777.17**	**1913.20**	**+ 136.04**

4.1.3 Sectoral Decomposition

The sectoral heatmap (Fig. 3) reveals that emission growth is concentrated overwhelmingly in a single sector. Battery Manufacturing accounts for 88.9% of the total cumulative increase, with an activity effect that exceeds the national cumulative total. LED Lighting and Household Appliances are the next largest

contributors, both showing large activity effects offset by negative structure and intensity effects. Three sectors achieved net reductions (Textile & Apparel, Paper Products, and Plastic Products) where intensity improvements exceeded output growth.

This concentration exposes a green transition paradox: the sector producing the batteries needed for electric vehicles and renewable energy storage, technologies central to SDG 7 and SDG 13, is the same sector generating the largest upstream emissions. Scope 3 supply chain emissions compound this challenge, accounting for 56.8% of total emissions in Battery Manufacturing versus 26.0% in Plastic Products, meaning that Scope 1–2 focused regulation systematically undercounts the carbon footprint in the sectors that matter most.

4.2 Tapio Decoupling Analysis

Figure 4 and Tables 7–8 present the Tapio decoupling results. The aggregate trend (Table 7) shows a volatile pattern, with decoupling gains remaining episodic and reverting to coupling once post-pandemic recovery takes hold. The final-period elasticity (0.980) sits just above the 0.8 threshold, leaving no margin for the sustained weak decoupling that would signal progress toward SDG 13.

Table 7
Aggregate Tapio Decoupling Trend, 2018–2022

Period	ΔC/C	ΔY/Y	ε	Decoupling State
2018–2019	0.037	0.391	0.095	Weak decoupling
2019–2020	0.243	0.048	5.107	Expansive negative decoupling
2020–2021	0.044	0.125	0.350	Weak decoupling
2021–2022	0.189	0.193	0.980	Expansive coupling
Note: ε = (ΔC/C)/(ΔY/Y). Classification follows Tapio (2005*).*				

Province-level results (Table 8) reveal heterogeneity that the aggregate masks. Guangdong alone achieves strong decoupling, consistent with the large intensity offset documented in Table 4. Three provinces (Beijing, Fujian, and Zhejiang) show expansive negative decoupling, with Zhejiang's elasticity particularly notable given its dominance in cumulative emission growth.

Table 8
Province-Level Tapio Elasticities (Full Period 2018–2022)

Province	ε	Decoupling State
Beijing	1.291	Expansive negative decoupling
Fujian	1.202	Expansive negative decoupling
Guangdong	-1.057	Strong decoupling
Jiangsu	0.434	Weak decoupling
Shandong	0.642	Weak decoupling
Shanghai	15.981	Recessive decoupling
Tianjin	0.946	Expansive coupling
Zhejiang	2.126	Expansive negative decoupling

4.3 Interrupted Time Series: Policy Impact of the Dual Carbon Announcement

The Chow test does not identify a significant structural break in October 2020 (F = 0.86, p = 0.601), indicating that the Dual Carbon Announcement has not yet produced a detectable discontinuity in aggregate light manufacturing emission trajectories within the 2018–2022 observation window. Table 9 presents the ITS regression results.

Table 9
Interrupted Time Series Regression Results Aggregate National Monthly Emissions R^2 = 0.956, Adj. R^2 = 0.943, N = 60 months

Variable	Coeff.	Std. Err.	t-stat	p-value
Intercept (Pre-policy baseline)	497.49	15.35	32.40	0.0000***
Time trend (Pre-policy slope)	5.79	0.56	10.27	0.0000***
Level shift (post-policy, β_2)	-18.19	20.36	-0.89	0.3717
Slope change (post-policy, β_3)	+ 2.69	1.05	2.57	0.0101*

The ITS results (Fig. 5, Panel A) show a significant pre-policy growth trend (β_1 = 5.79, p < 0.001) and a non-significant level shift (β_2 = -18.19, p = 0.372), indicating no immediate discontinuity at the announcement. The post-policy slope change (β_3 = +2.69, p = 0.010) is positive and statistically significant at the 5% level, suggesting that emission growth accelerated rather than decelerated in the post-announcement period. This counterintuitive finding likely reflects two confounding factors within the short post-intervention window: (1) the post-COVID production recovery of 2021–2022, which generated a temporary demand surge across light manufacturing, and (2) the limited statistical power of

26 months of post-break data to isolate a gradual policy effect from cyclical recovery dynamics. The non-significant Chow test (F = 0.86) supports the interpretation that the policy effect, if present, is not yet distinguishable from pre-existing trends and concurrent shocks at the aggregate level.

Province-level ITS results (Table 10) reveal substantial heterogeneity that the aggregate null result obscures. Beijing exhibits the strongest response (-127.2% level shift, $p < 0.001$; slope − 0.49, $p < 0.001$), consistent with intensive environmental enforcement in the capital. Tianjin shows the opposite: a significant positive level shift (+ 11.7%, $p < 0.001$), consistent with carbon leakage from regulated to less-regulated provinces. All provinces except Zhejiang show significant slope changes ($p < 0.05$), confirming that the spatial heterogeneity is concentrated in the trajectory dimension rather than the level dimension.

Table 10
Province-Level Interrupted Time Series Results

Province	Level Shift	p-value	Slope Δ	p-value	R^2
Beijing	-127.2%	0.000***	-0.49	0.000***	0.785
Fujian	+ 3.6%	0.446	+ 1.19	0.000***	0.947
Guangdong	-0.6%	0.264	+ 0.37	0.000***	0.980
Jiangsu	+ 7.3%	0.003**	-1.52	0.000***	0.892
Shandong	-32.7%	0.004**	+ 3.24	0.000***	0.800
Shanghai	+ 1.7%	0.596	+ 0.22	0.022*	0.818
Tianjin	+ 11.7%	0.000***	+ 0.19	0.000***	0.963
Zhejiang	-7.1%	0.893	-0.50	0.599	0.915

4.4 Threshold Regression: Nonlinear Emission Dynamics

Threshold regression identifies a significant carbon intensity tipping point at $\hat{\gamma}$ = 1,547.74 ($F = 15.7$, $p < 0.001$; bootstrap 95% CI: 140.77-1,547.74), with the threshold model RSS (4.54) substantially below the linear model (5.22). Table 11 summarizes the regime-specific results.

Table 11
Threshold Regression Results Carbon Intensity Threshold

Parameter	Regime 1 ($I \le \hat{\gamma}$)	Regime 2 ($I > \hat{\gamma}$)	Difference
Observations (N)	273	47	
R^2	0.9937	0.9780	
Energy elasticity (β)	+ 1.0249***	+ 1.0791***	+ 0.0542
Output elasticity (β)	+ 0.0779***	-0.0408	−0.1187
Bootstrap 95% CI	[140.77, 1547.74]		

Energy elasticity is near unity in both regimes, with a modest difference. The regime distinction operates through output elasticity: positive and significant in Regime 1, negative and non-significant in Regime 2. This sign reversal indicates that the emission-production relationship changes fundamentally above the threshold. High-intensity province-sectors appear to have exhausted the marginal emission content of output expansion, with emissions driven almost entirely by energy consumption.

4.5 Policy Scenario Projections (2023–2030)

Table 12 and Fig. 6 present the Monte Carlo projections.

Table 12
Monte Carlo Policy Scenario Projections, 2023–2030 (N = 10,000)

Scenario	Base	2030 Proj.	Δ%	Target %	¥/ton	90% CI
BAU	9846.2	10511.4	+ 6.8	0	0	[8145–13205]
Energy Efficiency (-30%)	9846.2	9001.0	-8.6	0	127	[6934–11397]
Renewable (40% share)	9846.2	9325.1	-5.3	0	243	[7227–11728]
Supply Chain (-25%)	9846.2	9268.9	-5.9	0	184	[7103–11682]
Integrated Portfolio	9846.2	7281.9	-26.0%	10%	165	[5584–9269]

Baseline (2022): 9,846.17. BAU growth: 1.03%/year. Growth uncertainty (σ): 5.19%. 40% reduction target: 5,907.70.

No single-instrument scenario approaches the 40% target, with all three achieving 0% target probability across 10,000 simulations. Energy efficiency remains the most cost-effective intervention (127 ¥/ton) but achieves only − 8.6% as a standalone measure. The Integrated Portfolio produces the largest reduction (-26.0%) but meets the 40% target in only 10% of simulations, with a wide prediction interval indicating substantial uncertainty. The 14-percentage-point gap between the integrated projection and the target cannot be closed by parameter adjustments alone, suggesting that additional instruments (carbon pricing, demand management, or output regulation) are needed.

4.6 Robustness Checks

Five robustness checks were conducted. (1) LMDI base year sensitivity: re-estimating with 2019 as base confirms same-sign results for activity, structure, and intensity; the carbon coefficient differs trivially. (2) ITS alternative breaks: the COVID break (January 2020) is significant on both level and slope; the ETS break (July 2021) shows significant slope only; the placebo (January 2019) shows non-significant slope ($p = 0.410$), confirming that the post-2020 dynamics are not attributable to pre-existing trends. The non-significant Chow test at October 2020 in the main specification therefore likely reflects the confounding overlap between COVID recovery and the policy announcement rather than the absence of any policy effect. (3) Threshold alternatives: all three alternative variables (carbon intensity, energy intensity, log

output) produce significant thresholds (F = 13.8, 13.2, 22.5; all p < 0.001). (4) Scenario sensitivity: ±20% parameter variation in the integrated portfolio yields a range of -30.2% to -22.1%, none exceeding the 40% target, confirming that the policy gap is structural. (5) LMDI residual validation: maximum residual of 0.000000% confirms perfect decomposition.

5. Discussion

5.1 Activity Dominance and the Green Transition Paradox

The LMDI results confirm activity growth as the dominant cumulative emission driver (+ 4,946.26), consistent with the broader literature on Chinese industrial emissions (Xian & Wang, 2025; Zhu et al., 2024). Comparable decomposition patterns have been documented across sectors and geographies: Su et al. (2020) show that economic scale is the dominant driver across G7 and BRICS economies, while Igwe et al. (2025) find that output growth consistently dominates in Nigeria's cement industry. The cross-context consistency suggests that the activity-intensity tension is a structural feature of industrial development rather than a China specific phenomenon.

However, the finding that energy intensity improvements provide the largest single offset (-3,561.17, absorbing 72% of the activity effect) complicates the standard narrative. Intensity is not failing; it is doing substantial work. The policy gap arises not because efficiency is inadequate but because activity growth continues to outpace it. He et al. (2025) document an analogous pattern in EU28 consumption sectors, where low-carbon technology adoption improved household consumption intensity yet economic output remained a persistent emission driver, confirming that intensity policy is necessary but insufficient when output growth is rapid.

Battery Manufacturing's 88.9% share of cumulative emissions creates a green transition paradox with direct implications for sustainable industrial policy. Current policy frameworks do not differentiate between emission-intensive production that serves decarbonization objectives (batteries for EVs and renewable storage) and that which does not. Lv et al. (2025), analyzing embodied carbon in China's light industry export trade using nested MRIO tables, document a related finding: certain light manufacturing subsectors achieve "positive synergistic relationships" between low emissions and high employment, while others exhibit fundamental trade-offs. Their synchronicity index approach confirms that subsector-level differentiation is essential for policy design, rather than applying uniform emission caps across all light manufacturing. Making this distinction explicit in sectoral carbon governance would allow targeted clean energy procurement for decarbonization-enabling sectors without constraining the output needed for downstream decarbonization (Wang et al., 2015; Lin & Guan, 2023). Liu et al. (2025a) provide direct empirical support, demonstrating that technology-differentiated policy design can decouple output from emissions in manufacturing sectors.

5.2 Dual Carbon Policy Effects: An Inconclusive Signal with Provincial Divergence

The aggregate ITS null result has important implications for the dual carbon implementation pathway. The non-significant Chow test ($F = 0.86$, $p = 0.601$) does not necessarily indicate policy failure; rather, it likely reflects the confounding overlap between COVID recovery dynamics and the policy announcement within a short post-intervention window (26 months). Province-level ITS models reveal where the aggregate obscures genuine policy heterogeneity. Beijing's strong negative level shift (-127.2%, $p < 0.001$) is consistent with intensive environmental enforcement capacity in the capital. Tianjin's positive level shift (+ 11.7%, $p < 0.001$) is consistent with carbon leakage, the displacement of production from regulated to less regulated jurisdictions. This leakage pattern aligns with evidence from the EU context (Olasehinde-Williams & Akadiri, 2025), China's green credit policy (Zheng & Men, 2025), and cross-city carbon transfer governance (Xing et al., 2025/2026), collectively establishing that regulatory stringency differentials reliably generate carbon displacement across jurisdictions. The Tianjin result therefore likely reflects a generalizable governance failure rather than a province-specific anomaly.

This finding has direct practical implications: provincial emission reductions achieved through production displacement do not represent genuine abatement at the national level. Inter provincial carbon governance harmonization, including coordinated carbon pricing and cross jurisdictional monitoring, is a prerequisite for effective emission reduction in light manufacturing. Sun (2026) provides recent empirical confirmation from 30 Chinese provinces that carbon emission efficiency exhibits positive spatial spillover effects, meaning that governance improvements in one province propagate to neighbors, underscoring both the opportunity for and necessity of inter-provincial coordination. Jiang et al. (2026) similarly emphasize that Fujian's carbon peaking pathway requires integrated multi-policy coordination rather than single-instrument approaches, corroborating that the coordination challenge we identify extends across Chinese provincial governance contexts.

5.3 Threshold Effects and Targeting Implications for Sustainable Industrialization

The threshold regression identifies a significant carbon intensity tipping point ($\hat{\gamma} = 1{,}547.74$, $F = 15.7$, $p < 0.001$) that separates two fundamentally different emission regimes. In Regime 1 (below threshold), output growth contributes positively to emissions (+ 0.078), meaning that both energy and output policies are needed. In Regime 2 (above threshold), output elasticity turns negative and non-significant (-0.041), suggesting that high-intensity province-sectors have exhausted the marginal emission content of output expansion, with emissions driven almost entirely by energy consumption.

This nonlinear structure is consistent with Duan and Zhu (2025), who identify an inverted U-shaped relationship between high-quality urban development and carbon emissions in Chinese provinces, and with Li and Allen (2025), who document a nonlinear threshold of municipal-level digital governance capacity for carbon reduction. Both findings suggest that the threshold dynamics identified here are a systemic feature of China's emission landscape rather than an artifact of the light manufacturing context.

The practical implication is that a one-size-fits-all policy approach will underperform. Province sector combinations below the threshold require a policy mix that addresses both output management and energy efficiency simultaneously: structural policies to shift production toward lower-intensity subsectors, combined with efficiency mandates to reduce energy per unit of output. Province-sector combinations above the threshold, by contrast, are best served by energy-focused interventions alone: fuel switching programs, renewable electricity procurement mandates, and grid decarbonization, since output regulation in these units no longer produces measurable emission reductions. Technology transfer programs that diffuse efficiency practices from low-intensity to high-intensity production units would support progressive movement down the intensity distribution.

5.4 The Policy Gap: Abatement Pathways and Carbon Peaking Feasibility

The Monte Carlo results reveal a substantial policy gap between current trajectories and stated climate commitments. No modelled scenario, including the integrated portfolio, closes the gap to the 40% reduction target. The gap is structural: the robustness sensitivity analysis (range: -30.2% to -22.1%) confirms that no parameter combination closes it.

This finding is consistent with the system dynamics results of Jiang et al. (2025) for Fujian Province, where baseline scenarios without policy constraints also fail to achieve carbon peaking by 2030, and where even optimized multi-policy scenarios (combining industrial structure, technology investment, energy structure, and residential energy savings) produce peaking values concentrated between 30,932 and 31,900 million tons, far from the aggressive reductions needed. The convergence of our Monte Carlo projections with their system dynamics simulations across different methodological frameworks strengthens the conclusion that the policy gap is robust and not an artifact of any single modelling approach.

The implication is that policy instruments beyond the five modelled here are needed, including carbon pricing, demand-side management, and output regulation. Li et al. (2025) provide direct evidence from the Chinese household sector that scenario projections systematically underestimate the policy effort required when technology diffusion is slower than assumed, confirming that the integrated portfolio gap identified here is likely a lower bound on the true shortfall under realistic technology adoption trajectories. Li and Allen (2025) additionally demonstrate that climate policy uncertainty itself increases corporate carbon emissions, suggesting that the credibility and stability of China's dual carbon commitment schedule is a direct determinant of whether the BAU growth trajectory in our projections can be bent downward.

The supply chain dimension is particularly relevant: Scope 3 emissions account for 56.8% of total emissions in Battery Manufacturing versus 26.0% in Plastic Products, meaning that regulation focused only on direct emissions (Scope 1–2) systematically undercounts the carbon footprint in the sectors that matter most. Mandatory Scope 3 supply chain carbon disclosure would directly address this information asymmetry and unlock abatement potential currently invisible to regulators.

5.4.1 Synthesis: Implications for sustainable development practice

Taken together, the four sets of findings expose interlocking challenges for sustainable industrial development that extend well beyond the Chinese context. The activity-intensity tension illustrates a structural conflict that faces any economy pursuing simultaneous industrialization and decarbonization. Wang et al. (2024) show that industrialization in sub-Saharan Africa produces analogous tensions between economic development and climate objectives, confirming that the policy trade-offs identified here are not China-specific but represent a general challenge for countries at early and middle stages of industrial development. Southeast Asian economies now entering battery and EV supply chains will face the same green transition paradox documented here: scaling the production needed for global decarbonization while managing the upstream emissions that production generates.

The carbon leakage finding adds an important governance dimension. Subnational climate policy that tightens standards in some jurisdictions without coordinating across all jurisdictions does not eliminate emissions; it redistributes them. This dynamic has been documented in the EU's Carbon Border Adjustment Mechanism (Olasehinde-Williams & Akadiri, 2025), in China's green credit system (Zheng & Men, 2025), and now in the Dual Carbon Announcement's effect on light manufacturing. The consistency across policy instruments and geographic contexts suggests that leakage is an inherent feature of any climate governance system with regulatory heterogeneity, not a design flaw specific to any single policy.

For practitioners designing sustainable development strategies, these findings suggest three operational priorities. First, distinguish between emission-intensive production serving decarbonization objectives (battery manufacturing, renewable energy equipment) and production that does not, and design carbon governance that accounts for the downstream value of upstream emissions. Second, coordinate carbon governance across jurisdictions before tightening local standards, using harmonized carbon pricing or cross-jurisdictional monitoring to prevent the leakage documented here. Third, anticipate that closing the last 10–15 percentage points of emission reduction will require instruments that are politically costlier than the efficiency measures deployed first, including demand management, output regulation, and carbon pricing that directly constrains activity growth.

5.5 Limitations

Several limitations should be acknowledged, each pointing to productive future research directions. First, the post-intervention window for the ITS analysis comprises only 26 months. Zhang et al. (2025) demonstrate that the full effects of the CCER policy on carbon emission intensity in China emerged over a multi-year horizon. Extending the dataset beyond 2022 as CEADs data become available would provide a more definitive test of whether the aggregate null result reflects insufficient statistical power or genuine policy ineffectiveness. Second, the time-varying production output proxy is derived from static MRIO structural weights modulated by GDP growth and emission dynamics, rather than from directly observed production data. While this approach preserves cross-sectional structure and introduces

plausible time variation, it ties the output variable partially to the emission variable, potentially inflating the intensity effect. Independent production data at the province-sector-month level, when available, would strengthen the decomposition. Third, the panel covers eight coastal provinces. Excluding inland provinces may introduce geographic bias, particularly for sectors where production is relocating westward. Future research incorporating inland provinces would enable direct testing of the leakage hypothesis through spatial panel models. Sun (2026) provides a methodological template for spatially augmented carbon emission analysis at the provincial level that future extensions of this work could adopt. Fourth, the 40% reduction target used as a benchmark is a constructed scenario consistent with the pace implied by China's NDC commitments, not an official government figure for light manufacturing specifically. While this framing is appropriate for policy gap analysis, readers should note that the gap magnitude is conditional on target specification.

6. Conclusions and Policy recommendations

This study applies five integrated analytical methods to a province-sector-month panel across eight coastal provinces and eight light manufacturing sectors from 2018 to 2022, generating findings with direct relevance to sustainable industrial development and climate policy design in China and beyond. Four principal conclusions emerge.

First, activity growth (+ 4,946.26 cumulative) is the dominant emission driver, but energy intensity provides a substantial offset (-3,561.17), absorbing 72% of the activity effect. Battery Manufacturing alone accounts for 88.9% of the cumulative increase, creating a green transition paradox where the sector most needed for downstream decarbonization generates the largest upstream emissions. This paradox is not unique to China: any economy scaling battery manufacturing, renewable energy equipment, or EV supply chains will face the same tension between upstream production emissions and downstream decarbonization value.

Second, the Dual Carbon Announcement has not produced a detectable aggregate structural break in light manufacturing emissions within the 2018–2022 window. Province-level models reveal that the aggregate null result masks genuine heterogeneity: Beijing shows strong emission reductions while Tianjin exhibits carbon leakage. This leakage pattern is consistent with evidence from the EU, China's green credit policy, and cross-city carbon transfer governance, establishing that regulatory heterogeneity within a single national policy framework reliably generates emission displacement.

Third, a significant carbon intensity threshold separates two policy regimes: one where output growth contributes positively to emissions and another where it does not. This regime structure has direct governance implications: below the threshold, both output and energy policies are needed; above it, energy-focused interventions alone are effective.

Fourth, Monte Carlo projections expose a 14-percentage-point policy gap: the integrated portfolio achieves − 26.0% by 2030, with only 10% of simulations reaching the 40% target. The gap is structural and cannot be closed by optimizing existing instruments alone

6.1 Policy recommendations, differentiated by regime and province type:

For province-sector combinations in Regime 1 (below the carbon intensity threshold), policy should combine industrial structure adjustment with energy efficiency mandates. These units have room for both output management and intensity improvement. Specifically, shifting production composition toward lower-intensity subsectors (food processing, household appliances) and away from the highest-intensity activities would reduce the structural effect that currently amplifies activity-driven growth.

For province-sector combinations in Regime 2 (above the threshold), policy should focus exclusively on energy-side interventions: fuel switching, renewable electricity procurement mandates, and grid decarbonization. Output regulation in these units no longer produces measurable emission reductions because the marginal emission content of output expansion has been exhausted.

For leakage-prone provinces (Tianjin pattern), inter-provincial carbon governance coordination is the binding constraint. Harmonized carbon pricing across jurisdictions, potentially through an expanded national carbon market with full sectoral coverage, would eliminate the regulatory arbitrage that drives production displacement. Cross-jurisdictional emission monitoring and reporting would provide the transparency needed to detect and correct leakage in real time.

For decarbonization-enabling sectors (battery manufacturing), policy should mandate Scope 3 supply chain carbon disclosure and establish differentiated emission benchmarks that account for the downstream decarbonization value of production. Uniform emission caps applied without regard to the decarbonization function of output will constrain the production needed for the broader clean energy transition.

Beyond the Chinese context, the multi-method framework developed here, integrating decomposition, decoupling, quasi-experimental policy evaluation, nonlinear regime identification, and probabilistic scenario analysis, is transferable to other sector-province contexts where industrial development and climate objectives intersect. The green transition paradox, in particular, will become increasingly relevant as Southeast Asian, African, and Latin American economies enter decarbonization-enabling manufacturing value chains. Future research should extend this analysis to inland Chinese provinces to test the leakage hypothesis directly, incorporate longer post-2022 panels to strengthen the ITS evaluation, and apply spatial panel models to capture cross-provincial emission interdependencies that the current province level approach treats as independent.

Declarations

Data availability

The data presented in this study are available on request from the corresponding author.

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Figures

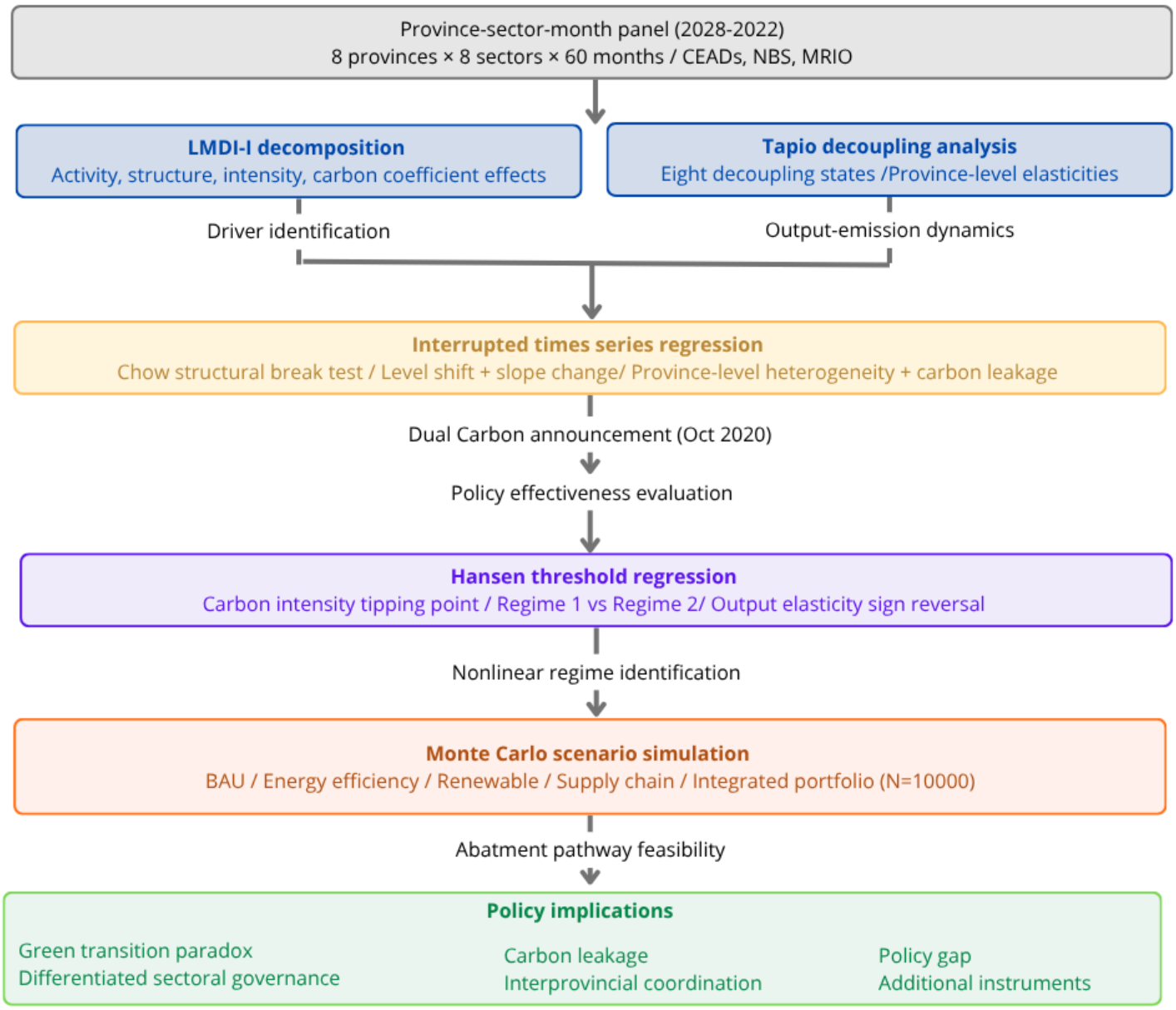

Figure 1

research framework

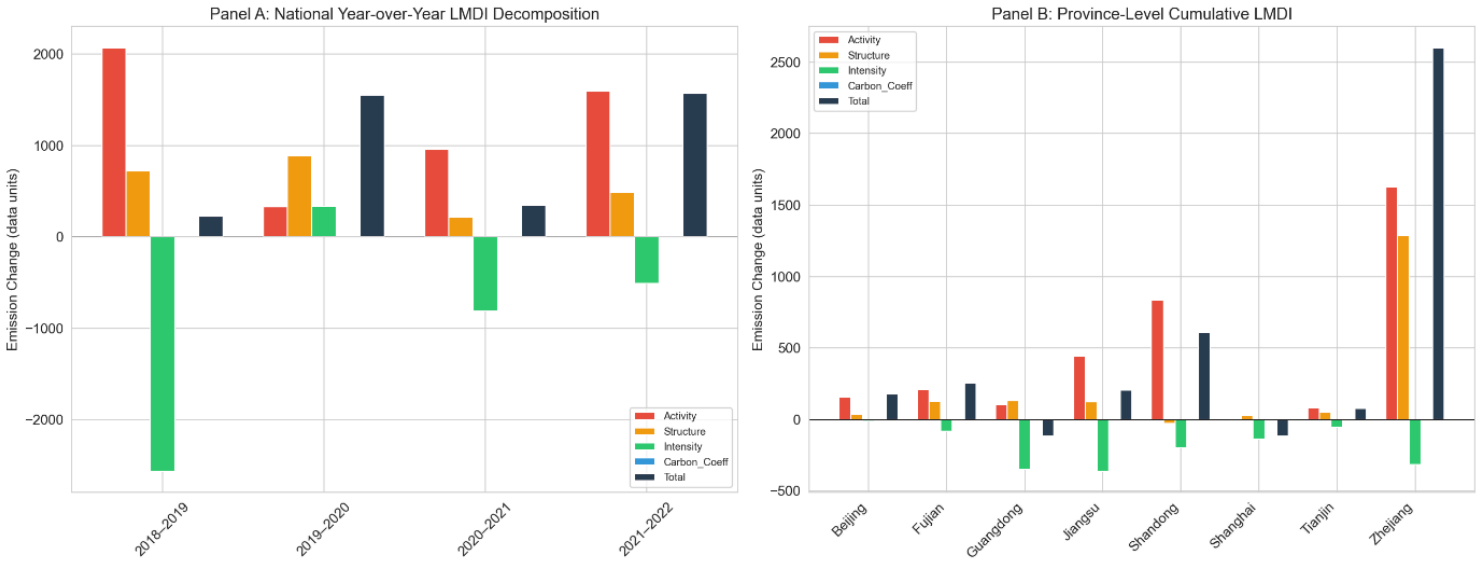

Figure 2

LMDI decomposition of CO_2 emission changes.

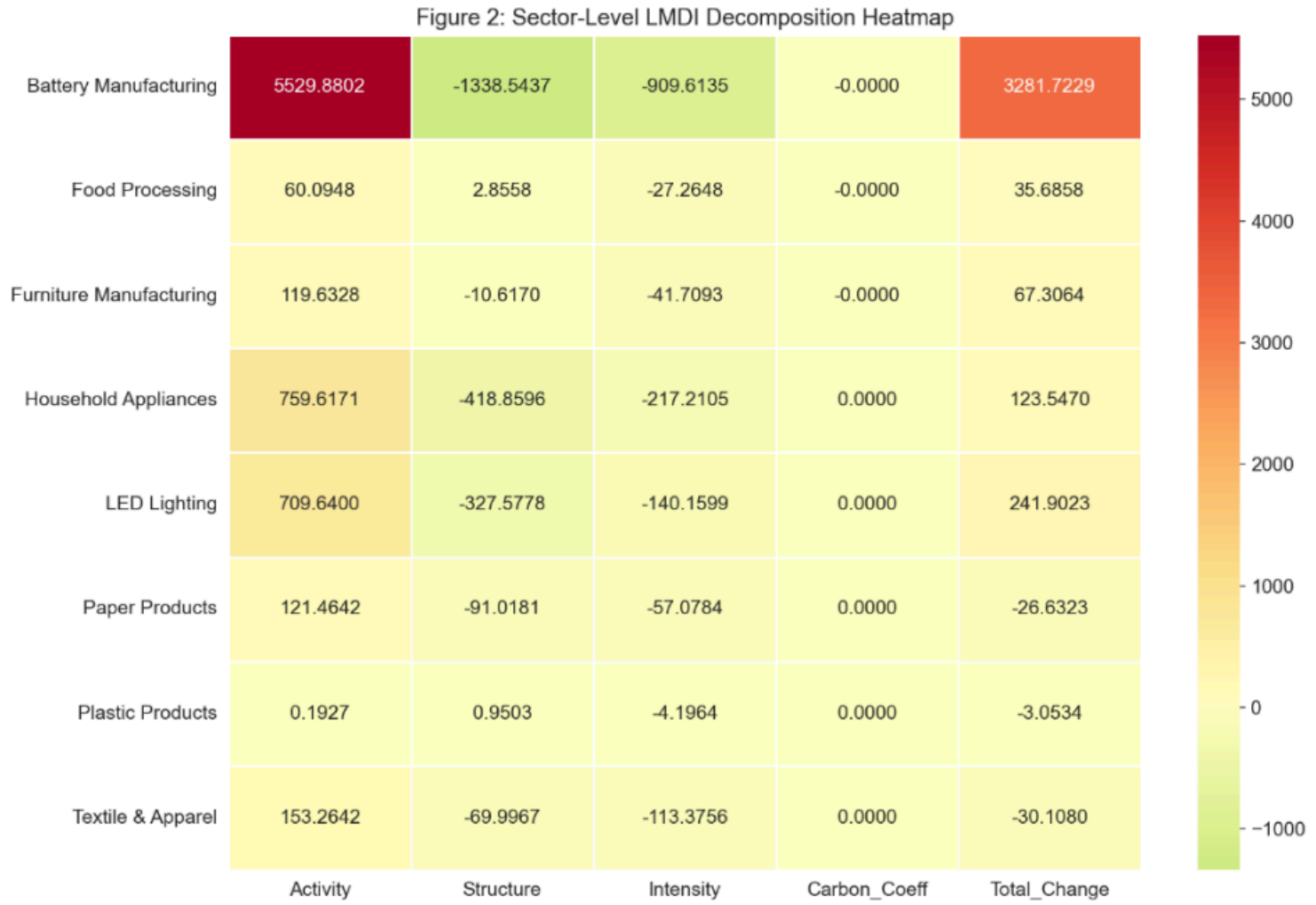

Figure 3

Sector-level LMDI decomposition heatmap (2018-2022, Million Tons CO_2).

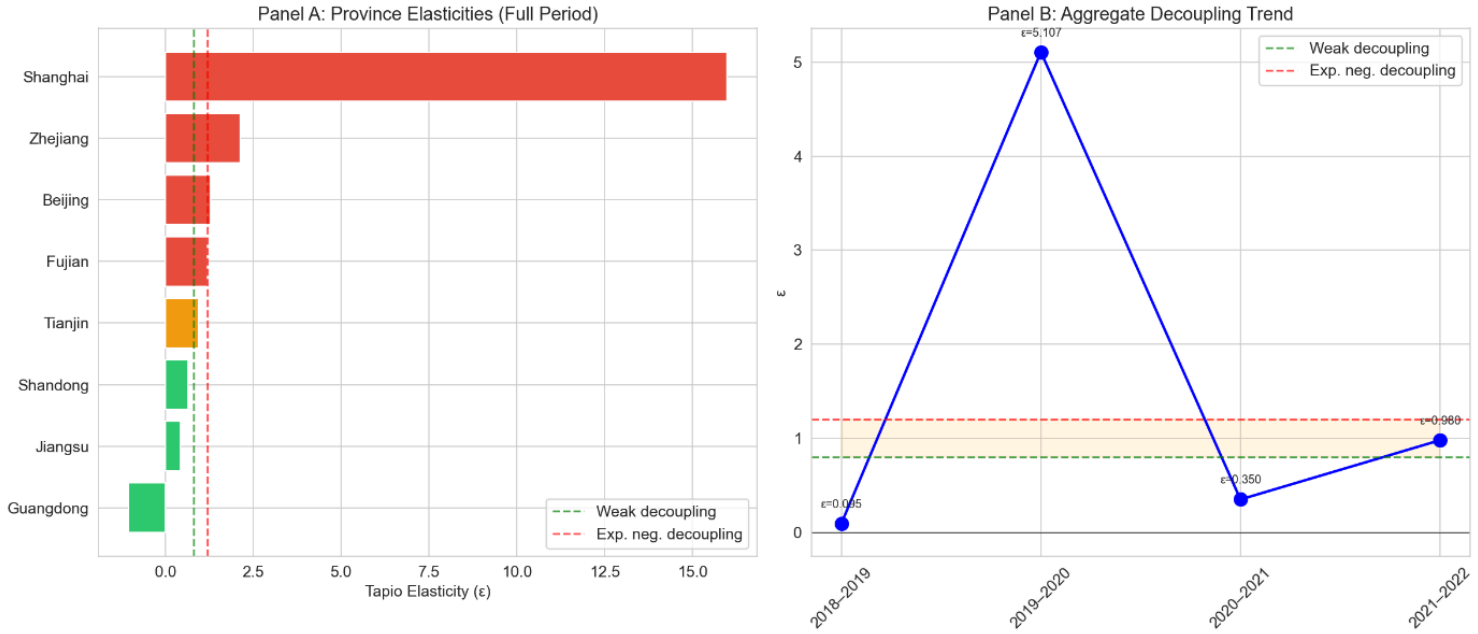

Figure 4

Tapio decoupling analysis.

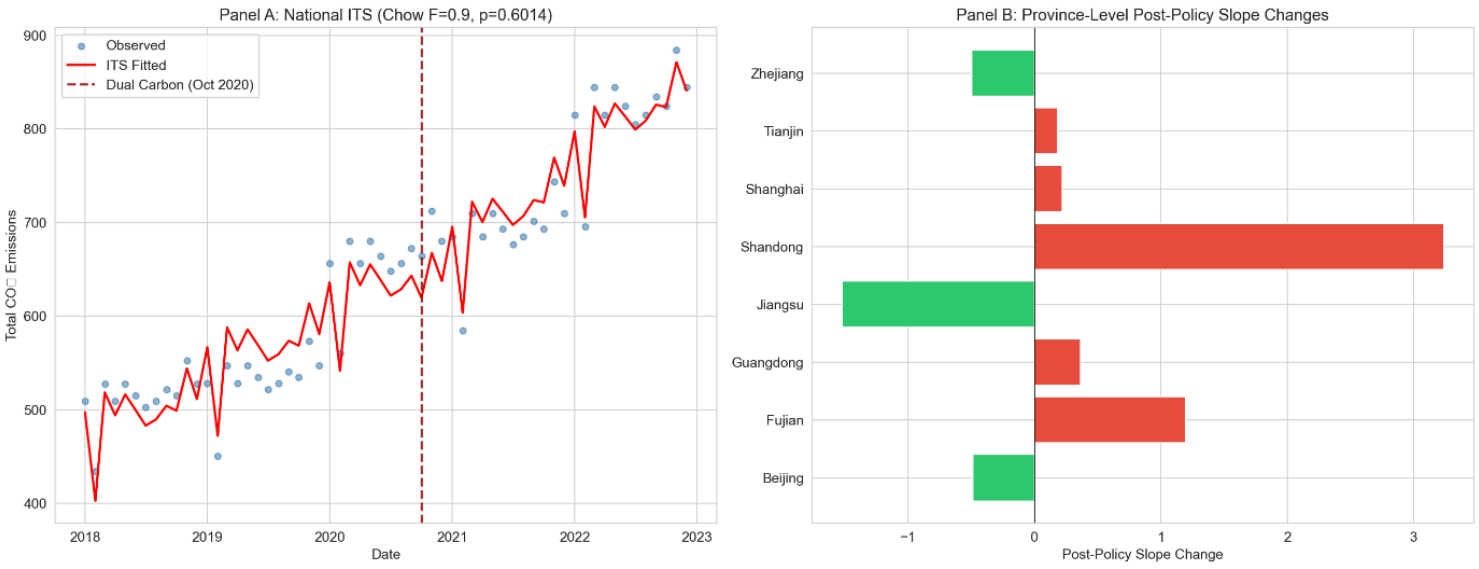

Figure 5

Interrupted time series analysis

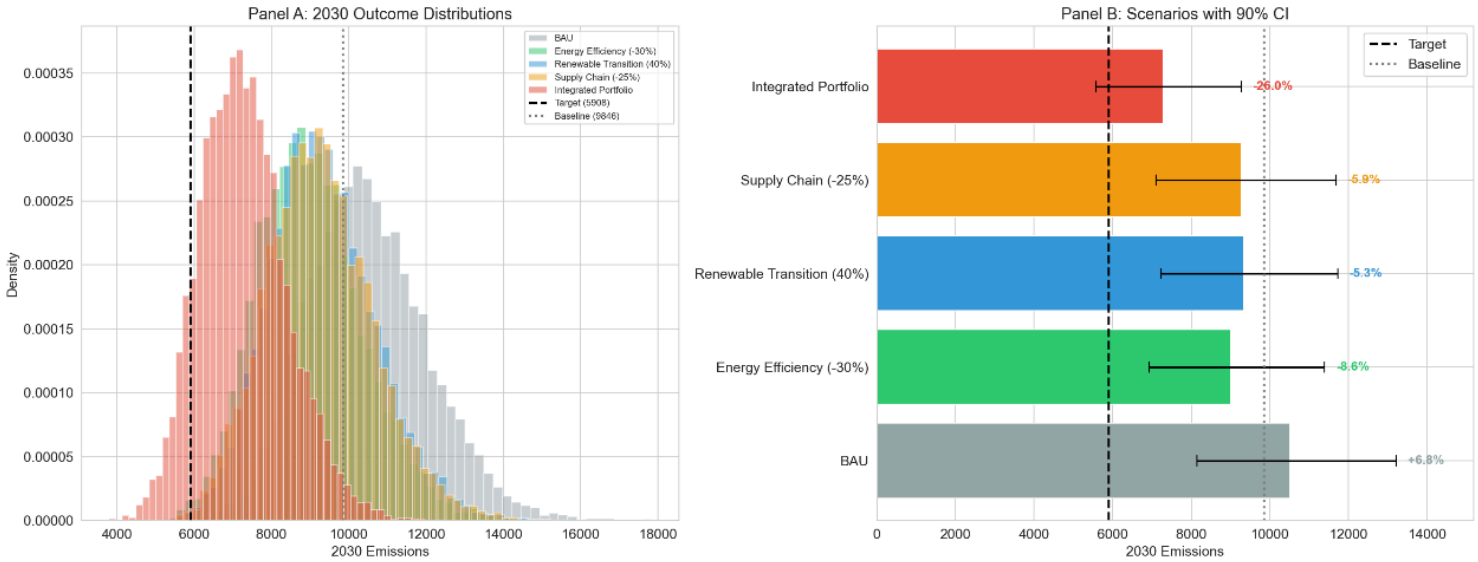

Figure 6

Monte Carlo policy scenario projections (2025–2030)