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Yuexin Chen

tp079282@mail.apu.edu.my

Asia Pacific University of Technology & Innovation

Haowei Yang

University of Houston

Xiaolong Guo

St. Francis Xavier University

Qiang Jin

China Agricultural University

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Towards Policy Synergy and a Just Industrial Transition in China through Integrated Scenario Assessment of Carbon Lock In and Stakeholder Alignment

Yuexin Chen[1],* · Haowei Yang[2] · Xiaolong Guo[3] · Qiang Jin[4],[5]

[1] Graduate School of Business, Asia Pacific University of Technology & Innovation (APU), Kuala Lumpur, Malaysia.

[2] Department of Decision & Information Sciences, C. T. Bauer College of Business, University of Houston, Houston, Texas, USA.

[3] Department of Earth and Environmental Sciences, St. Francis Xavier University, Antigonish, Nova Scotia B2G 2W5, Canada.

[4] College of Economics and Management, China Agricultural University, Beijing, China.

[5] Asia-Pacific Regional Innovation & Development Research Centre, Asia-Pacific Think Tank Institute, Kowloon, Hong Kong SAR, China.

Corresponding Author

Yuexin Chen
Graduate School of Business, Asia Pacific University of Technology & Innovation (APU)
Kuala Lumpur, Malaysia
Email: tp079282@mail.apu.edu.my

Author Email Addresses

Yuexin Chen: tp079282@mail.apu.edu.my

Haowei Yang: hyang38@cougarnet.uh.edu

Xiaolong Guo: x2024ghb@stfx.ca

Qiang Jin: qiang200102@163.com

Abstract

Industrial decarbonisation requires low-carbon technologies and the capacity to implement them under persistent structural constraints. This study develops an integrated scenario framework for China that connects technological, asset, institutional and network lock-in with stakeholder alignment and just-transition considerations. A two-round Delphi consultation with 15 experts informed indicator assessment and scenario design. Five scenarios compare business as usual, policy enhancement, technological change, collaborative governance and an integrated package over 2020–2050. Historical calibration of aggregate industrial energy demand over 2010–2020 gives $R^2 = 0.93$ and a mean absolute percentage error of 6.2%. Against the 2020 direct-emissions baseline of 1,000 Mt CO_2 for the selected manufacturing sectors, the integrated scenario reaches 410 Mt CO_2 in 2050, a 59.00% reduction. It exceeds the three narrower scenarios by 17.45–39.40 percentage points and raises the Power Alignment Index from 0.4800 to 0.7730. Energy and steel have the highest weighted lock-in scores. Analytical derivation and exact numerical verification over 9,251 feasible settings per capacity response identify positive synergy when deployment and implementation improve together under multiplicative or binding-bottleneck conditions. A support-threshold mechanism identifies additional actor backing from joint measures. The findings show how integrated policy can improve emissions outcomes and implementation capacity by addressing complementary constraints. Worker protection, local adjustment and participation provide additional criteria for evaluating a just industrial transition.

Keywords: industrial decarbonisation; policy synergy; carbon lock-in; stakeholder alignment; just transition; scenario analysis

Key policy insights

- Industrial climate policy should assess technology deployment alongside asset persistence, institutional constraints and the capacity to implement change.
- Joint improvements in technology deployment and implementation capacity generate additional emissions reductions when the two capacities are complementary or jointly binding.
- Support for carbon-intensive sectors should distinguish combustion emissions from fossil feedstock dependence and consider exposure to premature asset retirement.
- Policy assessment should combine emissions outcomes and actor support with worker protection, local fiscal adjustment and meaningful participation.

1 Introduction

China's industrial decarbonisation presents a policy challenge in which technological substitution, long-lived capital and institutional arrangements interact. Carbon-intensive infrastructure can continue operating even when lower-carbon alternatives become available. The resulting persistence reflects the costs of replacing assets, dependence on established production networks and incentives that favour existing systems (Erickson et al., 2015; Wen et al., 2026). A transition strategy therefore needs to address both the sources of emissions and the conditions under which governments, firms and financial institutions can implement change.

Industrial mitigation also extends beyond substituting energy sources. Reviews identify electrification, hydrogen, carbon capture, process change and material efficiency as options with different requirements for deployment (Davis et al., 2018; Rissman et al., 2020). Recent work on hard-to-abate sectors stresses remaining gaps in technology readiness, cost and access to supporting resources (Meng et al., 2025). These differences make the availability of an option and the ability to deploy it separate policy questions.

Research on industrial transition highlights carbon lock-in, policy consistency and stakeholder conflict (Gillingham et al., 2025; Herman et al., 2025; Sovacool et al., 2025; Zhou et al., 2025). Technical pathway analysis identifies substitution opportunities and emissions consequences. Governance analysis explains why actors support, delay or resist implementation. Connecting these perspectives matters because an available technology can face financing constraints, local economic dependence or uneven administrative capacity. Stakeholder support also depends on the options and resources available to implement change.

Recent evidence makes policy interaction an explicit research problem. Stechemesser et al. (2024) identify policy combinations among interventions associated with major emissions reductions across countries. For China, Liu et al. (2025) find that mitigation-policy interactions can also delay carbon neutrality in modelled pathways, with positive synergies restricted to particular combinations and outcomes. The two studies use different designs, but together motivate examining the conditions and scale of interaction rather than assuming that a broader package is necessarily super-additive.

Digital modelling offers a way to organise these relationships and compare policy assumptions. Studies of digital transformation and net-zero systems also examine the relationship between visualisation, technical capabilities and effective governance (Papadonikolaki and Anumba, 2023; Di et al., 2024). For national industrial transitions, the relevant task is to clarify how structural constraints and implementation conditions affect scenario outcomes. The framework developed here combines historical information and scenario assumptions to support transparent policy comparison and examination of implementation constraints.

The study asks how structural persistence constrains industrial transition, when deployment and implementation generate synergy, and how policy packages differ in emissions outcomes, actor support and transition exposure. It contributes a common assessment of multidimensional lock-in and stakeholder alignment for China, analytical conditions for complementarity through capacity and support-threshold mechanisms, and an integrated comparison of emissions reductions and implementation conditions. Fuel and feedstock pathways, asset exposure and sensitivity summaries place the scenario results within a broader transition assessment. Just-transition criteria connect this assessment to the distribution of adjustment costs and participation.

2 Analytical framework

2.1 Carbon lock-in and industrial transition

Carbon lock-in describes the persistence of carbon-intensive systems through mutually reinforcing technological, economic and institutional conditions. Past investment affects which options remain affordable and operationally feasible. Long asset lifetimes and sunk costs can discourage early replacement, while established suppliers, skills and infrastructure favour incumbent production routes (Erickson et al., 2015; Eitan and Hekkert, 2023). These conditions make the timing of industrial change important. A policy that improves the expected return on a low-carbon technology may still have a limited near-term effect when firms face inflexible assets or dependent production networks.

The foundational account of carbon lock-in emphasises the persistence of established technological and institutional systems (Unruh, 2000). Seto et al. (2016) distinguish infrastructural and technological, institutional and behavioural forms of persistence. The four-dimensional index used here adapts this broader concept to the industrial assessment by separating assets and production networks. It is an operational choice for organising constraints, rather than an exhaustive classification of all forms of lock-in.

The framework distinguishes technological reliance, asset persistence, institutional support for incumbent systems and dependence on industrial networks. These dimensions can overlap. Institutional persistence also concerns how problems and acceptable responses are framed (Buschmann and Oels, 2019). The composite index summarises selected constraints; its meaning depends on the evidence, scaling and weights used in its construction. Component scores remain necessary to explain why sectors with similar aggregate indices may need different interventions.

Committed-emissions research adds a temporal perspective. Existing infrastructure carries potential future emissions over its remaining operating life, making continued use and retirement assumptions central to assessment (Davis and Socolow, 2014; Tong et al., 2019). Plant-level analyses of coal power in China and global steel show the value of distinguishing facilities and retirement pathways (Cui et al., 2021; Xu et al., 2023). These studies motivate attention to asset age, operating conditions and the timing of replacement.

China's industrial transition also involves differences among sectors and places. Existing research examines carbon lock-in in relation to industrial structure, policy support and the availability of alternative pathways (Malz et al., 2023; Tu et al., 2025; Wen et al., 2026). This motivates a differentiated policy approach. A sector dominated by durable production assets may require a different transition schedule from one whose main constraint is fossil feedstock dependence or financing. Sectoral scores can organise these differences, but should not replace information on production routes, asset age and the costs of specific interventions.

2.2 Stakeholder alignment and implementation

Stakeholder alignment is used here to describe the extent to which actors' preferences and capacities support a policy package. It does not imply equal power, consensus or the absence of conflict. Central government, state-owned enterprises (SOEs), private firms, local authorities, financial institutions and public organisations have different responsibilities and exposures. A policy can receive strong central support while imposing substantial costs on firms or local economies. These differences affect whether formal commitments translate into implementation (Avelino et al., 2016; Hoppe and Miedema, 2020; Xie et al., 2025).

Carbon pricing and emissions standards increase pressure to reduce emissions, while technology support and finance address adjustment barriers. Actor responses depend on compliance costs, access to capital and the credibility of implementation. Policy mix research in China underscores the importance of considering instruments together and examining their consistency over time (Li and Taeihagh, 2020; Li et al., 2025). In this framework, policy preference, resource capacity, implementation capability and transition burden structure the comparison of actor alignment across scenarios.

A policy mix includes goals, instruments and the processes through which they are designed and implemented. Its consistency and credibility therefore matter alongside the number of instruments (Rogge and Reichardt, 2016; Kern et al., 2019). Transition policy can also need measures that support emerging alternatives and reduce continued support for incumbent systems (Kivimaa and Kern, 2016). In this study, pricing and standards

represent pressure to change, while technology support, finance and coordination represent conditions that can enable a response.

The composition and effects of a mix can change as policies and technologies develop together (Edmondson et al., 2019). Work measuring policy-mix dynamics also shows why balance and design features should be examined over time (Schmidt and Sewerin, 2019). The present scenarios simplify this development into selected transition settings. Their usefulness lies in exposing assumptions about policy and implementation, while a full account of policy evolution would require additional temporal evidence.

Implementation capacity connects policy design and actor alignment. Meckling and Benkler (2024) distinguish state capacity and fiscal space in explaining varieties of climate policy. Reddy et al. (2026) examine how policy entrepreneurship shapes mixes and institutional change in Dutch cycling policy. Together, these studies motivate explicit assessment of actor roles and implementation conditions, with attention to the institutional setting.

Alignment and justice address different aspects of transition. Powerful actors may support measures whose costs fall disproportionately on workers, smaller firms or local communities. Participation and the distribution of gains and losses therefore require specific assessment (Bennear, 2022; Clery et al., 2025; Gong and Lewis, 2024; Wang et al., 2024). Employment, income, public services and access to compensation extend the evaluation beyond asset exposure and actor support.

Just-transition scholarship situates adjustment within the political distribution of costs, benefits and decision-making power (Newell and Mulvaney, 2013). Reviews connect climate, energy and environmental justice and show that just transition includes several interpretations beyond employment alone (Heffron and McCauley, 2018; McCauley and Heffron, 2018; Wang and Lo, 2021). This study uses just transition as an evaluative perspective on industrial adjustment, with separate attention to distribution, recognition and participation.

2.3 Scenario tools for policy assessment

Scenario models compare the consequences of explicit assumptions about technologies, policies and behaviour. Policy simulation and strategic interaction have been applied to building-industry transition and steel-sector carbon unlocking (Sun et al., 2023; Tu et al., 2025). The present study examines structural persistence and actor support in a common framework. Digital visualisation helps organise pathway information and supports interpretation of the assumptions that connect inputs and outcomes (Papadonikolaki and Anumba, 2023).

The framework is an offline scenario tool informed by digital representations of physical and institutional systems. It organises historical information, structural indicators and stakeholder assumptions for comparison of future policy settings. Its intended use is examination of conditional pathways and implementation constraints at the industrial-transition scale.

2.4 Mechanisms and analytical expectations

The analytical framework connects structural constraints and policy implementation through two relationships. Higher lock-in increases the difficulty and perceived burden of replacing incumbent technologies and assets. Stronger stakeholder alignment improves the conditions for coordinated implementation through resources, execution capacity and transition-cost management. These relationships guide scenario design and the analytical interaction assessment.

Three expectations guide the analysis. Structural persistence constrains substitution. Joint improvement in deployment and implementation creates an additional gain when the two capacities are complementary. Actor support and transition exposure differ across groups. The analytical responses formalise capacity complementarity, while the scenario indicators compare outcomes under the selected settings.

Complementarity is defined around a specific outcome, reference and constraint. An intervention can improve the usefulness of another by supplying a missing input or easing a shared bottleneck (Markard and Hoffmann, 2016). This motivates two alternative capacity responses below. Coalition research supplies a related political mechanism, because policies can alter the groups with an interest in further decarbonisation (Meckling et al., 2015). These mechanisms justify testing interactions rather than presuming them from the simultaneous presence of instruments.

3 Methods

3.1 Data and system boundary

The framework draws on industrial energy and emissions statistics, policy documents, sectoral information and expert consultation. Statistical sources include the National Bureau of Statistics of China, the National Energy Administration, the Ministry of Ecology and Environment, sectoral statistical sources and the China Emission Accounts and Datasets (CEADs). Policy-document coding and secondary evidence inform the sectoral and stakeholder indicators. Two consultation rounds with 15 experts provide judgement on indicators and scenario design. Statistical observations define the historical context, expert assessment informs the indicators, and scenario assumptions describe future interventions.

Historical calibration covers 2010–2020, and the scenario horizon is 2020–2050. All five scenarios use 2020 as the common emissions reference and 2050 as the assessment endpoint. The statistical baseline is 1,000 Mt CO_2 of direct emissions from steel, cement, chemicals, automotive manufacturing and other building materials within the selected manufacturing boundary. The energy sector is assessed separately in the lock-in comparison.

Cement production is recorded separately from other building materials, which cover other non-metallic mineral products such as glass and ceramics. Automotive emissions cover vehicle and component manufacturing facilities. Energy-supply emissions, purchased-energy indirect emissions, vehicle use, upstream fuel production and end-of-life treatment lie outside the selected manufacturing direct-emissions boundary. This allocation avoids overlap between energy supply and manufacturing. The energy-demand and intensity benchmarks in Table 1 describe the broader energy-calibration context, while the 1,000 Mt CO_2 baseline defines the manufacturing emissions accounting.

Table 1 presents the statistical emissions baseline, energy-context values, scenario settings and historical fitting diagnostics. Tables S1 and S2 define the variables and scenario adjustments. Tables S3–S6 present the reciprocal weighting matrix, sector index comparison, stakeholder aggregates and absolute emissions accounting. The same weights, support threshold and emissions boundary apply throughout the assessment. Section 3.9 describes exact numerical verification of the response mechanisms and accounting identities.

The study completed a two-round Delphi consultation involving 15 experts. The panel comprised four experts in energy policy, three in industrial technology, three in environmental governance, three in enterprise transition and two in green finance. Both rounds used anonymous consultation and obtained 15 responses, a response rate of 100% in each round. The assessment covered four lock-in dimensions, four stakeholder-alignment components, six actor categories and the plausibility of the five scenarios. Expert judgement informed the scoring framework and scenario assumptions.

The sectoral index assigns weights of 0.30 to technology, 0.30 to assets, 0.20 to institutions and 0.20 to networks. Stakeholder aggregation assigns weights of 0.25, 0.20, 0.15, 0.15, 0.15 and 0.10 to central government, SOEs, private firms, local authorities, financial institutions and NGOs or public actors, respectively. Both vectors sum to 1. Equal-weight sectoral scores and unweighted actor means provide comparison benchmarks.

Table S3 presents a reciprocal representation of the adopted sector weights. Matrix entries are defined by $a_{ij} = \beta_i/\beta_j$. The positive eigenvector reproduces the weight vector, the maximum eigenvalue is 4, and the consistency index is $\mathrm{CI} = \frac{4-4}{3} = 0$. With $\mathrm{RI} = 0.90$ for four dimensions, $\mathrm{CR} = \mathrm{CI}/\mathrm{RI} = 0$. This algebraic consistency follows from the ratio construction. Expert consultation informs the assessment, while the reciprocal matrix documents the adopted weights. Table S4 compares the resulting CLI with an equal-weight calculation.

The support threshold is $\theta = 0.60$. An actor contributes its influence weight to the support share when its alignment score reaches or exceeds the threshold. The same actor weights and inclusion rule apply to every scenario. Table S5 presents PAI and the weighted threshold share for the six actor groups. The weighted support share describes the allocation of modelled influence above the cutoff.

The system boundary follows industrial mitigation research that considers production processes together with energy and materials. The Intergovernmental Panel on Climate Change (IPCC, 2022) assesses energy and material efficiency, circularity, electrification, fuel and feedstock changes, and carbon capture as interacting options. A review of industrial pathways connects technology deployment to policy commitment, demand

support and institutions (Bataille et al., 2018). These perspectives inform the selected technology, material and governance dimensions of the framework.

3.2 Policy scenarios

Five scenarios share the same historical starting point and emissions reference. They vary the strength and emphasis of policy, technology and implementation measures. S4 combines stronger interventions with more favourable implementation conditions. The assessment compares the resulting transition pathways under these assumptions.

S0 Business as usual represents existing policy conditions and autonomous technological change. Its reduction measures change from 2020 along the baseline pathway.

S1 Policy enhancement emphasises stronger carbon pricing, tighter emissions standards and additional green support. It represents a predominantly policy-led change in the incentives facing industrial actors.

S2 Technology breakthrough emphasises faster deployment of low-carbon processes, including carbon capture and storage and hydrogen-based industrial options. Supporting incentives facilitate the assumed technological change.

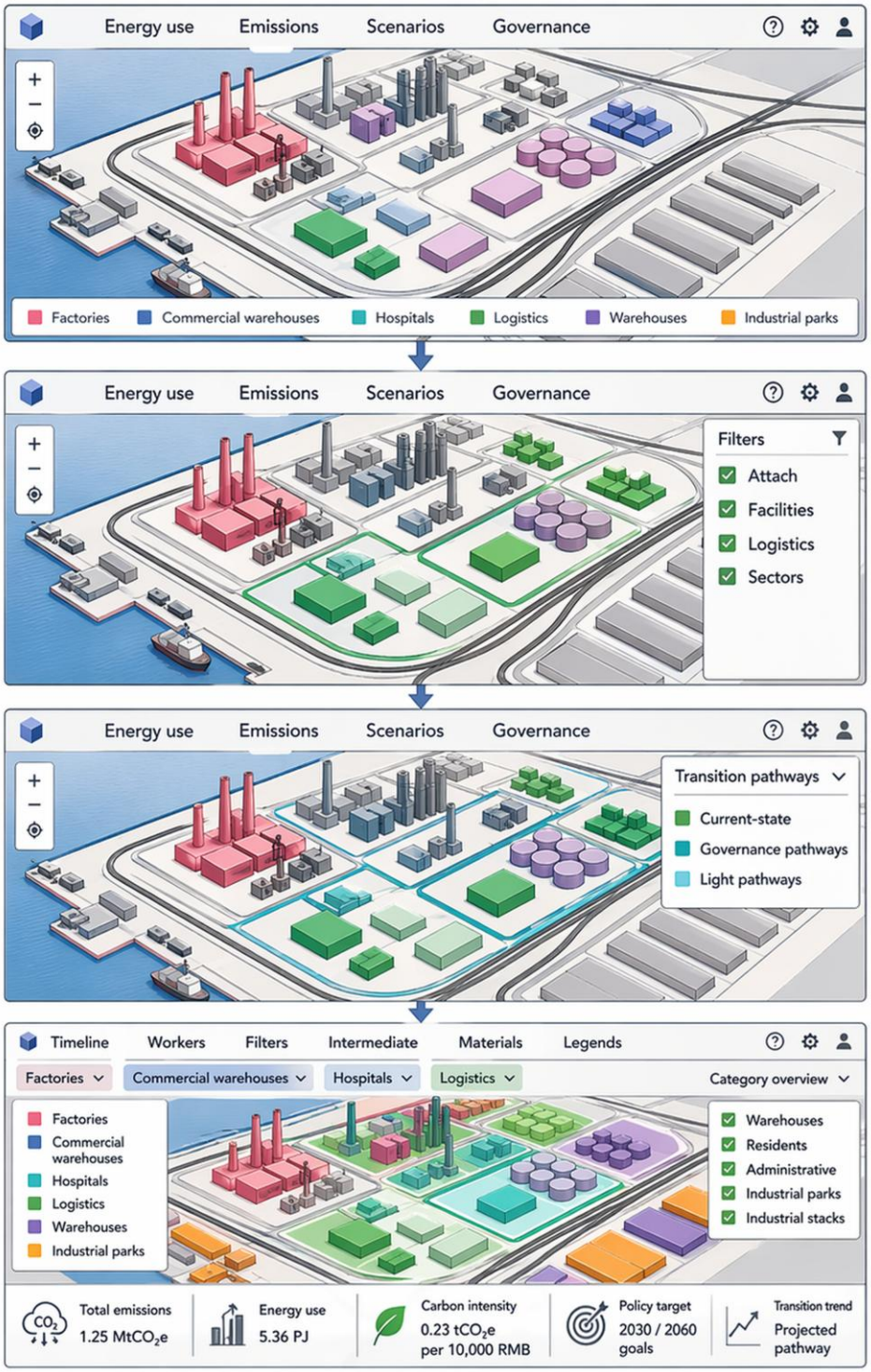
S3 Collaborative governance emphasises coordination among government, enterprises, financial institutions and other actors. Green finance and coordinated implementation are intended to reduce financing and execution barriers.

S4 Integrated scenario combines policy enhancement, technological change and collaborative governance. It assesses the performance of a broad intervention package under the specified deployment and implementation conditions.

3.3 Model structure and intended use

The framework has four analytical elements. Energy and emissions information establishes the industrial context. The lock-in module summarises structural constraints. The stakeholder module describes policy support and implementation conditions. Scenario and uncertainty analysis compare outcomes under alternative settings. The intended mechanism is that stronger structural constraints increase transition burdens, while improved resources and coordination can facilitate low-carbon adoption. Figure 2 summarises this conceptual organisation.

Figure 1 presents the decision-support interface for examining energy use, emissions, scenarios and governance information. Its four panels show information views, scenario selection, pathway exploration and assessment outputs. The interface supports interpretation of the study framework and organisation of policy information.



A Interface prototype

Assessment interface for mapping industrial energy use and emissions.

B Scenario controls

Scenario options and sector filters support comparison of assessment settings.

C Pathway display

Current conditions and alternative pathways are displayed for policy exploration.

D Assessment dashboard

Navigation across industrial indicators, scenarios and policy information.

Figure 1 Decision-support interface for industrial transition assessment. Panels A–D show information views, scenario selection, pathway exploration and assessment outputs. Maps and numerical readouts represent qualitative interface content.

The governance and structural modules summarise stakeholder alignment and carbon lock-in. Energy demand, technology replacement, asset retirement and emissions provide the transition context. Figure 2 connects these elements to scenario comparison and feedback from assessment.

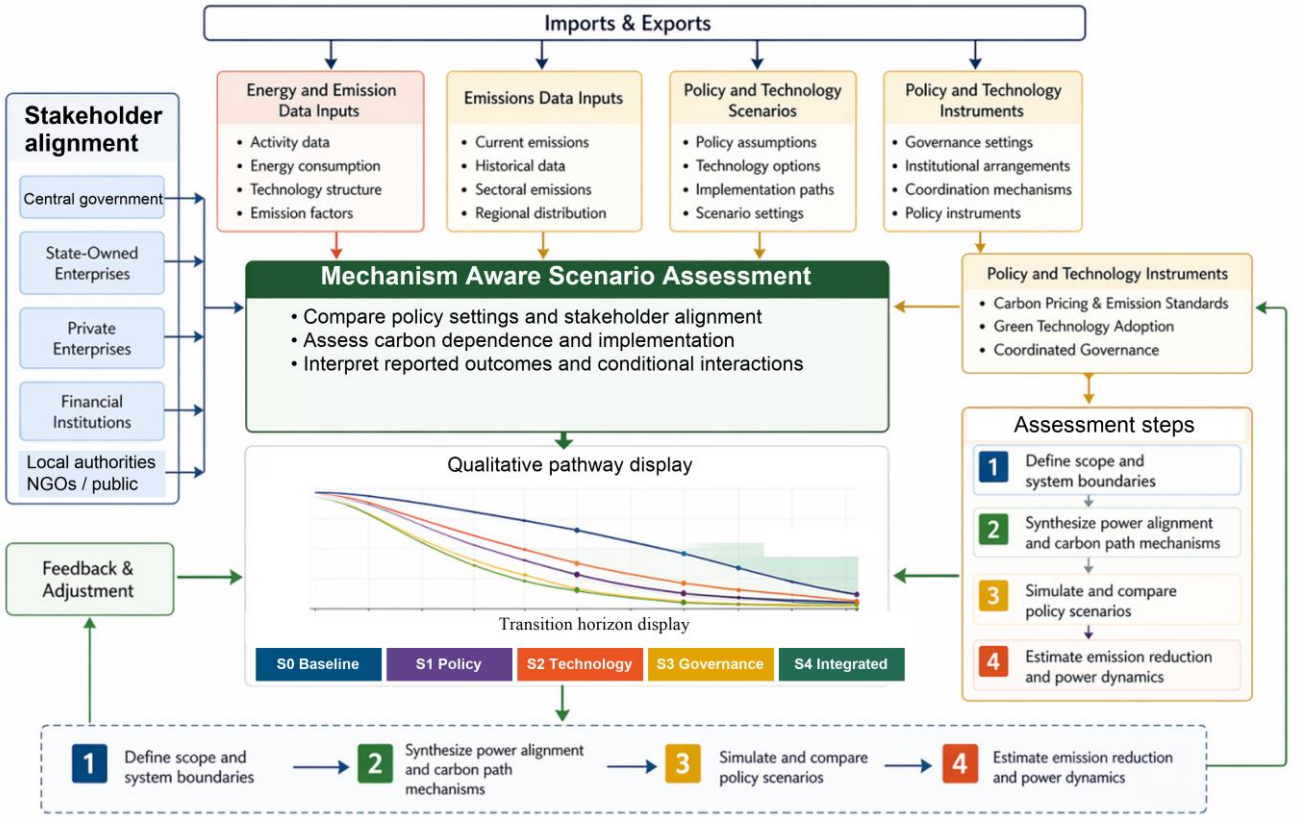


Figure 2 Organisation of the integrated scenario assessment. Energy and emissions information, stakeholder alignment and policy instruments inform the assessment. S0–S4 denote the five scenarios. Curves show qualitative pathway relationships, with quantitative scenario outcomes presented in Table 2.

3.4 Stakeholder alignment indicators

The stakeholder set comprises central government, SOEs, private firms, local authorities, financial institutions and non-governmental or public actors. Actor i is evaluated under scenario k using policy preference P_{ik}, resource capacity R_i, implementation capability C_i and perceived transition burden D_{ik}. The alignment score is defined as

$$A_{ik} = w_p P_{ik} + w_r R_i + w_c C_i - w_d D_{ik} \tag{1}$$

The weights w_p, w_r, w_c and w_d express the relative importance of the four components. Policy preference describes support for the package; resource and implementation capacity describe the ability to act; the burden term captures adjustment pressure or resistance. The weights satisfy

$$w_p + w_r + w_c + w_d = 1 \tag{2}$$

The component inputs are normalised to [0,1] before aggregation. The subtraction of transition burden gives the score a signed interpretation, with higher values indicating stronger alignment. The Power Alignment Index (PAI) aggregates the scenario actor scores using influence weights

$$\mathrm{PAI}_k = \sum_{i=1}^{n} \alpha_i A_{ik} \tag{3}$$

Here α_i is the relative influence weight of actor i. The influence weights satisfy

$$\sum_{i=1}^{n} \alpha_i = 1 \tag{4}$$

The scenario PAI uses actor weights of 0.25, 0.20, 0.15, 0.15, 0.15 and 0.10 in the six-actor order stated above. Weighted aggregation precedes rounding to four decimal places. The unweighted mean provides an additional descriptive benchmark.

The weighted threshold-support share is

$$\mathrm{CS}_k = 100 \, \frac{\sum_{i=1}^{n} \alpha_i \, \mathbf{1}(A_{ik} \geq \theta)}{\sum_{i=1}^{n} \alpha_i} \tag{5}$$

CS_k is the percentage of influence weights attached to actors with $A_{ik} \geq \theta$, where $\theta = 0.60$. The indicator takes the value 1 above or at the cutoff and 0 below it. PAI summarises average alignment, while CS measures threshold coverage. These two measures can rank scenarios differently. The unweighted mean is

$$\overline{A}_k = \frac{1}{6}\sum_{i \in S} A_{ik} \tag{6}$$

The sum covers the six actor categories. Aggregation precedes rounding to three decimal places.

Preference and burden assumptions are specified before interpreting the scenario outcome. This helps separate support assumptions from emissions results, while retaining uncertainty associated with judgement. Sensitivity to component weights, actor influence, scaling and the support threshold is therefore relevant alongside uncertainty about technologies and policy effectiveness.

3.5 Sectoral carbon lock-in indicators

For sector j, a general Carbon Lock-in Index (CLI) combines technological lock-in T_j, asset lock-in A_j, institutional lock-in I_j and network lock-in N_j

$$\mathrm{CLI}_j = \beta_t T_j + \beta_a A_j + \beta_i I_j + \beta_n N_j \tag{7}$$

The component weights satisfy

$$\beta_t + \beta_a + \beta_i + \beta_n = 1 \tag{8}$$

The sector comparison uses β_t = 0.30, β_a = 0.30, β_i = 0.20 and β_n = 0.20. The four dimensions share a 0–100 index scale. CLI is their weighted sum, rounded to two decimal places after aggregation. Table S4 provides an equal-weight reference with each dimension assigned 0.25. The scores organise structural constraints in index points.

Technological lock-in summarises normalised measures of technology lifetime LIFE_j, dependence on incumbent processes DEP_j and the fossil-based pathway share FOSS_j

$$T_j = \frac{\mathrm{LIFE}_j + \mathrm{DEP}_j + \mathrm{FOSS}_j}{3} \tag{9}$$

Asset lock-in combines normalised capital intensity CAP_j, fixed-asset persistence FIX_j and stranded-asset exposure STR_j

$$A_j = \frac{\mathrm{CAP}_j + \mathrm{FIX}_j + \mathrm{STR}_j}{3} \tag{10}$$

Institutional lock-in combines normalised regulatory dependence REG_j, persistence of incumbent support SUB_j and institutional inertia INER_j

$$I_j = \frac{\mathrm{REG}_j + \mathrm{SUB}_j + \mathrm{INER}_j}{3} \tag{11}$$

Network lock-in combines normalised upstream dependence SUP_j, industrial linkage dependence LINK_j and clustering dependence CLUS_j

$$N_j = \frac{\mathrm{SUP}_j + \mathrm{LINK}_j + \mathrm{CLUS}_j}{3} \tag{12}$$

Lifetimes, monetary quantities and shares are normalised before aggregation. Higher scores indicate greater structural persistence. The framework represents this persistence as a constraint on substitution. Ownership exposure and industrial linkages provide additional information about adjustment pressures.

3.6 Historical calibration and uncertainty

Historical calibration minimises weighted relative deviations between simulated and observed indicators over 2010–2020. Let Θ denote the parameter vector, m the calibration indicator and t the year. The calibration objective is

$$\min_{\Theta} \sum_{m=1}^{M} \omega_m \left[\frac{1}{T} \sum_{t=1}^{T} \left| \frac{Y_{m,t}^{\mathrm{sim}} - Y_{m,t}^{\mathrm{obs}}}{Y_{m,t}^{\mathrm{obs}}} \right| \right] \tag{13}$$

$Y_{m,t}^{\text{sim}}$ and $Y_{m,t}^{\text{obs}}$ denote simulated and observed values, ω_m is the target weight, M is the number of calibration indicators and T is the number of periods. Historical energy demand, carbon intensity, sectoral emissions and technology information establish the calibration context. The diagnostics in Table 1 summarise the fit of aggregate industrial energy demand.

Goodness of fit is described by the coefficient of determination and the mean absolute percentage error (MAPE)

$$R^2 = 1 - \frac{\sum_t \left(Y_t^{\text{obs}} - Y_t^{\text{sim}}\right)^2}{\sum_t \left(Y_t^{\text{obs}} - \overline{Y}^{\text{obs}}\right)^2} \tag{14}$$

$$\text{MAPE} = \frac{100}{T} \sum_{t=1}^{T} \left| \frac{Y_t^{\text{sim}} - Y_t^{\text{obs}}}{Y_t^{\text{obs}}} \right| \tag{15}$$

R^2 compares residual variation with variation in the observed series. MAPE expresses average absolute relative error as a percentage. Together, they describe correspondence between simulated and historical aggregate industrial energy demand over the calibration period.

Verification concerns whether an implementation performs its intended calculations, while validation concerns adequacy for its intended application (Sargent, 2013). Historical fit informs assessment of the energy-demand representation. Technology-cost assumptions also affect the interpretation of future pathways. Empirically grounded probabilistic forecasting provides an approach to examining future cost paths (Way et al., 2022). Deployment and cost uncertainty therefore remain relevant to scenario interpretation.

Uncertainty analysis considers policy effectiveness, technology adoption, renewable energy uptake, carbon capture performance, green investment and stakeholder response. Its Monte Carlo formulation represents an uncertain parameter x by a distribution around a baseline setting

$$x \sim \text{D}(\mu_x, \sigma_x) \tag{16}$$

The symbol D denotes the distribution, μ_x its central value and σ_x its dispersion parameter. Distributional assumptions determine the range and weighting of uncertain inputs. The fifth and ninety-fifth percentiles define the output interval

$$\text{UI}_p = \left[Q_{0.05}(Y_p), Q_{0.95}(Y_p)\right] \tag{17}$$

UI_p is the 90% uncertainty interval for output Y_p under the selected sampling assumptions. Local sensitivity measures the proportional output change relative to the proportional input change

$$\text{SI}_x = \frac{\Delta Y / Y}{\Delta x / x} \tag{18}$$

The sensitivity index measures response around a specified setting, whereas Monte Carlo percentiles summarise variation across sampled settings. Table 6 presents local sensitivity and error summaries for energy, technology, finance and transition timing. These summaries are interpreted within their respective test settings.

Local perturbations describe behaviour around chosen settings and may miss interactions elsewhere in the input space. Saltelli et al. (2019) review this issue in published sensitivity analyses. Joint variation in weights, thresholds and technology assumptions, examination of input dependence and comparison of response structures would extend the assessment. Table 6 provides the local summaries used here.

3.7 Mechanism contributions and transition exposure

Table 2 presents contributions assigned to technology substitution, structural adjustment, policy constraints and collaborative governance. Sequential mechanism activation supports comparison of their roles. Contributions can depend on activation order where mechanisms interact. The table therefore presents mechanism contributions alongside the scenario total and an explicit reconciliation residual.

Transition exposure is assessed by distinguishing physical asset retirement, financial impairment and the distribution of adjustment burdens. Table 5 summarises five support-related indicators and their unweighted mean. Distributional, procedural and recognition justice provide evaluative criteria for worker outcomes, regional fiscal exposure and participation.

3.8 Analytical complementarity and interaction assessment

To identify conditions for synergy, an analytical extension represents the reduction in sector j at a fixed assessment horizon as

$$r_j = e_j(1 - \ell_j)u_j g_j \tag{19}$$

Here e_j is reference emissions, ℓ_j is normalised lock-in, u_j is technical deployment capacity and g_j is effective implementation capacity. The latter three quantities lie in [0,1]. The multiplicative response represents a transition in which deployment and implementation are both necessary. It supplies an explicit analytical account of complementarity at a fixed assessment horizon. This approach connects interaction to the specific constraints addressed by instruments (Markard and Hoffmann, 2016).

An alternative response tests whether complementarity requires the multiplicative form. Suppose deployment and implementation are both necessary inputs, with the smaller capacity limiting the represented reduction. Define

$$b_j = e_j(1 - \ell_j)\min(u_j, g_j) \tag{20}$$

The symbol b_j denotes the bottleneck reduction. Its inputs and units match those of r_j, and ℓ_j remains fixed during comparison. The minimum operator represents a binding input whose shortage limits the reduction. Section 4.10 derives the finite interaction when the two capacities are equally binding at baseline.

For policy interaction, R_{ptg} denotes an outcome under fixed levels of policy enhancement p, technology support t and governance support g, each switched off or on. Other inputs and the outcome reference remain common. A two-factor interaction with the third factor held off is

$$I_{PT} = R_{110} - R_{100} - R_{010} + R_{000} \tag{21}$$

The corresponding three-factor interaction is

$$\begin{aligned} I_{PTG} = {} & R_{111} - R_{110} - R_{101} - R_{011} \\ & + R_{100} + R_{010} + R_{001} - R_{000} \end{aligned} \tag{22}$$

Eight configurations separate the pairwise and three-factor terms. A positive pairwise term indicates that the joint increment exceeds the sum of the individual increments on the chosen output scale. The three-factor term measures the additional joint contribution after accounting for baseline, individual and pairwise terms. The S1–S3 scenario packages contain partly overlapping instruments. Their comparison with S4 uses the common scenario reference and a descriptive additivity measure.

3.9 Exact numerical verification and emissions accounting

Deterministic enumeration verifies the multiplicative and bottleneck responses in Section 3.8. Each setting evaluates four configurations with fixed reference emissions and lock-in. Deployment and implementation improve individually and jointly. The finite interaction is the joint outcome minus the two individual outcomes plus the baseline outcome.

Reference emissions are normalised to 1. The baseline deployment and implementation capacities each take values from 0 to 1 in steps of 0.10. Lock-in uses the same eleven-point grid. Each capacity increment takes values of 0.05, 0.10 and 0.20. A configuration is retained only if both updated capacities remain at or below 1. Exhaustive enumeration gives 9,251 feasible input settings for each response. The same inputs are used for both capacity responses and an additive reference. The additive response is defined as

$$a_j = e_j(1 - \ell_j)\frac{u_j + g_j}{2} \tag{23}$$

The symbol a_j denotes the additive reference reduction in the same normalised units. The response uses the same lock-in multiplier and bounded capacity domain. Its four-configuration interaction is zero. Comparing the three responses identifies the role of the joint-input structure in generating additional reductions.

A separate enumeration verifies the support-threshold mechanism. Alignment takes values from 0 to 1 in steps of 0.05. The two non-negative increments each take values of 0.05, 0.10 and 0.20. Thresholds of 0.25, 0.50 and 0.75 test the generic mechanism across different cutoffs. These grid thresholds are separate from $\theta = 0.60$ used for the study scenario support shares. Cases with a final combined score above 1 are excluded. This produces 147

feasible cases per grid threshold and 441 in total. The four binary support indicators use the same greater-than-or-equal rule. Their finite interaction is measured in actor-indicator units.

The Python implementation uses exact rational arithmetic for comparisons, response evaluation and finite differences. Decimal export follows the exact calculation. Exhaustive enumeration records each feasible setting and its four outcomes in CSV files. The accounting calculations apply the same adopted weights, threshold and emissions boundary to Tables S3–S6.

4 Results

4.1 Historical fit and baseline settings

Table 1 presents the energy-context settings of 0.88 kg CO_2/kWh for carbon intensity, 5.0% for annual technology adoption and 12.0% for renewable energy share. Calibration of aggregate industrial energy demand over 2010–2020 gives $R^2 = 0.93$ and MAPE = 6.2%. These diagnostics provide a historical benchmark for the scenario assessment.

Table 1 Statistical baseline, energy context and study settings

Parameter or diagnostic	Value	Unit	Source or basis
2020 manufacturing direct emissions	1,000	Mt CO_2	Study statistical baseline; selected manufacturing boundary
Energy demand context	4,500	TWh/year	National Energy Statistical Yearbook, 2020
Energy carbon intensity context	0.88	kg CO_2/kWh	China's industrial carbon emission factor (2019)
Annual technology adoption	5.0	%	Assumed based on past technology penetration trends
Current renewable energy share	12.0	%	National Energy Development Plan (2021)
Assumed annual reduction in S1	3.0	% per year	Assumed based on policy package effectiveness
Government policy strength	0.60	–	Modelled from previous national carbon pricing policies
Private green technology investment	150	Billion USD	Estimated based on market trends and incentives for green investment
Historical energy demand fit	0.93	–	Fit of aggregate energy demand over 2010–2020
Historical energy demand MAPE	6.2	%	Fitting error for aggregate energy demand

Note. The 2020 baseline covers selected manufacturing direct emissions. Energy demand and carbon intensity define the broader energy-calibration context. Scenario settings and historical diagnostics are identified by their respective basis.

4.2 Intervention profiles and energy intensity

Energy-intensity improvement expresses the change in emissions or energy use per unit of output relative to a common baseline. Pricing and standards can encourage efficiency, technological change can alter production processes, and governance can improve deployment and execution. Figure 3 presents these three intervention profiles as a qualitative comparison.

The blue, green and purple profiles represent policy, technology and governance interventions, respectively. Their role is to organise the expected directions of change and the different channels through which interventions act. Quantitative scenario emissions outcomes are presented in Table 2.

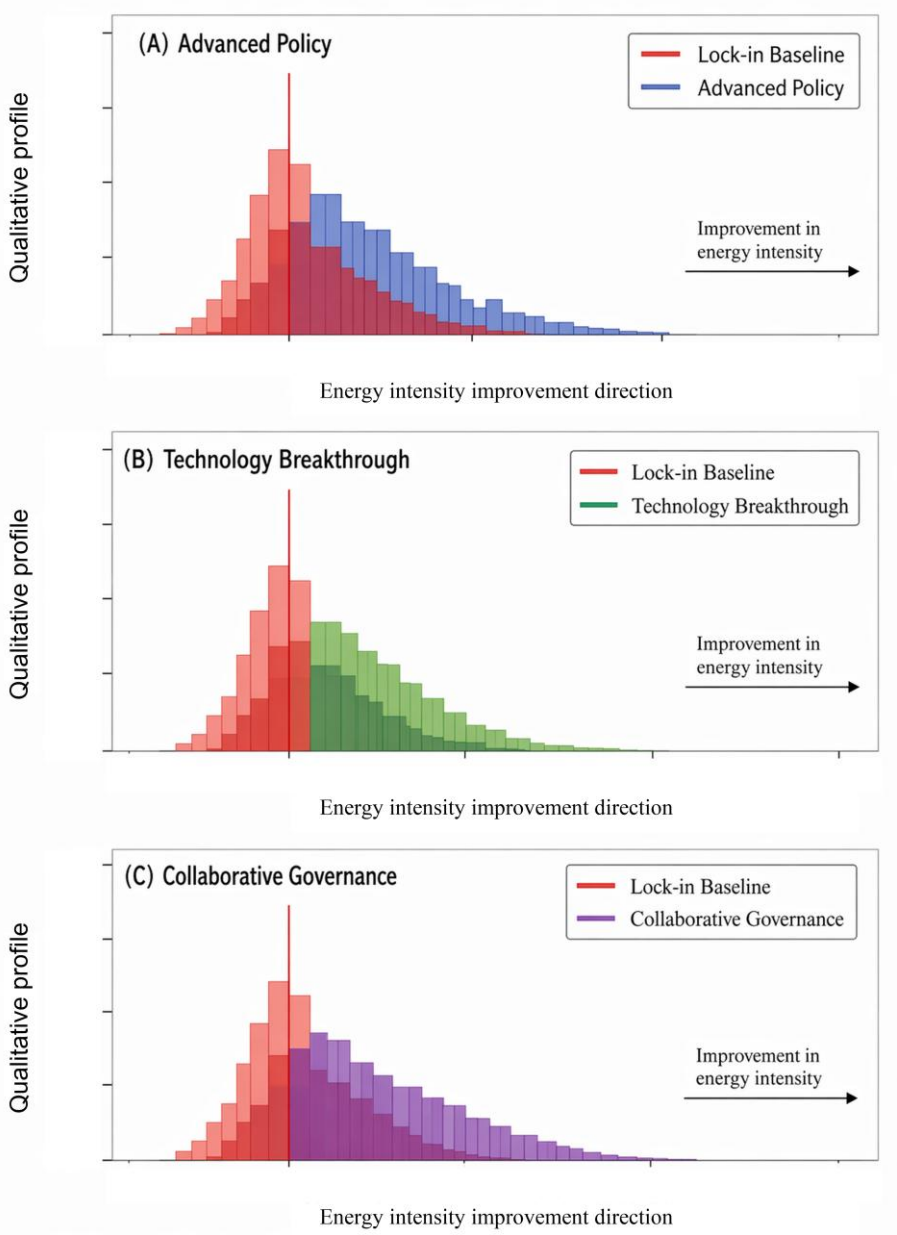


Figure 3 Qualitative intervention profiles for energy intensity. Panels A–C distinguish policy, technology and governance interventions. Colours and profiles organise the intervention channels and the expected direction of improvement.

4.3 Emissions reductions and mechanism contributions

The total emissions reductions from the common 2020 baseline to 2050 are 9.32% for S0, 19.60% for S1, 30.10% for S2, 41.55% for S3 and 59.00% for S4. Against the statistical baseline of 1,000 Mt CO_2, the corresponding 2050 emissions are 906.8, 804.0, 699.0, 584.5 and 410.0 Mt CO_2. The reduction amounts are 93.2, 196.0, 301.0, 415.5 and 590.0 Mt CO_2, respectively. Table S6 gives the full accounting. S0 includes autonomous change under existing conditions, so its 9.32% reduction is relative to 2020 rather than an additional intervention relative to itself. S4 has the largest reduction under the scenario settings.

Technology substitution contributes in every scenario and reaches 25.80% in S4. Governance contributions are larger in S3 and S4 than in S0–S2, consistent with their design. The difference between each scenario total and the sum of its listed contributions is +0.10 percentage points in S1 and −1.00 in S2 and S4. Table 2 includes these reconciliation residuals alongside the mechanisms. Sections 4.10 and 4.11 examine mechanism complementarity and the aggregate scenario comparison.

Table 2 Mechanism contributions and total emissions reductions

Mechanism	S0	S1	S2	S3	S4
Technology Substitution	5.12%	10.45%	20.30%	15.60%	25.80%
Structural Adjustment	2.30%	4.10%	5.25%	7.60%	9.80%
Policy Constraints	1.90%	3.85%	4.05%	8.20%	10.40%
Collaborative Governance	0.00%	1.10%	1.50%	10.15%	14.00%
Total emissions reduction	9.32%	19.60%	30.10%	41.55%	59.00%
Total less listed mechanism sum (pp)	0.00	+0.10	-1.00	0.00	-1.00

Note. Values use the common 2020 manufacturing direct-emissions reference and 2050 endpoint. The final row reconciles the scenario total with the sum of listed contributions. Residuals are expressed in percentage points.

4.4 Fossil fuel and feedstock dependence

Figures 4 and 5 organise fuel and feedstock uses and the stages of fossil-based material production. They distinguish energy use from material inputs and show how production routes connect to final uses. These qualitative diagrams define the categories relevant to transition assessment.

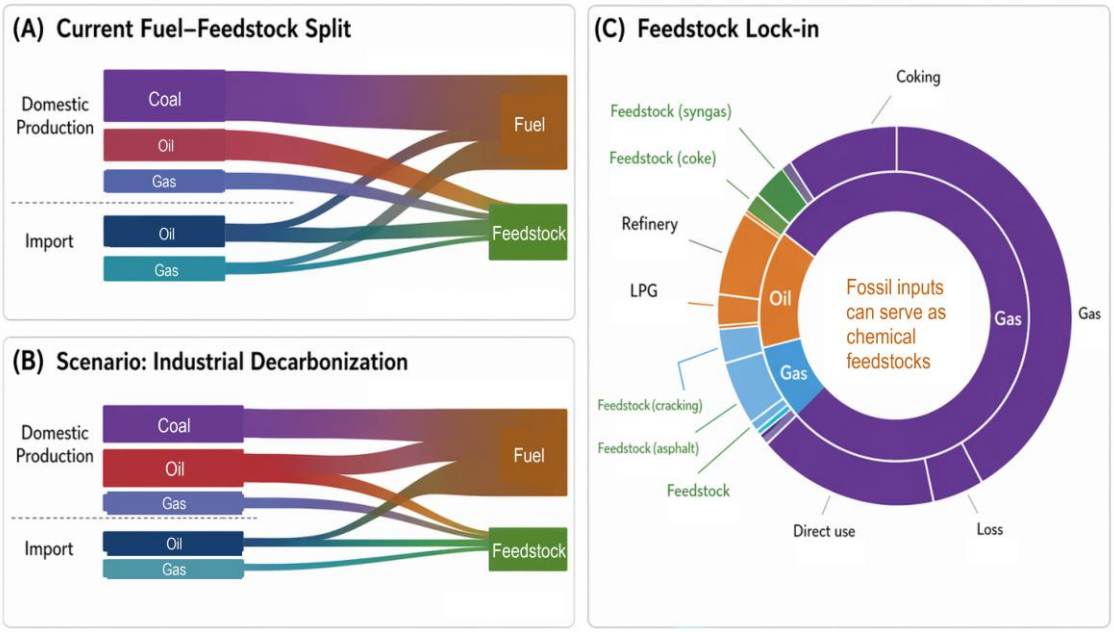


Figure 4 Qualitative organisation of fuel and feedstock uses. Panels A and B distinguish energy uses from material inputs. Panel C groups feedstock-related categories. Ribbon widths and sector angles serve a qualitative display function.

Cleaner energy addresses combustion emissions, while material production can remain dependent on fossil feedstocks. Feedstock substitution, material efficiency and changes in production routes therefore complement energy measures. Quantitative flow accounting requires common geographical and annual boundaries, consistent units and treatment of conversion losses, additional reactants and stock changes. Domestic supply and imports define sourcing categories within that accounting.

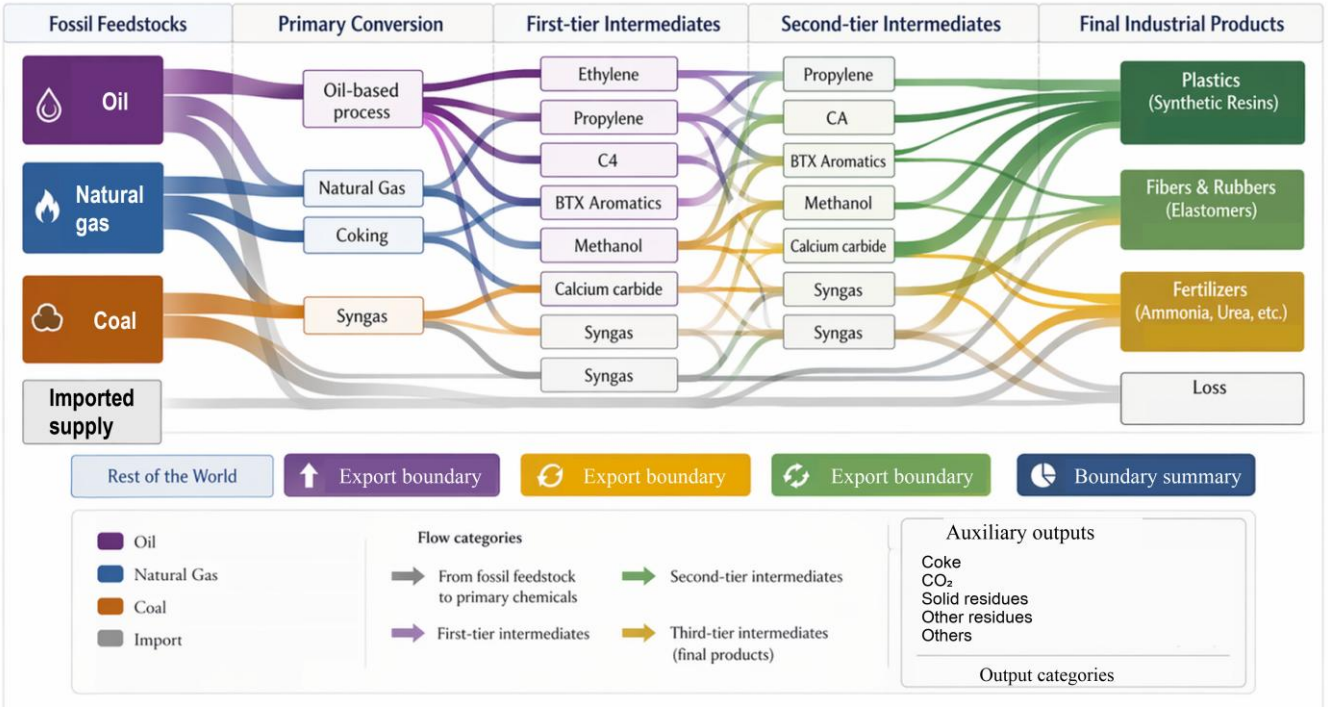


Figure 5 Qualitative fossil feedstock pathways. The five stages connect resource sourcing, processing, products and end uses. Imports and exports define sourcing boundaries. Ribbon widths represent qualitative relationships.

4.5 Product-level emissions profiles

Figure 6 presents energy-related and process-related emissions for ten production routes. Each total is the sum of the two components, expressed in t CO_2 per tonne of the labelled product. R1 represents propylene via methanol-to-propylene (MTP), with total intensity 12.1 t CO_2/t. R9 and R10 represent ethylene via steam cracking and ethane cracking, with totals of 1.6 and 0.8 t CO_2/t, respectively. Route identifiers distinguish the products and processes. The profiles show differences in the composition of production emissions, which inform the choice between energy substitution and process change.

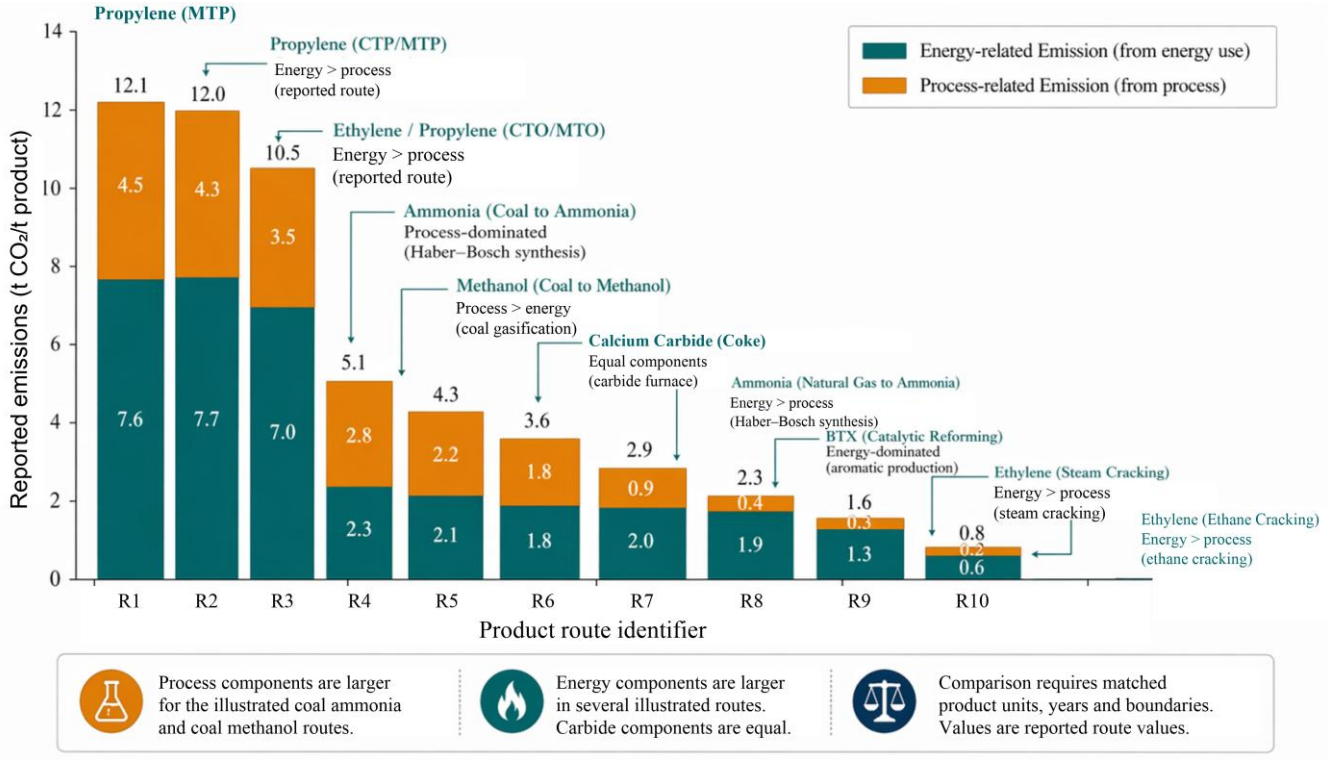


Figure 6 Energy and process emissions by production route. Totals sum the energy and process components in t CO_2 per tonne of the labelled product. R1 is propylene via methanol-to-propylene, R9 is ethylene via steam cracking and R10 is ethylene via ethane cracking. Route-level comparison uses the product and process identities in the key.

4.6 Stakeholder support across scenarios

Table 3 reports the highest alignment score in S4 for each of the six actor groups, exceeding S0 and each narrower intervention scenario. In S4, the scores are 0.80 for central government, 0.85 for SOEs, 0.69 for private firms, 0.74 for local authorities, 0.83 for financial institutions and 0.64 for non-governmental or public actors. Relative to S3, the respective increases are 0.06, 0.05, 0.14, 0.03, 0.04 and 0.12. The largest displayed improvements concern private firms and public actors. This pattern strengthens the case for assessing the distribution of modelled support alongside emissions outcomes. It remains conditional on the actor scoring assumptions.

The integrated scenario has the highest PAI, 0.7730, compared with 0.4800 in S0. S1, S2 and S3 have values of 0.5985, 0.6660 and 0.7045. Their unweighted actor means are 0.465, 0.578, 0.655, 0.685 and 0.758 for S0–S4. At $\theta = 0.60$, the weighted support shares are 0%, 60%, 85%, 75% and 100%. S2 exceeds S3 in threshold coverage despite its lower PAI. In S2, private firms and public actors cross the cutoff while local authorities remain below it. In S3, local authorities cross it while private firms and public actors remain below it. Average alignment and threshold coverage thus reveal different aspects of support.

Table 3 Actor alignment, PAI and weighted threshold support

Actor or indicator	S0	S1	S2	S3	S4
Central government	0.49	0.65	0.69	0.74	0.80
State-owned enterprises	0.59	0.72	0.76	0.80	0.85
Private firms	0.39	0.50	0.64	0.55	0.69
Local authorities	0.44	0.54	0.59	0.71	0.74
Financial institutions	0.54	0.60	0.64	0.79	0.83
NGOs or public actors	0.34	0.46	0.61	0.52	0.64
Unweighted mean alignment	0.465	0.578	0.655	0.685	0.758
Study PAI	0.4800	0.5985	0.6660	0.7045	0.7730
Weighted threshold support (%)	0.0	60.0	85.0	75.0	100.0

Note. Actor weights are 0.25, 0.20, 0.15, 0.15, 0.15 and 0.10 in the listed order. Threshold support includes $A_{ik} \geq 0.60$. PAI and actor means are rounded after aggregation to four and three decimal places, respectively.

4.7 Weighted sectoral lock-in and support indicators

Table 4 presents CLI with weights of 0.30, 0.30, 0.20 and 0.20. Scores are 90.39 for energy, 84.35 for steel, 78.16 for cement, 77.55 for chemicals, 68.47 for other building materials and 62.37 for automotive manufacturing. Asset scores are relatively high across sectors. Energy and steel remain the two highest-scoring sectors under equal weights, while cement and chemicals exchange positions. The comparison directs attention to persistent structural constraints and shows the sensitivity of intermediate rankings to the weighting scheme.

Table 4 Lock-in dimensions and study CLI

Sector	Technology	Assets	Institutions	Networks	Study CLI
Steel	85.4	92.1	80.2	75.3	84.35
Cement	78.9	88.3	70.4	69.6	78.16
Chemicals	72.1	85.6	74.0	77.2	77.55
Energy	90.5	95.0	85.7	88.0	90.39
Automotive manufacturing	60.3	68.4	63.2	55.6	62.37
Other building materials	66.7	75.0	67.5	62.3	68.47

Note. $\text{CLI} = 0.30\,\text{Technology} + 0.30\,\text{Assets} + 0.20\,\text{Institutions} + 0.20\,\text{Networks}$. Components and CLI use the common 0–100 index scale. Aggregation precedes rounding to two decimal places. Other building materials exclude cement. Energy is a separate comparison sector and is excluded from the manufacturing direct-emissions baseline. Equal-weight comparisons are in Table S4.

Table 5 presents five support-related indicators and their unweighted mean. The means are 10.34% in S0, 14.58% in S1, 19.38% in S2, 20.10% in S3 and 27.40% in S4. The integrated scenario has the highest mean and

the highest indicator value for each actor category. These results complement the alignment assessment by summarising scenario differences in support-related outcomes.

Table 5 Stakeholder support-related indicators across scenarios

Support-related indicator	S0	S1	S2	S3	S4
Government support (%)	10.5	15.2	22.5	20.7	30.1
SOE support (%)	12.0	18.7	28.3	24.1	33.8
Private support (%)	6.3	8.3	15.6	19.0	25.3
Local authority support (%)	14.2	20.5	18.2	21.5	28.7
NGO support (%)	8.7	10.2	12.3	15.2	19.1
Mean support indicator (%)	10.34	14.58	19.38	20.10	27.40

Note. Each scenario mean is the arithmetic mean of its five support-related indicators. These percentages and the alignment scores in Table 3 use different indicator definitions.

4.8 Ownership and asset exposure

Figure 7 organises asset exposure across SOEs, private firms, local governments and financial actors. The qualitative panels identify the groups relevant to financial adjustment and transition planning. Exposure is evaluated in relation to assets, income or fiscal capacity, alongside the ability to absorb losses. This perspective distinguishes enterprise balance-sheet effects from local public-service and investor risks.

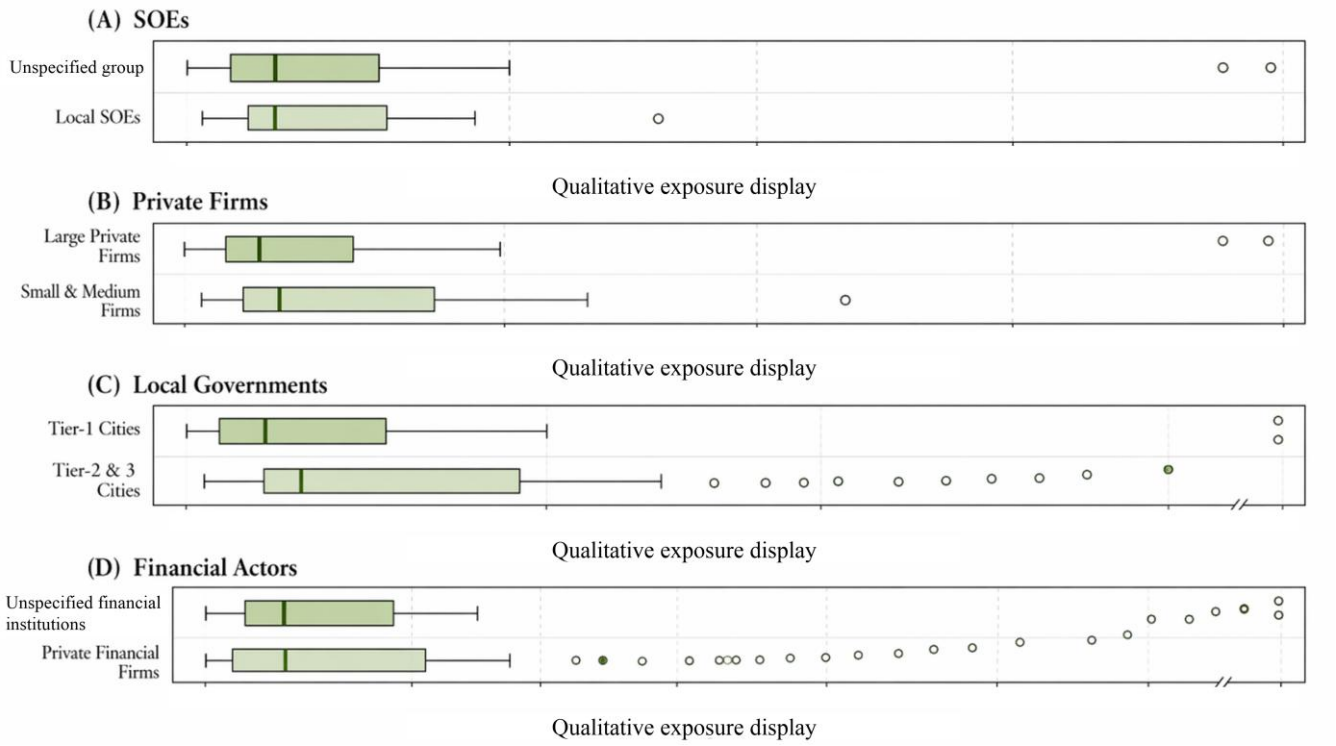


Figure 7 Qualitative asset-exposure display for stakeholder groups. Panels A–D organise exposure for SOEs, private firms, local governments and financial actors. The box-and-whisker marks serve as a qualitative display of the assessment categories.

Figure 8 separates physical asset status from financial impairment. An operating asset can experience value loss, while retirement can create both physical adjustment and financial consequences. The qualitative display presents these dimensions for the combined actor groups. Worker income, local public services and investor losses remain distinct outcomes for policy assessment.

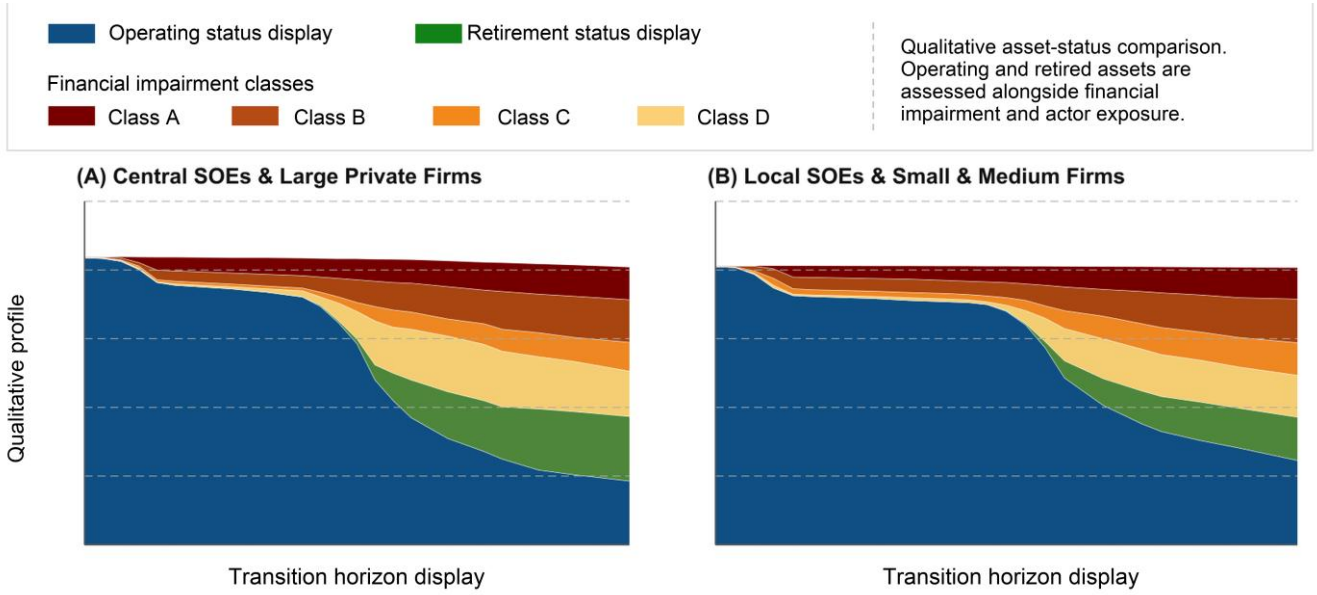


Figure 8 Qualitative physical asset status and financial impairment. Panels A and B organise the combined actor groups. Physical operation and retirement are assessed separately from financial impairment. The coloured areas provide a qualitative display.

4.9 Local sensitivity and error summaries

Table 6 presents six local test summaries for energy demand, carbon intensity, renewable energy share, private investment, carbon capture efficiency and transition timing. Sensitivity ranges from ±2.5% to ±6.0%, and error summaries range from ±1.8% to ±5.5% within the respective settings. Carbon capture has the largest listed sensitivity and error magnitudes, followed by renewable energy share.

Table 6 Local sensitivity and error summaries

Test	Scenario	Parameter	Setting	Sensitivity (%)	Error (%)
Energy test 1	S0	Total Energy Demand	4,500 TWh	±2.5	±1.8
Energy test 2	S1	Carbon Intensity (kg CO_2/kWh)	0.88	±3.1	±2.4
Technology test 1	S2	Renewable Energy Share (%)	12.0	±5.2	±4.5
Finance test	S3	Private Sector Investment (Billion USD)	150	±4.8	±3.9
Technology test 2	S2	Carbon Capture Efficiency (%)	75.0	±6.0	±5.5
Timing test	S0	Energy Transition Speed (Years)	20.5	±3.5	±2.1

Note. Sensitivity and error summaries apply to the respective parameter settings. Local sensitivity, fitting error and Monte Carlo uncertainty describe different aspects of model assessment.

These summaries identify technology and energy assumptions for closer examination. Comparisons across tests are interpreted within their parameter settings. Joint variation in actor weights, thresholds and response structures would provide a broader assessment of scenario stability.

4.10 Conditions for positive mechanism-level synergy

For $e_j > 0$ and $\ell_j < 1$, the analytical response has a positive mixed derivative

$$\frac{\partial^2 r_j}{\partial u_j \, \partial g_j} = e_j(1 - \ell_j) > 0 \tag{24}$$

If deployment and implementation rise by $\Delta u_j > 0$ and $\Delta g_j > 0$ within their feasible ranges, their finite interaction is

$$\begin{aligned}\Delta_{ug} r_j = r_j(u_j + \Delta u_j, g_j + \Delta g_j) \\ -r_j(u_j + \Delta u_j, g_j) - r_j(u_j, g_j + \Delta g_j) \\ +r_j(u_j, g_j) \\ = e_j(1 - \ell_j)\Delta u_j \, \Delta g_j > 0\end{aligned} \tag{25}$$

Expansion of the combined product cancels the individual and baseline terms, leaving the positive product of the two capacity increments. This term is the additional reduction from joint improvement. Greater lock-in reduces the interaction, and complete lock-in removes it. The derivation establishes the conditions under which deployment support and implementation support reinforce each other.

The bottleneck response gives a second, distinct reason for positive synergy. At a balanced baseline $u_j = g_j = c_j$ with $0 \le c_j < 1$, let both capacities increase by positive amounts within [0,1]. Increasing either capacity alone leaves the minimum at c_j. Increasing both raises it by the smaller increment. Defining the same four-term finite difference as above gives

$$\Delta_{ug} b_j = e_j(1 - \ell_j)\min(\Delta u_j, \Delta g_j) > 0 \tag{26}$$

The interaction is positive when $e_j > 0$ and $\ell_j < 1$. The minimum function thus produces a joint enabling gain when the two inputs are binding together. Away from the balanced baseline, the gain depends on whether the increments relieve the limiting constraint. Complete lock-in removes the gain. This result supports targeting deployment and implementation barriers together when both restrict transition.

A separate threshold mechanism can create additional coalition support. With fixed weights and threshold, define the interaction between two support-enhancing interventions as

$$\Delta_{pf}\mathrm{CS} = \mathrm{CS}_{11} - \mathrm{CS}_{10} - \mathrm{CS}_{01} + \mathrm{CS}_{00} \tag{27}$$

For an actor below the threshold at baseline, let the two non-negative score increments be d_i and f_i. If $A_{i0} + d_i < \theta$ and $A_{i0} + f_i < \theta$, but $A_{i0} + d_i + f_i \ge \theta$, only the combined intervention secures support. That actor contributes $+100\alpha_i$ to the interaction. If both interventions individually secure support, their combined contribution can be $-100\alpha_i$ because of overlap. Net threshold complementarity is positive when the influence associated with additional support exceeds the influence associated with overlapping coverage.

4.11 Integrated scenario advantage and descriptive additivity

With the common 2020 reference, S4 exceeds S1, S2 and S3 by 39.40, 28.90 and 17.45 percentage points, respectively. Its reduction above S0 is 49.68 percentage points. The narrower increments above S0 are 10.28 for S1, 20.78 for S2 and 32.23 for S3, summing to 63.29 percentage points. A descriptive comparison of the integrated increment with that sum gives

$$I_{\mathrm{desc}} = S_4 - S_1 - S_2 - S_3 + 2S_0 = -13.61\ \mathrm{pp} \tag{28}$$

The descriptive residual is −13.61 percentage points. In this expression, S0–S4 denote the total reductions in Table 2 and pp denotes percentage points. The measure compares overlapping scenario packages on their common output scale. Table 7 presents both the advantage of S4 over each alternative and this descriptive residual. The integrated package gives the largest reduction among the five scenarios, while the analytical mechanisms explain the conditions for additional gains from jointly addressing deployment and implementation constraints.

Table 7 Integrated scenario advantage and descriptive additivity

Quantity	Calculation from Table 2	Percentage points
S4 compared with S1	$59.00 - 19.60$	39.40
S4 compared with S2	$59.00 - 30.10$	28.90
S4 compared with S3	$59.00 - 41.55$	17.45
S1 above S0	$19.60 - 9.32$	10.28

Quantity	Calculation from Table 2	Percentage points
S2 above S0	$30.10 - 9.32$	20.78
S3 above S0	$41.55 - 9.32$	32.23
Sum of narrower increments	$10.28 + 20.78 + 32.23$	63.29
S4 above S0	$59.00 - 9.32$	49.68
Integrated less summed increments	$49.68 - 63.29$	−13.61

Note. All comparisons use the total reductions in Table 2 and a common 2020 reference. The final row compares the integrated increment with the sum of the narrower increments. Values are percentage points.

4.12 Numerical verification of conditional interactions

Table 8 summarises the completed enumeration. In the multiplicative response, 8,410 settings have a positive interaction and 841 have zero interaction. The zero cases all have complete lock-in. The computed interaction equals the analytical product in every feasible setting, with a maximum of 0.04 normalised emissions units on the specified grid. The bottleneck response has 1,370 positive and 7,881 zero interactions, with no negative values. Positive interactions occur where the combined improvements relieve a shared limiting constraint. Within the balanced-baseline subset, 850 of 935 cases are positive and the other 85 have complete lock-in. The additive reference gives zero interaction in all 9,251 settings.

The threshold enumeration gives 40 positive, 358 zero and 43 negative actor-indicator interactions. Positive cases obtain support only after combining the increments. Negative cases arise when both increments individually secure the same actor support, producing overlapping coverage. The counts summarise the specified finite grid. Together, the signs show why joint support measures work best when they address distinct barriers for actors close to the cutoff.

Table 8 Exact finite-grid verification of conditional interactions

Response	Cases	Positive	Zero	Negative	Interaction range
Multiplicative	9,251	8,410	841	0	0 to 0.04
Bottleneck	9,251	1,370	7,881	0	0 to 0.2
Additive reference	9,251	0	9,251	0	0 to 0
Threshold indicator	441	40	358	43	−1 to +1

Note. Capacity responses use normalised emissions units with reference emissions set to 1. Threshold responses use single-actor indicator units. Each capacity response uses 9,251 feasible settings. Counts summarise the specified grids, with exact arithmetic before decimal export.

Tables S4 and S5 apply the adopted weights consistently. Energy and steel have CLI values of 90.39 and 84.35, and cement ranks above chemicals. PAI is 0.4800, 0.5985, 0.6660, 0.7045 and 0.7730 for S0–S4. The corresponding support shares at $\theta = 0.60$ are 0%, 60%, 85%, 75% and 100%. Component scores, actor aggregates and main-table results agree under the common calculation rules.

Table S6 reconciles every scenario with the 2020 baseline of 1,000 Mt CO_2. Remaining emissions in 2050 plus the reduction amount equal the baseline in every case. The accounting connects the scenario percentages to absolute emissions under the selected manufacturing direct-emissions boundary. Analytical derivation, exact enumeration and consistent accounting together provide the basis for interpreting the transition mechanisms and scenario outcomes.

5 Discussion

5.1 Industrial policy under structural constraints

The sectoral comparison supports treating industrial transition as a differentiated policy problem. Technology, assets, institutions and production networks create different constraints on change. This interpretation is consistent with research on industrial path renewal and carbon lock-in (Herman et al., 2025; Sovacool et al., 2025). A common emissions target can guide national policy while implementation measures respond to sectoral conditions. For sectors with long-lived capital, transition planning should consider investment cycles and

retirement schedules. For feedstock-dependent production, the assessment should include material pathways alongside cleaner energy.

A high lock-in score identifies a sector for closer examination of its structural constraints. Public assistance can be linked to credible low-carbon deployment, performance conditions and retirement planning. This approach directs support towards transition while accounting for the persistence of incumbent assets. Expenditure, enforcement capacity and the distribution of adjustment costs form part of implementation planning.

Recent steel research strengthens the case for considering investment timing. Bachorz et al. (2026) examine strategic green investment as a way to avert further steel carbon lock-in. The framework points towards aligning technology support and enabling infrastructure with major asset decisions. Plant-level financing and retirement plans can then address the specific conditions under which new investment changes the production pathway.

Production-route differences also matter for cement and chemicals. Habert et al. (2020) identify cement and concrete mitigation opportunities across the value chain, including clinker reduction and changes requiring stakeholder engagement. The fuel and feedstock illustrations here serve a similar diagnostic purpose. A package aimed only at cleaner electricity can leave material and process constraints unresolved. Assessing these remaining constraints would help identify where deployment support, procurement or material-efficiency measures should accompany energy policies.

5.2 Policy packages and implementation capacity

The integrated scenario leads the emissions comparison, supporting joint consideration of instruments in China's energy policy mix (Li and Taeihagh, 2020; Zhou et al., 2025). Carbon pricing changes incentives, while technology support and finance address investment barriers. Research on finance and industrial carbon unlocking also examines financing and regulatory conditions together (Xu and Li, 2024). Coordination helps actors respond to these conditions. Resource-constrained policy design can extend this assessment by comparing the costs and delivery requirements of alternative packages.

The analytical responses explain how an integrated package can address complementary constraints. In the multiplicative response, improving one capacity raises the return to improving the other. In the bottleneck response, improving both binding inputs enables a reduction unavailable from either improvement alone. In the threshold mechanism, combined measures secure actor support when neither alone offsets the transition burden. Policy design can use these results to identify the constraints that need joint attention and avoid duplicating measures that already secure the same support.

The practical implication is to assess incentives alongside the capacity to respond. Standards depend on access to suitable processes and finance. Policy uncertainty also affects investment (Yue and Fu, 2026). Phasing, coordinated investment and targeted assistance can address these implementation conditions. Comparable cost information, including marginal abatement analysis (Zhang et al., 2025), would support evaluation of package efficiency under a resource constraint.

Policy sequencing offers one way to build the conditions for stronger intervention. Research examines how early support can develop constituencies and capabilities for subsequent decarbonisation policy (Meckling et al., 2017; Pahle et al., 2018). Evidence on net-zero policy mixes in Germany further emphasises policy needs associated with integrating energy sectors (Olbrich et al., 2024). These insights suggest coordinating industrial deployment with electricity, hydrogen and related infrastructure. The appropriate sequence for China remains sector- and institution-dependent.

The International Energy Agency (IEA, 2025) organises an industrial-decarbonisation policy toolbox that includes innovation, finance, infrastructure and market development. It supports the practical relevance of examining several barriers together. In this framework, an implementable package would identify the constraint each instrument addresses, the actors responsible for delivery, the conditions attached to support and the outcome used to assess progress. This turns the synergy argument into a testable design proposition rather than a presumption that adding instruments always improves performance.

5.3 Transition exposure and justice

Asset retirement and financial impairment affect different groups and policy responsibilities. Retirement can change employment, enterprise balance sheets, financial claims and local economic activity. Their consequences

depend on exposure relative to each actor's ability to absorb losses. Policy assessment therefore distinguishes worker and public-service protection from investor compensation, while considering the distribution of adjustment across enterprises and places.

Research on China's just transition stresses the political and distributive dimensions of moving away from carbon-intensive activity (Gong and Lewis, 2024; Wang et al., 2024). The framework connects asset and support assessment with worker participation, social protection and local adjustment. A broader evaluation would examine job displacement, wages, retraining outcomes, regional fiscal dependence and the views of affected groups. These outcomes provide concrete criteria for judging whether a feasible transition also distributes its costs and benefits fairly.

Three dimensions can make the just-transition assessment more concrete. Distributional justice concerns who bears adjustment costs and who gains access to benefits. Recognition concerns whether affected groups and their different circumstances are represented. Procedural justice concerns their ability to participate in decisions (Jenkins et al., 2016). Carley and Konisky (2020) show why a clean-energy transition can reproduce existing inequalities. Applying these dimensions here would distinguish workers, smaller suppliers, communities and local authorities within the broad actor categories, then assess access to assistance and meaningful participation.

Transition assistance should specify its beneficiaries and purposes. Green and Gambhir (2020) distinguish assistance strategies and beneficiary groups and emphasise implementation capacity. Survey evidence from the United States and India shows that compensation preferences vary with vulnerability to climate policy (Gaikwad et al., 2022). A review of supply-side decarbonisation directs attention to its social consequences (Beckfield and Evrard, 2023). These findings motivate income protection, retraining, regional adjustment and continuity of public services as explicit criteria alongside industrial support.

Compensation can facilitate transition but also requires a credible fiscal strategy. Nacke et al. (2024) examine the scale of compensation associated with rapid coal phase-out and the cost of extending such arrangements to major emitters. This reinforces the need to distinguish support for workers and communities from reimbursement of investor losses. For China, assistance could be assessed against exposure, fiscal capacity and a verifiable transition commitment. Its justice contribution would depend on who receives support and what outcomes follow, rather than on the average support proxy in Table 5.

5.4 Relevance beyond the Chinese case

The Chinese case is informative because industrial transition involves multiple levels of government, varied ownership structures and substantial dependence on incumbent production systems (Malz et al., 2023; Xie et al., 2025). The framework draws attention to the relationship between technological opportunity and implementation capacity. This question is also relevant to other economies where industrial assets, local employment and finance are tied to carbon-intensive production. The transferable contribution is the structure of the assessment, rather than the numerical parameter values or scenario rankings.

Application elsewhere would require redefining the actor set, policy instruments and system boundary. Influence weights and support thresholds would need to reflect the institutional context, while technology and asset assumptions would need local evidence. Directly transferring China-specific scores could conceal differences in authority, financing and participation. Comparison across settings should therefore examine which mechanisms remain relevant and which assumptions change. Such work could test the framework's broader usefulness without treating one national scenario as a universal pathway.

Transfer also depends on the wider industrial-policy setting. Juhász and Lane (2024) examine the political economy of industrial policy, while Allan and Nahm (2025) connect green-industrial strategies to firms' positions in global supply chains. Meckling (2025) highlights the growing role of geoeconomic competition in decarbonisation. These perspectives show why national capacity and external market conditions should be considered alongside domestic actor alignment. Applying the framework elsewhere would require examining these conditions before transferring policy instruments or expectations of synergy.

5.5 Limitations and interpretation

The assessment has several boundaries. Historical fitting diagnostics concern aggregate industrial energy demand over 2010–2020. Sector-level observations, an independent validation period and comparisons with alternative

transition models would extend the evaluation of projected pathways. Scenario results describe outcomes under the stated policy, technology and implementation assumptions.

Actor and sector scores incorporate expert judgement. The reciprocal matrix documents the adopted weight vector through its algebraic ratios. Sector rankings vary with weighting, as shown by the change in the relative positions of cement and chemicals. Broader variation in weights and thresholds would extend this comparison. More detailed actor categories would also reveal differences within firms, financial institutions and local authorities.

Synergy depends on response structure, the binding constraints and the outcome scale. The multiplicative and bottleneck results specify these conditions explicitly. The scenario packages vary in intervention intensity and contain overlapping instruments, so their additivity comparison is descriptive. Common-budget factorial comparisons and empirical calibration of the capacity relationships would extend analysis of the strength and efficiency of integrated policy. Finite-grid counts describe the tested parameter space.

A fuller just-transition assessment would measure employment, income, financial impairment, regional fiscal exposure and participation within compatible boundaries. The qualitative diagrams organise relevant categories, while the scenario indicators summarise emissions and support. The offline framework provides a basis for examining policy assumptions and implementation conditions. Evidence from implementation would connect these assessments to realised outcomes.

6 Conclusion

This study connects carbon lock-in, stakeholder alignment and policy complementarity in China's industrial transition. Two-round expert consultation and disclosed weights provide a common basis for the indicator assessment. The integrated scenario reduces emissions from the 2020 baseline of 1,000 Mt CO_2 to 410 Mt CO_2 in 2050 and achieves the highest PAI of 0.7730. Analytical derivation and exact finite-grid verification identify positive synergy between deployment and implementation under multiplicative and binding-bottleneck conditions. Threshold analysis shows when combined measures obtain additional actor backing and when their coverage overlaps. The results support integrated policy directed at complementary technological and implementation constraints. Worker protection, local fiscal adjustment and meaningful participation provide additional criteria for a just transition. Future common-budget comparisons and empirical assessment of capacity relationships would extend the policy application.

Data availability

The datasets and supporting materials generated and/or analyzed during the current study are available from the author upon reasonable request. No restrictions are imposed on access to the data.

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Conflict of Interest Statement

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Supplementary material

Table S1 Variable definitions and calculation rules

Symbol	Variable and definition	Scale or unit	Basis and calculation rule
S	Stakeholder set. Set of stakeholders included in the power alignment module	Categorical set	Model design. Includes central government, SOEs, private firms, local authorities, financial institutions, and NGOs/public actors
i	Stakeholder index. Index for individual stakeholder	Integer	Model notation. Used to distinguish stakeholder groups in scenario-specific alignment calculations
k	Scenario index. Index for policy scenario	Integer	Model notation. Refers to S0–S4 policy scenarios defined in the study

Symbol	Variable and definition	Scale or unit	Basis and calculation rule
A_{ik}	Alignment score. Alignment level of stakeholder i under scenario k	Score scale; depends on burden subtraction and any rescaling	Derived from model components. $A_{ik} = w_p P_{ik} + w_r R_i + w_c C_i - w_d D_{ik}$
P_{ik}	Policy preference. Degree of stakeholder support for a given policy package	0–1 (normalised)	Policy-document coding, scenario judgement, secondary evidence. Higher values indicate stronger support for scenario k; standardised before aggregation
R_i	Resource capacity. Financial, administrative, or organisational capacity of stakeholder i	0–1 (normalised)	Secondary statistics, institutional characteristics, scenario judgement. Reflects relative ability to mobilize resources for low-carbon transition; normalised across actor groups
C_i	Implementation capability. Ability of stakeholder i to implement or influence policy execution	0–1 (normalised)	Governance role assessment, secondary evidence, scenario judgement. Higher values represent stronger policy execution or influence capacity
D_{ik}	Transition burden. Perceived transition cost or resistance of stakeholder i under scenario k	0–1 (normalised)	Scenario-based assessment, policy burden estimation. Higher values indicate greater perceived cost, adjustment pressure, or resistance under scenario k
w_p , w_r , w_c , w_d	Alignment weights. Weights assigned to policy preference, resource capacity, implementation capability, and transition burden	Sum to 1	Model assumption / sensitivity setting. Non-negative component weights; sum to 1; assumption subject to sensitivity assessment
α_i	Power weight. Relative power or influence of stakeholder i	Sum to 1	Study actor weights. Central government 0.25; SOEs 0.20; private firms 0.15; local authorities 0.15; finance 0.15; public actors 0.10
PAI_k	Power Alignment Index. Overall weighted stakeholder coordination under scenario k	Score scale; depends on burden subtraction and any rescaling	Study actor weights. Weighted mean using α = (0.25, 0.20, 0.15, 0.15, 0.15, 0.10); final rounding to four decimal places
CS_k	Threshold-support share. Influence-weight share with alignment at or above the threshold	%	Study threshold $\theta = 0.60$. 100 times the actor-weight share with $A_{ik} \geq 0.60$; fixed rule across scenarios
θ	Support threshold. Minimum alignment score required for effective policy support	0.60 on the alignment scale	Adopted study cutoff. Includes A_{ik} equal to 0.60; fixed across S0–S4
j	Sector index. Index for industrial sector	Integer	Model notation. Refers to industrial sectors such as steel, cement, chemicals, energy, etc.
CLI_j	Study CLI. Composite carbon lock-in level of sector j	0–100 index points	Weighted component scores. $0.30T + 0.30A + 0.20I + 0.20N$; final rounding to two decimal places
T_j	Technological lock-in. Dependence on incumbent fossil-based technologies and long-lived production systems	Normalised input score; reported ×100	Sectoral characteristics, literature, judgement-based scoring. Calculated from technology lifetime, dependence on incumbent systems, and fossil-path share
A_j	Asset lock-in. Persistence of sunk capital and carbon-intensive infrastructure	Normalised input score; reported ×100	Sectoral characteristics, secondary statistics, judgement-based scoring. Calculated from capital intensity, fixed-asset persistence, and stranded-asset exposure
I_j	Institutional lock-in. Policy, regulatory, and governance inertia favouring incumbent systems	Normalised input score; reported ×100	Policy review, governance analysis, judgement-based scoring. Calculated from regulatory dependence, subsidy persistence, and institutional inertia
N_j	Network lock-in. Supply-chain, inter-firm, and clustering dependence	Normalised input score; reported ×100	Sectoral linkage assessment, industrial structure evidence. Calculated from supply-chain dependence, industrial linkage dependence, and clustering dependence

Symbol	Variable and definition	Scale or unit	Basis and calculation rule
$\beta_t, \beta_a, \beta_i, \beta_n$	Lock-in weights. Weights assigned to technological, asset, institutional, and network lock-in components	0.30, 0.30, 0.20, 0.20; sum to 1	Adopted study weights. Reciprocal matrix uses exact ratios of these weights; $\mathrm{CR} = 0$ follows its construction
LIFE_j	Technology lifetime. Average lifetime of incumbent technological systems in sector j	Years or normalised score	Sector reports, literature, engineering judgement. Longer lifetime implies stronger persistence of incumbent technology; rescaled before aggregation
DEP_j	Technology dependence. Dependence on established production technologies	0–1	Sectoral assessment. Higher values indicate lower substitutability and stronger dependence on incumbent production routes
FOSS_j	Fossil-path share. Share of fossil-based production pathways in sector j	% or 0–1	Energy/emissions statistics, sectoral evidence. Higher fossil-based pathway shares indicate stronger technological lock-in
CAP_j	Capital intensity. Capital embedded in incumbent systems	Monetary intensity or normalised score	Industrial statistics, sectoral evidence. Higher capital intensity implies greater resistance to rapid technology replacement
FIX_j	Fixed-asset persistence. Durability of fixed carbon-intensive assets	0–1	Sectoral characteristics, infrastructure life-cycle evidence. Higher values indicate stronger physical persistence of incumbent assets
STR_j	Stranded-asset exposure. Exposure of sector j to asset devaluation during transition	0–1 or %	Scenario estimation, sectoral asset-risk assessment. Higher values indicate greater risk of premature retirement or value loss
REG_j	Regulatory dependence. Dependence on incumbent regulatory arrangements	0–1	Policy analysis. Captures the extent to which existing rules favour current high-carbon production patterns
SUB_j	Subsidy persistence. Persistence of policy support for existing high-carbon systems	0–1	Policy analysis, institutional review. Higher values indicate stronger continuation of incumbent support structures
INER_j	Institutional inertia. Resistance to institutional change	0–1	Governance assessment. Higher values represent slower adaptation of administrative and regulatory systems
SUP_j	Supply-chain dependence. Dependence on upstream carbon-intensive inputs	0–1	Industrial linkage evidence. Higher values indicate stronger upstream dependence and slower transition flexibility
LINK_j	Industrial linkage dependence. Interdependence across production chains	0–1	Input-output logic, sectoral linkage assessment. Measures dependence on interconnected production systems and downstream lock-in effects
CLUS_j	Clustering dependence. Lock-in generated by spatial or industrial clustering	0–1	Spatial-industrial structure assessment. Higher values indicate stronger co-location and agglomeration-related transition rigidity
Θ	Parameter vector. Set of calibrated model parameters	Parameter vector	Model notation. Includes parameters adjusted during model calibration to minimise deviation from historical observations
m	Indicator index. Index for calibration target	Integer	Model notation. Refers to calibration targets such as energy demand, carbon intensity, sectoral emissions, and technology adoption
ω_m	Calibration weight. Weight assigned to calibration target m	Normalized weight	Model assumption. Reflects relative importance of each historical calibration target in the objective function
$Y_{m,t}^{\mathrm{sim}}$	Simulated value. Simulated value of indicator m in year t	Indicator-specific	Model output. Generated by the model for calibration comparison
$Y_{m,t}^{\mathrm{obs}}$	Observed value. Observed value of indicator m in year t	Indicator-specific	Statistical yearbooks, official inventories, sectoral databases. Historical benchmark used for calibration
Y_t^{sim}	Simulated output. Model-generated output in year t	Indicator-specific	Model output. Used in goodness-of-fit statistics
Y_t^{obs}	Observed output. Historical benchmark in year t	Indicator-specific	Historical data. Used in goodness-of-fit statistics

Symbol	Variable and definition	Scale or unit	Basis and calculation rule
$\overline{Y}^{\text{obs}}$	Mean observed value. Mean of observed values across the calibration interval	Indicator-specific	Derived from historical observations. Arithmetic mean of observed outputs in the fit calculation
T	Number of periods. Length of the calibration interval	Count of observation periods	Study design. Corresponds to the number of years used in calibration
R^2	Coefficient of determination. Goodness-of-fit metric for simulated versus observed trends	≤1; negative values possible	Derived statistic. 1 minus squared-error sum divided by observed variation; requires non-zero variation
MAPE	Mean absolute percentage error. Calibration error metric	%	Derived statistic. Lower values indicate smaller average percentage deviation between simulated and observed values
x	Uncertain parameter. Parameter varied in uncertainty analysis	Parameter-specific	Model notation. Represents uncertain policy, technology, finance, or governance parameters
$\mathrm{D}(\mu_x, \sigma_x)$	Parameter distribution. Assumed probability distribution of uncertain parameter x	Distributional form	Model assumption informed by plausible ranges. General distribution notation; actual family, bounds and dependence require specification
μ_x	Central parameter value. Central value under the chosen distribution parameterisation	Parameter-specific	Calibrated baseline / scenario setting. Central value around which uncertainty is explored
σ_x	Dispersion parameter. Spread of uncertain parameter x	Parameter-specific	Model assumption. Determines the width of the uncertainty distribution
UI_p	Uncertainty interval. Range between the fifth and ninety-fifth percentiles of an output	Interval	Derived statistic. Defined using the 5th and 95th percentiles of repeated simulation outputs
$Q_{0.05}, Q_{0.95}$	Percentile operators. 5th and 95th percentiles used to define uncertainty bounds	Percentiles	Derived statistic. Calculated from Monte Carlo simulation outputs
SI_x	Sensitivity index. Proportional sensitivity of output Y to parameter x	Elasticity-like ratio	Derived statistic. $\frac{\Delta Y/Y}{\Delta x/x}$; defined where reference values and perturbation are non-zero
e_j	Reference emissions. Emissions at the common assessment horizon	Emissions quantity	Analytical extension. Fixed across the compared capacity combinations
ℓ_j	Normalised lock-in. Share of transition capacity constrained in the analytical response	[0,1]	Analytical assumption. Held fixed when deployment and implementation are compared
u_j	Deployment capacity. Technical capacity for represented low-carbon deployment	[0,1]	Analytical assumption. Technical deployment capacity in the analytical response
g_j	Implementation capacity. Effective capacity to carry out the represented transition	[0,1]	Analytical assumption. Distinct from the binary governance switch in R_{ptg}
r_j	Analytical reduction. Reduction represented by the capacity response	Same unit as e_j	Derived in Section 3.8. $r_j = e_j(1-\ell_j)u_j g_j$
R_{ptg}	Factorial outcome. Outcome for binary policy technology and governance switches	Common output scale	Interaction test definition. Eight configurations with common reference and fixed instrument levels
I_{PT}, I_{PTG}	Policy interaction. Pairwise and three-factor finite differences	Outcome units	Interaction test definition. Positive values indicate super-additivity on the chosen scale
$\Delta\mathrm{u}_j, \Delta\mathrm{g}_j$	Capacity increments. Changes in deployment and implementation capacities	Positive feasible increments	Analytical comparison. Joint interaction equals $e_j(1-\ell_j)\Delta u_j \Delta g_j$
d_i, f_i	Support increments. Non-negative changes in the actor alignment score	Alignment score units	Threshold analysis. Their sum can cross the threshold when neither increment alone does

Symbol	Variable and definition	Scale or unit	Basis and calculation rule
I_{desc}	Descriptive residual. Difference between integrated and summed narrower increments above S0	Percentage points	Calculated from Table 2 totals. $S_4 - S_1 - S_2 - S_3 + 2S_0$; comparison of overlapping scenario packages
b_j	Bottleneck reduction. Analytical reduction constrained by the smaller capacity	Same unit as e_j	Alternative response in Section 3.8. $b_j = e_j(1 - \ell_j)\min(u_j, g_j)$
c_j	Balanced baseline capacity. Common deployment and implementation capacity before the changes	[0,1)	Bottleneck comparison. $u_j = g_j = c_j$; inputs remain within [0,1] after increments
$\overline{A}_k$	Unweighted mean alignment. Arithmetic mean of six actor alignment scores	Same scale as A_{ik}	Calculated from Table 3. Sum of the six displayed scores divided by 6; final rounding to three decimal places
E_{2020}	Statistical emissions baseline. Direct emissions from selected manufacturing in 2020	1,000 Mt CO_2	Study statistical baseline. Excludes energy supply and indirect purchased energy; other building materials exclude cement
a_j	Additive reference reduction. Capacity response used for the structural comparison	Same unit as e_j	Numerical verification. $e_j(1 - \ell_j)(u_j + g_j)/2$; four-configuration interaction is zero

Note. The symbol A_{ik} denotes actor alignment, while A_j denotes asset lock-in. Sector dimensions use a common 0–100 reporting scale. Component inputs are normalised before aggregation. Capacity-response inputs are dimensionless and bounded by [0,1].

Table S2 Scenario assumptions and alignment outcomes

Parameter	S0	S1	S2	S3	S4
Carbon pricing	Existing level	Higher price and enforcement	Moderate innovation incentive	Moderate coordinated increase	Highest combined level
Emissions standards	Current stringency	Stricter sector standards	Current or moderately stronger	More consistent implementation	Strictest coordinated standards
Green subsidies	Current framework	Expanded package	Targeted advanced technology	Coordinated actor support	Broad combined package
Technology adoption	Baseline diffusion	Moderately accelerated	Strongly accelerated	Moderate coordinated acceleration	Fastest combined diffusion
Renewable share	Baseline structure	Moderate increase	Larger substitution increase	Moderate coordinated increase	Largest integrated increase
Carbon capture	No major acceleration	Selective policy support	Accelerated core deployment	Selective coordinated deployment	Most extensive feasible deployment
Hydrogen processes	Minimal baseline expansion	Incremental policy support	Accelerated hard-to-abate uptake	Coordinated demonstration and adoption	Fastest combined uptake
Green finance	Current conditions	Improved package support	Targeted technology finance	Strong direct coordination	High broad-based support
Actor coordination	Current fragmented pattern	Improved policy-led coordination	Technology-centred coordination	Strong cross-actor coordination	Highest broad coordination
Transition burden	Current pressure	Higher short-term compliance burden	Adjustment costs and technology support	Partial coordination and risk-sharing offset	Partial support and coordination offset
Lock-in reduction	Slowest	Moderate policy-led	Faster technology-led	Moderate-to-fast coordinated	Fastest combined
Mean alignment	0.465	0.578	0.655	0.685	0.758

Parameter	S0	S1	S2	S3	S4
PAI	0.4800	0.5985	0.6660	0.7045	0.7730
Threshold share (%)	0.0	60.0	85.0	75.0	100.0

Note. All scenarios start from the 2010–2020 calibration and use the 2020 direct-emissions baseline of 1,000 Mt CO_2 with the 2050 endpoint. Technology adoption starts at 5.0% annually, renewable share at 12.0%, and the private green investment benchmark is USD 150 billion. Carbon capture and hydrogen initially have limited deployment. Scenario uncertainty is organised around the calibrated, policy-adjusted, technology-adjusted, governance-adjusted and combined settings for S0–S4, respectively. Qualitative entries specify the direction of scenario assumptions. Alignment outcomes use the common weights and $\theta = 0.60$.

Table S3 Reciprocal representation of adopted sector weights

Dimension	Technology	Assets	Institutions	Networks	Weight
Technology	1	1	$\frac{3}{2}$	$\frac{3}{2}$	0.30
Assets	1	1	$\frac{3}{2}$	$\frac{3}{2}$	0.30
Institutions	$\frac{2}{3}$	$\frac{2}{3}$	1	1	0.20
Networks	$\frac{2}{3}$	$\frac{2}{3}$	1	1	0.20

Note. Matrix entries are ratios of adopted weights. Their normalised positive eigenvector is (0.30, 0.30, 0.20, 0.20). The matrix has $\lambda_{\max} = 4$, $\mathrm{CI} = 0$, $\mathrm{RI} = 0.90$ and $\mathrm{CR} = 0$. These values express algebraic consistency of the ratio construction.

Table S4 Sectoral CLI under study and equal weights

Sector	Equal-weight CLI	Study CLI
Steel	83.25	84.35
Cement	76.80	78.16
Chemicals	77.23	77.55
Energy	89.80	90.39
Automotive manufacturing	61.88	62.37
Other building materials	67.88	68.47

Note. Study weights are 0.30, 0.30, 0.20 and 0.20, while equal weights are 0.25 each. Both calculations use the same component scores and rounding to two decimal places. Values are index points. Cement and other building materials are separate categories. Energy is a separate comparison sector.

Table S5 Actor means and weighted support indicators

Scenario	Mean alignment	PAI	Threshold support (%)
S0	0.465	0.4800	0.0
S1	0.578	0.5985	60.0
S2	0.655	0.6660	85.0
S3	0.685	0.7045	75.0
S4	0.758	0.7730	100.0

Note. Actor weights are 0.25, 0.20, 0.15, 0.15, 0.15 and 0.10 in the main-text order. The support threshold is 0.60 and includes scores equal to the cutoff. S2 exceeds S3 in threshold share while its PAI is lower.

Table S6 Emissions accounting against the 2020 baseline

Scenario	Reduction (%)	2020 baseline (Mt CO_2)	2050 emissions (Mt CO_2)	Reduction (Mt CO_2)
S0	9.32	1000.0	906.8	93.2
S1	19.60	1000.0	804.0	196.0
S2	30.10	1000.0	699.0	301.0
S3	41.55	1000.0	584.5	415.5

Scenario	Reduction (%)	2020 baseline (Mt CO_2)	2050 emissions (Mt CO_2)	Reduction (Mt CO_2)
S4	59.00	1000.0	410.0	590.0

Note. The baseline is 1,000 Mt CO_2 of selected manufacturing direct emissions. $\text{Reduction}\,(\%) = 100\,\frac{E_{2020}-E_{2050}}{E_{2020}}$. Remaining emissions plus the reduction amount equal the baseline in each scenario.