

Domestic Substitution versus Regional Diversification: A Strictly Matched Counterfactual Analysis of China's Manufacturing Supply Chains

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1 Domestic Substitution versus Regional Diversification: A Strictly Matched

2 Counterfactual Analysis of China's Manufacturing Supply Chains

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7 Abstract

8 Which approach more effectively reduces supply-chain exposure: domestic substitution or
9 regional diversification? Using OECD Inter-Country Input-Output data for 2016–2022, we
10 compare the performance of 19 Chinese manufacturing industries under these two strategies
11 through strictly matched counterfactual simulations. Strict matching holds the target industry,
12 donor economy, upstream industry, and input coefficient reduction identical within each pair,
13 varying only the replacement supply destination. The analysis traces direct and indirect
14 production requirements and distinguishes total external exposure, source concentration, and
15 exposure to the largest single source.

16 The results show that domestic substitution yields a larger reduction in total external exposure in
17 all 399 matched pairs. Regional diversification produces lower source concentration in 242
18 pairs, but its advantage narrows as adjustment intensity increases. More notably, at an
19 adjustment intensity of 20%, regional diversification reduces the Herfindahl–Hirschman index
20 (HHI) in all 133 industry–year observations while increasing total external exposure in 122 of
21 them. This occurs because alternative suppliers generate additional indirect foreign production
22 requirements through their upstream networks. The central finding distinguishes reducing
23 external dependence from redistributing it: a more balanced distribution of sources does not
24 imply lower overall external dependence. We provide a transparent basis for evaluating sourcing
25 configurations across multiple dimensions.

26 **Keywords:** Supply-chain exposure; Domestic substitution; Regional diversification;
27 Counterfactual simulation; Strict matching; Production networks.

28 **1 Introduction**

29 Global supply chains provide specialized inputs that lower costs and improve efficiency but
30 create dependencies across countries (Antràs and Chor 2022). Domestic assembly may rely on
31 foreign materials, components, and services. When trade disputes, natural disasters, pandemics,
32 or geopolitical conflicts disrupt supply, delayed recovery can spread the effects beyond direct
33 trading partners to other industries, countries, and individuals (Carvalho et al. 2021; Baldwin
34 and Freeman 2022).

35 Successive shocks have prompted governments and firms to reconsider sourcing through two
36 strategies: domestic substitution, replacing foreign inputs with domestic production, and
37 international diversification, shifting procurement from a major foreign supplier to more
38 countries (Alfaro and Chor 2023). Neither guarantees protection from disruption: domestic
39 producers may require imported inputs, while replacement foreign suppliers may depend on the
40 country being replaced.

41 Conventional trade statistics miss some of these dependencies. Switching from one foreign
42 supplier to another may reduce recorded bilateral dependence while preserving upstream
43 reliance if the replacement uses inputs from the original source. Domestic substitution likewise
44 retains foreign dependence when Chinese producers use imported intermediates. Evaluating
45 sourcing adjustments therefore requires tracing both direct purchases and supporting indirect
46 production (Baldwin et al. 2023).

47 Using international input-output tables, Baldwin et al. (2022, 2023) show that direct import
48 shares can differ substantially from total foreign production exposure once indirect suppliers are
49 included. Inomata and Hanaka (2024) distinguish concentration measured by transaction
50 volumes from concentration measured by network-link frequencies. These studies motivate

51 examining dependence and concentration separately: lower concentration need not imply lower
52 total exposure.

53 Comparing domestic substitution and regional diversification also requires comparable
54 adjustments. If scenarios reduce inputs from different suppliers or industries, or transfer
55 different quantities, outcome differences reflect both replacement destinations and the inputs
56 adjusted. Replacing substantial electronics inputs domestically, for example, is not directly
57 comparable to diversifying smaller chemical inputs internationally.

58 This paper addresses this problem through a strictly matched counterfactual design. For each
59 industry and year, it identifies the largest foreign source of traceable upstream requirements.
60 Both strategies then use identical source economy–upstream industry–target industry
61 combinations and actual transfer quantities, differing only in replacement destination: the
62 corresponding Chinese industry or eligible alternative Regional Comprehensive Economic
63 Partnership (RCEP) economies. Inputs that cannot be transferred regionally are also excluded
64 from domestic transfers.

65 Using the 2025 OECD Inter-Country Input-Output tables for 19 Chinese manufacturing
66 industries over 2016–2022, the analysis evaluates foreign production requirements as a share of
67 total upstream requirements, concentration across identifiable foreign sources, and absolute
68 exposure to the largest foreign source. It separates direct and indirect changes and tests
69 sensitivity to measurement definitions, allocation rules, and anomalous observations.

70 Domestic substitution reduces total external exposure in all 399 strictly matched industry–year–
71 intensity comparisons. Regional diversification performs better on concentration in 242
72 comparisons and domestic substitution in 157, with diversification’s advantage becoming less
73 frequent as adjustment intensity increases. Diversification can also lower concentration while
74 raising total exposure because replacement suppliers introduce additional foreign production
75 requirements through upstream networks. The strategies thus improve different dimensions of
76 dependence.

77 This paper makes three contributions. First, strict matching establishes a common adjustment
78 basis for comparing the strategies; the contribution is the comparison design, not a new input-
79 output model. Second, jointly evaluating total exposure, source concentration, and largest-
80 source dependence demonstrates the limitations of any single risk indicator. Third,
81 decomposition by source economy and production tier distinguishes direct sourcing changes
82 from upstream effects. The results describe structural exposure under specified sourcing
83 configurations, not disruption probabilities, adjustment costs, welfare effects, or economic
84 losses during actual supply interruptions.

85 **2 Literature Review**

86 **2.1 Production Networks and the Transmission of Shocks**

87 Supply chains form production networks linking suppliers to their own upstream suppliers,
88 allowing shocks to spread beyond initially affected industries and regions. Network structure
89 helps determine whether sectoral shocks dissipate or generate aggregate fluctuations. Acemoglu
90 et al. (2012) show that asymmetric sectoral positions can prevent local shocks from cancelling
91 out: sectors supplying many industries generally transmit shocks more widely than peripheral
92 sectors. Carvalho and Tahbaz-Salehi (2019) review how these networks connect firm- and
93 industry-level shocks to aggregate outcomes.

94 Empirical evidence confirms this propagation. Carvalho et al. (2021) show that the 2011 Great
95 East Japan Earthquake affected firms in disaster areas and their suppliers and customers. Boehm
96 et al. (2019) find that US affiliates of Japanese multinationals experienced output declines
97 roughly proportional to their import declines, indicating limited input substitutability. Barrot and
98 Sauvagnat (2016) likewise find stronger propagation through specialized inputs. Using Japanese
99 firm-network simulations, Inoue and Todo (2019) show that limited substitutability, complex
100 linkages, and feedback loops can amplify and prolong indirect production effects.

101 These studies show why direct imports alone cannot capture supply-chain dependence and
102 clarify this paper's scope. Input-output production requirements identify structural linkages, not
103 actual disruption losses, which also depend on inventories, spare capacity, alternative suppliers,
104 prices, contracts, and disruption duration. This paper therefore measures upstream production
105 exposure rather than predicting realized losses.

106 **2.2 Measuring Foreign Supply-Chain Exposure**

107 Measured foreign dependence depends on where tracing stops. Direct import measures end at
108 the first cross-border transaction; input-output methods trace suppliers' upstream production,
109 revealing foreign involvement absent from bilateral trade data.

110 Baldwin et al. (2022) emphasize that no single indicator suits all supply-chain questions: direct
111 imports, gross output, value added, and final demand capture different economic relationships.

112 Baldwin et al. (2023) show that limited direct imports from an economy can coexist with
113 indirect dependence through other suppliers. Burman et al. (2024) distinguish direct and
114 indirect, domestic and foreign transmission channels, showing that trade shocks can propagate
115 through foreign intermediate-input networks.

116 Other studies examine dependence across suppliers. Inomata and Hanaka (2024) distinguish
117 concentration based on transaction volumes from network-link frequencies. Chinese studies
118 using international input-output data examine external exposure levels, structures, and dynamics
119 and simulate alternative sourcing configurations (Ding and Ge 2024). These studies motivate
120 our distinction between three dimensions: foreign production requirements as a share of total
121 upstream requirements measure overall foreign dependence; source concentration captures the
122 distribution of identifiable foreign requirements across economies; and absolute exposure to the
123 largest source measures the importance of the leading foreign source. Different denominators
124 and network features allow these indicators to move in opposite directions.

125 This paper therefore reports the three indicators separately. Combining them into a supply-chain
126 security index would require weights for overall dependence, source concentration, and largest-
127 source dependence. Without supporting evidence, aggregation could obscure their distinct
128 implications.

129 **2.3 Reshoring, Diversification, and Supply-Chain Resilience**

130 Domestic substitution and sourcing diversification are often viewed as competing paths to
131 supply-chain resilience. The former reduces some cross-border dependencies through domestic
132 production; the latter spreads sourcing across locations. Their relative effectiveness depends on
133 the shock and replacement suppliers' production structures.

134 Bonadio et al. (2021) find that renationalizing supply chains does not systematically protect
135 economies from pandemic-related labor supply shocks. When domestic and foreign producers
136 are simultaneously affected, reshoring may relocate risk without reducing aggregate contraction.
137 Grossman et al. (2023) show that optimal diversification policy depends on demand conditions
138 and the divergence between private and social incentives. Ahn and Tan (2025) further relate
139 diversification's welfare benefits to trade rigidities and shock probabilities. Neither strategy is
140 universally superior.

141 Resilience also extends beyond location. Miroudot (2020) distinguishes maintaining production
142 during shocks from recovering afterward. Concentrating production domestically can therefore
143 create concentration risk despite self-sufficiency (Arriola et al. 2020). OECD research
144 emphasizes diversification, inventories, information sharing, production flexibility, and
145 international cooperation rather than merely shorter supply chains (Thakur-Weigold and
146 Miroudot 2024).

147 Trade shifts further distinguish sourcing locations from underlying dependencies. Freund et al.
148 (2024) find that China's US import share declined after tariff increases, while countries
149 expanding exports to the United States remained closely connected to Chinese production

150 networks. Diversifying direct sources may therefore leave upstream dependence on the original
151 economy intact.

152 Existing research thus identifies conditions governing strategy effectiveness rather than a
153 universal ranking. Holding adjusted inputs strictly constant, this paper compares domestic and
154 regional replacement supply across three dimensions of structural exposure. It neither identifies
155 a welfare-maximizing strategy nor equates improved structural indicators with uninterrupted
156 production during crises.

157 **2.4 Counterfactual Analysis and the Remaining Comparison Problem**

158 Input-output counterfactual simulations modify specific production linkages and recalculate
159 direct and indirect requirements, revealing structural changes under specified allocation rules.
160 The hypothetical extraction method provides a foundation by wholly or partially removing
161 industries or linkages to assess their network roles. Dietzenbacher and Lahr (2013) extend it to
162 specific activities and reorganized input-output accounts. In international networks, however,
163 extraction alone leaves replacement supply unspecified.

164 Dietzenbacher, van Burken, and Kondo (2019) address this issue by requiring researchers to
165 specify which economies undertake replacement production and in what quantities. Although
166 essential to supply-chain reconfiguration analysis, this does not ensure comparability between
167 strategies. Domestic substitution and regional diversification may target different suppliers,
168 inputs, or transfer quantities, confounding replacement-location effects with differences in the
169 inputs adjusted.

170 This paper therefore strictly matches four elements: the original foreign source, upstream
171 industry, Chinese target industry, and actual direct input coefficient transferred. Comparisons
172 include only input cells where transfers are feasible under both strategies. Rather than
173 reproducing firms' decisions, this design establishes a transparent basis for interpreting scenario
174 differences within clearly defined limits.

Existing research explains indirect production linkages, develops foreign exposure measures, and examines substitution and diversification under different economic conditions. What remains less clear is how these strategies affect distinct exposure dimensions when identical actual adjustments are imposed on the same production linkages. The following analysis addresses this gap.

3 Research methods

We compare domestic substitution and regional diversification by requiring both strategies to reallocate exactly the same direct inputs. First, we trace the upstream production activities supporting Chinese manufacturing. Second, we construct matched sourcing adjustments and recalculate three dimensions of external exposure. Finally, we use accounting decompositions to identify the sources of change. The input-output framework provides the accounting foundation, while strict matching establishes a common benchmark for comparing the two sourcing arrangements.

3.1 Data and upstream production requirements

We use the 2025 edition of the OECD Inter-Country Input-Output tables for 2016–2022 (OECD 2025). The Regular/SML tables cover 80 individual economies and the rest of the world (ROW), with 50 industries per economy, yielding 4,050 economy–industry nodes. The calculations retain the full international production network and report results for 19 Chinese manufacturing industries, with further analysis of five key industries: chemicals (C20), computer, electronic and optical products (C26), electrical equipment (C27), machinery and equipment (C28), and motor vehicles (C29).

196 **Table 1 A simplified representation of the inter-country input–output system**

Supplying economy and industry	Intermediate use by		Final use	Total output
	Chinese target industry j	other industries		
Chinese industries	$Z_{C,j}$	$Z_{C,-j}$	Y_C	X_C
Donor economy g_j	$Z_{gj,j}$	$Z_{gj,-j}$	Y_{gj}	X_{gj}
Other RCEP economies	$Z_{R,j}$	$Z_{R,-j}$	Y_R	X_R
Other foreign economies	$Z_{O,j}$	$Z_{O,-j}$	Y_O	X_O
Value added	$V A_j$	$V A_{-j}$	—	—
Total input	X_j	X_{-j}	—	—

197 *Notes:* Rows identify the economies and industries in which inputs are produced, whereas columns identify the
198 industries that use these inputs. $Z_{r,j}$ records intermediate inputs supplied by economy group r to Chinese target
199 industry j . Dividing each entry by the gross output of the purchasing industry gives the corresponding direct input
200 coefficient. The Leontief inverse then traces the production required from direct suppliers and all upstream
201 suppliers.

202 An input – output table records who supplies inputs to whom. Let $Z = (z_{ij})$ denote
203 intermediate transactions, x gross output, and f final demand summed over all final users. Entry
204 z_{ij} is the monetary value of inputs supplied by node i to node j . Dividing by the purchasing
205 industry's output gives its direct input requirements per monetary unit of output:

$$206 \quad a_{ij} = z_{ij}/x_j, \quad A = Z[\text{diag}(x)]^{-1}, \quad x = Ax + f. \quad (1)$$

207 For nonnegative A with spectral radius below one, the Leontief inverse traces direct suppliers,
208 their suppliers, and all subsequent production stages (Miller and Blair 2009):

$$209 \quad B = (I - A)^{-1} = I + A + A^2 + \dots, \quad U = B - I. \quad (2)$$

$$210 \quad d_j = Ae_j, \quad h_j = (B - I - A)e_j, \quad u_j = Ue_j = d_j + h_j. \quad (3)$$

211 Here e_j is a unit vector selecting target industry j . The vector u_j measures upstream gross
212 production required per monetary unit of final demand for that industry; d_j captures direct

requirements and h_j requirements beyond the first stage. Subtracting I removes only the final product itself and retains upstream feedback to the same industry. These are monetary production requirements accumulated across stages, not value added or physical quantities. This distinction follows the broader need to choose exposure measures that match the research question (Baldwin et al. 2022).

Let C and S denote the sets of economies and industries, c China (CHN), and J the 19 target industries. A supplying node is indexed by (r, s) . The foreign set is $\mathcal{F} = \{r \in C: r \neq c\}$, while identifiable foreign sources are $\mathcal{F}^* = \{r \in C: r \neq c, r \neq \text{ROW}\}$. Thus, foreign coverage follows the ICIO classification of nodes outside CHN. Year subscripts are suppressed unless needed; every counterfactual is compared with its own same-year baseline.

3.2 Measuring three dimensions of foreign exposure

We first aggregate upstream requirements by source economy. For industry j , define total, direct and indirect requirements from economy r as:

$$n_{rj} = \sum_{s \in S} U_{(r,s),j}, \quad n_{rj}^D = \sum_{s \in S} a_{(r,s),j}, \quad n_{rj}^I = n_{rj} - n_{rj}^D. \quad (4)$$

$$D_j = \sum_{r \in C} n_{rj}, \quad F_j = \sum_{r \in \mathcal{F}} n_{rj}, \quad F_j^* = \sum_{r \in \mathcal{F}^*} n_{rj}. \quad (5)$$

The first indicator asks how much of all upstream production takes place abroad. Total foreign exposure and its direct and indirect components are

$$E_j = \frac{F_j}{D_j}, \quad E_j^D = \frac{\sum_{r \in \mathcal{F}} n_{rj}^D}{D_j}, \quad E_j^I = \frac{\sum_{r \in \mathcal{F}} n_{rj}^I}{D_j}, \quad E_j = E_j^D + E_j^I. \quad (6)$$

The second asks how evenly identifiable foreign requirements are distributed across economies. The third asks how large the greatest single-source exposure is relative to all upstream requirements:

$$p_{rj} = \frac{n_{rj}}{F_j^*}, \quad H_j = \sum_{r \in \mathcal{F}^*} p_{rj}^2, \quad e_{rj} = \frac{n_{rj}}{D_j}, \quad M_j = \max_{r \in \mathcal{F}^*} e_{rj}. \quad (7)$$

235 Here H_j is the Herfindahl–Hirschman index (HHI). ROW remains in total foreign exposure but
236 is excluded from concentration and the largest identifiable source because it combines multiple
237 economies. The term “absolute source exposure” refers to e_{rj} with the common total-upstream
238 denominator; it remains a share, not a monetary amount. We identify the largest source again in
239 each scenario and also track the baseline largest source separately. Ratios are undefined when
240 their denominators are zero.

241 These indicators answer different questions and are not combined into a single safety index. A
242 more even foreign distribution can coexist with a larger foreign share of production. Likewise, a
243 lower HHI does not account for correlated disruptions across suppliers. Supplementary industry
244 diagnostics, including upstream-sector shares, are defined in Appendix A.

245 **3.3 Strictly matched sourcing counterfactuals**

246 This paper addresses a specific question: when the same Chinese industry reduces
247 identical inputs from the same foreign source by exactly the same amount, how does
248 upstream exposure differ depending on whether replacement supply comes from China or
249 other regional economies? We call this a strictly matched counterfactual design. Strict
250 matching applies to individual input linkages, not merely the total adjustment for an
251 industry.

252 Dietzenbacher et al. (2019) emphasize that specifying who undertakes replacement
253 production is central to global input-output counterfactual analysis. This paper further
254 requires both replacement arrangements to reduce exactly the same input linkages by
255 identical coefficient amounts. This requirement constitutes the contribution of strict
256 matching to the comparative design. It is neither statistical matching of treated and control
257 firms nor a modification of the underlying Leontief model or accounting identities used in
258 existing approaches.

259 3.3.1 Selecting the source and eligible replacements

260 Superscript 0 denotes the baseline. For each target industry, the donor economy—the source
 261 whose direct supplies are reduced—is its largest identifiable foreign source in total traced
 262 requirements:

$$263 \quad g_j = \operatorname{argmax}_{r \in \mathcal{F}^*} n_{rj}^0. \quad (8)$$

264 This selection uses direct and indirect exposure, but the intervention changes only the donor's
 265 direct input coefficients to the target industry. A major indirect source can therefore have limited
 266 direct inputs available for reassignment. Ties are resolved using a fixed ordering of economies.
 267 Let R contain China, Japan, Korea, Australia, New Zealand and the ten ASEAN economies.
 268 This fixed RCEP grouping is applied throughout the sample as a geographical scenario
 269 definition, without treating the agreement as effective in all sample years. An alternative
 270 regional supplier must already supply inputs from upstream industry s directly to target
 271 industry j in the baseline:

$$272 \quad R_{sj} = \{r \in R: r \neq c, r \neq g_j, r \neq \text{ROW}, a_{(r,s),j}^0 > \varepsilon\}, \quad \varepsilon = 10^{-10}. \quad (9)$$

$$273 \quad w_{rsj} = \frac{a_{(r,s),j}^0}{\sum_{\ell \in R_{sj}} a_{(\ell,s),j}^0} \quad (r \in R_{sj}). \quad (10)$$

274 Weights are zero outside this set. A positive baseline link establishes eligibility in the observed
 275 network; it does not establish spare capacity, product equivalence or the commercial feasibility
 276 of expansion. The baseline-share rule distributes replacements proportionally across eligible
 277 suppliers and does not solve for optimal procurement.

278 3.3.2 Defining the common transfer before assigning destinations

279 For an adjustment intensity $\alpha \in \{0.1, 0.2, 0.3\}$, we define one common transfer for both
 280 strategies:

$$281 \quad \delta_{sj}(\alpha) = \alpha a_{(g_j,s),j}^0 \mathbf{1}\{a_{(g_j,s),j}^0 > \varepsilon, |R_{sj}| > 0\}, \quad m_j = \sum_s \delta_{sj}. \quad (11)$$

282 Here the indicator equals one when both stated conditions hold and zero otherwise. Thus, a link
 283 with no eligible regional replacement is left unchanged in both scenarios. The domestic scenario
 284 is deliberately restricted to the same set of adjustable links, even where additional domestic
 285 replacement might otherwise be imposed. This common eligibility restriction prevents the
 286 domestic strategy from being credited with a larger or differently composed intervention. The
 287 effective fraction of all foreign direct inputs reassigned is

$$288 \quad \alpha_j^{\text{eff}} = \frac{m_j}{\sum_{r \in \mathcal{F}} \sum_s a_{(r,s),j}^0}. \quad (12)$$

289 The nominal intensity therefore does not mean that all imports or all foreign upstream
 290 requirements decline by 10%, 20% or 30%. Moreover, m_j is a sum of monetary input
 291 coefficients per unit of target output, not an observed shipment quantity.

292 **Table 2 What is held constant in the strictly matched comparison**

Element of the adjustment	Domestic substitution	Regional diversification	Matched across strategies
Year	Year t	The same year t	Yes
Chinese target industry	Industry j	The same industry j	Yes
Foreign source being reduced	Donor economy g_j	The same donor g_j	Yes
Input being reduced	Upstream industry s	The same upstream industry s	Yes
Implemented reduction	δ_{sj}	The same δ_{sj}	Yes
Eligibility of the input link	A regional replacement must exist	A regional replacement must exist	Yes
Destination of replacement supply	Corresponding Chinese industry	Eligible RCEP suppliers	No
Allocation across destinations	Entire amount assigned to China	Distributed using w_{rsj}	No

293 *Notes:* Strict matching is imposed at the level of each donor-economy–upstream-industry–target-industry link. The
294 two scenarios remove the same coefficient amount from the same link. Their systematic difference is the destination
295 of replacement supply.

296 Regional diversification (DV) assigns this common transfer to eligible foreign suppliers.

297 Domestic substitution (DS) assigns it to the corresponding Chinese upstream industry:

$$298 \quad a_{(r,s),j}^{DV} = a_{(r,s),j}^0 - \mathbf{1}\{r = g_j\}\delta_{sj} + w_{rsj}\delta_{sj}. \quad (13)$$

$$299 \quad a_{(r,s),j}^{DS} = a_{(r,s),j}^0 - \mathbf{1}\{r = g_j\}\delta_{sj} + \mathbf{1}\{r = c\}\delta_{sj}. \quad (14)$$

300 For example, suppose the common reduction in one input coefficient is 0.02. DS adds 0.02 to
301 the corresponding Chinese supplier. With regional weights of 0.6 and 0.4, DV adds 0.012 and
302 0.008 to two eligible foreign suppliers. Both remove the same 0.02 from the same donor–

upstream-industry–target-industry link. This is a hypothetical illustration, not an empirical estimate.

Equations (11)–(14) establish the matching unit: the same year, donor economy, upstream industry, Chinese target industry and implemented coefficient reduction. They imply

$$\sum_{r \in C} a_{(r,s),j}^q = \sum_{r \in C} a_{(r,s),j}^0, \quad m_j^{DS} = m_j^{DV} = m_j, \quad q \in \{DS, DV\}. \quad (15)$$

DV preserves the total foreign direct-input coefficient of each target industry, whereas DS reduces it by m_j . Both preserve direct requirements summed across supplying economies within each upstream industry. This controls the monetary coefficient amount and input-industry composition, not physical input equivalence, prices, quality or adjustment costs. Domestic replacement can expand an existing link or create a link to the corresponding domestic industry; no domestic capacity limit is estimated.

3.3.3 Recomputing the network and interpreting the comparison

All 19 target columns are modified simultaneously within one scenario matrix; all other columns remain unchanged. We recompute $B^q = (I - A^q)^{-1}$ and $U^q = B^q - I$, holding the unit final-demand basis common across scenarios. Hence each industry's result includes feedback from the simultaneous changes in other target industries. We do not add together isolated industry simulations. The inverse identity gives

$$U^{DS} - U^{DV} = B^{DS}(A^{DS} - A^{DV})B^{DV}. \quad (16)$$

At each adjusted link, the matrix difference on the right is $\delta_{sj}(\mathbf{1}\{r = c\} - w_{rsj})$: the common donor reduction cancels. The remaining difference is the replacement allocation, propagated through the two resulting networks. This explains why matching improves the interpretation of the comparison. It does not turn the simulation into a causal estimate of an implemented policy or a comparison at equal economic cost. Domestic substitution represents procurement reassignment, not a model of firms physically relocating factories.

3.4 Comparing effects and explaining their sources

For $K \in \{E, H, M\}$, scenario effects, relative reductions and the paired strategy gap are

$$\Delta K_j^q = K_j^q - K_j^0, \quad RR_{K,j}^q = 100 \frac{K_j^0 - K_j^q}{K_j^0}, \quad G_{K,j} = K_j^{DS} - K_j^{DV}. \quad (17)$$

A negative $G_{K,j}$ means that DS achieves a lower indicator; a positive value favours DV.

Changes in E and M are reported in percentage points, while HHI changes remain in index units. Relative reductions are percentages and require a positive baseline. Seven years, 19 industries and three intensities yield 399 paired comparisons for each indicator. These are deterministic model comparisons, not independent random observations for significance testing. For cross-industry comparisons, the reduction per unit of implemented adjustment is

$$\eta_{K,j}^q = \frac{K_j^0 - K_j^q}{m_j^q}, \quad K \in \{E, H\}, \quad m_j^q > 0. \quad (18)$$

Exposure enters this expression as a fraction, not in percentage points. This is a finite-change accounting measure, not a marginal effect or monetary cost efficiency. Within a strictly matched pair, its ranking is algebraically identical to the ranking of indicator reductions because the denominators are equal. We first calculate annual ratios and then take arithmetic means over valid years; industry aggregates weight the 19 industries equally. Undefined ratios remain missing, with valid counts reported.

To explain exposure changes, we separate changes in direct requirements, indirect requirements and the total-upstream denominator. For a fixed source economy r , the following exact symmetric decomposition averages the two polar forms (Dietzenbacher and Los 1998):

$$\Delta e_{rj} = \frac{n_{rj}^q - n_{rj}^0}{2} \left(\frac{1}{D_j^0} + \frac{1}{D_j^q} \right) + \frac{n_{rj}^0 + n_{rj}^q}{2} \left(\frac{1}{D_j^q} - \frac{1}{D_j^0} \right). \quad (19)$$

Splitting the first term into direct and indirect requirements gives percentage-point contributions

$$C_{rj}^D = 50(n_{rj}^{D,q} - n_{rj}^{D,0}) \left(\frac{1}{D_j^0} + \frac{1}{D_j^q} \right). \quad (20)$$

$$C_{rj}^I = 50(n_{rj}^{I,q} - n_{rj}^{I,0}) \left(\frac{1}{D_j^0} + \frac{1}{D_j^q} \right). \quad (21)$$

$$C_{rj}^{den} = 50(n_{rj}^0 + n_{rj}^q) \left(\frac{1}{D_j^q} - \frac{1}{D_j^0} \right). \quad (22)$$

$$100\Delta E_j = \sum_{r \in \mathcal{F}} (C_{rj}^D + C_{rj}^I + C_{rj}^{den}), \quad \Delta H_j = \sum_{r \in \mathcal{F}^*} [(p_{rj}^q)^2 - (p_{rj}^0)^2]. \quad (23)$$

There is no residual. The denominator term records how changes in total upstream requirements affect the exposure share. These components allocate an accounting change; they do not identify independent causal mechanisms. This is distinct from value-added trade accounting (Johnson and Noguera 2012; Koopman et al. 2014), which is unnecessary for our production-requirement question. For maximum-source exposure, we compare the scenario-specific maxima first and then trace fixed sources, since the identity of the largest source may change.

3.5 Sensitivity analysis and interpretation

Beyond the baseline, four supplementary checks are conducted: comparing adjustment intensities of 10%, 20%, and 30%; replacing DV's baseline-share weights with equal weights among the same eligible recipients; extending GD eligibility beyond RCEP to all identifiable foreign economies except the original donor while retaining positive baseline direct linkages for each target industry–upstream industry pair; and introducing a domestic benchmark. Because expanded eligibility changes actual transferable quantities, GD–DV differences reflect more than geographical scope. The domestic benchmark proportionally reduces all foreign direct inputs and reallocates them to corresponding Chinese industries, matching only the total reduction to m_j under strict matching. Its different source composition makes it a reference rather than part of the main comparison. Further checks examine anomalous input-output columns and the inclusion of final products in the exposure denominator. Appendix A reports transformations, ranking statistics, and numerical checks. These assess sensitivity to accounting definitions and allocation assumptions, not adjustment costs or disruption probabilities.

Input coefficients are fixed within scenarios, with changes across scenarios imposed exogenously. The model neither estimates substitution elasticities nor endogenizes prices, spare capacity, inventories, adjustment costs, or shock probabilities. Strict matching therefore supports a controlled comparison of structural exposure under domestic and regional replacement supply with identical reductions in the same input linkages. The contribution is to examine whether these arrangements simultaneously improve different exposure dimensions and identify the upstream changes underlying their differences. It neither establishes welfare rankings nor guarantees supply-chain resilience during actual disruptions.

4 Empirical results

4.1 Baseline exposure and industry profiles

Using OECD ICIO data for 19 Chinese manufacturing industries over 2016–2022, we trace upstream requirements through $U=B-I$, where $B=(I-A)^{-1}$. For industry j , total external exposure is $Ej=Fj/Dj$, where Dj denotes total upstream production requirements induced by unit final demand and Fj their foreign component, including ROW. This measures neither direct import dependence, foreign value added nor disruption losses.

Two complementary indicators describe source structure: HHI uses identifiable foreign requirement shares, excluding China and ROW; maximum-source exposure divides the largest identifiable foreign source's requirements by Dj . Together, the indicators distinguish the extent of foreign dependence, its concentration and the importance of the largest source.

Table 3 Total foreign exposure of China's 19 manufacturing industries, 2016 and 2022

Industry code	Industry	2016 (%)	2022 (%)	Change (pp)
C19	Coke and refined petroleum products	23.71	39.08	+15.37
C24B	Basic precious and other non-ferrous metals	21.50	27.09	+5.58
C26	Computer, electronic and optical products	25.98	25.55	-0.43

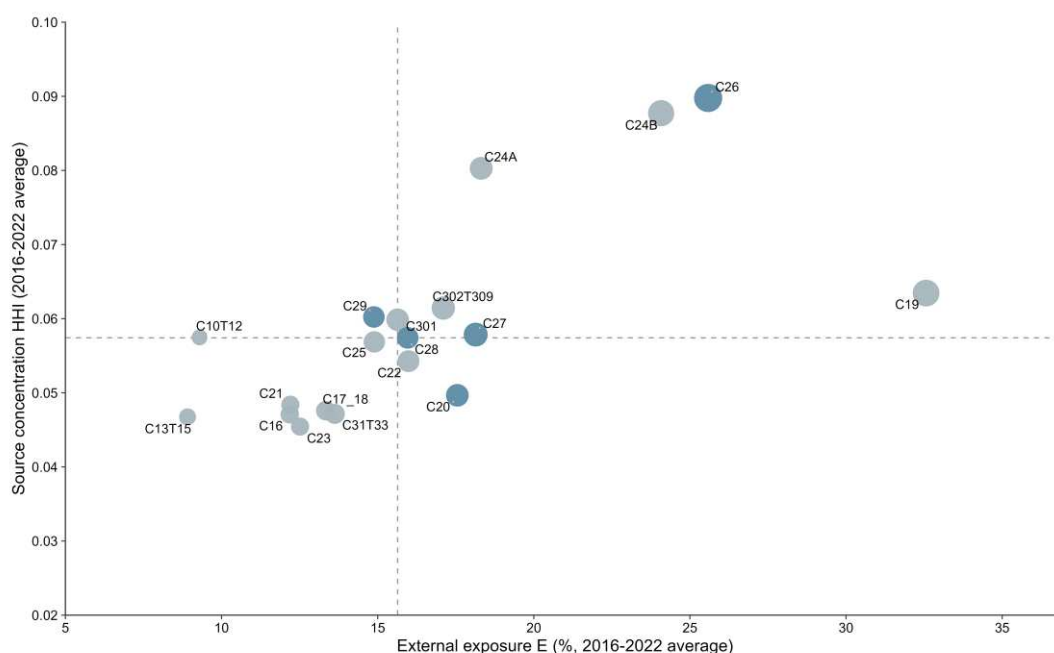
Industry code	Industry	2016 (%)	2022 (%)	Change (pp)
C24A	Basic iron and steel	14.62	19.37	+4.74
C27	Electrical equipment	17.41	18.57	+1.16
C20	Chemicals and chemical products	14.37	18.52	+4.15
C302T309	Other transport equipment	17.36	16.49	-0.87
C22	Rubber and plastic products	13.64	16.23	+2.60
C28	Machinery and equipment n.e.c.	14.41	16.22	+1.81
C25	Fabricated metal products	13.47	15.93	+2.45
C29	Motor vehicles, trailers and semi-trailers	13.42	15.10	+1.67
C301	Building of ships and boats	14.34	14.90	+0.56
C23	Other non-metallic mineral products	10.68	14.21	+3.54
C31T33	Furniture, other manufacturing, and repair and installation	12.50	13.98	+1.48
C17_18	Paper products and printing	11.39	13.78	+2.39
C21	Pharmaceutical products	10.93	13.76	+2.83
C16	Wood and cork products	10.89	11.93	+1.04
C10T12	Food products, beverages and tobacco	7.36	10.18	+2.82
C13T15	Textiles, wearing apparel and leather products	8.19	8.26	+0.07

Notes: Industries are ranked by exposure in 2022. Changes are calculated from unrounded values and may therefore differ slightly from differences between the displayed percentages. “pp” denotes percentage points.

Alongside the comparison of all 19 manufacturing industries, this paper examines five key cases: chemicals (C20), computer, electronic and optical products (C26), electrical equipment (C27), general- and special-purpose machinery and equipment (C28), and motor vehicles (C29). These industries are not the five highest-ranked by total external exposure; rather, they are selected because indirect requirements account for a large share of their foreign exposure. Over 2016–2022, their average annual indirect shares were approximately 81.54%, 77.15%, 84.47%,

400 85.13%, and 86.29%, respectively. Direct import linkages alone therefore cannot fully capture
 401 their upstream external dependence, making indirect production linkages essential to evaluating
 402 replacement supply arrangements.

403 Between 2016 and 2022, external exposure in C19 rose from 23.71% to 39.08%, an increase of
 404 15.37 percentage points, while C24B rose from 21.50% to 27.09%, an increase of 5.58
 405 percentage points. C26 declined slightly from 25.98% to 25.55% but remained among the five
 406 most exposed industries in every sample year. Industries thus differ in both exposure levels and
 407 directions of change. These endpoint comparisons do not imply monotonic changes over the
 408 intervening years, nor do they establish that any particular trade policy or event caused the
 409 changes.



410
 411 **Figure 1 Baseline foreign exposure and source concentration across Chinese manufacturing**
 412 **industries**

413 *Notes:* The horizontal and vertical axes report industry-level means of total foreign exposure and the source HHI
 414 over 2016–2022. Bubble area is proportional to mean foreign upstream requirements per unit of final demand.
 415 Dashed lines indicate the cross-industry medians: 15.64% for exposure and 0.0574 for the HHI. These are
 416 descriptive sample benchmarks, not thresholds for disruption risk.

Figure 1 screens external dependence across 19 manufacturing industries using annual averages for 2016–2022. The axes show total external exposure E and source concentration HHI. Bubble area is proportional to average foreign upstream requirements induced by unit final demand; darker bubbles mark the five selected cases. Cross-sectional medians of E and HHI (15.64% and 0.0574), with median-equal observations assigned to the high group, define four categories: eight high-dependence–high-concentration, seven low-dependence–low-concentration, two high-dependence–low-concentration, and two low-dependence–high-concentration industries. These describe baseline structural characteristics, not risk levels based on actual shock probabilities.

Coke and refined petroleum products (C19) have the highest average external dependence (32.56%). Computer, electronic and optical products (C26) combine external dependence of 25.58% with the highest HHI (0.0898), representing a high-dependence–high-concentration case. Basic precious and other non-ferrous metals (C24B) and basic iron and steel (C24A) also exhibit elevated risks along both dimensions. Chemicals and chemical products (C20), with external dependence of 17.55% and HHI of 0.0497, fall into the high-dependence–low-concentration category. Motor vehicles (C29), with below-median external dependence of 14.88% and HHI of 0.0602, fall into the low-dependence–high-concentration category. These categories guide subsequent scenario analysis without predetermining strategy performance. High-dependence–high-concentration industries require attention to both total foreign requirements and source distribution. For high-dependence–low-concentration industries, the question is whether diversified sourcing reduces external dependence traced through the production network. For low-dependence–high-concentration industries, low total exposure does not exclude concentrated source dependence. Bubble area represents foreign production requirements induced by unit final demand, not actual total imports, industry size, or policy importance, and cannot directly determine resource allocation priorities. Figure 1

therefore provides a baseline structural diagnosis for the strictly matched counterfactual analysis, not a policy ranking.

4.2 Comparing domestic substitution and regional diversification

4.2.1 Results under strict matching

DV reallocates 10%, 20% or 30% of direct inputs from each industry's largest identifiable baseline foreign source to eligible RCEP economies, weighted by positive baseline linkages in the same upstream industry. RCEP is a fixed analytical grouping. DS matches each feasible DV transfer by donor, upstream industry, target industry and coefficient reduction, redirecting supply to China. All 19 industries are adjusted simultaneously. In the code, DV10–30 correspond to RD10–30 and DS to DS_SAME_RD.

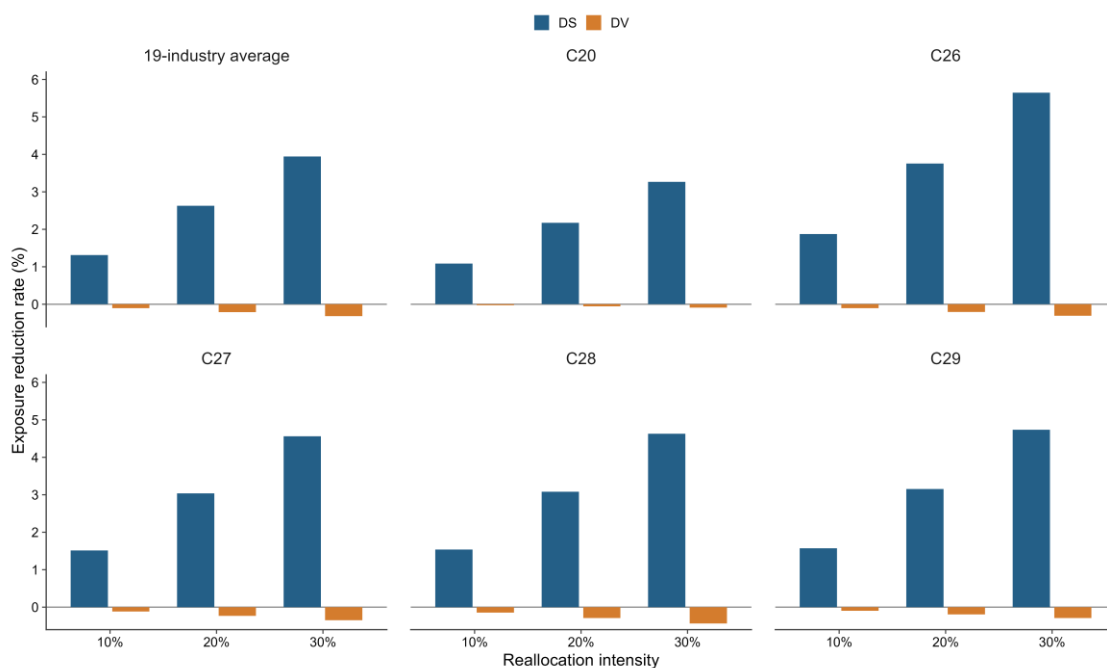
Matching equalizes coefficient reductions, not costs, quality or capacity. DS reduces foreign direct inputs, whereas DV preserves their total; DS's exposure advantage therefore partly reflects scenario design, requiring complementary HHI and maximum-source comparisons. DS reduces total exposure more in all 399 pairs. DV achieves larger HHI reductions in 242 versus 157 for DS, but its wins decline from 93 to 80 and 69 of 133 as intensity increases. Its concentration advantage is thus frequent but not universal.

Table 4 Strictly matched scenario effects for the five case industries, 2022, 20% intensity

Industry	DS: ΔE (pp)	DV: ΔE (pp)	DS: ΔHHI	DV: ΔHHI
C20	-0.2763	+0.0505	-0.001228	-0.001105
C26	-0.9441	+0.0824	-0.004152	-0.003088
C27	-0.5460	+0.0307	-0.002180	-0.001959
C28	-0.4879	+0.0249	-0.002546	-0.002441
C29	-0.4604	+0.0168	-0.002678	-0.003112

Notes: Changes are measured against the common baseline. Negative values indicate reductions. Exposure changes are expressed in percentage points; HHI changes are expressed in index units.

461 In 2022, DS20 reduces C26's external exposure by 0.9441 percentage points, whereas DV20
462 increases it by 0.0824; HHI falls by 0.004152 and 0.003088, respectively. DS20 also achieves
463 larger reductions in exposure, HHI and maximum-source exposure in C20, C27 and C28; only
464 C29 favours DV for HHI reduction. Thus, concentration reduction is not exclusive to DV.
465 Across 399 strictly matched pairs, DS reduces maximum-source exposure more in 379,
466 highlighting its distinction from HHI. Under DV20, HHI falls in all 133 year–industry
467 observations, but total exposure rises in 122. Diversification can therefore lower concentration
468 while increasing exposure under the specified network and allocation rules; this implies neither
469 that diversification is ineffective nor that lower dependence improves welfare.



470
471 **Figure 2 Mean relative reductions in total foreign exposure under strictly matched scenarios, 2016–**
472 **2022**

473 *Notes:* Relative reductions are calculated as $100(E^0 - E^q)/E^0$. Positive values indicate lower exposure than in the
474 baseline; negative values indicate higher exposure. Annual ratios are calculated first and then averaged over 2016–
475 2022. The 19-industry average assigns equal weight to each industry. DS denotes domestic substitution and DV
476 regional diversification. Horizontal-axis values indicate adjustment intensities.

477 Figure 2 reports relative exposure reductions, $RR_E = 100 \times (E_{\text{baseline}} - E_{\text{scenario}}) / E_{\text{baseline}}$, averaged
478 over seven years with equal industry weights, rather than output weights. Positive values

479 indicate improvement, not percentage-point changes. At 10%, 20% and 30% intensities, mean
480 DS reductions rise approximately linearly from 1.31% to 2.63% and 3.95%, whereas DV yields
481 -0.11% , -0.21% and -0.32% . Thus, preserving foreign direct inputs while reallocating suppliers
482 can slightly increase total exposure through indirect linkages.

483 At 20%, DS reductions across the five case industries range from 2.18% to 3.76%, with C26
484 highest, although this does not imply the greatest reduction per unit of adjustment. DV exposure
485 reductions range from -0.29% to -0.06% , while its HHI reductions reach 3.63%–6.07%, rising
486 to 4.96%–8.15% at 30%. These concentration improvements are relative to the baseline;
487 advantages over DS require the 399 strictly matched comparisons.

488 **4.2.2 Why the matching rule matters**

489 To assess whether differences in the inputs being reduced affect strategy comparisons, this paper
490 compares amount-only matching with strict matching. The former equalizes the total technical
491 coefficients actually adjusted under the two strategies, without requiring identical reductions by
492 source economy and upstream industry. Strict matching additionally aligns the donor economy,
493 upstream industry, and actual reduction in each corresponding input cell. It therefore provides a
494 clearer comparison of the network effects of domestic versus regional replacement supply under
495 identical direct input reductions.

496 **Table 5 Strategy comparisons under amount-only and strict matching**

Matching rule	Intensity	Pairs	E: DS lower	HHI: DS lower	HHI: DV lower	M: DS lower	M: DV lower
Amount-only	10%	133	133	0	133	7	126
Amount-only	20%	133	133	0	133	19	114
Amount-only	30%	133	133	0	133	28	105
Strict	10%	133	133	40	93	128	5
Strict	20%	133	133	53	80	126	7
Strict	30%	133	133	64	69	125	8

497 *Notes:* E denotes total foreign exposure, HHI source concentration, and M maximum-source exposure. Exposure
498 indicators use the U-based denominator. “Lower” refers to the lower scenario value and may represent either a
499 larger reduction or a smaller increase relative to the baseline. No ties occur in these comparisons.

500 Both matching approaches show an advantage for domestic substitution in total external
501 exposure across all 399 comparisons, but concentration and largest-source exposure are more
502 sensitive to matching conditions. Under amount-only matching, DV achieves a larger HHI
503 reduction in all 399 comparisons. Under strict matching, this falls to 242, with DS performing
504 better in the remaining 157. For absolute exposure to the largest source, the number of
505 comparisons favoring DV falls from 345 to 20, with the better-performing strategy changing in
506 331 comparisons between the two matching approaches.

507 These differences show that controlling only the total adjustment is insufficient to eliminate the
508 influence of the composition of input reductions. DV’s concentration advantage under amount-
509 only matching cannot be attributed entirely to foreign replacement supply; it also reflects
510 structural differences in the inputs being reduced. Under strict matching, domestic substitution
511 can likewise alter the source distribution. This paper therefore uses strict matching for the main
512 comparison and amount-only matching as supplementary evidence of sensitivity to matching
513 conditions. Neither set of findings is treated as a universal result independent of scenario design.

4.3 Explaining exposure changes: direct requirements, indirect requirements and the denominator

To explain these differences, this paper decomposes changes in source-specific exposure ratios into contributions from direct requirements, indirect requirements, and the total upstream requirements denominator, then sums these contributions across sources. The decomposition uses a symmetric two-factor identity, further separating changes in requirement quantities into direct and indirect components. The contributions sum exactly to the change in total exposure. They are accounting components, not independently identified causal channels.

Table 6 Decomposition of total foreign exposure changes under DV, 2022, 20% intensity

Industry	Direct contribution (pp)	Indirect contribution (pp)	Denominator contribution (pp)	Total change (pp)
C20	0.000000	+0.065086	−0.014625	+0.050461
C26	0.000000	+0.141454	−0.059021	+0.082433
C27	0.000000	+0.044218	−0.013533	+0.030685
C28	0.000000	+0.033937	−0.009081	+0.024857
C29	0.000000	+0.024158	−0.007357	+0.016801

Notes: Contributions follow the exact symmetric decomposition in Section 3 and are summed across foreign sources, including ROW. Direct contributions are zero up to numerical precision. Minor differences between displayed components and totals reflect rounding.

Table 6 shows that the contribution from changes in direct foreign requirements is close to zero for all five industries under regional diversification, consistent with the scenario's preservation of total foreign direct inputs. However, indirect requirement contributions are positive, while denominator contributions are negative. The former outweigh the latter, resulting in a slight increase in total external exposure.

For C26, the indirect requirement contribution is 0.141454 percentage points, while the denominator contribution is −0.059021 percentage points, together raising total exposure by

0.082433 percentage points. Thus, unchanged total foreign direct inputs do not imply unchanged foreign requirements traced through the production network: upstream reconfiguration alters the allocation of production requirements at higher tiers.

This finding shows that direct input measures and network-traced measures provide information at different levels. Importantly, B-I captures cumulative production linkages across multiple tiers. These results neither identify a unique supply path nor measure the number of times goods circulate or the volume of actual orders relocated.

4.4 Where dependence is located and how it shifts

4.4.1 Source economies and upstream industries

Between 2016 and 2022, the combined share of the three largest identifiable foreign sources declined in all five case industries, although their composition changed. C26 recorded the largest decline, from 49.87% to 40.91%, yet retained the highest mean HHI among the 19 manufacturing industries. Taiwan replaced Korea as its largest source in 2020 and accounted for 16.75% of identifiable foreign requirements in 2022. These endpoint changes describe sourcing patterns rather than continuous trends or causal effects.

Upstream industry composition also varied. In 2022, chemicals and crude petroleum and natural gas accounted for 21.67% and 15.43% of C20's identifiable foreign requirements, respectively. Electronics accounted for 39.33% in C26, with Taiwan an important source, while motor vehicles accounted for 13.10% in C29. These patterns locate the production relationships underlying the source-economy distribution.

Common upstream dependencies nevertheless extended across industries. Wholesale and retail trade, including motor-vehicle repair (G45T47), and metal ores (B07) appeared among the five largest upstream industries in all five cases in 2022; electronics appeared in four. Across the annual top-five lists over 2016–2022, the mean indirect shares for selected G45T47 and B07 records were 80.6% and 95.8%, respectively. These shared, predominantly indirect requirements

motivate tracing how replacement suppliers reshape upstream dependence in the counterfactual analysis. They do not, by themselves, establish capacity bottlenecks, technological irreplaceability or disruption probabilities.

4.4.2 Changes in the largest source: the C26 example

Diversification can reduce dependence on the original largest source while increasing dependence on another. Under DV at the 20% intensity in 2022, the largest source changes from the United States to Korea in C20, from Taiwan to Korea in C26, and from Japan to Korea in C27. Japan remains the largest source in C28 and C29.

Table 7 Source-specific and maximum-source exposure in C26, 2022

Scenario	Taiwan exposure (%)	Korea exposure (%)	Maximum-source exposure (%)	ΔE (pp)	ΔHHI
Baseline	4.1282	3.7980	4.1282	0.0000	0.000000
DV, 10%	3.7738	3.9417	3.9417	+0.0413	-0.001817
DV, 20%	3.4201	4.0853	4.0853	+0.0824	-0.003088
DV, 30%	3.0669	4.2285	4.2285	+0.1235	-0.003822
GD, 20%	3.4198	4.0023	4.0023	+0.0561	-0.004385
DV-EQ, 20%	3.4121	3.8499	3.8499	+0.0358	-0.007031

Notes: Source-specific exposure is measured relative to total upstream requirements, not total identifiable foreign requirements. GD denotes global diversification with baseline-share weights; DV-EQ denotes regional diversification with equal recipient weights. Taiwan is the largest source in the baseline, while Korea is the largest source in all reported adjustment scenarios.

Table 7 shows that higher DV intensity reduces exposure to Taiwan but increases exposure to Korea. At 30%, Korea's exposure reaches 4.2285%, exceeding the baseline maximum of 4.1282%, despite a lower HHI. Thus, lower HHI does not guarantee lower maximum-source exposure; the three intensities demonstrate this possibility without identifying an exact switching threshold.

At 20%, exposure to Korea rises by 0.287287 percentage points, comprising direct (+0.095734), indirect (+0.200644), and denominator (−0.009091) contributions. Exposure to Vietnam, Singapore and Malaysia rises by approximately 0.1730, 0.0959 and 0.0814 percentage points, respectively. Replacement supply therefore propagates through multiple upstream relationships rather than transferring exposure one-for-one between economies.

Alternative allocations change these magnitudes. At 20%, global diversification raises C26 exposure by 0.0561 percentage points and lowers HHI by 0.004385; equal-weight regional diversification raises exposure by 0.0358 percentage points and lowers HHI by 0.007031, with exposure to Korea at 3.8499%. These conditional comparisons do not establish equal-weight allocation as optimal.

4.4.3 Extending the recipient set beyond the region

Table 8 Regional and global diversification at the 20% intensity, 2016–2022

Indicator	Regional diversification	Global diversification
Mean ΔE (pp)	+0.038584	+0.012506
Mean ΔHHI	−0.004025	−0.004088
Mean ΔM (pp)	−0.219282	−0.225386
Observations with lower E	11/133	44/133
Observations with lower HHI	133/133	133/133

Notes: Means assign equal weight to the 19 industries and seven years. Exposure indicators use the U-based denominator. Changes are relative to the baseline.

Expanding eligible recipients from RCEP to global candidates reduces the average increase in total external exposure from 0.038584 percentage points under DV20 to 0.012506 under GD20, while observations with declining exposure rise from 11 to 44. Seven-year average exposure changes are lower under GD20 in all 19 industries, indicating improved outcomes under these settings. However, the positive sample-average change means exposure still rises on average.

Both scenarios reduce HHI in all 133 industry–year observations. Based on seven-year industry averages, GD20 achieves larger HHI reductions in 14 industries and larger reductions in absolute exposure to the largest source in 11. Broader geographical choice therefore improves some outcomes, but not every industry and indicator.

This supplementary comparison also allows changes in feasible transfer quantities and their distribution across upstream industries. Differences cannot therefore be attributed solely to geographical scope or establish global diversification’s superiority in costs, capacity, or practical feasibility.

4.5 Exposure reductions per unit of implemented adjustment

We define $\eta_E = (E_{\text{baseline}} - E_{\text{scenario}})/m$ and $\eta_H = (HHI_{\text{baseline}} - HHI_{\text{scenario}})/m$, where m is the target industry’s actual transferred direct input coefficient and E is measured on a 0–1 scale. Annual ratios are averaged across years. These indicators measure finite effects per unit of coefficient adjustment, not marginal effects, cost–benefit ratios or welfare efficiency; their magnitudes are not directly comparable across indicators. Strict matching equalizes m within each pair, so normalization does not independently test strategy rankings.

At 10%, 20% and 30% intensities, mean η_E under DS is 2.625, 2.628 and 2.630, respectively, versus approximately -0.207 under DV. DS outperforms DV in all 19 industries. Mean η_H is 2.025, 1.967 and 1.905 under DS, versus 2.305, 2.154 and 2.003 under DV. Based on annual industry averages, DV leads in 14, 11 and 10 industries, respectively.

Within-strategy rankings are stable across intensities: DS exposure-efficiency rankings are identical, while all other rankings change by at most one position, with Spearman correlations of at least 0.9965 and Kendall correlations of at least 0.9766. Nevertheless, the strategy with higher HHI efficiency switches in C20, C27, C28 and C301, distinguishing ranking stability within strategies from advantages between them.

Baseline exposure does not directly predict adjustment efficiency (Figure 1; Appendix Table A1). C26 ranks 16th in DS exposure efficiency and 18th in DV HHI efficiency, while C19, with the highest external dependence, ranks last in DS exposure efficiency. C29, whose dependence is below the industry median, ranks fifth and eighth on the respective measures. Rankings also depend on objectives and signs: C25 ranks near the top in DS exposure efficiency and HHI efficiency under both strategies, but last in DV exposure efficiency. C26's third-place DV exposure-efficiency ranking indicates a smaller exposure increase, not a reduction. Baseline classifications identify structural dependence, while counterfactual and per-unit results assess alternative adjustments. None alone establishes policy priorities: at 20% intensity in 2022, DV reduces HHI more in C29, whereas DS does so in highly concentrated C26.

4.6 Sensitivity analysis

4.6.1 Treatment of negative-value-added columns

The negative value-added sensitivity check retains the original data for the main results and separately caps input coefficient columns meeting the anomaly criteria through proportional scaling, preserving their internal relative structure. Baseline and scenario outcomes are recalculated under each data specification. The cap of 0.999999 serves solely as a numerical diagnostic of anomalous columns' influence, not as an economic correction to the official input-output data. Strictly matched DS and DV follow the same matching rules within each specification.

638 **Table 9 Sensitivity of scenario effects to the treatment of negative-value-added columns**

Indicator	Maximum absolute difference in effects	Comparisons	Effect-direction changes
E, U-based denominator (pp)	0.0000126547	798	0
E, B-based denominator (pp)	0.0000086849	798	0
HHI	0.0000009812	798	0
M, U-based denominator (pp)	0.0000211595	798	0
M, B-based denominator (pp)	0.0000142128	798	0

639 *Notes:* The 798 comparisons comprise seven years, 19 industries and six main scenarios: DS and DV at three
640 intensities. They are deterministic scenario comparisons, not independent statistical observations. Maximum
641 differences compare scenario effects under the original and alternative treatments.

642 Table 9 shows unchanged effect directions across all five indicator–denominator combinations,
643 with maximum differences of approximately 0.00001265 percentage points for E under the B-I
644 definition and 0.0000009812 for HHI. Treating anomalous columns leaves strategy rankings
645 unchanged across all 399 strictly matched pairs under applicable denominator definitions. Under
646 the main specification, DS remains superior in all 399 comparisons for E; DS and DV prevail in
647 157 and 242 comparisons for HHI, and 379 and 20 for absolute exposure to the largest source.
648 The main findings are therefore unaffected by this treatment of negative value-added columns.

649 **4.6.2 Recipient allocation weights**

650 We replace baseline-share weights with equal weights while retaining the same eligible DV
651 recipients. Industry rankings remain positively associated but differ: Spearman correlations
652 range from 0.891 to 0.925 and Kendall correlations from 0.731 to 0.813. Mean absolute rank
653 changes are 1.47–1.89 positions, with maximum shifts of six to seven positions; only 26.3%–
654 31.6% of industries retain their ranks, and top-five overlap is 60%–80%.

655 Equal weighting increases concentration reduction per unit of adjustment in all 19 industries.

656 Across the three intensities, mean η_H rises from 2.305, 2.154 and 2.003 to 3.118, 2.984 and

2.850, respectively. Mean η_E improves from approximately -0.207 to -0.100 but remains negative. Allocation weights thus affect both the magnitude and distribution of effects, although equal weighting is not necessarily economically preferable: the model does not establish recipients' ability to supply equal amounts at comparable cost or quality.

4.6.3 Exposure denominator

The main specification measures exposure relative to upstream requirements using $U=B-I$. The alternative specification includes the final product itself in the denominator, using the corresponding column sum of B . For a Chinese target industry, this increases the denominator by one while leaving the foreign numerator unchanged within a given scenario.

Table 10 Relative reductions in total foreign exposure under DS using the B-based denominator, 2022

Industry	10% intensity (%)	20% intensity (%)	30% intensity (%)
C20	0.7278	1.4568	2.1872
C26	1.7716	3.5539	5.3468
C27	1.4385	2.8824	4.3317
C28	1.4754	2.9551	4.4393
C29	1.5046	3.0137	4.5274

Notes: Values are relative reductions from the baseline, calculated using the denominator from each corresponding baseline or scenario matrix. These are results for 2022, not seven-year averages.

Table 10 shows that including the final product slightly reduces relative reductions in all five case industries without changing the main exposure comparison. At 20% intensity, reductions under the B-based versus U-based denominator are 3.5539% versus 3.6952% for C26 and 1.4568% versus 1.4918% for C20.

Four total-exposure effects switch from negative to positive: GD20 for C25 in 2016 and all three DV intensities for C22 in 2019. Their absolute magnitudes remain below 0.0001 percentage

676 points, although the changes exceed numerical tolerance. Total-exposure rankings remain
677 unchanged across all 399 matched pairs. For maximum-source exposure, five pairs switch from
678 favouring DS to DV—C26 in 2016 at 20% and 30%, and C19 in 2020 at all intensities—with
679 paired differences below 0.003 percentage points. DS-favouring comparisons consequently fall
680 from 379 to 374, while DV-favouring comparisons rise from 20 to 25.
681 HHI is unchanged by construction because it uses shares within identifiable foreign
682 requirements; this invariance provides no additional empirical robustness evidence.

683 **4.7 Discussion**

684 The strictly matched results show that, under the specified production network and allocation
685 rules, domestic substitution consistently achieves larger reductions in total external exposure
686 and often lowers source concentration. Regional diversification has an HHI advantage in more
687 matched pairs, but this advantage varies by industry and intensity and does not guarantee a
688 simultaneous reduction in dependence on the largest single source. Decompositions by source
689 and into direct and indirect requirements further show that unchanged total foreign direct inputs
690 can coexist with increased foreign requirements traced through the network, while dependence
691 may become concentrated in existing sources. This study therefore explains how alternative
692 replacement arrangements change structural exposure and its source distribution, rather than
693 identifying a strategy that is superior in every respect.

694 These findings support evaluating sourcing configurations along three dimensions: total
695 exposure, source concentration, and exposure to the largest single source. Their interpretation is
696 limited to structural exposure. HHI does not incorporate correlations between shocks across
697 sources, and the simulations do not measure disruption probabilities, recovery speed, welfare
698 losses, substitution costs, or recipients' capacity. Annual changes reflect each year's input-output
699 structure and may capture both price and structural changes; they cannot be interpreted directly
700 as causal effects of a particular event. The reduction in foreign inputs under DS is closely tied to

701 the scenario design. The more informative evidence lies in differences across indicators, indirect
702 contributions, and shifts in the largest source, rather than the design-driven finding that DS
703 reduces E.

704 **5 Conclusions and implications**

705 **5.1 Main findings**

706 Using strictly matched counterfactuals for Chinese manufacturing, this paper identifies three
707 main findings.

708 First, total exposure, source concentration and maximum-source exposure need not improve
709 together. DS reduces total exposure more in all 399 matched pairs, partly reflecting its reduction
710 of foreign direct inputs. DV achieves lower HHI in 242 pairs, but this advantage becomes less
711 frequent at higher intensities. Under DV20, HHI falls in all 133 industry–year observations
712 while total exposure rises in 122.

713 Second, indirect linkages can offset improvements in direct sourcing. Although DV preserves
714 total foreign direct input coefficients, replacement suppliers may generate additional upstream
715 foreign requirements. In C26 in 2022, these indirect effects outweigh the denominator effect,
716 increasing exposure by 0.0824 percentage points under DV20. Under DV30, exposure to Korea
717 reaches 4.2285%, exceeding baseline maximum-source exposure of 4.1282% despite a lower
718 HHI. Reducing dependence on the original largest source therefore need not reduce maximum-
719 source exposure.

720 Third, higher baseline exposure does not imply larger reductions per unit of adjustment. Industry
721 rankings are stable across intensities but more sensitive to recipient weights. The DS–DV
722 ranking for total exposure remains unchanged under negative-value-added treatments and
723 alternative denominators, although the latter alter a few maximum-source rankings.

724 Combining strict matching, multiple indicators and accounting decompositions shows how
725 identical initial sourcing reductions yield different upstream outcomes through replacement

726 suppliers. The central contribution is distinguishing reductions in external dependence from its
727 redistribution, without establishing either strategy's universal superiority.

728 **5.2 Policy implications**

729 The findings suggest that supply-chain adjustments should begin with a clear objective. If the
730 aim is to reduce the foreign share of upstream production requirements, domestic substitution is
731 more effective under this paper's scenario assumptions. However, this advantage partly reflects
732 its designed reduction in total foreign direct inputs and does not imply lower adjustment costs or
733 greater resilience to actual shocks. If the aim is to diversify foreign sources, regional
734 diversification can help, but total external exposure and exposure to the largest single source
735 must also be monitored. Lower concentration alone does not establish reduced external
736 dependence.

737 Assessment should extend beyond direct suppliers. Indirect requirements account for most
738 foreign production requirements in the five key industries, and the simulations show that
739 replacement suppliers may introduce additional upstream dependencies. Before changing
740 sourcing arrangements, policymakers and firms should therefore examine both prospective
741 suppliers and their upstream networks, particularly whether multiple replacement suppliers
742 depend on the same upstream economy or industry. Otherwise, lower concentration may merely
743 shift dependence further upstream.

744 Industry adjustment priorities should jointly consider baseline exposure, adjustment effects, and
745 implementation feasibility. Exposure levels alone cannot identify which industries would benefit
746 most from substitution. Domestic substitution requires assessing production capacity, input
747 quality, and adjustment costs; regional diversification requires examining recipients' supply
748 capacity and allocation shares. The scenarios identify configurations worth further investigation,
749 but implementation requires information beyond input-output accounts.

5.3 Limitations and future research

This paper measures structural exposure, not realized resilience. Coefficients are fixed within scenarios, excluding endogenous prices, substitution elasticities, inventories, adjustment costs and capacity constraints. Strict matching equalizes coefficient reductions, not substitution costs or feasibility; domestic substitution reallocates sourcing rather than relocating firms or factories. HHI omits cross-source shock correlations, and simulations do not estimate disruption probabilities, recovery times or welfare losses. Industry aggregation may obscure product and supplier differences, while annual changes reflect both prices and production structures. Future research could extend this matched framework with product- or firm-level data, capacity and cost constraints, and simultaneous supplier shocks to assess when lower exposure translates into smaller production losses or faster recovery.

List of abbreviations

Abbreviations used in the manuscript on domestic substitution and regional diversification of China's manufacturing supply chains.

Abbreviation	Full term or meaning
ASEAN	Association of Southeast Asian Nations
CHN	China (economy code)
CR3	Three-source concentration ratio; sum of the three largest identifiable foreign source shares
DS	Domestic substitution
DV	Regional diversification
DV-EQ	Regional diversification with equal recipient weights
GD	Global diversification
HHI	Herfindahl–Hirschman index
ICIO	Inter-Country Input-Output
OECD	Organisation for Economic Co-operation and Development
pp	Percentage points
RCEP	Regional Comprehensive Economic Partnership
ROW	Rest of the world
RRE	Relative reduction in total external exposure

Abbreviation	Full term or meaning
US	United States

764 **Scenario labels.** The suffixes 10, 20 and 30 denote adjustment intensities of 10%, 20% and
765 30%, respectively. RD10–30 are the code labels corresponding to DV10–30; DS_SAME_RD
766 identifies the strictly matched DS scenarios.

767 **Declarations**

768 **Availability of data and materials:**

769 The original data used in this study are from the OECD Inter-Country Input – Output (ICIO)
770 tables, 2025 edition, covering 2016 – 2022, and are available at
771 <https://www.oecd.org/en/data/datasets/inter-country-input-output-tables.html>. The R code and
772 derived datasets supporting the findings are maintained by the authors and are available from the
773 corresponding author upon reasonable request.

774 **Competing interests:**

775 The authors declare that they have no competing interests.

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785 **Authors' contributions:**

786 YG and JC jointly formulated the research questions and designed the research framework. YG
787 conducted the literature review, curated the data, developed the code, performed the simulations
788 and analyses, verified and interpreted the results, prepared the figures and tables, and drafted
789 and revised the manuscript. JC provided research supervision and acquired project funding.
790 Both authors read and approved the final manuscript.

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883 **Appendix A Supplementary definitions and implementation**

884 **A1 Industry diagnostics**

885 For each industry, annual E and H are averaged over 2016–2022. Cross-sectional medians
886 across the 19 industries divide the means into high and low groups, assigning equality to the
887 high group. These are relative descriptive categories, not probability-based risk thresholds.

888 Bubble size is mean F_j per unit of final demand, not observed import expenditure. The foreign
889 indirect share is $\omega_j = \sum_{r \in \mathcal{F}} n_{rj}^l / F_j$, distinct from E_j^l . CR3 sums the three largest p_{rj} in each
890 year, allowing the selected sources to change.

$$891 \quad Q_{sj} = \sum_{r \in \mathcal{F}^*} U_{(r,s),j}, \quad \pi_{sj} = Q_{sj} / F_j^*, \quad \theta_{r|sj} = U_{(r,s),j} / Q_{sj}. \quad (A1)$$

$$892 \quad \omega_{sj} = \frac{\sum_{r \in \mathcal{F}^*} (U - A)_{(r,s),j}}{Q_{sj}}. \quad (A2)$$

893 For each case industry and year, the five largest Q_{sj} identify leading upstream industries and
 894 their largest sources. Mean indirect shares for these records are conditional on selection into the
 895 annual top five. These diagnostics identify substantial production requirements, not proven
 896 bottlenecks or input non-substitutability.

897 **A2 Alternative allocations and rankings**

898 Equal-weight regional allocation sets $w_{rsj} = 1/|R_{sj}|$ for eligible suppliers. The amount-only
 899 domestic control uses:

$$900 \quad \beta_j = \frac{m_j}{\sum_{r \in \mathcal{F}} \sum_s a_{(r,s),j}^0}, \quad a_{(r,s),j}^{AM} = (1 - \beta_j) a_{(r,s),j}^0 \quad (r \in \mathcal{F}). \quad (A3)$$

$$901 \quad a_{(c,s),j}^{AM} = a_{(c,s),j}^0 + \beta_j \sum_{r \in \mathcal{F}} a_{(r,s),j}^0. \quad (A4)$$

902 Industry rankings use descending mean annual η , with average ranks for ties. Stability is
 903 described by Spearman correlation, Kendall's tie-adjusted τ_b , mean absolute rank changes, and
 904 the fraction of overlap between the two reported top-five sets. We additionally report maximum
 905 rank changes and the proportion of unchanged ranks. These statistics describe model-output
 906 stability, not sampling uncertainty.

907 **A3 Anomalous columns and denominator sensitivity**

908 Industry labels are matched through a fixed code crosswalk and row-column ordering is
 909 verified. Zero-output nodes without transactions retain zero coefficient columns; zero output
 910 with nonzero inputs or transactions is flagged and stops calculation. Negative value added is
 911 retained in the main data. For sensitivity analysis, let $\ell_k = \sum_i a_{ik}^0$ and define:

$$912 \quad \mathcal{K} = \{k: x_k > \varepsilon, \forall A_k < -\varepsilon \text{ or } \ell_k \geq 1 - \varepsilon\}. \quad (A5)$$

$$913 \quad \lambda_k = \begin{cases} \min\{1, \kappa/\ell_k\}, & k \in \mathcal{K}, \\ 1, & k \notin \mathcal{K}, \end{cases} \quad \kappa = 0.999999. \quad (A6)$$

914 Scaling requires a positive column sum. The same column factors are applied to the original
 915 baseline and all original scenarios, holding donors, eligible suppliers and weights fixed:

$$\tilde{A}^q = A^q \text{diag}(\lambda), \quad \tilde{\delta}_{sj} = \lambda_j \delta_{sj}, \quad \tilde{m}_j = \lambda_j m_j. \quad (A7)$$

$$S_{K,j}^q = (\tilde{K}_j^q - \tilde{K}_j^0) - (K_j^q - K_j^0). \quad (A8)$$

This preserves within-column proportions and is a sensitivity transformation, not an economic correction of official data. We examine effect differences, changes in direction and paired winners. Magnitude screening uses 0.01 percentage points for E and M , and 0.0001 for HHI, separately from numerical tie tolerances.

Using B rather than U leaves foreign numerators unchanged for Chinese targets and adds one to each scenario's total denominator:

$$E_j^{B,q} = \frac{F_j^q}{D_j^q + 1}, \quad M_j^{B,q} = \frac{\max_{r \in \mathcal{F}^*} n_{rj}^q}{D_j^q + 1}. \quad (A9)$$

HHI is unchanged by construction. To diagnose a sign change between two states, let $L = N_1 D_0 - N_0 D_1$ for the corresponding numerators and denominators. Then

$$\frac{N_1}{D_1} - \frac{N_0}{D_0} = \frac{L}{D_0 D_1}, \quad \frac{N_1}{D_1 + 1} - \frac{N_0}{D_0 + 1} = \frac{L + N_1 - N_0}{(D_0 + 1)(D_1 + 1)}. \quad (A10)$$

The two states can be the baseline and one scenario, or DV and DS. For M , each numerator is its own state's largest identifiable-source requirement. All direction and ranking exceptions are retained and reported with their magnitudes.

A4 Numerical implementation

A full inverse need not be stored. With $P = [e_j]_{j \in J}$ selecting the 19 target columns, solve:

$$(I - A^q)Y^q = P, \quad U^q P = Y^q - P, \quad (I - A^q)v^q = \mathbf{1}. \quad (A11)$$

For nonnegative A^q , a strictly positive solution v^q certifies $A^q v^q = v^q - \mathbf{1} < v^q$ and hence a spectral radius below one. Implementation checks use maximum elementwise solution residuals of 10^{-8} , matching and input-conservation errors of 10^{-9} , and percentage-point identity residuals of 10^{-8} . Nonnegativity and direct-indirect and source aggregation are also

938 checked. Strategy ties use 10^{-6} percentage points for E and M , and 10^{-8} for HHI. These
 939 are floating-point tolerances, not significance or economic-importance thresholds.

940 **Table A1 Rankings of reductions per unit of implemented adjustment across 19 manufacturing**
 941 **industries (2016–2022)**

Industry Code	DS: η_E	DS: η_H	DV: η_E	DV: η_H
C10T12	15/15/15	3/3/2	2/2/2	2/2/2
C13T15	3/3/3	2/2/3	9/9/9	3/3/3
C16	10/10/10	10/10/10	12/12/12	9/9/9
C17_18	7/7/7	8/8/7	13/13/13	11/11/11
C19	19/19/19	19/19/19	15/14/14	19/19/19
C20	12/12/12	17/17/17	4/4/4	17/17/17
C21	13/13/13	6/6/6	11/11/11	7/7/7
C22	11/11/11	14/14/14	1/1/1	16/16/16
C23	2/2/2	4/4/4	18/18/18	6/5/5
C24A	18/18/18	5/5/5	7/7/7	4/4/4
C24B	17/17/17	11/11/11	5/5/5	5/6/6
C25	1/1/1	1/1/1	19/19/19	1/1/1
C26	16/16/16	18/18/18	3/3/3	18/18/18
C27	8/8/8	15/15/15	10/10/10	15/15/15
C28	6/6/6	12/12/12	14/15/15	12/12/12
C29	5/5/5	7/7/8	8/8/8	8/8/8
C301	9/9/9	13/13/13	6/6/6	13/13/13

Industry Code	DS: η_E	DS: η_H	DV: η_E	DV: η_H
C302T309	14/14/14	16/16/16	16/16/16	14/14/14
C31T33	4/4/4	9/9/9	17/17/17	10/10/10

942 Note: Each cell reports rankings at intensity levels of 10%, 20%, and 30%, respectively. Rankings are determined
943 by first calculating the annual reduction per unit of implemented adjustment for each industry, then computing the
944 arithmetic mean for the 2016 – 2022 period, and finally ranking the industries from highest to lowest within the
945 same strategy, indicator, and intensity level (with 1 indicating the highest rank). DS employs a strictly matched
946 design, DV uses a baseline-share allocation rule, and E utilizes the U-based denominator. When efficiency is
947 negative, a higher rank indicates only a smaller negative impact, not the achievement of positive mitigation. Refer
948 to Table 3 in the main text for industry names.