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1 **International Trade Reduces Emissions through Technology Transfer Led by Key**
2 **Emitters**

3
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23 **Abstract**

24 The Paris Agreement highlights technology transfer for climate mitigation, yet the disparities in
25 technology ownership and diffusion slow global decarbonization. While trade agreements serve as
26 institutional pathways for technological diffusion, the decarbonization potential of patent transfers
27 remains unassessed. Here using data on carbon emissions, trade, and patents from 1995 to 2023, we
28 evaluate how membership in trade agreements influences global carbon emission through technological
29 accumulation. Our analyses show that while trade agreements have heterogeneous effects on emissions,
30 they lead to a robust 2.8% reduction among key emitters. These reductions are mediated more by cross-
31 border general technology transfers than by specific climate innovation. Scenario analyses further
32 suggest that full technology transferring from key emitters to all their partners could reduce emissions
33 by 587 Mt, equivalent to 1.6% of global emissions in 2021. These results demonstrate that incorporating
34 technology transfer mechanisms into trade agreements is critical for maximizing their decarbonization
35 potential.

36 **Main text**

37 Technological progress is widely recognized as essential to achieving global climate goals¹⁻³, yet uneven
38 technology transfer and innovation are delaying collective progress toward global emission reductions^{4,5}.
39 International Energy Agency (IEA) estimates indicate that advances in clean energy technologies have
40 already avoided around 2.6 Gt CO₂ annually over the past five years⁶, underscoring the critical role of
41 innovation in bending emission trajectories. Nevertheless, substantial regional disparities in
42 technological ownership and transfer persist. About 85.7% of methane abatement inventions transfers-
43 out or flow between 2017 and 2019 were confined to developed countries or directed toward China,
44 South Korea and Brazil, leaving other developing countries less involved⁷. This concentration pattern
45 extends to broader climate change mitigation technologies: the top ten inventing countries, largely
46 overlapping with the key emitters responsible for 67.8% of global emissions⁸, account for almost 90%
47 of global inventions while most middle-income economies have not caught up⁹. In contrast, emerging
48 and developing economies—where emissions are projected to continue growing through 2050—possess
49 a small fraction of these technologies but face a growing responsibility for mitigation^{10,11}. Transitioning
50 toward more technology-intensive industries thus presents a critical opportunity for developing countries
51 to achieve sustainable development^{12,13}. Despite this urgent need for effective technology transfer to
52 facilitate emission reduction, existing research has not yet quantified the global emission reduction
53 potential of optimal technology transfer.

54 While technology transfers through multiple channels, including international trade, foreign direct
55 investment, academic collaboration, and multinational enterprise activity¹⁴⁻¹⁶, international trade
56 provides a particularly powerful pathway. Trade directly integrates into global value chains, thus exerting
57 a broader impact on the carbon emissions through the outsourcing of industries, causing potential carbon

58 leakage¹⁷⁻²², as evidenced by estimation that complete tariff elimination among Regional Comprehensive
59 Economic Partnership (RCEP) members would increase the yearly global CO₂ emissions from fuel
60 combustion by about 3.1%²². Conversely, unlike spontaneous technology diffusion through market
61 mechanisms, trade agreements offer a critical institutional alternative. Deeper regional agreements
62 demonstrate this potential by showing enhanced technology spillovers among member countries²³,
63 embedding legally binding provisions on intellectual property, environmental standards, and technical
64 cooperation that systematically guide technology transfer²⁴⁻²⁶. Nevertheless, how trade agreements shape
65 technology-driven emission reductions, and the extent of their decarbonization potential through patent
66 transfers, remains unexplored.

67 To fill these gaps, this study develops a multi-stage empirical framework to evaluate the impact of
68 trade agreements on national carbon emissions and to assess the mediating role of technological change.
69 Integrating country-year panel data from 1995 to 2023 for 16 major trade agreements, we estimate the
70 total effect of trade agreements on emissions using a system generalized method of moments (System
71 GMM) with external instruments, test for indirect effects via technology channel with causal mediation
72 analysis, and explore heterogeneity through moderation and stratification. Throughout this analysis, we
73 quantify technology using the cumulative stock of general patents and apply patent families filed in at
74 least two jurisdictions to quantify high-quality climate inventions, and track address changes within these
75 families to represent international technology flows. Finally, we conduct a scenario analysis to quantify
76 potential emissions reductions under three distinct technology transfer regimes. Overall, the study
77 highlights the nuanced role of trade agreements in promoting technology-driven emission reductions and
78 underscores the promising role of technology transfers in global carbon reductions.

79

80 Trade agreements and heterogeneous carbon emission impacts

81 To examine how trade agreements influence carbon emissions through technological channels, we first
82 analyzed emission trends and technological capacity across major trade agreements.

83 Analysis of emission trends from 1995 to 2023 reveals notable disparities across agreements
84 (Figure 1). Countries within the Belt and Road Initiative (BRI) and RCEP experienced significant
85 emissions growth of 127.55% and 165.52%, respectively, largely driven by China's rapid
86 industrialization. In contrast, emissions from agreements such as United States-Mexico-Canada
87 Agreement (USMCA) and the European Union (EU) showed stabilization. Key emitters, defined
88 dynamically as those whose annual emissions exceed 1% of global total in any given year (Figure 1b),
89 contribute more than half of the emissions within their respective agreements (Figure S1). Additionally,
90 trade-embodied emissions and its share in total CO₂ emissions stabilized globally (Figure S2 & S3).
91 Meanwhile, the global carbon emission intensity demonstrates a discernible downward trajectory (Figure
92 S4), though per capita carbon emission trends reveal heterogeneous trends (Figure S5).

93 Technology accumulation serves as a vital indicator of emission reduction potential. The
94 distribution of general patent stocks highlights overlap between countries with high emissions and those
95 with extensive carbon reduction patent portfolios (Figure 1c), a pattern mirrored in climate and cross-
96 border patents stock (Figures S6 & S7). The growth trend in cumulative climate (Figure S8) and general
97 patents (Figure S9) within these agreements is like the growth in emissions. Furthermore, overlapping
98 membership, such as Japan in both RCEP and Comprehensive and Progressive Agreement for Trans-
99 Pacific Partnership (CPTPP), suggest potential cross-agreement spillover effects.

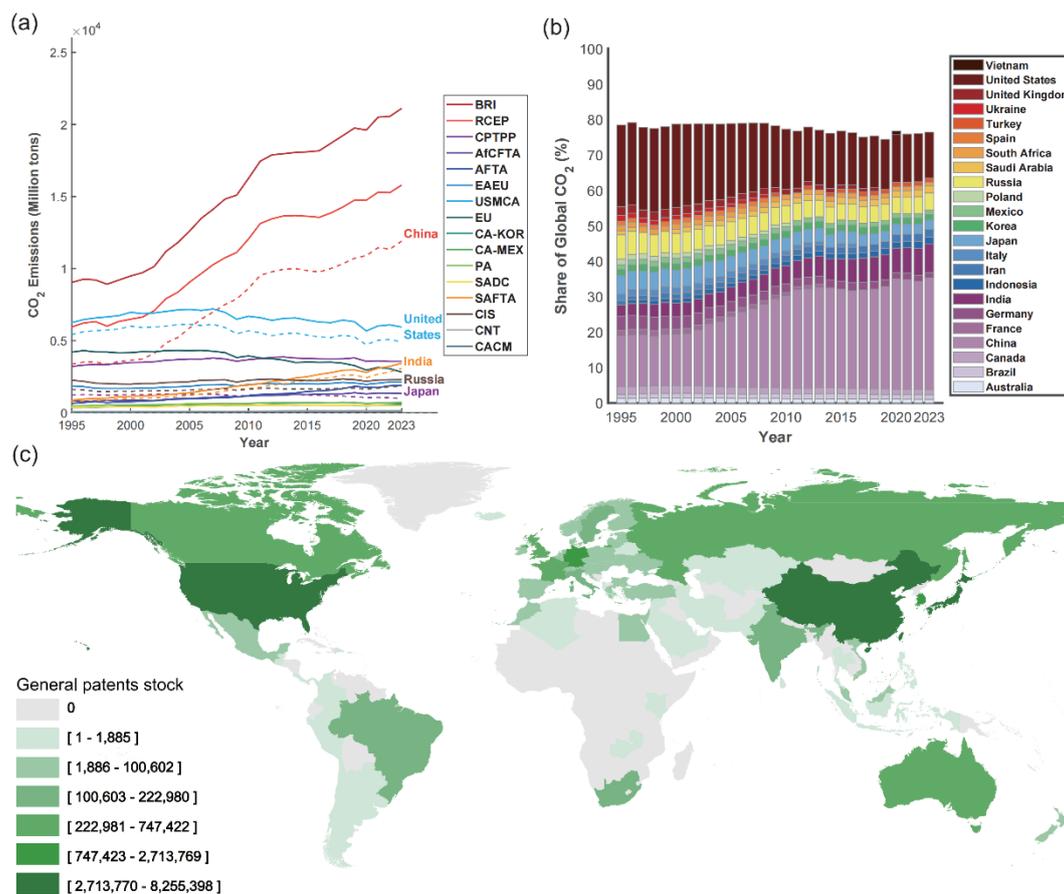
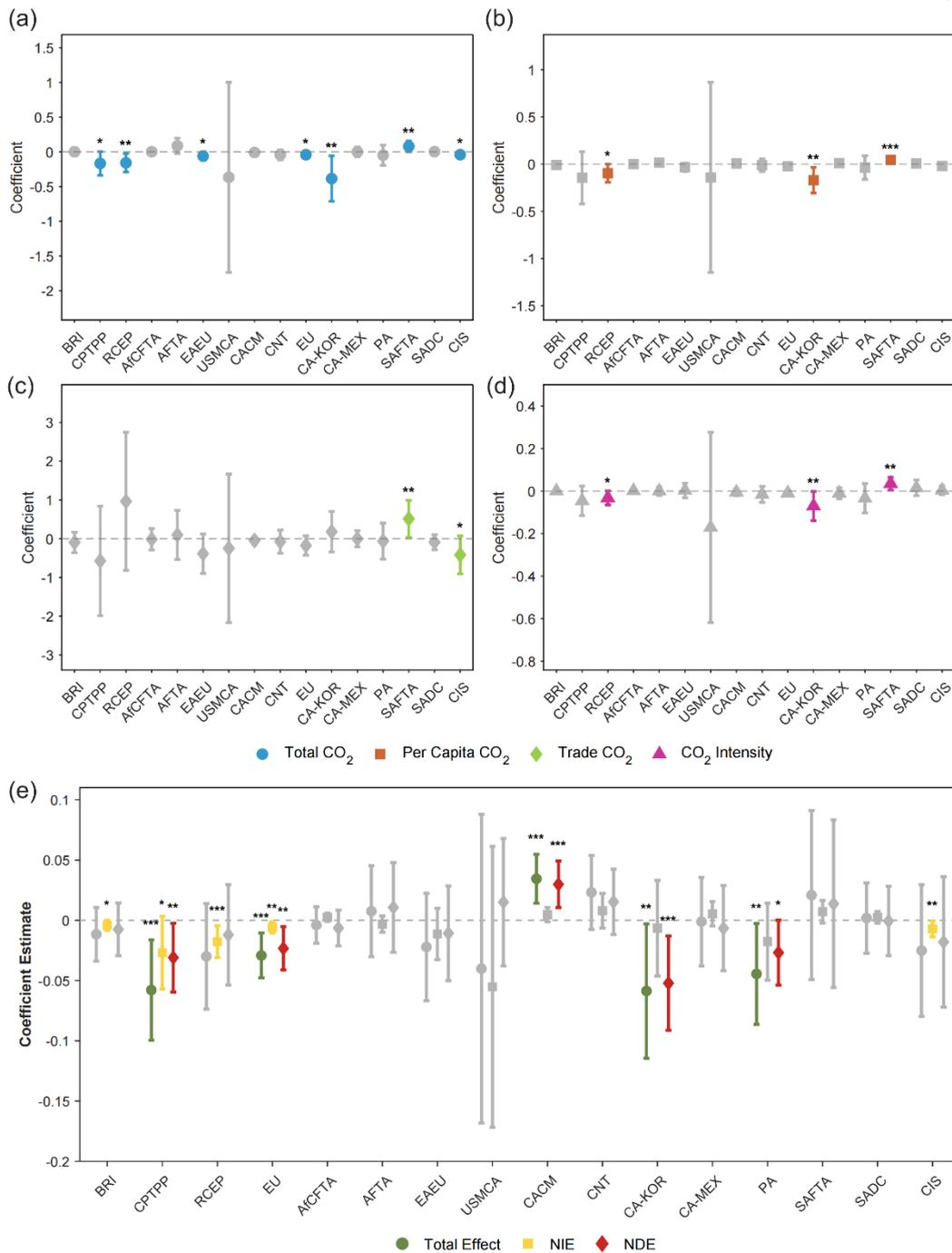


Fig. 1 | The temporal CO₂ emission of trade agreements and key countries. (a) Trends in emissions by trade agreements. The solid line represents total carbon emissions. The dotted line indicates the top five key countries (countries with $\geq 1\%$ of global carbon emissions in any year). Full agreement names and membership are provided in [Table S1](#). (b) Temporal trends in the share of global carbon emissions of key countries. Only years in which a country's emissions exceeded 1% of the global total are shown. (c) Cumulative general patents stock as of 2023.

Beyond descriptive trends, we employed a System GMM with external instruments approach to assess the influence of trade agreements on emissions. The results reveal heterogeneity in the impact of different agreements on emissions ([Figures 2a-2d](#)). The primary results are based on a two-year lag of treatment variable to account for the typical delay between signing and implementation. While overall effects vary in direction and significance across agreements, participation in the EU is associated with a robust and statistically significant reduction in total emissions. Specifically, at a zero-year lag, EU membership reduces emissions by approximately 5.6% ($\beta_1 = -0.056$, $SE = 0.023$, $p < 0.05$). This reduction effect persists across multiple specifications (e.g., $\beta_1 = -0.055$, $SE = 0.023$, $p < 0.05$ at Lag

115 1). Similarly, the CPTPP agreement shows significant abatement effects ($\beta_1 = -0.359$, SE = 0.158, $p <$
 116 0.05 at Lag 3). However, for many other agreements, the total effect remains statistically insignificant or
 117 shows divergent patterns across emission indicators (Tables S2–S8). A supplementary analysis at
 118 different lags (0, 1 and 3 years) indicates that impacts appear most pronounced within two years
 119 following treatment (Figures S10–S12).



120

121 **Fig. 2 | Effect of agreement and mediation effect of technology on emissions.** (a-d) Treatment effects
122 of agreements on different emission indicators. The results are based on a two-year lag of treatment
123 variable. (a) Total CO₂ emissions (n = 4,176 country-year observations). (b) Per capita CO₂ (n = 4,176).
124 (c) Trade-embodied CO₂ (n = 2,040). Net CO₂ emissions embedded in trade are the net of CO₂ which is
125 imported or exported via traded goods with an economy. (d) CO₂ intensity (n = 4,173). (e) Mediation effect
126 of cross-border general patent flows on total CO₂ emissions (n = 4,324). The mediation results presented
127 are for the treatment variable with a one-year lag and the mediator with a one-year lag. Data are presented
128 as regression coefficients (point estimates) with error bars indicating 95% confidence intervals (CIs) for
129 the total effects of trade agreements (β_1), as well as the natural indirect effect (NIE), and natural direct
130 effect (NDE) from the mediation model. Statistical significance was assessed using two-sided t-tests;
131 ***p<0.01, **p<0.05, *p<0.1; non-significant results ($p \geq 0.1$) shown in gray. No adjustments were made
132 for multiple comparisons. Exact P-values and test statistics for all estimates presented here are available
133 in the Source Data file.

134

135 **Cross-border technology transfer partially drives reductions**

136 Although the overall treatment effects are not uniformly robust across all agreements, the subsequent
137 mediation analysis reveals that technology channels may operate as an important pathway. We next
138 investigate whether trade agreements facilitate technological accumulation to achieve indirect emission
139 reductions.

140 When testing climate technology flow as a mediating variable across the full set of agreements, only
141 the EU exhibited a statistically significant indirect effect ($p < 0.05$) that remained robust across multiple
142 lag combinations (Table S9). For CPTPP and RCEP, significant NIE was observed under specific
143 configurations (i.e., zero-year treatment lag and one-year mediator lag), but these effects were not robust
144 across alternative lag structures (Figures S13–S16). For other agreements and lag specifications, no
145 significant NIE was detected. Similarly, general patent stock, general patent flow, and climate patent
146 stock did not emerge as robust mediators across the full set of analyses. These findings suggest that
147 promoting climate-specific technologies alone may not constitute a sufficiently potent pathway to alter
148 overall emissions through trade agreements.

149 However, a more nuanced picture emerges when examining specific agreements cross-border

150 general patent flows serve as a statistically significant and robust mediator of emission reductions. For
151 the EU, this channel yields a significantly negative NIE (NIE = -0.006, SE = 0.002, $p < 0.05$) under one-
152 year treatment lag and one-year mediator (**Figure 2e**), and this finding remains robust across multiple
153 lag combinations (**Table S10**). Notably, RCEP exhibits an even larger indirect effect through this channel
154 (NIE = -0.018, SE = 0.007, $p < 0.01$; **Table S11**). Significant negative NIEs are also observed for CPTPP,
155 BRI, and Commonwealth of Independent States (CIS), with effects remaining robust across various lag
156 specifications (**Tables S12–S14**). These results show that cross-border general patent flows emerge as a
157 more robust mediator than climate-specific patents. Moreover, the technology-mediated decarbonization
158 channel exists not only in the EU but also in other agreements.

159

160 **Reduction effects depend on national absorptive capacity**

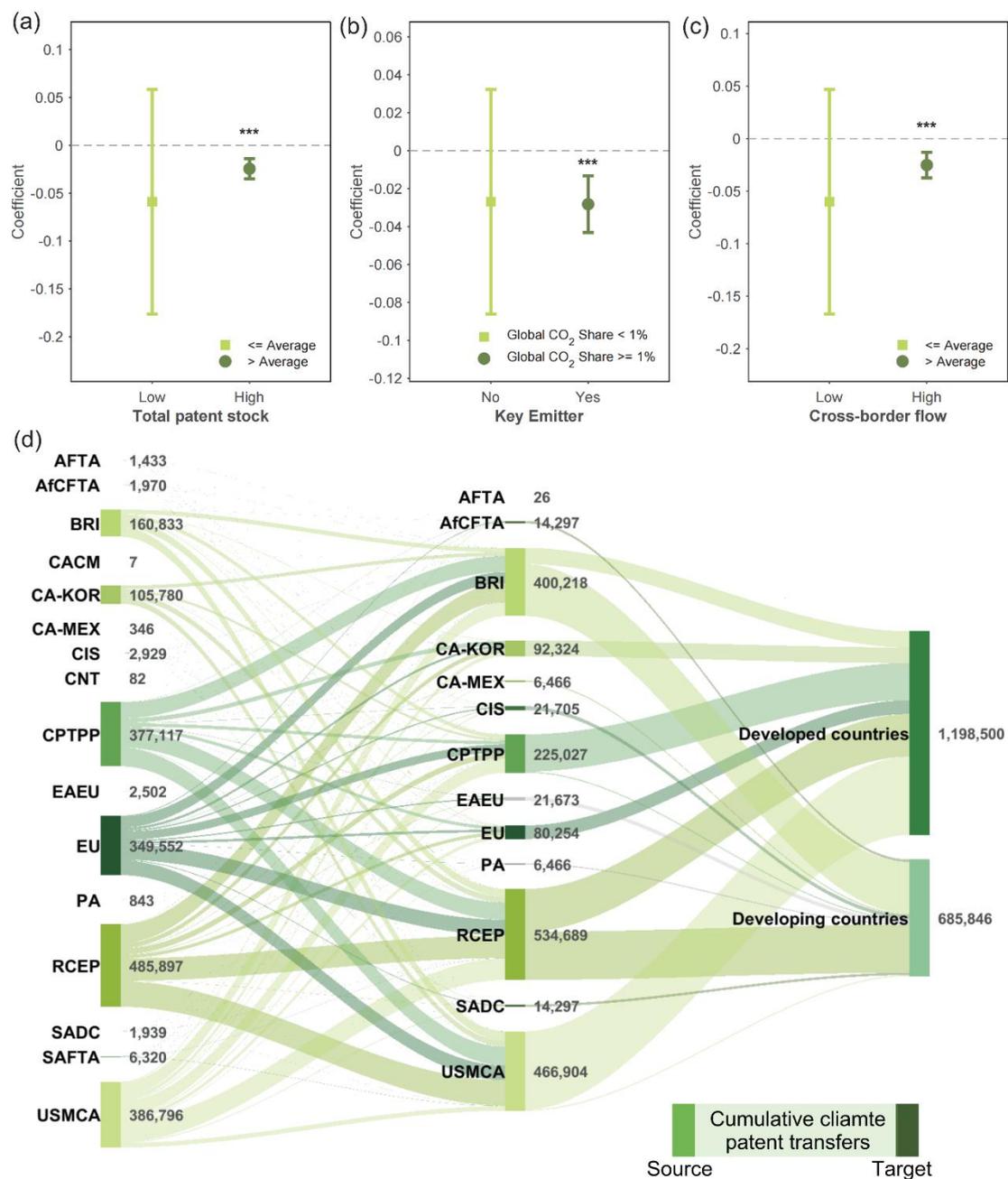
161 While mediation analysis reveals that climate technology and cross-border technology transfer are potential
162 decarbonization pathways for advanced agreements like the EU, RCEP, CPTPP and BRI, this mechanism
163 remains latent for many other agreements. To investigate this disparity, we conducted moderation and
164 stratified analyses to examine whether pre-existing technological capacity conditions the emissions
165 reduction effects.

166 The emission-reducing effects of trade agreements are also highly heterogeneous and conditional
167 on countries' initial technological capabilities. In the pooled sample of all countries, the moderation
168 results reveal a robust and significant negative interaction effect between agreement participation and
169 technological stock. The interaction coefficient for cumulative general patents is consistently negative
170 across all lag structures (e.g., $\beta_4 = -0.006$, SE = 0.002, $p < 0.05$ at Lag 2; **Table S15**), indicating that a
171 strong innovation foundation significantly amplifies the emission-reducing effects of joining an

172 agreement. Marginal effect analysis further confirms a distinct threshold effect: agreement participation
173 triggers substantial and robust reductions only for countries above the median technological stock (i.e.,
174 75th percentile), with no meaningful impact for those below it (i.e., 25th percentile). Similar significant
175 moderating effects were found for cumulative climate patents stock (Table S16) and cross-border patent
176 stocks (Table S17).

177 Stratified analyses further corroborate this capacity-dependent dynamic. When disaggregating by
178 general technology stock (Figure 3a & Table S18), countries with higher technological accumulation
179 exhibit significant emission reductions upon any agreement participation ($\beta_5 = -0.024$ to -0.028 , $p <$
180 0.01), while those below it show no significant effect. A similar pattern emerges when stratifying by
181 emitter status (Figure 3b & Table S19): key emitters exhibit significant 2.8% reductions ($\beta_5 = -0.028$
182 to -0.029 , $p < 0.01$), a result we interpret as a proxy for their higher emissions and technological density.
183 A higher cross-border patent flow also links to significant reductions (Figure 3c & Table S20).
184 Furthermore, examining technology diffusion roles reveals that both net technology senders and receivers
185 in the climate sector achieve emission reductions (Table S21), suggesting that active participation in the
186 global technology innovation network is essential to realizing emissions reduction co-benefits of trade.

187 Technology-emissions elasticity estimation further confirms that technology exerts a significant
188 decarbonization effect independent of trade institutional frameworks. Elasticity analysis reveals that
189 cumulative patent stocks significantly reduce emissions with a three to five years lag (Table S22-S23). A
190 1% increase in total and cross-border patent stocks is associated with a 0.6–0.8% reduction in CO₂, with
191 the maximum effect realized at Lag 5 for both total ($\varphi = -0.007$, SE = 0.003, $p < 0.05$) and cross-border
192 patents ($\varphi = -0.008$, SE = 0.003, $p < 0.05$).



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Fig. 3 | Heterogeneous effects and technology transfer patterns. (a) Stratified analysis by technology stock levels. Sample sizes: Low stock (n = 2,019 country-year observations), High stock (n = 1,518). (b) Stratified analysis by key emitter status. Sample sizes: Non-key emitters (n = 2,976), Key emitters (n = 561). (c) Stratified analysis by cross-border flow intensity of general patent. Sample sizes: Low flow (n = 2,324), High flow (n = 1,213). Figures a to c presented with a two-year lag for the treatment variable. Data are presented as regression coefficients (point estimates) with error bars indicating 95% confidence intervals. Statistical significance was assessed using two-sided t-tests; ***p<0.01, **p<0.05, *p<0.1. Exact P-values and test statistics for all estimates presented here are available in the Source Data file. No adjustments were made for multiple comparisons. (d) Flow of cumulative climate patent transfers among trade agreements as of 2021. The diagram shows the source of transfers (left), the recipient (middle), and the economic status of the recipient (right).

206 **Imbalanced technology diffusion limits capacity building**

207 The moderation analysis established that sufficient technological stock is a prerequisite for trade
208 agreements to trigger emission reductions. While domestic innovation is a long-term driver of this stock,
209 international technology transfer serves as a crucial accelerator.

210 Cumulative cross-border climate patent transfer flows as of 2021 reveal a significant imbalance
211 (Figure 3d). Developed economies, which already possess extensive technological capabilities, were the
212 recipients of 1,198,500 climate patents—constituting 63.6% of the total transfers. In contrast, developing
213 countries, where green technologies are most urgently needed, have received only 685,846 patents.
214 Regarding the current landscape of cumulative general patent transfers (Figure S20), the global flow is
215 also dominated by the very agreements—EU, CPTPP, RCEP, and BRI—that our mediation analysis
216 identified as capable of driving reductions through the technology channel. If the intensity of such
217 international transfers could be further strengthened and balanced, it could unlock greater abatement
218 potential.

219 Even though there are clear provisions within trade agreements aiming to promote technological
220 transfer, intra-agreement technology flows remain constrained, indicating that technology diffusion
221 remains dominated by cross-agreement flows. Direct tests on technology transfers confirm that no
222 agreement promoted intra-agreement climate patent transfers. The limited evidence of direct intra-
223 agreement transfers may be attributable to the private and strategic nature of patent licensing, which is
224 often negotiated bilaterally and may be reported in public data. As such, these findings are interpreted as
225 reflecting the broader role of trade agreements in fostering an innovative environment, rather than their
226 direct effect on specific licensing transactions.

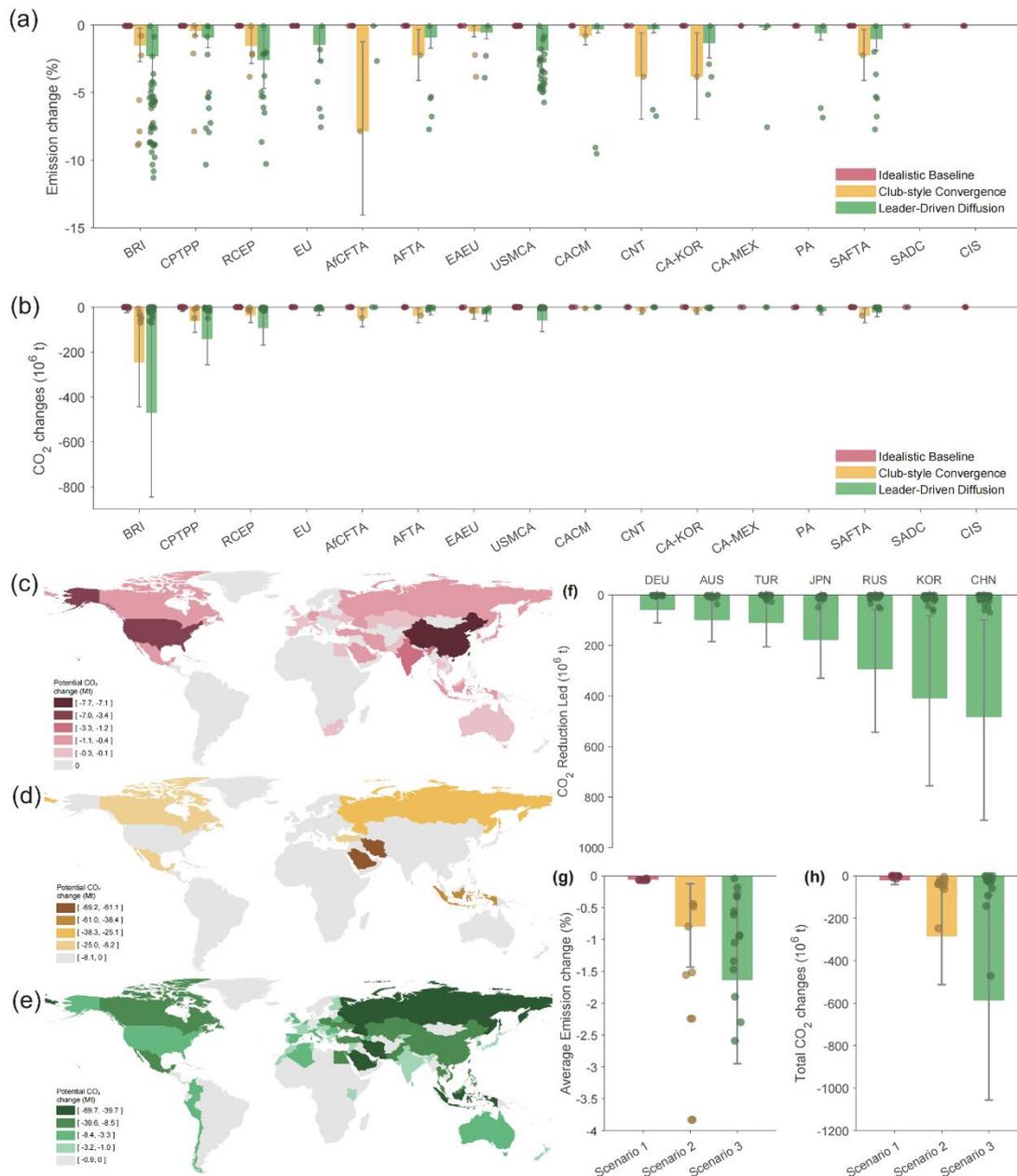
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228 **Leader-driven diffusion holds untapped reduction potential**

229 Finally, a series of scenario analyses was conducted to explore the emission reduction potential of
230 technological progress and diffusion within the framework of trade agreements. The 2021 total emissions
231 for each country served as the baseline.

232 Three scenarios were defined to reflect varied degrees of technological progress and transfer.
233 Scenario 1 ("Idealistic Baseline") assumes all countries achieve a uniform 10% improvement in patent
234 stock. Scenario 2 ("Club-style Convergence") simulates technology diffusion among key emitters within
235 each agreement. Scenario 3 ("Leader-Driven Diffusion") assumes each key emitter transfers its improved
236 technology stock to all partners across its trade networks (see [Table S24](#) for key emitters included in
237 scenario analysis).

238 Results indicate distinct variation in potential emission reductions across agreements. In terms of
239 percentage reduction ([Figure 4a](#)), the range of average emission reductions across the three scenarios is
240 -7.9% to -0.1%, with the AFTA exhibiting high relative changes. As for absolute emission reduction
241 potential ([Figure 4b](#)), agreements with large economic scale (BRI, CPTPP, RCEP) naturally show
242 substantial reduction capacity across all scenarios due to their higher baseline emissions.



243

244 **Fig. 4 | Potential carbon reductions under three technology scenarios.** (a) Percentage of emission
 245 reductions per agreement. Bars represent weighted average reductions across member countries
 246 (weighted by baseline emissions; measure of center). Individual data points represent country-level
 247 percentage reductions; Sample sizes vary by agreement (n, number of countries with non-zero values;
 248 see [Supplementary Table S25](#) for details). (b) Absolute amount of emission reductions per agreement.
 249 Bars represent the sum of country-level reductions. Individual data points represent country-level absolute
 250 reductions; Sample sizes as in figure a. (c-e) Country-level reductions under Scenario 1 (Idealistic
 251 Baseline), Scenario 2 (Club-style Convergence), and Scenario 3 (Leader-Driven Diffusion), with darker
 252 shades indicating greater abatement. Gray indicates that data are not available or that the emission
 253 reductions are zero. (f) Ranking of the key countries' total leadership impact in scenario 3. Bars represent
 254 the sum of emission reductions across affected countries (measure of center for aggregated data). Only
 255 key countries with emission reduction potential led greater than 50 Mt are shown. Individual data points
 256 represent contributions from each affected country. Country codes follow ISO 3166-1 alpha-3 standard.

257 Sample sizes (n, number of affected countries): DEU (n = 27), AUS (n = 13), TUR (n = 28), JPN (n = 17),
258 RUS (n = 38), KOR (n = 43), CHN (n = 43). (g-h) Comparison of the three scenarios (ns₁ = 16 trade
259 agreements, ns₂ = 10, ns₃ = 14). Individual data points represent agreement-level values. Bars show
260 weighted averages (figure g) or totals (figure h). For scenarios 2 and 3, overlapping memberships may
261 introduce double counting; In such cases, the highest reductions estimate is used. Error bars indicate the
262 95% confidence interval. Detailed country-level data are provided in [Supplementary Table S26](#).

263 The country-level analysis in Scenario 3 ([Figure 4f](#)) identifies China, Korea and Russia as having
264 the highest leadership-driven reduction potentials (483 Mt, 409 Mt, and 295 Mt, respectively). As major
265 emitters and innovation leaders engage in multiple trade agreements, these countries are uniquely
266 positioned to drive substantial regional and global decarbonization through strategic technology transfers.

267 The comparison of the scenarios reveals distinct patterns in overall reduction potential ([Figures 4g](#)
268 & [4h](#)). Scenario 1 achieves a modest global reduction of only 22 Mt (95% CI: [3, 42]). Scenario 2 could
269 reduce emissions by 286 Mt (95% CI: [45, 513]; approximately 0.8% of 2021 global emissions),
270 suggesting that internal technology transfers confined to major emitters have limited effectiveness. In
271 contrast, Scenario 3 offers the highest potential, with reductions reaching 587 Mt (95% CI: [92, 1,056];
272 approximately 1.6% of 2021 global emissions). However, the spatial distribution of emission reductions
273 varies ([Figures 4c-4e](#) & [Table S26](#)), underscoring that realizing this potential requires moving beyond
274 the facilitation of goods trade to actively promoting technology transfer, thereby building the necessary
275 absorptive capacity in developing member countries.

276

277 **Discussion and policy implications**

278 This study advances current knowledge by providing the first quantification of the emission reduction
279 potential of technology transfer within trade agreements. While trade is known to affect the environment
280 through scale, composition, and technique effects²⁷, our analysis further indicates that the technique
281 effect on emissions reduction is primarily driven by the cross-border diffusion of general technological

282 capacity, rather than the promotion of specific climate innovations. This implies that general industrial
283 upgrading serves as a prerequisite for environmental efficiency, enhancing the absorptive capacity
284 necessary to assimilate cleaner production methods²⁸. The contrast between the EU (where both climate
285 and general channels work) and other agreements highlights that while general diffusion provides a
286 baseline reduction, while specialized climate technology represents the next frontier of policy integration.

287 The technology-mediated effect unfolds temporally in distinct phases: initial technological
288 accumulation requires approximately 0 to 2 years, followed by an additional 0 to 2 years needed for this
289 new technology to translate into a measurable reduction in carbon emissions. It is crucial to recognize
290 that this impact represents only the early returns, and the full benefits are realized over a much more
291 extended period as they depend on successful commercialization, widespread adoption, and the gradual
292 replacement of older capital stock^{14,29,30}. Spatially, this mediation effect is concentrated in deeply
293 integrated frameworks with meaningful absorptive capacity like the EU, RCEP, CPTPP, and BRI (Table
294 S27), leaving less integrated agreements with insufficient diffusion density to trigger economy-wide
295 decarbonization.

296 The climate benefits of trade agreements are conditional. While complementary provisions — such
297 as provisions on technical barriers to trade³¹, mandatory environmental impact assessments³², non-
298 regression clauses³³, and the phased removal of fossil fuel subsidies³⁴ — are vital institutional framework,
299 their effectiveness is often constrained by the absorptive capacity and development priorities^{25,28,35}. Our
300 moderation results confirm that the emission-reducing effects are significantly amplified by a country's
301 pre-existing technological stock with stratified analysis showing that key emitters and active participants
302 in the climate technology network drive the observed reductions. Sufficient domestic absorptive capacity
303 is crucial for integrating externally sourced technologies^{36,37}. Thus, structural imbalances in technology

304 diffusion not only limit current reductions but actively restrict the accumulation of the very absorptive
305 capacity needed to unlock future benefits.

306 Scenario analyses quantify the profound opportunity cost of this imbalance. Market-driven "North-
307 North" circulation yields limited gains (Scenario 2), whereas a "Leader-Driven Diffusion" pattern
308 unlocks a maximum reduction potential (Scenario 3). Although idealized, this underscores that unlocking
309 trade's full climate potential hinges on the dual role it plays for these leading nations. On the one hand,
310 trade acts as a catalyst for innovation, creating both the competitive pressure that force surviving firms
311 to accelerate technological upgrading to defend their market share^{38,39}. On the other hand, trade can be a
312 pathway for dissemination. The potential for the global benefits of this induced innovation to be realized
313 is contingent upon the willingness of technology leaders to proactively disseminate advancements, in
314 alignment with the cooperative framework for technology transfer delineated in Article 10 of the Paris
315 Agreement⁴⁰.

316 While technology transfer could enhance climate benefits, implementation confronts fundamental
317 trade-offs. For technology leaders, mandatory transfer risk eroding the competitive advantages and
318 decelerating the aggregate pace of global low-carbon innovation. Simultaneously, recipient nations
319 lacking absorptive capacity face dependency traps and prohibitive transaction costs under rigid
320 intellectual property regimes^{41,42}. To navigate these barriers, policy frameworks must be designed based
321 on the observed heterogeneity.

322 First, trade agreements should adopt reciprocal innovation clauses that grant these technology hubs
323 preferential market access in exchange for verified technology dissemination, balancing global diffusion
324 with the innovation rents required to sustain research and development (R&D) incentives.

325 Second, simple liberalization is insufficient for developing nations. Instead, Aid-for-Trade funds

326 must be explicitly linked to human capital and R&D infrastructure to help recipients cross this threshold
327 and avoid industrial lock-in.

328 Finally, policy must extend beyond green-only provisions to remove barriers on foundational
329 industrial technologies. Moreover, intellectual property regimes under the Agreement on Trade-Related
330 Aspects of Intellectual Property Rights (TRIPS) must accommodate climate needs through flexibility
331 mechanisms that reduce transaction costs without undermining the incentive to innovate^{43,44}.

332 Several limitations and sources of uncertainty are acknowledged. First, patents reflect the legal
333 potential for innovation but may overlook informal knowledge spillovers, suggesting our technological
334 effect estimates are conservative. Sensitivity analyses with alternative indicators—such as the Global
335 Innovation Index (GII), R&D expenditure, Total Factor Productivity (TFP), Foreign Direct Investment
336 (FDI), and scientific publications—failed to exhibit significant mediation (Tables S28-S55). This
337 divergence suggests trade agreements primarily catalyze proprietary, commercial technology, though null
338 results may also reflect limited temporal coverage or data gaps in the Global South. Second, while our
339 analysis isolates the effect of trade agreements on innovation, it is acknowledged that even in the absence
340 of trade agreements, climate mitigation technologies can be transferred directly through spontaneous
341 market mechanisms like foreign direct investment and licensing^{45,46}. Third, our analysis of 16 plurilateral
342 agreements during 1995–2023 may not generalize to bilateral arrangements or sector-specific agreements.
343 Newer agreements (e.g., RCEP, CPTPP) have limited post-implementation observation, and technology-
344 emission dynamics unfold over decades. Finally, insufficient patent coverage for low-income countries
345 and estimation of average treatment effect may not fully capture the substantial heterogeneity across
346 member countries.

347 Collectively, these limitations imply that our findings represent a conservative baseline, and the true

348 emission reduction potential of technology transfer through trade agreements is likely to exceed our
349 estimates. Future research should prioritize the use of firm-level data to investigate how intellectual
350 property provisions influence innovation decisions and explore diversified, sector-specific technological
351 transition pathways as granular global data becomes available, providing a more comprehensive
352 understanding of how trade can be leveraged for a just and effective global climate transition.

353

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359

360 **Author contributions**

361 J.W., P.W. and L.H. designed the study. J.W. wrote the codes, led the analyses and visualization. S.-C.H.,
362 P.H., Y.W. and Y.S. contributed to framing the manuscript. J.W., P.W. and L.H. drafted the manuscript.
363 J.W., P.W., S.-C.H., P.H., Y.W., F.R., Y.W., W.C., J.B., L.H. and Y.S. contributed to the writing, editing,
364 and improving of the paper. L.H. and P.W. supervised and coordinated the overall research.

365

366 **Competing interests**

367 The authors declare no competing interests.

368

369 **Figure Legends/Captions (for main text figures)**

370 **Fig. 1 | The temporal CO₂ emission of trade agreements and key countries.** (a) Trends in emissions
371 by trade agreements. The solid line represents total carbon emissions. The dotted line indicates the top
372 five key countries (countries with $\geq 1\%$ of global carbon emissions in any year). Full agreement names
373 and membership are provided in [Table S1](#). (b) Temporal trends in the share of global carbon emissions of
374 key countries. Only years in which a country's emissions exceeded 1% of the global total are shown. (c)
375 Cumulative general patents stock as of 2023.

376

377

378 **Fig. 2 | Effect of agreement and mediation effect of technology on emissions.** (a-d) Treatment effects
379 of agreements on different emission indicators. The results are based on a two-year lag of treatment
380 variable. (a) Total CO₂ emissions (n = 4,176 country-year observations). (b) Per capita CO₂ (n = 4,176).
381 (c) Trade-embodied CO₂ (n = 2,040). Net CO₂ emissions embedded in trade are the net of CO₂ which is
382 imported or exported via traded goods with an economy. (d) CO₂ intensity (n = 4,173). (e) Mediation effect
383 of cross-border general patent flows on total CO₂ emissions (n = 4,324). The mediation results presented
384 are for the treatment variable with a one-year lag and the mediator with a one-year lag. Data are presented
385 as regression coefficients (point estimates) with error bars indicating 95% confidence intervals (CIs) for
386 the total effects of trade agreements (β_1), as well as the natural indirect effect (NIE), and natural direct
387 effect (NDE) from the mediation model. Statistical significance was assessed using two-sided t-tests;
388 ***p<0.01, **p<0.05, *p<0.1; non-significant results (p \geq 0.1) shown in gray. No adjustments were made
389 for multiple comparisons. Exact P-values and test statistics for all estimates presented here are available
390 in the Source Data file.

391

392

393 **Fig. 3 | Heterogeneous effects and technology transfer patterns.** (a) Stratified analysis by technology
394 stock levels. Sample sizes: Low stock (n = 2,019 country-year observations), High stock (n = 1,518). (b)
395 Stratified analysis by key emitter status. Sample sizes: Non-key emitters (n = 2,976), Key emitters (n =
396 561). (c) Stratified analysis by cross-border flow intensity of general patent. Sample sizes: Low flow (n =
397 2,324), High flow (n = 1,213). Figures a to c presented with a two-year lag for the treatment variable. Data
398 are presented as regression coefficients (point estimates) with error bars indicating 95% confidence
399 intervals. Statistical significance was assessed using two-sided t-tests; ***p<0.01, **p<0.05, *p<0.1. Exact
400 P-values and test statistics for all estimates presented here are available in the Source Data file. No
401 adjustments were made for multiple comparisons. (d) Flow of cumulative climate patent transfers among
402 trade agreements as of 2021. The diagram shows the source of transfers (left), the recipient (middle), and
403 the economic status of the recipient (right).

404

405

406 **Fig. 4 | Potential carbon reductions under three technology scenarios.** (a) Percentage of emission
407 reductions per agreement. Bars represent weighted average reductions across member countries
408 (weighted by baseline emissions; measure of center). Individual data points represent country-level
409 percentage reductions; Sample sizes vary by agreement (n, number of countries with non-zero values;
410 see [Supplementary Table S25](#) for details). (b) Absolute amount of emission reductions per agreement.
411 Bars represent the sum of country-level reductions. Individual data points represent country-level absolute
412 reductions; Sample sizes as in figure a. (c-e) Country-level reductions under Scenario 1 (Idealistic
413 Baseline), Scenario 2 (Club-style Convergence), and Scenario 3 (Leader-Driven Diffusion), with darker

414 shades indicating greater abatement. Gray indicates that data are not available or that the emission
 415 reductions are zero. (f) Ranking of the key countries' total leadership impact in scenario 3. Bars represent
 416 the sum of emission reductions across affected countries (measure of center for aggregated data). Only
 417 key countries with emission reduction potential led greater than 50 Mt are shown. Individual data points
 418 represent contributions from each affected country. Country codes follow ISO 3166-1 alpha-3 standard.
 419 Sample sizes (n, number of affected countries): DEU (n = 27), AUS (n = 13), TUR (n = 28), JPN (n = 17),
 420 RUS (n = 38), KOR (n = 43), CHN (n = 43). (g-h) Comparison of the three scenarios ($ns_1 = 16$ trade
 421 agreements, $ns_2 = 10$, $ns_3 = 14$). Individual data points represent agreement-level values. Bars show
 422 weighted averages (figure g) or totals (figure h). For scenarios 2 and 3, overlapping memberships may
 423 introduce double counting; In such cases, the highest reductions estimate is used. Error bars indicate the
 424 95% confidence interval. Detailed country-level data are provided in [Supplementary Table S26](#).

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559

560 **Methods**

561 This study develops a multi-stage empirical framework to evaluate the impact of trade agreements on
562 national carbon emissions and to assess the mediating role of technological change. Integrating country-
563 year panel data from 1995 to 2023 for 16 major trade agreements, sourced from Deep Trade Agreements
564 (DTAs) database, United Nations Commodity Trade (UN Comtrade), and IncoPat patent records, our
565 framework proceeds in four steps: (i) estimating the total effect of trade agreements on emissions using
566 a system generalized method of moments estimator instrumented by a Bartik-style shift-share design; (ii)
567 testing for indirect effects via technology channel with causal mediation analysis; (iii) exploring
568 heterogeneity through moderation and stratification; and (iv) directly quantifying the technology-
569 emissions elasticity to validate the mechanism. Throughout this analysis, we quantify technology using
570 the cumulative stock of general patents and apply patent families filed in at least two jurisdictions to
571 quantify high-quality climate inventions, and track address changes within these families to represent
572 international technology flows. Finally, we conduct a scenario analysis to quantify potential emissions
573 reductions under three distinct technology transfer regimes: an "Idealistic Baseline" of uniform domestic

574 improvement, a "Club-style Convergence" among key emitters, and a "Leader-Driven Diffusion" model
575 where technology leaders disseminate innovations through their trade networks.

576

577 **Data for evaluating the emission reduction effect and data processing**

578 This study only selected 16 agreements spanning from 1995 to 2023 among all records to conduct the
579 formal analyses, to ensure all these are in force and plurilateral agreements. There are four types of data
580 we use: agreements data, patent transfer flows, terrestrial CO₂ emissions, and bilateral trade flows data.

581 **Data for Trade agreements.** Trade agreements data were sourced from the DTAs database
582 (<https://datatopics.worldbank.org/dta/table.html>). For this study, we restricted our scope to 16 plurilateral
583 major agreements spanning from 1995 to 2023 to ensure the analysis focused on high-impact, multi-
584 country agreements currently in force. For each agreement, the database covers the stated objectives and
585 substantive commitments, as well as aspects relating to transparency, procedures, and enforcement. From
586 this we obtained the current signatories, date of signature, that each agreement contains. Specially, we
587 also took the BRI into account as an emerging type of agreement. Detailed descriptions of the agreements
588 involved are listed in the [Supplementary Table S1](#).

589 **Emission data.** Annually carbon emission data of each country was obtained from OWID
590 (<https://ourworldindata.org/co2-emissions>). OWID provides detailed and long-term datasets on CO₂
591 emissions, including both production-based and consumption-based metrics. The dataset includes annual
592 CO₂ emissions from fossil fuels, cement production, and land-use changes, extending back to 1750 for
593 some regions. For this study, we focused on the period from 1990 to 2023, taking advantage of the
594 dataset's granularity to analyze emissions trends across different trade agreements and regions. For
595 control variables with incomplete temporal coverage (energy structure from WDI, extending only to

596 2021), we employed trend extrapolation: values for 2022–2023 were imputed as $\hat{X}_t = X_{t-1} \times$
597 $(Proxy_t / Proxy_{t-1})$, where *Proxy* is the corresponding OWID variable with complete coverage.

598 **Patent data and processing procedure.** The patent data utilized in this study came from the
599 IncoPat database (<https://www.incopat.com/>). To ensure data quality, we filtered for granted invention
600 patents that belong to patent families filed in at least two jurisdictions. This approach mitigates the poor
601 international comparability and wide-ranging quality issues which often associated with single-country
602 filings or large volumes of low-value patents⁷. The included dataset encompasses 32,518,589 granted
603 patents from 1985 to 2024 (see [Table S56](#) for patent retrieval strategy). Using the Cooperative Patent
604 Classification (CPC) system, we further identified climate-related patents under the Y02 categories
605 (technologies or applications for mitigation or adaptation against climate change), which includes
606 subcategories Y02A through Y02W covering climate change mitigation technologies across energy
607 production, buildings, transportation, industrial production, carbon capture, and smart grids.

608 Each record was assigned to specific countries and years based on the applicant's nationality and
609 the application date. These patent records are then aggregated to track cumulative or annual innovation
610 activities, while cross-border changes in patent family addresses are used descriptively to capture patent
611 transfer flows.

612 First, the cumulative count of high-quality climate patents was calculated for each country and year
613 reflects its accumulated technological capacity. We constructed three distinct technology stock variables:
614 (1) total patent stock (cumulative count of all CPC-classified patents), (2) cross-border patent stock
615 (cumulative count of patents that have been transferred internationally), and (3) climate patent stock
616 (cumulative count of Y02-classified climate patents). This differentiation allows us to distinguish
617 between domestic innovation capacity and internationally acquired technology. Notably, this measure is

618 based on individual patent records, not the count of families—although the patent family classification
619 serves as the quality filter.

620 Second, to approximate international patent transfer, we trace address changes of applicants across
621 filings within the same patent family over time. Specifically, following the existing literature and
622 common practices^{7,9}, a transfer is recorded when a new applicant from a different country enters the
623 family, and the earliest jurisdiction (typically the priority country) is marked as the source of the transfer
624 and subsequent filings within the same family as the recipients. We interpret this as evidence of cross-
625 border transfer or commercialization of proprietary technology. Transfers within the same country are
626 excluded to focus exclusively on international flows. This yields 16,093,291 cross-border patent transfers
627 in total, including 1,630,638 climate-specific transfers between 1985 and 2024. See [Figure S21](#) for the
628 flowchart of patent data processing.

629 While this method captures formal transfer behavior (i.e., patent assignments), we recognize it does
630 not fully reflect informal knowledge spillovers or technology sharing (e.g., licensing)¹⁶. As such, we use
631 "patent transfers" as a precise and measurable indicator of a formal channel for technology diffusion,
632 employing it for descriptive flows among agreements and as a dependent variable to directly test the
633 agreement's effect on this channel. In subsequent panel regressions, we use cumulative patent stocks to
634 quantify how these agreements shape the broader technological environment linked to emission
635 outcomes.

636 Although such patent transfers may also occur independently of trade agreements (e.g., through
637 market-based licensing), we mapped these flows into corresponding trade agreements based on mutual
638 membership status and time, enabling us to evaluate both intra- and inter-agreement patent transfers. In
639 addition, transfers were also categorized by development status: countries classified as high-income were

640 considered developed, while those categorized as low- and middle-income were treated as developing
641 countries. We acknowledge that patent data primarily captures formal technology diffusion (e.g.,
642 assignment and commercialization) and may overlook informal knowledge spillovers. While we
643 considered alternative metrics such as GII, R&D expenditure and TFP were considered (see [Table S57](#))
644 we retained patents as the primary metric due to their superior temporal coverage (1995–2023) and
645 granularity (distinguishing climate-specific vs. general technologies). Those alternative indicators serve
646 as the sensitivity analyses for mediation effect.

647 **Trade data.** Bilateral trade flows data were obtained from the UN Comtrade database
648 (<https://comtradeplus.un.org/>). Based on the reporter and partner countries associated with each trade
649 flow record, along with their respective trade agreements, we calculated annual import and export trade
650 value indicators for each country within the scope of each trade agreement. These indicators were then
651 integrated into the panel dataset to enable a more granular analysis of the impact of trade agreements on
652 trade volumes. This methodological approach allows for a detailed examination of trade dynamics at
653 both the national and agreement-specific levels.

654 The final panel includes data from 1995 to 2023 and covers 201 countries or dependent territories
655 with valid emission and economic data. Of the countries in the study, 145 participated in at least one of
656 the 16 selected trade agreements, 86 have valid data on the number of general patents granted and 85
657 have valid data on the number of patent transfers.

658

659 **Empirical framework**

660 This study adopts a multi-stage empirical framework to evaluate how trade agreements affect national
661 carbon emissions, and to assess whether these effects are mediated through technological channel. A

662 central methodological challenge in estimating the effects of trade agreements on emissions is the
663 potential for endogeneity and dynamic feedback. Trade agreement participation is likely non-random,
664 which means countries with specific economic characteristics, environmental priorities, or technological
665 capacities may self-select into certain agreements. Moreover, emissions outcomes from previous periods
666 may influence both current participation decisions and technological accumulation, creating dynamic
667 feedback that can bias standard fixed effects estimators.

668 To address these concerns, we employ a system GMM estimator (implemented via `xtabond2` in Stata)
669 that offers several advantages: (1) it incorporates lagged dependent variables to model emissions
670 dynamics explicitly; (2) it uses internal instruments (lagged levels and differences) to address
671 endogeneity of predetermined and potentially endogenous variables; and (3) it allows incorporation of
672 external instrumental variables to strengthen identification.

673
674 **Rationale for Instrument Selection.** A range of candidate instruments were assessed, incorporating
675 gravity-based predictors, neighbor or partner diffusion measures, and political alignment indices, among
676 others. Most of these instruments did not satisfy the relevance tests (first-stage $F < 10$) (see [Table S58](#)).
677 In contrast to the effectiveness of gravity variables in bilateral Free Trade Agreements (FTAs), plurilateral
678 agreements require instruments that capture geopolitical rather than purely economic drivers of
679 participation.

680
681 **Instrumental variables construction.** To resolve the self-selection bias of the treatment variable, we
682 construct interaction-based instrumental variables following the Bartik-style shift-share approach. For
683 each agreement s , the instrument is defined as:

684
$$Z_{i,s,t} = Share_{i,s}^{pre} \times Shock_{s,t}$$

685 where $Share_{i,s}^{pre}$ is country i 's pre-treatment exposure to agreement s , measured as the average
 686 trade share with agreement members during the pre-treatment period 1995–2000. The variable $Shock_{s,t}$
 687 is a binary time-series indicator capturing exogenous geopolitical events that affect the relevance or
 688 intensity of agreement participation exogenously to domestic environmental policies (e.g. the 2017 US
 689 withdrawal from TPP; See [Table S59](#) for shocks list). The validity of this instrument rests on the
 690 exclusion restriction that the interaction of pre-determined trade dependency with external shocks affects
 691 emissions only through effective agreement participation. The base-period dependency is measured
 692 before most agreements' environmental provisions took effect, mitigating concerns about reverse
 693 causality. The external shocks are driven by geopolitical events unrelated to individual countries'
 694 environmental policies. For all IV-GMM specifications, we conduct diagnostic tests (Arellano-Bond AR
 695 (2) for serial correlation, Hansen J-test for overidentifying restrictions) and focus on results only for
 696 specifications that pass both tests.

697
 698 **Estimating the overall effect of trade agreements.** Our primary objective is to estimate the average
 699 treatment effect on the treated (ATT) of trade agreements on national carbon emissions. The baseline
 700 specification is:

701
$$\ln(Y_{i,t}) = \alpha + \rho \ln(Y_{i,t-1}) + \beta_1 Treated_{i,t-k,s} + X'_{i,t} \delta + \mu_i + \varepsilon_{i,t} \quad (1)$$

702 In this equation, $\ln(Y_{i,t})$ is the natural logarithm of the carbon emissions outcome for country i
 703 in year t . We measure this outcome in several ways based on the data from OWID: total territorial CO₂
 704 emission, which do not account for emissions embedded in traded goods; total territorial CO₂ per capita;
 705 net trade embodied CO₂ emission (the net balance of CO₂ imported and exported in traded goods); CO₂

706 emission intensity, defined as total carbon emission per unit of GDP. α is the constant term. The term
707 $\rho \ln(Y_{i,t-1})$ is the lagged dependent variable that captures emission dynamics and persistence.
708 $Treated_{i,t-k,s}$ is a binary indicator that equals 1 if country i is an active member of a selected
709 agreement s in the year t based on the signing date, and 0 otherwise. Here, $k \in \{0,1,2,3\}$ denotes the
710 lag order to account for implementation delays. Its coefficient, β_1 , captures average effect of agreement
711 participation on emissions. Country fixed effects (μ_i) absorb time-invariant heterogeneity. The vector
712 $X_{i,t}$ contains a vector of time-varying control variables to account for potential confounding factors that
713 influence emissions: log GDP per capita; trade openness (the sum of exports and imports as share of
714 GDP), industry structure (industry value added as share of GDP); energy structure (the share of
715 renewables in electricity generation) to account for economic scale, structure, and shifts in the energy
716 system. Equation (1) is estimated using system GMM with the shift-share instruments described above
717 serving as external instruments for the treatment variable.

718

719 **Causal Mediation Analysis.** We further conduct a causal mediation analysis to test general technology
720 and climate technology mediate the relationship between trade agreements and emissions based on the
721 established casual mediation framework⁴⁷. This analysis decomposes the total effect (β_1) into the natural
722 indirect effect operating through the mediator, and the natural direct effect. The core model consists of
723 two equations for the mediator ($M_{i,t}$) and outcome ($Y_{i,t}$):

$$724 \quad M_{i,t} = \rho_M M_{i,t-l} + \theta Treated_{i,t-k} + X'_{i,t} \delta + \mu_i + \varepsilon_{i,t} \quad (2)$$

$$725 \quad \ln(Y_{i,t}) = \rho_Y \ln(Y_{i,t-1}) + \tau' Treated_{i,t-k} + \varphi M_{i,t-l} + X'_{i,t} \delta + \alpha_i + \varepsilon_{i,t} \quad (3)$$

726 where $M_{i,t}$ is the mediator variables in country i at year t . Given the multifaceted nature of
727 technological change, we test multiple mediator variables including cumulative general patent stock,

728 general patent flows, cumulative climate patent stock, climate patent stock, and annual cross-border
 729 patent flows. The coefficient θ captures the impact of agreement participation on technological
 730 accumulation (Path A). In the outcome equation, τ' represents the NDE—the effect of agreements on
 731 emissions not operating through technology, while φ captures the effect of the technology mediator on
 732 emissions (Path B). The NIE is quantified by the product of coefficients ($\theta \times \varphi$), denotes the full
 733 percentage change in CO₂ emissions attributable to an agreement's influence on technology.

734 Furthermore, to account for the time it takes for policy to influence innovation and for innovation
 735 to impact emissions, we test a range of dynamic lag structures. Specifically, we estimate the mediation
 736 effects for various lag combinations of the treatment ($Treated_{i,t-k}$) and the mediator ($M_{i,t-l}$), where
 737 lags k and l range from 0 to 3 years. By systematically testing all combinations of treatment and
 738 mediator lags, we can identify the time required for an agreement to stimulate technological accumulation
 739 and the subsequent time for that technology to translate into a measurable emissions reduction.

741 **Moderation and Heterogeneity Analysis.** To understand why the environmental effects of trade
 742 agreements are heterogeneous, we conducted a pooled analysis across all agreements to test whether the
 743 treatment effect is systematically conditional on general country characteristics.

744 The primary method for the pooled analysis is to introduce interaction terms into our baseline model.
 745 We use the full sample of countries and define the treatment variable, $Any_Treated_{i,t}$, as a binary
 746 indicator equal to 1 if a country is an active member of any of the agreements in year t . The moderation
 747 model is specified as:

$$\begin{aligned}
 748 \quad \ln(Y_{i,t}) = & \rho \ln(Y_{i,t-1}) + \beta_2 Any_Treated_{i,t} + \beta_3 Mod_{i,t} + \beta_4 (Any_Treated_{i,t} \times Mod_{i,t}) + X'_{i,t} \delta + \\
 749 \quad & \alpha_i + \varepsilon_{i,t} \tag{4}
 \end{aligned}$$

750 where $Mod_{i,t}$ is the moderator variable includes continuous measures such as cumulative patent
 751 stocks (general, climate and cross border). The coefficient of interest, β_4 , captures how the moderator
 752 alters the treatment effect.

753 As a complementary approach, we conduct stratified regressions by re-estimating our baseline
 754 specification (Equation 1) on different subgroups.

$$755 \quad \ln(Y_{i,t}) = \rho \ln(Y_{i,t-1}) + \beta_5 Any_Treated_{i,t} + X'_{i,t} \delta + \alpha_i + \varepsilon_{i,t} \quad (5)$$

756 We stratify the sample along several theoretically relevant dimensions: (i) "key emitters" (countries
 757 exceeding 1% of global annual emissions) versus others; (ii) general patent stock and cross-border flow
 758 (above vs. below average); (iii) technology orientation based on the ratio of outgoing to incoming climate
 759 patent transfers, distinguishing technology "net senders" from "net receivers." The entire stratification is
 760 predicated on mean split within the $Any_{Treated} = 1$ sample.

761

762 **Technology-Emissions Elasticity Estimation.** To directly quantify the independent effect of technology
 763 accumulation on emissions, we further estimate the technology-emissions elasticity without conditioning
 764 on trade agreement participation. The specification is:

$$765 \quad \ln(Y_{i,t}) = \rho \ln(Y_{i,t-1}) + \varphi Tech_{i,t-l} + X'_{i,t} \delta + \alpha_i + \lambda_t + \varepsilon_{i,t} \quad (6)$$

766 where $Tech_{i,t-l}$ represents various technology stock indicators with lag $l \in \{0,1,\dots,5\}$ years. We test
 767 multiple technological measures including annual climate patent flows, cumulative climate patent stock,
 768 annual total patent flows, cumulative total patent stock, annual cross-border patent flows, and cumulative
 769 cross-border patent stock. The coefficient φ is interpreted as the percentage change in carbon emissions
 770 associated with a one-unit increase in log technology stock.

771 See [Table S60](#) for a comprehensive variable definition table for all key terms and variables used in

772 the analysis.

773

774 **Uncertainty evaluation.** We implement a comprehensive framework to assess uncertainty across
775 statistical estimation, model specification, and scenario projections. Statistical uncertainty is quantified
776 via standard errors and 95% CIs for all coefficient estimates. To address model specification uncertainty,
777 we conduct extensive sensitivity analyses using alternative dynamic lag structures (0–3 years for
778 treatment; 0–2 years for mediators) and various technology indicators (general vs. climate patents; stocks
779 vs. flows), as detailed in Supplementary [Tables S27–S54](#). Finally, we propagate statistical uncertainty
780 into the scenario analysis by using the upper and lower bounds of the 95% CIs of the elasticity estimates
781 to construct error bars for projected emission reductions.

782

783 **Scenario analysis to quantify CO₂ reduction potential of technical advancement and transfers**

784 To explore the impact of technological progress on emission reduction, we developed a scenario analysis
785 framework. This framework leverages the key parameters estimated from the main empirical models to
786 project emissions reductions under three distinct, policy-relevant scenarios. Due to limitations in the
787 availability of general patent data, we used 2021 as the baseline for scenario modeling to calculate the
788 abatement potential under different scenarios.

789 Rather than using agreement-specific NIE coefficients, we adopt a unified approach using
790 technology-emissions elasticity coefficient, φ , estimated from the independent technology effect model
791 (Equation 6) using the full sample. This provides a consistent and statistically robust basis for cross-
792 agreement scenario comparisons. Specifically, we employ two elasticity coefficients: Scenario 1 Uses
793 the coefficient for total cumulative patent stock (φ_{total}), representing the reduction of emissions from

794 domestic technological accumulation. Scenarios 2 & 3 uses the coefficient for cumulative cross-border
 795 patent stock (φ_{cross}), representing the emissions reduction specifically from internationally transferred
 796 technology. For this analysis, we assume that the technology-emissions elasticity (φ) is uniform for all
 797 member countries i within a given agreement s . To maximize the estimated emission reduction
 798 potential, we choose the coefficient from the lag specification that yields the most negative statistically
 799 significant effect while passing all diagnostic tests.

800 The projected change in CO₂ emissions ($\Delta CO2_i$) for country i in year 2021 under a given scenario
 801 is calculated using the following core formula:

$$802 \quad \Delta CO2_i = CO2_{i,base} \times (e^{\varphi \cdot \Delta \ln(Tech_i)} - 1) \quad (7)$$

803 where $CO2_{i,base}$ is the baseline CO₂ emissions of country i in year 2021, and $\Delta \ln(Tech_i)$ is the
 804 counterfactual change in the log of its general patents stock under the assumptions of the specific scenario.

805 To quantify scenario uncertainty, we propagate the statistical error by calculating the upper
 806 (pessimistic) and lower (optimistic) bounds of projected reductions using the 95% confidence interval
 807 limits of the elasticity coefficient φ . These uncertainty bands are visualized as error bars in scenario
 808 comparison figures.

809 We then designed three scenarios to reflect varying degrees of technological advancement and
 810 diffusion:

811 Scenario 1: Idealistic Baseline. This scenario simulates an idealistic, broad-based improvement in
 812 efficiency with which technology translates into emissions reductions. We assume that all countries
 813 uniformly improve their patent stock by 10%, representing general advancements in clean energy and
 814 industrial efficiency without cross-border transfers.

$$815 \quad Tech_{i,S1} = 1.1 \times Tech_{i,base} \quad (8)$$

816
$$\Delta \ln(Tech_{i,S1}) = \ln Tech_{i,S1} - \ln Tech_{i,base} = \ln 1.1 \approx 0.0953 \quad (9)$$

817 In this scenario, the change in emissions is therefore calculated as:

818
$$\Delta CO2_{i,S1} = CO2_{i,base} \times (e^{\varphi_{total} \cdot \Delta \ln(Tech_{i,S1})} - 1) \quad (10)$$

819 Scenario 2: Club-style Convergence. This scenario simulates optimal technology diffusion among
 820 key emitters within each agreement. We assume that all key emitters will improve their patent stock by
 821 10% and subsequently converge to the highest technological level newly observed within their respective
 822 agreement. This reflects a dynamic consistent with today's uneven innovation landscape, where gains
 823 primarily circulate among major emitters.

824
$$Tech_{i,key,S2} = 1.1 \times Tech_{i,key,base} \quad (11)$$

825 Then, all key emitting countries reach the highest cumulative patent level observed within the
 826 agreement. For any non-leading key emitter i within agreement s , its technology stock increases from
 827 its enhanced baseline level, $Tech_{i,key,S2}$, to match that of the agreement's leader, L , denoted as
 828 $Tech_{L,key,S2}$. The corresponding change in the log of technology stock is:

829
$$\Delta \ln(Tech_{i,S2}) = \ln(Tech_{L,key,S2}) - \ln(Tech_{i,key,S2}) \quad (12)$$

830 The emissions reduction for each catching-up country is calculated by substituting $\Delta \ln(Tech_{i,S2})$
 831 into the core framework (Equation 7). In this scenario, the change in emissions is therefore calculated as:

832
$$\Delta CO2_{i,S2} = CO2_{i,base} \times (e^{\varphi_{cross} \cdot \Delta \ln(Tech_{i,S2})} - 1) \quad (13)$$

833 Scenario 3: Leader-Driven Diffusion. This scenario quantifies the potential global impact of
 834 technology diffusion originating from individual, highly innovative nations ("technology leaders"). For
 835 each technology hub, identified as the key emitter with the highest cumulative patents across all
 836 agreements it participates in. We assume the leading country L enhances its technology by 10%, and
 837 the process for each leading country L is as follows:

838
$$Tech_{L,S3} = 1.1 \times Tech_{L,base} \quad (14)$$

839 Subsequently, the leader L is assumed to fully transfer its enhanced technology stock, $Tech_{L,S3}$,
 840 to all its partner countries j across all trade agreements in which L participates. For each recipient
 841 country j , its technology stock is raised to this new frontier, resulting in a change of

842
$$\Delta \ln(Tech_{j,S3}) = \ln(Tech_{L,S3}) - \ln(Tech_{j,base}) \quad (15)$$

843 In this scenario, the change in emissions of each recipient country j is therefore calculated as:

844
$$\Delta CO2_{j,S3} = CO2_{j,base} \times (e^{\varphi_{cross} \Delta \ln(Tech_{j,S3})} - 1) \quad (16)$$

845 For each leading country L , we further calculate its own emissions reduction from its 10% domestic
 846 advancement and sum it with the total emissions reductions achieved by all its partners receiving the
 847 technology transfer. This sum represents the total global mitigation potential driven by that single leader.
 848 We then rank all identified technology leaders by this total potential to prioritize which countries'
 849 leadership in technology diffusion could be most impactful.

850 Finally, we present bar charts comparing the three scenarios (in both percentage and absolute terms)
 851 with uncertainty bands reflecting the 95% confidence intervals of the underlying coefficients, and an
 852 overall comparison chart, along with a ranking of the top contributing key emitters across agreements.

853

854

855 **Data availability**

856 This study uses data from multiple sources. Country-level CO₂ emissions are obtained from Our World
 857 in Data (OWID, <https://ourworldindata.org/co2-emissions>); macroeconomic indicators such as GDP and
 858 population are from the World Bank's World Development Indicators (WDI,
 859 <https://datacatalog.worldbank.org/search/dataset/0037712/World-Development-Indicators>); and

860 information on trade agreements is sourced from the World Bank’s Deep Trade Agreements (DTA)
861 database (<https://datatopics.worldbank.org/dta/table.html>). Bilateral trade flows are retrieved from the
862 United Nations Commodity Trade (UN Comtrade) database (<https://comtradeplus.un.org/>), and Climate
863 patent records are from IncoPat (<https://www.incopat.com/>). Due to license restrictions from the
864 providers, the raw trade and patent data cannot be shared. To facilitate reproducibility, the full data
865 processing and analysis codes are available at <https://doi.org/10.24433/CO.1738407.v1>. The data
866 necessary to reproduce the main results are available via Figshare at
867 <https://doi.org/10.6084/m9.figshare.31295878>⁴⁸. Background political boundaries used in maps are from
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870 Attribution 4.0 International license (<https://creativecommons.org/licenses/by/4.0/>)⁴⁹.

871

872 **Code availability**

873 MATLAB R2022b was used for data processing and visualization. The analysis for impact of agreements
874 and technology is conducted using Stata 18. All codes in this study are available at
875 <https://doi.org/10.24433/CO.1738407.v1>⁵⁰.

876

877

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