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Trade shocks redraw the global carbon map but do not shrink it: product-level evidence from integration and fragmentation

Florian Pothin*

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Abstract

Trade policy is argued for on climate grounds, yet whether it cuts the carbon embodied in trade or only moves it is untested at the resolution policy uses. We build a product-level (HS6) life-cycle measure of carbon embodied in bilateral trade for 1995–2023 and track how trade shocks reshape it. Three natural experiments (China’s accession to the World Trade Organization, the US–China tariff war, and the 2022 sanctions on Russia) are generalized across 35 accessions and 9 sanction episodes with a heterogeneity-robust estimator. One pattern holds throughout. Integration pulls carbon-intensive production in slowly (+31% at ten years, +69% at fifteen); fragmentation pushes it out fast (to −88% off the sanctioner’s market at ten years). The carbon moves rather than vanishing: Russia’s lost exports reappear in China, India and Turkey (+236%), and retention against a counterfactual growth path is 0.92 for Russia and 3.17 for China, so neither episode reduces the total. The Russian estimates are the sharper of the two. A border carbon adjustment, priced with a trade elasticity estimated from these shocks rather than calibrated, cuts the embodied carbon of the covered sectors by 2 to 4%, and between a third and all of that cut leaks. Trade-driven national decarbonization is, to first order, redistribution.

Keywords: embodied carbon; carbon leakage; trade shocks; border carbon adjustment; trade elasticity; life-cycle assessment.

JEL classification: F18; Q56; F14; Q54.

1 Introduction

About a quarter of global CO₂ is emitted producing goods that cross a border before they are used (Davis and Caldeira, 2010; Peters et al., 2011). Trade policy has become climate policy.

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The European Union’s Carbon Border Adjustment Mechanism (CBAM) prices the carbon in imports; sanctions sever trade ties; friend-shoring moves supply chains along political lines. Each instrument changes who buys carbon-intensive goods from whom. Each is defended, in part, as a way to cut emissions. All of them share one question: when a trade shock hits, does the carbon embodied in trade shrink, or does it move?

This paper measures the answer. We build a bilateral embodied-carbon panel at the product level, follow it through three decades of trade shocks, and estimate what integration and fragmentation do to the geography of carbon-intensive production. The answer is the same in both directions: trade shocks redraw the carbon map and leave the total roughly unchanged. Integration pulls carbon-intensive production in, slowly. Fragmentation pushes it out, fast, and the displaced carbon reappears elsewhere. A border carbon adjustment run with a trade elasticity estimated from these shocks, rather than calibrated, cuts the embodied carbon of the covered sectors by a few percent, and between a third and all of that cut leaks.

Two obstacles explain why the answer is not already known. The first is measurement. The workhorse of embodied-carbon accounting, multi-regional input–output (MRIO) analysis, resolves trade at 35–65 sectors and gives every product in a sector one emission intensity. Within-sector intensity varies widely, so coarse sectors bias embodied-carbon estimates by 24–36% (Bouwmeester and Oosterhaven, 2013; Steen-Olsen et al., 2014). Worse, a trade shock acts on a specific object: one supplier replaces another in one product. That object sits at the product $\times$ country-pair level, and sector accounts cannot see it. The second obstacle is identification. The leakage literature has leaned on simulation: computable-general-equilibrium and gravity models predict leakage rates of 5–30% and more (Böhringer et al., 2012; Larch and Wanner, 2017; Bellora and Fontagné, 2023), a range a meta-analysis of that literature puts at 5–25% for border adjustment (Branger and Quirion, 2014), and the measurement of leakage risk is itself contested (Fowlie and Reguant, 2018). Ex-post causal evidence is scarce, and what exists is firm-level (Barrows and Ollivier, 2021). On a trade network, the treatment also spills over by construction. When sanctions close one market, the displaced supply reappears in third countries. A difference-in-differences would use those countries as controls, but they are treated too. The 2018 tariffs have been studied for their price and welfare incidence (Amiti et al., 2019) and for the reallocation of supply chains toward third countries (Alfaro and Chor, 2023), which is the movement the carbon measure prices here.

We address the measurement obstacle with the audited product-level account of the companion measurement paper (Pothin, 2026). Cradle-to-gate life-cycle intensities (ecoinvent cut-off and Agribalyse; Wernet et al., 2016) are mapped onto bilateral HS6 trade from BACI and aggregated to HS2 $\times$ country-pair $\times$ year: 22.4 million flows, 231 exporters, 29 years. The HS-to-LCA matching behind the account carries a blind-audited error rate: 17 wrong assignments per 100 before the repair of its matching filter, 8 after. The account is validated against an independent inventory and against consumption footprints (Section 2). We address the identification obstacle with designs matched to the network. Within-exporter event studies compare a treated exporter’s flows to treated destinations against its flows to its own other markets, so contaminated third-country controls drop out. Placebo petrostates test the remaining threats. A heterogeneity-robust staggered estimator (Callaway and Sant’Anna, 2021) generalises the

case studies over 35 WTO accessions and 9 sanction episodes. The trade elasticity is estimated at the product level from the US Section-301 schedule (Fajgelbaum et al., 2020), not taken from calibration (Section 3).

Three results follow. First, fragmentation reroutes carbon rather than cutting it. After the 2022 sanctions, Russia’s carbon exports to the sanctioning bloc fall 31% in the first year and 74% by 2023. The carbon does not vanish. Bloc-bound flows fall from 268 to 86 Mt; shipments to China, India and Turkey rise from 125 to 243 Mt; the relative shift is +236%. The same shift in trade value is +253%, so the rerouting is a property of the trade, not a weighting effect. The US tariffs on China cut China’s US-bound carbon by 44% by 2023 with the same signature. Second, integration is the mirror image, at the opposite speed. China’s WTO accession triples its carbon exports to the West by 2008. Across all 35 accessions, carbon exports build to +31% ten years out and +69% at fifteen; the sanctions profile is −31% at onset and −88% ten years on. The asymmetry is a finding in itself: building carbon-intensive export capacity takes a decade, losing a market takes a year.

Third, the estimates price the policy instrument. The trade elasticity is $\hat{\theta} \approx 1.1$ pooled and 2.1 at the 2023 horizon, well below the 4–6 the CBAM simulation literature calibrates. At \$100 per tonne, a CBAM run at the estimated elasticity cuts the embodied carbon of the covered sectors by 2.1% short run and 3.9% at the 2023 horizon, against 8.3% under a calibrated $\theta = 5$. On the scope the regulation covers, which is a sixth of the bloc’s embodied carbon rather than a half, the same prices give 3.6% and 6.6%. Propagating the elasticity’s standard error puts that cut between 1.5% and 4.7%, so the distance to calibration is a difference in the parameter and not in precision. A capacitated transport re-solve bounds the supply response: leakage runs from a third, when clean suppliers can expand freely, to complete, when supply is locked. To first order, the instrument relocates carbon.

The question is old: trade changes the scale, composition and technique of production, and the net environmental sign depends on which dominates (Antweiler et al., 2001; Copeland and Taylor, 2004). Two literatures disagree on what trade does to emissions. One argues that trade helps the climate: it routes demand to cleaner producers (Shapiro, 2021; Le Moigne et al., 2024) and transfers technology (Wang et al., 2026). The other documents leakage: emissions move rather than fall when one region tightens policy (Aichele and Felbermayr, 2015; Meng et al., 2023). Our evidence reconciles them, because both are right about different objects. Trade greens production when demand can route freely toward cleaner suppliers. A shock that forces reshuffling relocates carbon instead. The distinction is invisible at sector resolution and central at product resolution.

The paper contributes on three fronts. To the measurement of embodied carbon in trade, it brings a bilateral product-level panel whose construction error is measured rather than assumed. To the empirics of carbon leakage, it replaces simulated leakage rates with ex-post causal estimates at the resolution the shocks act on, and handles the network spillover that contaminates standard designs. To the evaluation of border carbon adjustment, it supplies the missing behavioural parameter from a tariff experiment and shows that the calibrated values in use overstate the instrument’s bite by a factor of two to four.

Section 2 describes the data and Section 3 the designs. Sections 4 to 8 report the results,

and Section 9 discusses what they imply for border-adjustment design.

2 Data

Construction of the embodied-carbon measure is reported in Online Appendix A1.

Scope. The measure is an exposure measure on gross flows. It attaches a cradle-to-gate intensity to every bilateral flow, so upstream emissions are counted once per border crossing: the emissions of a Chinese component enter the China–Vietnam flow, and enter again inside the intensity of the Vietnamese assembly shipped onward. That is the right object for the question here, because a trade shock hits a shipment, and the carbon at risk on that shipment is its full upstream. It gives a world total of 14,368 MtCO₂e in 2023, or 40% of the 35.9 GtCO₂ of territorial emissions of the 120 countries with a Global Carbon Budget series. The reconciliation of the gross total with the consumption-accounting literature is given where the account is built (the net counterpart sums to 2,619 MtCO₂e over net-importing countries, 7.3% of the same denominator, and 85% of the benchmark net transfers); here we use the account as given.

Relation to the national footprint. Country by country, territorial emissions plus net embodied imports and the benchmark consumption-based account diverge. The median absolute gap is 23% of the benchmark, 57% of countries fall within 25%, and the net positions agree in sign for 76% of countries with a rank correlation of 0.49 (Table 2). The two series do correlate at 0.997 in level across the 119 countries, but on magnitudes running from a few Mt to twelve thousand that is close to mechanical and tests little; the dispersion figures are the informative ones. Two things drive the divergence. A net position is a small difference between two large gross flows, so it inherits their errors magnified. And this boundary is goods-only and cradle-to-gate, while the benchmark is a full-economy input–output account including services. The identification below runs on the gross flow of one pair, in one product, in one year, and on how that flow responds to a shock, which is a quantity the divergence leaves untouched.

Why product-level. Sector-level MRIO assigns one intensity per 35–65 sectors; within-sector intensity dispersion is large and aggregation biases embodied-carbon estimates by 24–36% (Bouwmeester and Oosterhaven, 2013; Steen-Olsen et al., 2014). Relocation of sourcing occurs at the product $\times$ pair resolution that sector MRIO cannot resolve, which is why we work at HS2 $\times$ pair.

Data sources. Table 1 lists every input.

Table 2 summarises the panel and the estimation samples.

3 Empirical strategy

3.1 The embodied-carbon measure

We use the audited product-level account of the companion measurement paper (Pothin, 2026): cradle-to-gate life-cycle carbon intensities (ecoinvent cut-off, industrial and materials activities; Agribalyse, agri-food; via the ADEME Base Empreinte; Wernet et al., 2016), characterized with IPCC 2013 GWP 100a, mapped onto HS6 bilateral trade values and quantities from BACI

Table 1: Data sources.

Source	Use	Detail
BACI (CEPII) (Gaulier and Zignago, 2010)	bilateral trade	HS6 value + quantity, 1995–2023, ~5,000 products
ecoinvent (Wernet et al., 2016) + Agribalyse (ADEME, 2023)	cradle-to-gate factors	industrial/materials + agri-food (HS $\leq$ 24)
Global Carbon Budget (Friedlingstein et al., 2023)	production emissions (PBE)	national territorial CO ₂
EXIOBASE (Stadler et al., 2018); ICE (Hammond and Jones, 2008)	measure validation	consumption footprints; independent cradle-to-gate
CEPII gravity (Conte et al., 2022)	bilateral distance	PPML gravity of embodied carbon
USTR Section 301 (Office of the United States Trade Representative, 2018)	elasticity θ	2018 US add-on tariffs on China, at HS6
GSDB (Felbermayr et al., 2020)	fragmentation DiD	9 onsets meeting the selection rule
WTO accession dates	integration DiD	36 accessions after 1995; 35 enter the estimation
WDI (World Bank, 2024)	population, GDP	per-capita normalisation

Table 2: The bilateral embodied-carbon panel and the estimation samples.

<i>Panel A. Panel dimensions, 1995–2023</i>					
Years	29	Exporters	231	HS2 chapters	96
Country pairs	45,395	Importers	232	Flow observations	22,363,214
World embodied carbon in traded goods: 7,127 MtCO ₂ e (2000), 14,016 (2019), 14,368 (2023)					
<i>Panel B. Distribution across flows (exporter $\times$ importer $\times$ HS2 $\times$ year)</i>					
	Mean	Std. dev.	p10	Median	p90
Embodied carbon (tCO ₂ e)	13,978	268,996	0.06	22.3	5,228
Trade value (thousand USD)	17,373	386,266	0.41	61.3	7,589
Carbon intensity (kgCO ₂ e/USD)	0.98	1.59	0.04	0.42	2.47
<i>Panel C. Estimation samples</i>					
Within-exporter event study, Russia 2022	1,857 obs., 215 destinations				
Within-exporter event study, US–China 2018	2,094 obs., 210 destinations				
Staggered DiD, integration: WTO accessions	35 treated, 196 never-treated				
Staggered DiD, fragmentation: sanction onsets	9 treated, 222 controls				
Gravity, Poisson pseudo-maximum-likelihood	27,143 country pairs				
Trade elasticity, HS6 tariff design	24,981 obs., 4,448 clusters				

Panel A counts distinct reporters in the bilateral panel; the product dimension is aggregated to the 96 HS2 chapters after the HS6 match, so the flow count is the panel actually estimated on, not the HS6 count behind the measure. World totals are the control quantities of the audited account. Panel B is computed over flows with positive trade value, which is every observation in the panel. The distributions are extremely right-skewed: the median flow carries 22 tonnes and the mean 14 thousand, so all estimation is in logs or Poisson. Carbon intensity is the flow’s own ratio, and its interquartile range spans more than an order of magnitude, which is the heterogeneity a sector-average account cannot represent. Panel C reports each design’s own sample. The event-study designs are estimated within one treated exporter at a time: that exporter’s flows are summed over HS2 chapters to the destination $\times$ year cell, which is the unit of estimation, so their samples are two thousand cells rather than the 22.4 million flows of the full panel. They are drawn from the 9,094,911 flows of the panel’s 2014–2023 window. The elasticity is estimated on US imports at HS6 from the Section-301 schedule and is the only quantity not drawn from the carbon panel.

(CEPII), 1995–2023, and aggregated to HS2 $\times$ country-pair. The HS-to-LCA matching is filtered by deterministic admissibility rules and carries a blind-audited error rate (17 then 8 wrong assignments in 100, before and after the repair of the matching filter); orphaned products inherit a stage-matched family median. The measure matches the independent ICE inventory (median ratio 1.04; log-log $r = 0.91$) and captures the EXIOBASE footprint at an emissions-weighted median ratio of 0.90 (83% within $3\times$). It is a gross exposure measure: upstream emissions are counted once per border crossing, so the world total is not a consumption-responsibility account and the national identity closes only in level, not country by country (Section 2, Table 2). What the designs below use is the gross flow of one pair in one product in one year, which does not depend on that identity. Construction and validation: Section 2.

3.2 Within-exporter event studies

On a trade network, the spillover is not a nuisance; it is the object of study. When a sanction closes one market, the displaced supply reappears in third countries. Third countries are treated too. A cross-country difference-in-differences would use them as controls, and the bias runs in the direction of the effect it looks for. We therefore identify within the treated exporter. For each shock we estimate, by Poisson pseudo-maximum-likelihood (Santos Silva and Tenreyro, 2006),

$$\mathbb{E}[C_{d,t}] = \exp \left(\sum_{\tau} \beta_{\tau} \text{Treated}_d \cdot \mathbb{1}\{t = \tau\} + \delta_d + \delta_t \right),$$

where $C_{d,t}$ is the treated exporter’s carbon exports to destination d in year t and Treated_d marks the sanctioning bloc (Russia) or the United States (China). The destination effects δ_d absorb level differences across markets. The year effects δ_t absorb everything that moves the exporter’s supply as a whole, including sanctions on its import side and the commodity-price cycle. The window is 2014–2023 (9,094,911 flows). The omitted year is the last pre-shock year: 2021 for Russia, 2017 for China. Standard errors are clustered by destination, the level of the identifying variation.

The coefficients measure how shipments to treated destinations diverge from the exporter’s shipments to its own other markets. That contrast is the estimand we want: where the carbon goes. But it bundles two movements, the decline on the treated market and the rerouting toward the control destinations. The raw levels separate them. Russia’s bloc-bound carbon falls from 268 to 86 Mt between 2021 and 2023. The collapse is real on the treated side; it is not a composition effect of rising control flows.

The identifying assumption is weaker than flat pre-trends, and it has to be. The pre-event coefficients show a slow decline of the bloc share: four of seven pre-years differ from zero at 5%, and the placebo petrostates share the drift (four of seven for Saudi Arabia). Commodity exports were moving away from the sanctioning bloc before 2022. What the design requires is that no contemporaneous non-sanction break of comparable size occurred, and the placebos test that directly. We rerun the full design for five non-sanctioned commodity exporters (Nigeria, Saudi Arabia, Brazil, Indonesia, India). Four of ten cells are significant, three of them positive, and the one significant negative movement (-10.4% , Brazil 2023) is a seventh of Russia’s -74% (Table 7). The 2022–2023 break is an order of magnitude larger than any pre-event movement,

and no placebo comes near it.

That comparison can be made precise rather than left as a ratio of magnitudes. Under the relative-magnitudes restriction of Rambachan and Roth (2023), a differential trend is allowed to move after treatment by at most $\bar{M}$ times its largest movement before treatment, and the question becomes how large $\bar{M}$ can be before the estimate loses its sign. For Russia in 2023 the answer is 3.2, and 2.1 for its 95% bound: the post-onset trend would have to break three times harder than it ever broke in the eight pre-onset years for the effect to vanish (Table 3). China’s 2023 coefficient absorbs 1.4, and 1.1 at its 95% bound, so it survives a violation as large as the worst pre-tariff step but not much more. Across the nine sanction onsets the onset-year effect absorbs 1.5.

The same exercise says nothing about the integration result, and the reason is arithmetic rather than substantive. The bound lets bias accumulate linearly with the horizon, so eleven periods after an accession it permits eleven times $\bar{M}d_{\max}$, which swamps a 0.27 log-point effect for any $\bar{M}$ above about 0.1. A conservative bound over a decade cannot discipline a slow-building effect. What carries the accession result is the shape reported in Table 9: no pre-onset coefficient is individually significant, and the path is flat for nine years before it rises.

Table 3: Sensitivity to pre-treatment trends: how large a differential trend the estimates absorb.

Design	Horizon	$\hat{\beta}$	(s.e.)	$d_{\max}$	$\bar{M}^*$	$\bar{M}_{95}^*$
Russia, bloc-bound carbon	+2	−1.347	(0.246)	0.209	3.23	2.07
China, US-bound carbon	+2	−0.232	(0.018)	0.069	1.69	1.42
	+6	−0.580	(0.058)	0.069	1.41	1.13
Sanction onsets, all nine	0	−0.367	(0.145)	0.245	1.50	0.34
	+3	−1.111	(0.300)	0.245	1.13	0.53
	+10	−2.085	(0.782)	0.245	0.77	0.20
WTO accessions, all 35	+10	+0.274	(0.119)	0.245	0.10	0.02

Relative-magnitudes sensitivity in the sense of Rambachan and Roth (2023). Writing the event-study coefficients as an effect plus a differential trend, the restriction allows the post-treatment period-to-period movements of that trend to be at most $\bar{M}$ times the largest movement observed before treatment, $d_{\max}$. Since the trend is anchored at zero in the base year, the bias reachable l periods out is at most $l\bar{M}d_{\max}$, so the estimate keeps its sign for $\bar{M}$ below $\bar{M}^* = |\hat{\beta}|/(l d_{\max})$, and its 95% bound keeps its sign below $\bar{M}_{95}^*$. Here l counts periods from the *base* period, not from treatment, which is why the +3 horizon of a design based at -1 enters with $l = 4$. This is a conservative plug-in: the pre-period bound enters at its estimate, the bias accumulates linearly, no smoothness is imposed, and it is not the fixed-length confidence interval of that paper. It therefore understates robustness rather than overstating it. $d_{\max}$ is computed over every available pre-period; restricting it to the five nearest raises $\bar{M}^*$ for the sanction onsets from 1.50 to 2.78 at onset and from 0.77 to 1.44 at +10, because the widest pre-treatment step falls at -10 . The exercise is informative where effects are large and fast and uninformative where they are small and slow, which is a property of the linear bound rather than of the estimates: eleven periods after a WTO accession the reachable bias is eleven times $\bar{M}d_{\max}$, so no $\bar{M}$ above roughly 0.1 leaves a 0.27 log-point effect signed. For the integration result the relevant evidence stays what Table 9 reports, that no pre-onset coefficient is individually significant over the ten years before accession and the effect is flat for nine years before it builds.

Inference. The treatment varies across destinations, so standard errors are clustered there. How many destinations an episode treats then decides which test carries the inference. The 2022 sanctions treat 36 of Russia’s 215 destinations, a range in which clustering is well behaved. The 2018 tariffs treat one, the United States. Inference for both episodes therefore rests on randomization over destinations, which requires no clustering asymptotics: each alternative assignment takes its turn as the treated set, the specification is re-estimated, and the 2023

coefficient is read against the resulting placebo distribution.

For Russia the randomization test reproduces the clustered result. Across 500 random draws of 36 destinations from the same pool, $|\hat{\beta}|$ reaches the estimated value in 0.2% of draws, against a median placebo of 0.49. For China the test is exact: each of the other 207 destinations takes its turn as the single treated market. Two things come out of it. The relevant comparison is with destinations of similar size, where the estimate stands out, at $p = 0.05$ against the top twenty by pre-2018 volume and $p = 0.04$ against the top fifty. Across the whole pool it does not, at $p = 0.27$, because single-market event studies on small destinations swing across three log points and set a null that no plausible effect would clear. One size-matched placebo is more negative than the United States: Hong Kong, at -0.69 against -0.58 , China’s entrepot hub, which the same tariffs reshaped. Excluding it, the United States is the most negative of the size-matched pool. The US–China effect is significant at conventional levels on this test, which is the level of precision the single treated destination supports.

3.3 Generalised staggered difference-in-differences

The two case studies generalise to episode families with staggered timing: 35 WTO accessions after 1995 and 9 major sanction onsets (episode lists in Section 6). Under staggered adoption with growing effects, the two-way fixed-effects estimator uses already-treated units as controls and can weight some comparisons negatively. We therefore estimate cohort-by-horizon effects with the Callaway and Sant’Anna (2021) estimator and aggregate them to an event study. Controls are never treated: pre-1995 GATT members for the accessions (35 treated against 196 controls) and never-sanctioned countries for the sanctions (9 against 222). The outcome is log carbon exports, to the world for accessions and to the West for sanctions.

Two assumptions carry the design, and they bind differently in the two families. No anticipation: accession terms are negotiated years ahead, so exporters could in principle adjust early. The pre-event coefficients near the event are small (0.15 at -3 , 0.02 at -1 ; Table 9). The effect builds gradually after zero ($+31\%$ at ten years, $+69\%$ at fifteen). That is the signature of tariff phase-in and supply relocation; anticipation would show before zero. Sanctions arrive faster and their onset effect (-31%) is immediate. Parallel trends against never-treated countries: joining the WTO is a choice. The estimates therefore answer the timing question, what happens to carbon exports when an accession happens, not the selection question, who joins. At long horizons the aggregation thins. The sanctions coefficient at $+15$ is identified by the single 2002 cohort, so we read horizons beyond $+10$ as illustrative.

3.4 Gravity, the estimated elasticity, and the CBAM counterfactual

Bilateral carbon follows a gravity structure: Poisson pseudo-maximum-likelihood with exporter and importer fixed effects gives a distance elasticity of -1.11 ($p = 4.9 \times 10^{-38}$, $N = 27,143$ pairs). A border-adjustment counterfactual on this structure needs one behavioural parameter, the trade elasticity θ . We estimate it from a shock rather than calibrate it.

Identification uses the US Section-301 schedule at the product level (Fajgelbaum et al., 2020). The tariffs covered 5,114 HS6 lines, listed in successive tranches, with an average add-on of 22.2 percentage points. Which lines were listed, and when, was chosen by the importing

government. The outcome is the log of US imports from China minus the log of US imports from the rest of the world, per HS6 line and year, so demand shocks common to all origins difference out. The regressor is $\ln(1 + \text{add-on})$. HS6 and year fixed effects absorb product composition and aggregate trends. Standard errors are clustered by HS6 line (4,448 clusters; $N = 24,981$, 2016–2021). The pooled coefficient gives $\hat{\theta} = 1.09$ (s.e. 0.18). The add-on is zero for every product before 2018 by construction, so the usual pre-trend plot does not exist. We instead fix each line’s exposure at its 2019 value and trace calendar years around a 2017 base: the 2016 coefficient is +0.17 (s.e. 0.22), flat before the tariffs. Interacting the tariff with calendar years traces the adjustment path, from 0.58 in 2018 to 2.07 by 2023; the endpoint is the $\theta \approx 2.1$ we use as the long-horizon value.

Two limits bound what θ can carry into the counterfactual. It is estimated on one bilateral tariff episode and applied to a multilateral border adjustment, so the exercise assumes the substitution measured under the 2018 tariffs transfers to a carbon tariff. And it is a value elasticity: the counterfactual moves import value across origins and recomputes carbon as $\text{value} \times \text{intensity}$ at fixed intensities, so within-origin abatement is shut down by construction. The counterfactual mechanics and the leakage bounds are in Section A3.

4 Descriptive patterns

We set the shocks in a 30-year context. We group countries into a Western bloc and a China–Russia bloc. Embodied carbon traded across the two blocs rose from 11.6% of world embodied-carbon trade in 2005 to a 12.9% peak in 2010, held above 11% until 2021, then fell sharply to 9.8% by 2023 (Figure 1a). The fall is almost all Russia. The West’s carbon imports from Russia dropped 68% (2017–2023). Its imports from China rose 4% over the same period, despite the decoupling rhetoric (Figure 1b). The expected carbon decoupling from China does not show up in the trade data. The one sharp cross-bloc break is the sanctions shock. A systemic measure cut by discrete, opposite-signed shocks calls for a shock-by-shock analysis, not a single trend.

5 Fragmentation reroutes carbon

Sanctions and tariffs raise trade costs by origin, like a carbon tariff. We use two as natural experiments, identified within the treated exporter (Section 3).

After the February 2022 sanctions, Russia’s carbon exports to the sanctioning bloc fell 31% in the first year and 74% by 2023 (Figure 2a; Table 4). That figure is a differential against Russia’s own other destinations, and those destinations include the countries absorbing the displaced supply, so part of it is their growth: excluding them leaves -58% , and the level decline of 68% recorded between 2021 and 2023 sits between the two (Section 8). The pre-event coefficients show a slow decline of the bloc share that placebo petrostates share; the 2022–2023 collapse is an order of magnitude larger than any pre-event movement and is specific to Russia: placebo exporters (Nigeria, Saudi Arabia, Brazil, Indonesia, India) show no such break, and several rise as they take the market Russia left (Table 7). The carbon did not vanish. Russian carbon-intensive exports moved from Europe to Asia: shipments to China,

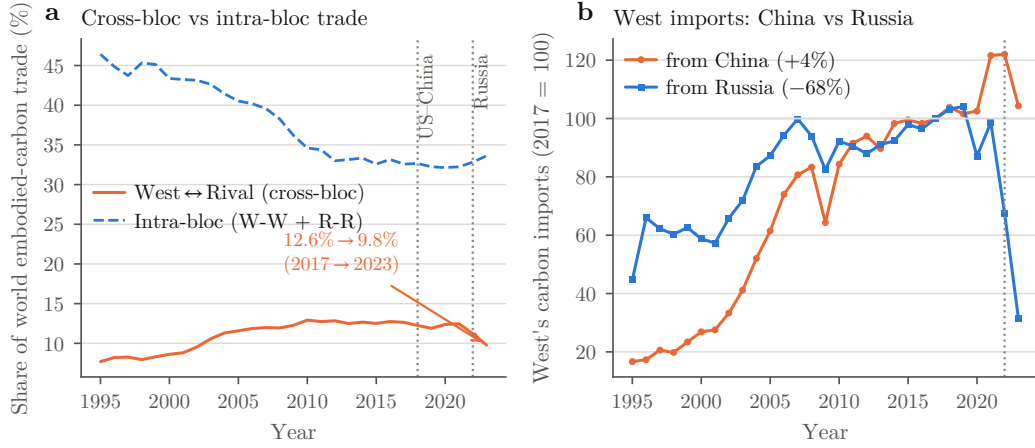


Fig. 1 Cross-bloc carbon trade and the decoupling mirage. (a) Embodied carbon traded across the Western and China–Russia blocs (red) versus intra-bloc (blue), as a share of world embodied-carbon trade, 1995–2023; the cross-bloc share breaks down after 2021. (b) The West’s carbon imports from China (+4%) versus Russia (−68%), 2017=100: the one sharp carbon decoupling is the Russia sanctions shock.

Notes. Bloc definitions in Section A4. Vertical rules mark the 2018 US–China tariffs and the 2022 sanctions on Russia. *Source:* author’s calculations on the audited product-level embodied-carbon account (BACI (Gaulier and Zignago, 2010) $\times$ ecoinvent (Wernet et al., 2016) and Agribalyse (ADEME, 2023) cradle-to-gate factors, IPCC 2013 GWP 100a); shares computed over all 22.4 million bilateral flows.

India, and Turkey rose from 125 to 243 Mt while exports to the bloc fell from 268 to 86 Mt. Those levels give the simplest reading of the reallocation: 118 of the bloc’s 182 Mt cut, about 65%, reappears as absorber growth. The +236% figure quoted alongside is a different object. It is the non-bloc $\times$ post-2022 coefficient of a Poisson difference-in-differences on the flow panel, with destination and year fixed effects, and it cannot be recovered from the four aggregates above: the ratio of their ratios is +506%, because the regression weights flows and absorbs common year movements while the aggregates do neither ($p < 10^{-6}$; Figure 3, top; time series in Figure 2). The figures describe one event from three sides. The bloc’s imports from Russia fall 68% over 2017–2023 as a long difference; Russia’s bloc-bound exports fall 74% by 2023 in the within-exporter design; and its non-bloc shipments rise 236% relative to bloc shipments. For the 2018 US–China tariffs, China’s carbon exports to the United States fell 44% relative to its other destinations, significant against comparable-size destinations ($p = 0.04$ – 0.05) but not against the full donor pool, and not recovered by the product-side design, so the estimate is design-dependent (Figure 2b; Table 5): real, but smaller, in line with China’s continued and partly indirect role in Western supply chains.

Specification. A difference-in-differences on the bilateral carbon network with “other exporters” as controls violates SUTVA: the rerouting we study is itself a spillover, so control origins absorb the treated exporter’s displaced supply. We therefore identify *within* the treated exporter, comparing its flows to treated versus its own untreated destinations. We estimate by Poisson PML (Santos Silva and Tenreyro, 2006):

$$\mathbb{E}[C_{d,t}] = \exp\left(\sum_{\tau \neq \bar{t}} \beta_{\tau} (\text{Treated}_d \cdot \mathbb{1}\{t = \tau\}) + \delta_d + \delta_t\right),$$

where $C_{d,t}$ is the treated exporter’s embodied-carbon exports to destination d . Treated des-

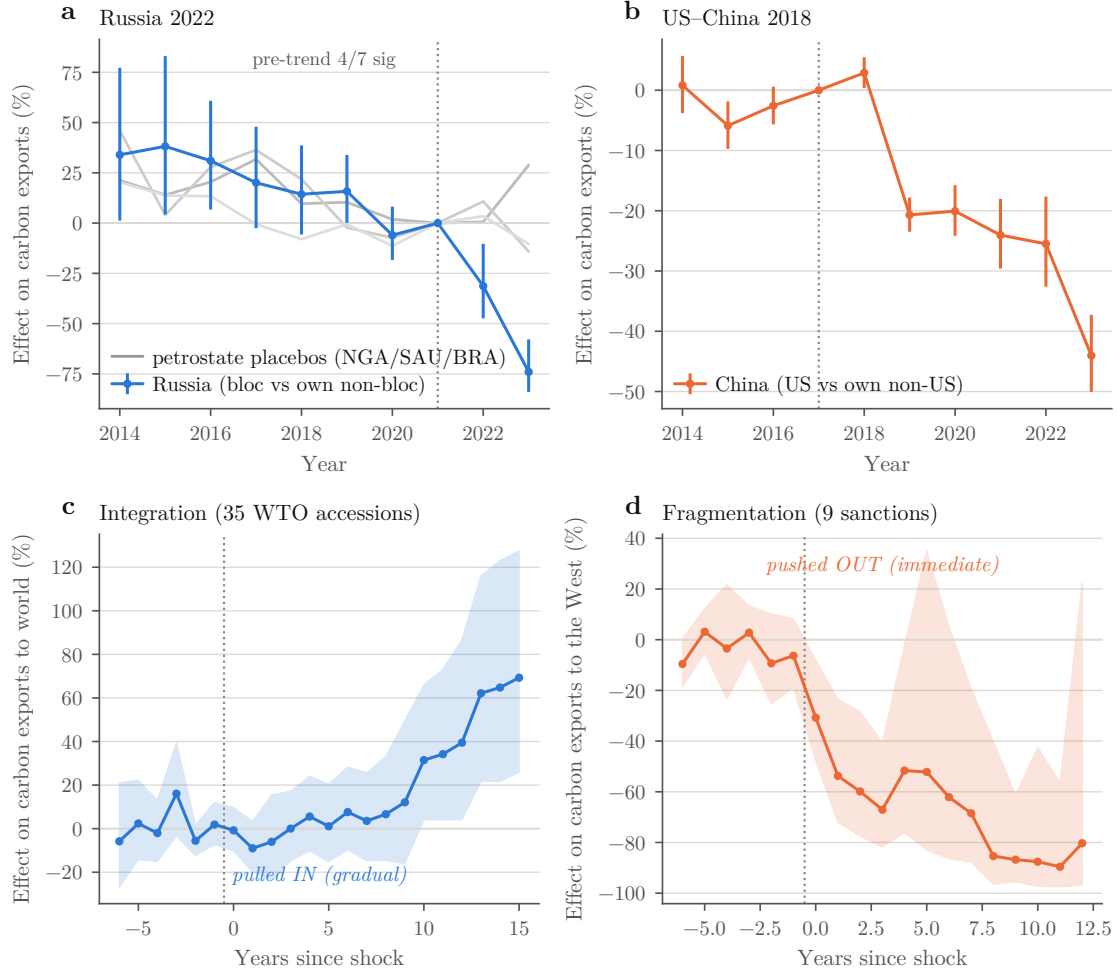
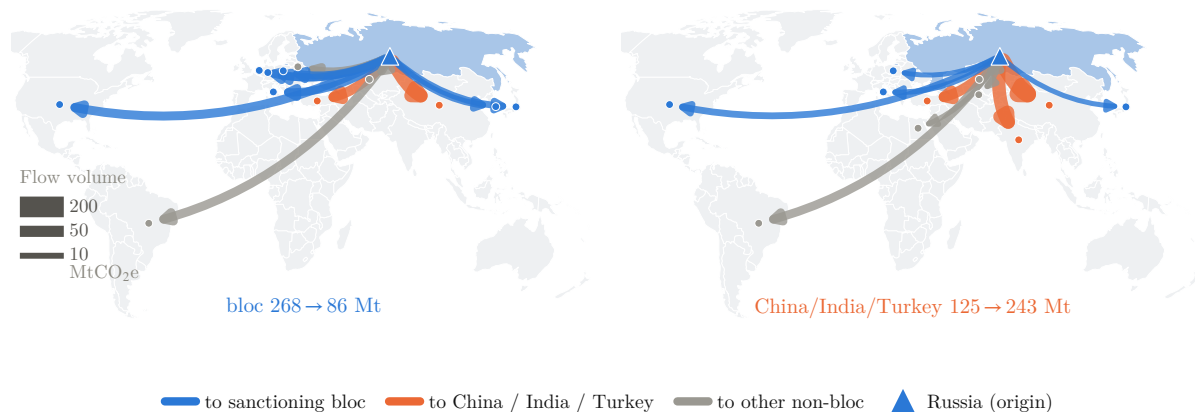


Fig. 2 Causal identification and generalization. (a,b) Within-exporter event studies (PPML, 95% CI): Russia’s bloc-bound carbon collapses after 2022 (a); China’s US-bound carbon falls after 2018 (b). Russia’s pre-event coefficients are not flat, and neither are those of the petrostate placebos: four of the seven pre-years differ from zero for Russia and four for Saudi Arabia, a shared decline in the bloc share. What is specific to Russia is the break, which is an order of magnitude larger than any pre-event movement. (c,d) Heterogeneity-robust (Callaway and Sant’Anna, 2021) event studies over all major episodes: integration (35 WTO accessions) pulls carbon in gradually (c); fragmentation (9 sanctions) pushes it out at once (d).

Notes. Panels (a) and (b) are PPML within-exporter event studies with destination and year fixed effects; whiskers are exp-transformed 95% Wald intervals. Panels (c) and (d) aggregate the Callaway and Sant’Anna (2021) estimator over all episodes; bands are pointwise 95%. *Source:* author’s calculations on the audited product-level embodied-carbon account (BACI (Gaulier and Zignago, 2010) $\times$ ecoinvent (Wernet et al., 2016) and Agribalyse (ADEME, 2023) cradle-to-gate factors, IPCC 2013 GWP 100a); episode lists in Section 6.

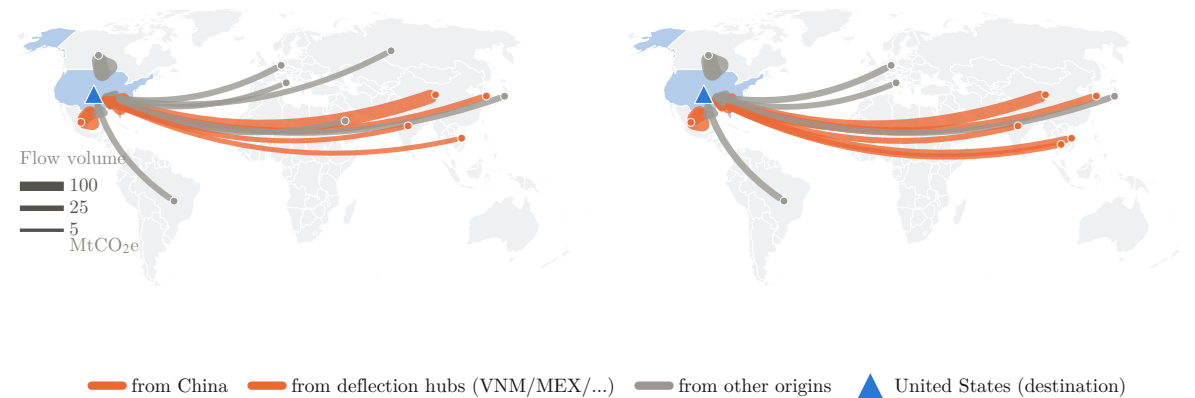
2021 — before sanctions

2023 — after sanctions



2017 — before tariffs

2023 — after tariffs



2001 — WTO accession

2008 — integrated

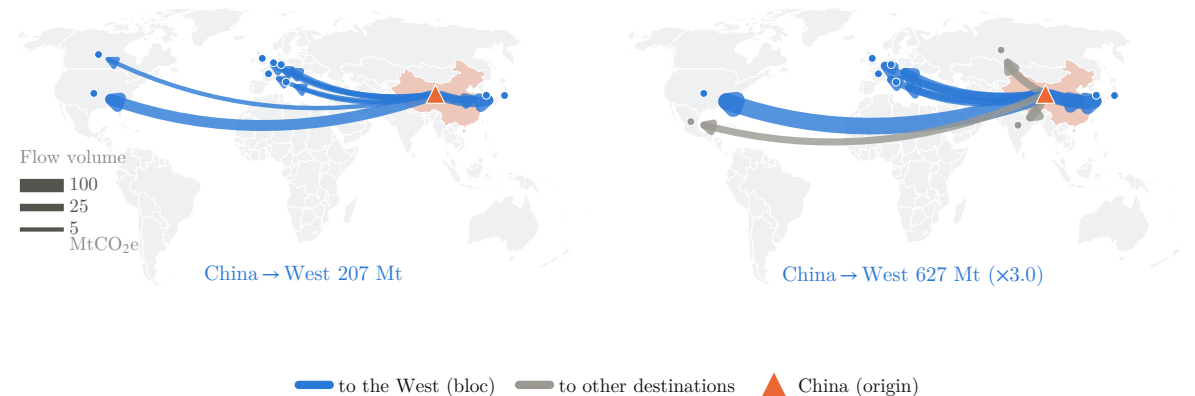


Fig. 3 Trade shocks redraw the carbon map. Flow maps of carbon exports (arrow width $\propto$ MtCO₂e), before versus after each shock. Top: Russia's exports move from the sanctioning bloc to China/India/Turkey (2021 vs 2023). Middle: US imports recede from China as deflection hubs grow (2017 vs 2023). Bottom: China's WTO accession pulls carbon-intensive exports to the West in (×3.0, 2001 vs 2008). The origin is marked by a triangle.

Notes. Arrow width is proportional to the square root of the flow, on a scale shared by both panels so the two years are comparable; the width key gives three reference volumes. Only the twelve largest destinations are drawn, while the annotated totals cover every destination in the group. *Source:* author's calculations on the audited product-level embodied-carbon account (BACI (Gaulier and Zignago, 2010) × ecoinvent (Wernet et al., 2016) and Agribalyse (ADEME, 2023) cradle-to-gate factors, IPCC 2013 GWP 100a); boundaries from Natural Earth, centroids from CEPII (Conte et al., 2022).

tinations are the sanctioning bloc (Russia) or USA (China). The year fixed effects δ_t absorb the exporter’s overall trend, so β_τ isolates the treated-destination differential. SE clustered by destination; base year $\bar{t} = 2021$ (Russia), 2017 (China).

5.1 Russia after the 2022 sanctions

Table 4: Within-exporter event study: Russia after the 2022 sanctions (bloc against Russia’s own non-bloc destinations).

Year	2014	2015	2016	2017	2018	2019	2020	2022	2023
$\hat{\beta}$	+0.292 (0.143)	+0.323 (0.144)	+0.270 (0.105)	+0.183 (0.106)	+0.134 (0.098)	+0.147 (0.074)	−0.062 (0.072)	−0.375 (0.136)	−1.347 (0.246)
Effect (%)	+34.0	+38.2	+31.0	+20.1	+14.4	+15.8	−6.0	−31.3	−74.0
Observations 1,857 Clusters (destinations) 215 Treated 36 Control 179 PPML; destination and year fixed effects; base year 2021; standard errors clustered by destination									

Within-exporter design: Russia’s flows to the 36 sanctioning destinations against its flows to its own other destinations, so third countries that absorb the displaced supply stay out of the control group. Coefficients are log points, the effect is $\exp(\hat{\beta}) - 1$. The pre-onset path is a slow decline of the bloc share, four of seven years significant at 5%, shared by the placebo petrostates (Table 7); the sanction is identified by the size of the break, and the largest pre-onset coefficient (0.323) is a quarter of the 2023 coefficient (1.347). Inference is confirmed by randomization over destinations: across 500 random draws of 36 destinations from the same pool, $|\hat{\beta}|$ reaches the estimated value in 0.2% of draws, against a median placebo of 0.49. With 36 treated destinations the clustered and randomization tests agree.

5.2 China after the 2018 tariffs

Table 5: Within-exporter event study: China after the 2018 US tariffs (the United States against China’s own other destinations).

Year	2014	2015	2016	2018	2019	2020	2021	2022	2023
$\hat{\beta}$	+0.008 (0.024)	−0.061 (0.021)	−0.026 (0.016)	+0.029 (0.013)	−0.232 (0.018)	−0.224 (0.027)	−0.275 (0.039)	−0.294 (0.051)	−0.581 (0.058)
Effect (%)	+0.8	−5.9	−2.6	+2.9	−20.7	−20.1	−24.0	−25.5	−44.0
Observations 2,094 Clusters (destinations) 210 Treated 1 Control 209 PPML; destination and year fixed effects; base year 2017; standard errors clustered by destination									

Same design, China’s flows to the United States against its flows to its own other destinations. One destination is treated, so inference comes from randomization over destinations rather than from the clustered variance, and the standard errors above are reported for scale. Giving each of the other 207 destinations its turn as the single treated market, the estimate stands out against destinations of comparable pre-period size, at $p = 0.05$ against the top twenty by pre-2018 volume and $p = 0.04$ against the top fifty. Against the whole pool it does not, at $p = 0.27$, because single-market event studies on small destinations swing across three log points. One size-matched placebo is more negative than the United States, Hong Kong at -0.69 , China’s entrepot hub, which the same tariffs reshaped; excluding it the United States is the most negative of the pool. The 2023 effect is significant at conventional levels on this test, which is the precision a single treated destination supports.

The same shock identified on product-level treatment intensity. The design above treats one destination. The Section-301 schedule offers a second reading of the same shock that treats thousands of products: the add-on was set line by line at HS6, and the lines it hit were chosen for reasons unrelated to their carbon content. Regressing the China-minus-rest log carbon gap on $\ln(1 + \text{add-on})$ with HS6 and year fixed effects gives -1.87 (s.e. 0.30) over

2,654 product clusters, and the response grows with the horizon exactly as the destination-level path does, from -1.27 in 2018 to -2.39 in 2023 (Table 6). It survives clustering at HS4 and HS2, dropping mineral fuels, and dropping the three chapters that carry the most carbon, and a placebo that assigns the 2019 schedule to 2017 finds nothing.

One limit of this second design deserves as much emphasis as its precision. Weighting products by the carbon China shipped to the United States before the tariff turns the coefficient insignificant and positive, and a Poisson regression in levels does the same. The tariff moved the typical tariffed product without moving the mass, so the product-level design speaks to composition while the volume statements in this paper rest on the destination-level and staggered designs.

Table 6: The 2018 tariffs identified on product-level treatment intensity.

Year	2018	2019	2020	2021	2022	2023
$\hat{\beta}$	-1.265	-1.486	-1.676	-1.695	-2.213	-2.394
	(0.350)	(0.331)	(0.367)	(0.396)	(0.407)	(0.418)
Pooled $\hat{\beta} = -1.867$ (0.299), $N = 19,485$, 2,654 HS6 clusters						
<i>Robustness of the pooled coefficient</i>						
clustered at HS4: -1.867 (0.342), 859 clusters						
clustered at HS2: -1.867 (0.423), 91 clusters						
excluding mineral fuels (HS27): -1.845 (0.298)						
excluding the three largest carbon chapters (HS85, HS84, HS94): -2.121 (0.341)						
weighted by pre-tariff Chinese carbon: $+0.451$ (2.532) – not significant						
placebo, the 2019 schedule assigned to 2017: $+0.169$ (0.483)						

Dependent variable: the log of China’s embodied carbon in US imports minus the log of the rest of the world’s, by HS6 and year. Regressor: $\ln(1 + \text{add-on})$ from the Section-301 schedule at HS6, interacted with year dummies in the top panel. HS6 and year fixed effects throughout, standard errors clustered on HS6 unless stated. Carbon is physical: the flow’s kilograms times the account’s own HS6 cradle-to-gate factor, so no price enters the dependent variable. There is no pre-period to test because the add-on is zero by construction before 2018; the placebo line supplies the equivalent check by assigning the 2019 schedule to 2017 and finds nothing. This design answers the objection that the destination-level event study of Table 5 treats a single destination: here the treatment varies across 2,654 products, and the response grows monotonically with the horizon, from -1.27 in 2018 to -2.39 in 2023. *What it does not show is a movement in carbon volumes.* Weighting products by the carbon China shipped before the tariff turns the coefficient insignificant and positive, and a Poisson regression in levels does the same ($+0.72$, s.e. 1.35). The tariff moved the typical tariffed product; it did not move the mass. Both readings are reported because the paper’s claim is about volumes and only the first of these supports a claim about products.

5.3 Placebo exporters

Placebo exporters. Non-sanctioned exporters’ bloc-vs-non-bloc split moves too. Four of the ten placebo cells are significant at 5%, three of them positive, which is what replacement suppliers look like. None of them breaks on Russia’s scale: the most negative placebo cell is Saudi Arabia’s 2023 coefficient at -0.152 , nine times smaller than Russia’s -1.347 , and Saudi Arabia and Nigeria are the closest analogues Russia has as fossil exporters. A generic “fossil exporter lost the EU market” trend would show up there, and it does not (Table 7). A sector placebo does *not* separate (Russia’s non-targeted products also collapse to the bloc), indicating a broad geoeconomic rupture rather than a narrow sectoral measure, consistent with the fragmentation framing.

Table 7: Control-exporter placebos: the same bloc-against-own-other-destinations design run on five non-sanctioned commodity exporters.

	Nigeria	Saudi Arabia	Indonesia	Brazil	India
<i>2022</i>					
$\hat{\beta}$	+0.006 (0.144)	+0.102 (0.060)	+0.124 (0.046)	+0.034 (0.062)	+0.243 (0.106)
Effect (%)	+0.6	+10.8	+13.2	+3.4	+27.5
<i>2023</i>					
$\hat{\beta}$	+0.253 (0.204)	−0.152 (0.229)	−0.020 (0.049)	−0.110 (0.051)	+0.230 (0.107)
Effect (%)	+28.8	−14.1	−1.9	−10.4	+25.8
Observations	1,695	1,868	2,125	2,182	2,166
Clusters	198	205	218	225	223

PPML, destination and year fixed effects, base year 2021, standard errors clustered by destination. Each column treats the 36 sanctioning destinations as if that exporter had been sanctioned. Four of the ten cells are significant at 5%: Indonesia 2022, India 2022 and 2023, Brazil 2023. The controls move, three of the four significant cells upward, which is what replacement suppliers do. What separates Russia is magnitude: its 2023 coefficient is -1.347 , while the most negative placebo cell is Saudi Arabia at -0.152 , nine times smaller. Several placebos rise, which is what replacement suppliers should do.

5.4 Retention: what becomes of the displaced carbon

The event studies establish that carbon leaves the closed market. Whether it leaves the world is a separate question, and this section estimates it. The quantity of interest is the share of the displaced carbon that reappears, either on the exporter’s remaining markets or on the closed market from other origins, over the same product chapters. It is a statement about tonnes, so no price deflator enters.

Two readings of the same event coexist and measure different things. In raw levels, 118 of the 182 Mt the bloc stopped importing from Russia reappears as absorber growth, about 65% (Section 5). That figure is control-free and reads directly off the aggregates, but it counts one channel and credits whatever growth those markets would have had anyway. The estimates below count both channels and net out that growth, which is why they do not reduce to 65%.

The measurement has to net out trend growth. Both reappearance channels rise with world demand, so a raw comparison over a six-year window would credit ordinary growth as replacement, and for China it does: the uncorrected ratio is 7.5. Each quantity is therefore measured against a counterfactual growth path, chapter by chapter, with the 221 non-sanctioned exporters supplying the counterfactual for the exporter’s own flows and the replacing origins’ open markets supplying their own. The displaced volume is itself the shortfall against that path, not the raw decline. Confidence intervals are bootstrapped over the HS2 chapters.

The headline retention statistic is the carbon-weighted one: weighting HS2 chapters by the carbon each displaced, the median retention is 1.21, and mineral fuels (61% of Russia’s displaced carbon) return 1.21 on their own. The unweighted point estimates are 0.92 for Russia and 3.17 for China (Table 8), and they carry wide intervals. Read the two together. Russia’s point estimate is complete retention, and its interval, $[-1.89, 2.90]$, is too wide to separate that from either extreme: 91 chapters enter and the small ones carry unstable counterfactuals. Weighting chapters by the carbon each displaced brings the median to 1.21, and mineral fuels, which are

61% of Russia’s displaced carbon, return 1.21 on their own. China’s interval excludes complete retention from below, which under a tighter counterfactual would mean the shock raised the global total; over six years the counterfactual will not carry that reading, and the defensible statement is that retention is at least complete. So the two episodes carry the claim to different depths. China’s interval rules out shrinkage. Russia’s point estimate is complete retention, and its interval settles nothing either way. That is the evidence behind the claim that the map is redrawn rather than reduced, and it is weaker than the rerouting result that precedes it.

The reshuffled supply is also slightly dirtier per dollar. Within chapter and within 2023, so that neither product mix nor inflation enters, Russia’s redirected supply carries 27% more carbon per dollar than the supply that replaced it in the bloc, [+9%, +97%]; China’s figure is 33% with an interval spanning zero. The Russian number needs one caution: Russian crude sells to its new buyers at a discount, and a lower price on unchanged physical volume raises carbon per dollar by construction. So 27% bounds any difference in production technology from above rather than measuring it.

Table 8: Retention: the displaced carbon measured against what reappears elsewhere.

	Russia, 2021–2023		China, 2017–2023	
	Mt	ratio [95% CI]	Mt	ratio [95% CI]
Displaced	197	—	171	—
Reappears, other markets	52	0.26 [−0.40, 0.46]	369	2.16 [1.32, 4.14]
Reappears, other origins	130	0.66 [−1.75, 2.82]	173	1.01 [0.17, 1.99]
Retention		0.92 [−1.89, 2.90]		3.17 [1.73, 5.76]
Intensity gap (log)		+0.239 [+0.09, +0.68]		+0.284 [−0.08, +0.69]
HS2 chapters	91		81	

Quantities in MtCO_{2e}. Each is measured against a counterfactual growth path rather than as a raw change, because both reappearance channels grow with world demand and a six-year window would otherwise credit ordinary growth as replacement. For each HS2 chapter, excess = base × (actual growth − counterfactual growth); the counterfactual for the exporter’s own flows is the growth of the 221 non-sanctioned exporters in the same chapter to the same destinations, and the counterfactual for the replacing origins is their own growth to markets the shock left open. The displaced volume is the shortfall against that path. Retention is the two reappearance channels over the displaced volume, so one means the carbon moved without shrinking. Intervals are bootstrapped over HS2 chapters, 2,000 resamples. The Russian interval is wide because small chapters carry unstable counterfactuals; weighting chapters by the carbon each displaced, the median returns 1.21, and mineral fuels alone, 61% of Russia’s displaced carbon, return 1.21. Values above one are not evidence that the shock raised global emissions: over six years the counterfactual is too imprecise to carry that reading. The intensity gap is measured within chapter and within 2023, so neither product mix nor current-dollar inflation enters; it says the redirected supply carries 27% more carbon per dollar than its replacement for Russia and 33% for China, with only the Russian interval excluding zero. For Russia that bounds any difference in production technology from above, because Russian crude sells to its new buyers at a discount and a lower price on unchanged physical volume raises carbon per dollar by construction.

6 Integration, and the pattern generalises

Integration is the mirror. China’s 2001 WTO accession pulled carbon-intensive production in: its carbon exports to the West tripled, from 207 to 627 Mt by 2008 (×3.0; Figure 3, bottom), gradually and relative to control exporters.

Three cases invite a selection question, so we estimate the average effect across all major episodes with the Callaway and Sant’Anna (2021) estimator. A pooled two-way fixed-effects

event study is biased here by comparisons among already-treated units; the Callaway–Sant’Anna estimator uses only clean comparisons against never-treated controls. Across 35 post-1995 WTO accessions, accession raises carbon exports gradually: near zero for a few years, then +31% at ten years and +69% at fifteen (0.27 and 0.53 log points, s.e. 0.12 and 0.15). No pre-onset coefficient is individually significant across the ten years before accession (Figure 2c; Table 9). Across 9 major sanction episodes, the target’s carbon exports to the West fall at once, by 31% in the onset year and by 88% ten years on (Figure 2d). The two sides are symmetric: open the barriers and carbon comes in, slowly; raise them and it goes out, fast.

Pooled two-way fixed-effects event studies over staggered shocks are contaminated by forbidden comparisons between already-treated units (de Chaisemartin and D’Haultfœuille, 2020; Goodman-Bacon, 2021); applied to the WTO accessions they return an uninterpretable flat offset. We therefore use the heterogeneity-robust estimator of Callaway and Sant’Anna (2021) with never-treated controls, aggregated to an event study. Three other estimators target the same clean cohort-by-horizon comparisons: the interaction-weighted estimator of Sun and Abraham (2021), the `didmultiplgt` family of de Chaisemartin and D’Haultfœuille (2020), and the imputation estimator of Borusyak et al. (2024), with Roth et al. (2023) on when the four diverge. Both designs here have never-treated controls available, the case in which the Callaway–Sant’Anna aggregation carries the lightest assumptions, so that is the one we use. Integration: 35 post-1995 WTO accessions, controls = pre-1995 GATT members, outcome = log embodied-carbon exports to the world. Fragmentation: 9 major sanction onsets, controls = never-sanctioned countries, outcome = log embodied-carbon exports to the West.

Table 9: Callaway–Sant’Anna event study over all episodes: integration and fragmentation.

Years since shock	−3	−1	0	+3	+6	+10	+15
Integration	+0.149 (0.094)	+0.019 (0.048)	−0.008 (0.051)	+0.000 (0.081)	+0.073 (0.089)	+0.274* (0.119)	+0.526* (0.151)
Fragmentation	+0.027 (0.050)	−0.065 (0.074)	−0.367* (0.145)	−1.111* (0.300)	−0.971 (0.521)	−2.085* (0.782)	−1.714* (0.095)
Integration: 35 WTO accessions, 196 never-treated controls (pre-1995 GATT members)							
Fragmentation: 9 sanction onsets, 222 never-sanctioned controls							

Coefficients in log points with analytic standard errors in parentheses; * marks horizons whose pointwise 95% band excludes zero. Outcome is log embodied-carbon exports, to the world for the accessions and to the 36-member bloc for the sanctions. The estimator aggregates only clean cohort-by-horizon comparisons against never-treated units, so the forbidden comparisons that bias a pooled two-way fixed-effects event study do not enter (de Chaisemartin and D’Haultfœuille, 2020; Goodman-Bacon, 2021). Pre-onset coefficients are individually insignificant across the ten years before treatment in both designs; one distant horizon in each is significant at 5% (−20 for the accessions, −13 for the sanctions), which is what a pointwise test produces over more than twenty coefficients. Inside the fragmentation row the profile is not monotone and the middle horizons are imprecise: +6 is not significant while +3 and +10 are, which is what nine episodes at staggered horizons deliver. The +15 horizon rests on the single 2002 cohort (Zimbabwe), the only onset observed fifteen years out, and *its standard error should not be read*: with one cohort left there is no between-cohort variance to aggregate, so the analytic figure collapses to within-cohort noise and prints smaller than at +10 rather than larger. Horizons beyond +10 are illustrative. Specification: outcome-regression estimator with no covariates, so the doubly-robust, inverse-probability and outcome-regression variants coincide; varying base period; no anticipation window; analytic standard errors without bootstrap; inference at the exporter level. Two upgrades are flagged rather than done: simultaneous confidence bands by multiplier bootstrap (the Callaway–Sant’Anna default), which would state which horizons survive joint inference, and a cohort-count line per horizon, which would make the thinning of the design visible in the table itself.

Episodes, the log outcome, and Russia in both families is reported in Online Appendix A2.

7 The trade elasticity and the CBAM counterfactual

Does a carbon border adjustment change this? A theoretical literature prices carbon directly on production networks: King et al. (2019) show that when only some sectors can be taxed, the network structure decides which reforms cut emissions, and Planelles and Sanin (2025) carry carbon taxation into a global production network where input-output linkages propagate the tax across borders. Our exercise is the empirical counterpart on the observed bilateral carbon network, which follows a clean gravity structure (Poisson pseudo-maximum-likelihood distance elasticity -1.11 , $p = 4.9 \times 10^{-38}$). We build a partial-equilibrium CBAM counterfactual: the bloc taxes imports in proportion to their origin’s carbon intensity, and importers reallocate across origins with a constant-elasticity rule. The key parameter is the trade elasticity. The CBAM literature calibrates it at 4–6. We estimate it from the 2018 US–China tariffs (a real, carbon-tariff-like shock) using product-level tariff variation (Fajgelbaum et al., 2020), and get $\hat{\theta} \approx 1.1$ pooled and 2.1 at the 2023 horizon, below the calibrated range (Figure 4a; Section A3).

With the estimated elasticity, a carbon price of \$100/tCO₂ on the covered sectors cuts their embodied carbon by 2–4%, against ~8% under calibrated $\theta = 5$ (Figure 4b; Table 10). Calibration overstates the shift by two to four times, and that ratio is the same at either scope because it is a ratio. Whether even that small cut is a global reduction depends on supply elasticity: leakage runs from about a third, when clean suppliers expand freely, to essentially complete when supply is locked, with the capacitated transport re-solve putting leakage at 59% once a tenth of the available headroom can move, and a floor of 33.7% (Table 11). Across that whole range the CBAM, like the shocks, mostly moves carbon.

Gravity, the estimated elasticity, and the counterfactual rule is reported in Online Appendix A3.

7.1 The counterfactual

The right way to hold these numbers is as an order of magnitude with a signed bias, because the chain behind them has five links of which three are untested (the elasticity is estimated on one bilateral shock, transferred to a multilateral instrument, and applied at a uniform rate): at most a few per cent of the covered base at realistic prices, with the untested transfers pushing the true cut *down* (substitution toward bloc production is not modelled) and the inelastic-supply bound of the leakage table capping what any of it can deliver globally.

Leakage depends on supply elasticity. At one end the answer is an identity rather than an estimate: if supply is inelastic, the displaced volume is re-sold to non-bloc buyers at unchanged carbon intensity, so nothing global is cut and leakage is complete by construction. To trace the full range we re-solve the global allocation as a capacitated transport problem and vary how far clean suppliers may expand to serve the bloc, from locked at current output to their full physical capacity (Table 11). Leakage falls steeply as soon as suppliers can move at all, from essentially complete when supply is locked to 59% at a tenth of the available headroom, and then flattens in a band of 33.7–36.6% once a third of the headroom is usable. The flattening

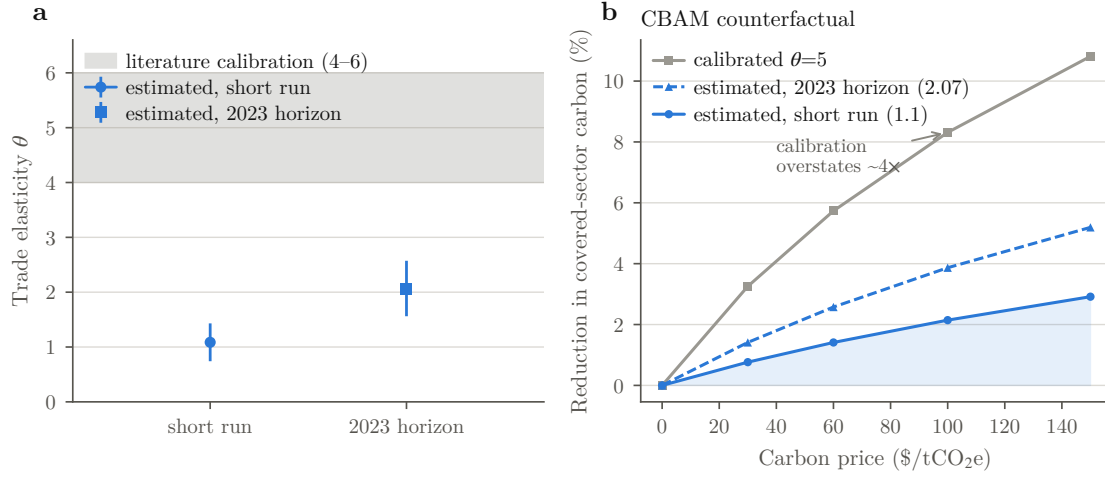


Fig. 4 A CBAM relocates rather than reduces. (a) Trade elasticity θ estimated from the US–China tariffs ($\hat{\theta} \approx 1.1$ short-run, 2.1 at the 2023 horizon) versus the literature calibration (4–6). (b) The counterfactual: with the estimated elasticity the reduction in the covered sectors’ carbon is two to four times smaller than under calibrated θ ; most of it leaks under inelastic supply.

Notes. Panel (a) shows the estimated elasticity at both horizons with 95% intervals against the range the CBAM literature calibrates. Panel (b) solves the counterfactual at each estimated elasticity and at the calibrated value. *Source:* author’s calculations on the audited product-level embodied-carbon account (BACI (Gaulier and Zignago, 2010) $\times$ ecoinvent (Wernet et al., 2016) and Agribalyse (ADEME, 2023) cradle-to-gate factors, IPCC 2013 GWP 100a); elasticity estimated from the Section-301 schedule (Office of the United States Trade Representative, 2018).

is mechanical: further headroom raises the bloc’s own cut and the global cut together, so their ratio stops moving. What the re-solve adds is the shape away from that end, and it is a wide reading of a 33.7–100% range, not a point estimate. The sign of the result (the CBAM moves more carbon than it cuts) holds across the whole range: even at full physical capacity, a third of the bloc’s reduction reappears elsewhere.

7.2 Leakage under supply constraints

How much of the bloc’s cut is a global cut turns on something the demand-side counterfactual cannot say: whether cleaner suppliers are able to take the displaced volume. To bound it we re-solve the whole allocation as a capacitated transport problem and vary that ability, from suppliers locked at their current exports to suppliers free to reach full physical capacity. The instrument in this exercise is deliberately strong and its levels sit on a different scale from the per-tonne cuts of Table 10; what transfers is the ratio, and the ratio has a floor (Table 11). The ratio travels between instruments in a way the levels do not, because it is set by how much clean capacity can move rather than by how hard the shock pushes: raising the tariff moves the bloc’s cut and the reabsorption in step, while freeing capacity moves only the second.

How to read the two tables together. Table 10 gives the size of the cut (an ad-valorem tariff with constant-elasticity reallocation); Table 11 gives the fraction of any cut that leaks (a capacitated transport re-solve). The instruments and scales differ, so levels are not comparable across the two; what transfers is the ratio of the second table applied to the cut of the first.

Table 10: A carbon price on the bloc’s covered sectors: the effect at the legislated scope and at a broad one.

Trade elasticity	Reduction (%) at P in \$/tCO ₂ e			
	30	60	100	150
<i>Panel A. Broad scope, ten carbon-intensive chapters: 3816 Mt, 52% of the bloc’s embodied carbon</i>				
$\hat{\theta} = 1.09$, short run	−0.75 [−0.52, −0.99]	−1.39 [−0.96, −1.82]	−2.12 [−1.47, −2.75]	−2.88 [−2.00, −3.72]
$\hat{\theta} = 2.07$, 2023 horizon	−1.41 [−1.08, −1.74]	−2.58 [−1.97, −3.16]	−3.87 [−2.98, −4.71]	−5.19 [−4.03, −6.29]
$\theta = 5$, calibrated	−3.25	−5.73	−8.31	−10.81
<i>Panel B. Legislated CBAM scope: 1161 Mt, 16% of the bloc’s embodied carbon</i>				
$\hat{\theta} = 1.09$, short run	−1.35 [−0.93, −1.77]	−2.43 [−1.67, −3.17]	−3.58 [−2.48, −4.66]	−4.72 [−3.28, −6.11]
$\hat{\theta} = 2.07$, 2023 horizon	−2.53	−4.50	−6.55	−8.52
$\theta = 5$, calibrated	−5.85	−10.00	−13.96	−17.41
<i>Panel C. The border leg alone, extra-bloc origins only, at $\hat{\theta} = 1.09$</i>				
Broad scope, 1,750 Mt	−3.17	−5.88	−8.99	−12.30
Legislated scope, 484 Mt	−7.67	−13.91	−20.70	−27.51

Reduction in the embodied carbon of the covered sectors, in per cent of the covered base, on the 2019 network. Panels A and B price carbon on every shipment into a bloc destination, which is how the European system works: producers inside the bloc pay through the emissions trading scheme and importers through the border adjustment. The quantity that moves is therefore the bloc’s total embodied carbon in those sectors, not its imports, and the denominators are stated accordingly. The bloc’s embodied carbon in all bloc-bound flows is 7,302 MtCO₂e in 2019, which is the denominator behind the percentages quoted for Panels A and B; its extra-bloc part, 2,967 Mt, is the denominator for Panel C. Panel C isolates the border leg by pricing extra-bloc origins only, and there the quantity is an import cut. Brackets give the 95% interval implied by the elasticity’s sampling error, propagated by re-solving at each endpoint. The legislated scope is cement, iron and steel, aluminium and fertilisers, approximated at HS2 as chapters 25, 72, 73, 76 and 31; the regulation defines it at the tariff line, so this slightly over-states coverage. Mineral fuels, chapter 27, are the largest single chapter in the bloc’s imported carbon and are *not* in scope, which is why the broad panel is not a CBAM. The two scopes together give the coverage margin: as legislated the instrument reaches 16% of the bloc’s embodied carbon, and extending it to all carbon-intensive trade would reach 52%. No leakage column is reported here. Under an inelastic-supply bound the displaced volume is re-sold at unchanged intensity, so leakage is complete by construction rather than estimated; Table 11 traces what happens once supply can respond, which is where the informative variation is.

8 Robustness: not a measurement effect

Our outcome weights flows by life-cycle intensity, so the diversion could in principle reflect the weighting. It does not. Re-estimated on trade value alone, the Russia rerouting (+253% against +236% carbon-weighted) and the China–US decline (−17% against −19%) match the carbon-weighted results (Table 12, Figure 1 in Appendix A6). The diversion is a property of trade flows. The life-cycle measure adds the climate content: the rerouted Russian flows are carbon-intensive, so the move matters for emissions, not only for trade.

8.1 Factor uncertainty carried into the estimates

The account’s matching is audited at 8 wrong assignments in 100, and the companion measurement paper supplies a distribution for each product’s factor rather than a point. Neither has been carried into an estimate here or elsewhere, so we do it. Drawing a complete factor set from that distribution, rebuilding embodied carbon from physical quantities at HS6, and

Table 11: Carbon leakage as clean suppliers become able to expand (capacitated transport re-solve, 2019).

Capacity headroom used	Bloc cut (MtCO ₂ e)	Global cut (MtCO ₂ e)	Bloc cut vs own baseline (%)	Leakage (%)
0%, supply locked	−562.0	0.0	−15.7	100.0
2%	−594.0	−56.0	−16.6	90.6
5%	−629.0	−154.0	−17.5	75.5
10%, near-inelastic	−723.0	−294.0	−19.9	59.3
15%	−783.0	−391.0	−21.5	50.1
25%, low elasticity	−864.0	−508.0	−23.7	41.2
35%	−931.0	−591.0	−25.5	36.5
50%, moderate	−968.0	−627.0	−26.9	35.2
70%	−1068.0	−708.0	−29.6	33.7
100%, full physical capacity	−1167.0	−748.0	−32.2	35.9

Leakage = (bloc cut − global cut) / bloc cut, and the two cut columns carry a decimal so that the ratio reproduces exactly from the printed figures rather than from the solver’s unrounded output. The minimum (33.7%) is reached at 70% headroom, not at full capacity: the last tranche of usable capacity raises the bloc’s own cut faster than the global cut, so the ratio ticks back up to 35.9%. This table answers a different question from Table 10 and uses a different instrument, so *its levels are not comparable with the per-tonne cuts reported there*. Table 10 prices carbon at a stated \$/tCO₂e and lets importers reallocate by a constant-elasticity rule. Here the global allocation is re-solved as a capacitated transport problem that minimises normalised bilateral distance plus a carbon term on bloc-bound shipments, weighted so that a supplier of median intensity pays a carbon cost equal to the median distance cost. That is a far stronger instrument than a \$100 tariff and a cost-minimising rather than a demand-side rule, which is why the cuts here are an order of magnitude larger. The purpose is not to size the cut but to trace how the *ratio* behaves as supply is freed, and only that ratio is carried into the argument. For the same reason the percentage column is measured against this model’s own no-tariff solution at the same headroom, re-solved for every row, so its base moves down the table by construction rather than through rounding. “Capacity headroom used” interpolates each supplier’s bound from its current exports, where supply is locked, to its full physical capacity. Capacity bounds are denominated in value and so do not depend on the emission basis; only the intensities do. The curve was solved on eighteen points and ten are shown. It falls steeply while supply is nearly locked, from 100% to 41.2% by the time a quarter of the headroom is usable, then flattens: across the whole upper range it stays between 33.7% and 36.6%, the minimum falling on the 70% row. The flattening is mechanical, since extra headroom raises the bloc’s own cut and the global cut together, from −931 and −591 MtCO₂e at a third of headroom to −1167 and −748 at full capacity, so their ratio stops moving. The small non-monotonicity inside the plateau is the re-solve switching which supplier absorbs the displaced volume as capacity bounds bind in steps, and it is smaller than the spacing of the grid. What carries the argument is the floor: leakage never falls below 33.7%, so between a third and all of the bloc’s reduction reappears elsewhere. The ~73% of Table 10 is that model’s own inelastic-supply bound and belongs to its scale, not this one; placed on this curve for orientation only, it would sit between the 5% and 10% headroom rows.

re-running the Russia event study 200 times puts the 2023 coefficient at −1.33 with a 95% range of [−1.52, −1.15], a band of 27% of the coefficient, and every draw keeps the sign. Factor uncertainty widens the estimate; it does not threaten it.

Two limits on that statement. The reconstruction used for the draws applies quantities times an HS6 factor and omits the account’s upstream-only mineral-fuel override, its validity cap and its fallback layers, so it is a simplified account. For Russia this costs nothing, since it returns −1.341 against the −1.347 the full account gives, but for China it returns −0.32 against −0.58, so the exercise is reported for Russia alone: a diverse manufacturing basket depends on the parts of the recipe the simplification drops. And the draws are independent across products, whereas a matching error is more likely to repeat within a product family, so the band is a lower bound on measurement uncertainty rather than a full accounting of it.

Table 12: The same shocks measured in carbon and in trade value.

	Embodied carbon	Trade value	Difference
Russia rerouting (non-bloc $\times$ post-2022) clustered p	+236.1% 1.7×10^{-7}	+253.1% 7×10^{-7}	17.0 pp
US imports from China (post-2018) randomization p , size-matched	-18.9% 0.31	-16.9% 0.42	2.0 pp

This table asks whether the reallocation is a property of the trade or a weighting effect, so the third column carries the answer. Both shocks give nearly the same magnitude in tonnes and in dollars, which they would not if the life-cycle intensities were driving the result. The two rows rest on different tests, because they treat different numbers of units. The Russia row is a difference-in-differences over non-bloc against bloc destinations, with many destinations treated, so clustering on the destination carries the inference. The China row treats US imports at the origin $\times$ year level with China as the only treated origin, so inference comes from randomization over origins, and across origins of comparable pre-2018 size the pooled post-2018 decline sits inside the placebo distribution (0.31 in carbon, 0.42 in value). Evidence for the China shock accordingly rests on the event study of Table 5, whose 2023 coefficient does separate from size-matched placebos. The two magnitudes measure different quantities: -18.9% averages every post-2018 year, including 2018 when the effect had not yet appeared, and is estimated on origin aggregates, while the -44.0% of Table 5 is the 2023 coefficient, the deepest point of the path, estimated within China across its destinations.

8.2 The basis is physical, so no deflator enters the carbon series

Embodied carbon here is a physical quantity times a physical factor: the flow's weight in kilograms times a cradle-to-gate factor in kgCO_{2e} per kilogram. Flows with no usable declared quantity fall back to a monetary layer at a donor intensity, and that layer carries 0.6% of emissions. So 99.4% of the measure never passes through a price, and no deflator question arises for any result stated in tonnes: the two event studies, the staggered estimator, the retention estimates and the bloc shares.

Current dollars enter in three places, and each is bounded. The value-weighted regressions of Table 12 are in current dollars with year fixed effects, so a price index common to all flows in a year is absorbed and a deflator would move the levels while leaving the difference-in-differences coefficient untouched. A destination-specific price movement is not absorbed, and the 2022 episode contains one: the discount Russia grants its new buyers raises the dollar figure relative to the tonnage figure. That is why the comparison in Table 12 is read in the direction it is, with the tonnage estimate carrying the conclusion and the value estimate serving only to show that the reallocation is visible in trade as well as in carbon. The CBAM's tariff is ad valorem, so its size depends on the price level, and Table 10 therefore reports the cut across a range of carbon prices rather than at one. The intensity comparisons divide carbon by value and so do move with relative prices, which is a real limitation and bites in exactly one place: the 27% gap of Section 5.4 is inflated by the discount Russia grants its new buyers, and is stated there as an upper bound for that reason.

8.3 Re-exports and entrepot trade

Trade is recorded as declared, so goods that transit a hub are attributed to the hub, and a shock that re-routes shipments through one would look like a fall in direct trade. Hong Kong is the case that matters: it is China's entrepot, and it is the one size-matched placebo whose coefficient exceeds the United States'. Merging Hong Kong into the Chinese origin and removing

it from the destinations leaves the estimate slightly larger, -45.7% against -44.0% (Table 13). Re-routing through Hong Kong was masking a small part of the decline rather than creating it.

The mirror worry for Russia runs through the control group. The three absorbing destinations sit in it, so their growth widens the treated-control differential on its own. Dropping them leaves -58.2% against -74.0% : a third of the published differential is the absorber side. Both readings are defensible, and the level decline settles between them without needing a control group at all, since Russia’s bloc-bound carbon falls 68% between 2021 and 2023 in levels, a different window from the 2017–2023 long difference quoted in Section 5 that happens to round to the same figure.

Table 13: Entrepot trade and absorber controls: the 2023 coefficient re-estimated.

	As published		Robustness variant	
	$\hat{\beta}$ (s.e.)	effect	$\hat{\beta}$ (s.e.)	effect
China: Hong Kong merged into the origin	-0.580 (0.058)	-44.0%	-0.611 (0.044)	-45.7%
Russia: absorbers out of the controls	-1.347 (0.246)	-74.0%	-0.872 (0.173)	-58.2%

Same PPML specification, destination and year fixed effects, in both columns. In the China variant Hong Kong is added to the origin and removed from the destinations, so carbon shipped to the United States through the entrepot is counted as Chinese either way; the coefficient grows slightly, from -0.581 to -0.611 , which is the opposite of what re-routing through Hong Kong would produce. In the Russia variant the three absorbing destinations are dropped from the control group, which removes the part of the differential that comes from their growth rather than from the bloc’s withdrawal. That is the conservative reading and it costs a third of the estimate, -58.2% against -74.0% , with the coefficient still five standard errors from zero. The level decline needs no control group at all: Russia’s bloc-bound carbon falls from 268 to 86 MtCO_{2e} between 2021 and 2023, or -68% , and the two differential estimates bracket it.

9 Discussion

The result is consistent across integration and fragmentation, at the product level, identified causally and generalized over dozens of episodes: trade shocks move the geography of embodied carbon; they do not shrink it. Retention of the displaced carbon is 0.92 for Russia and 3.17 for China; the Chinese interval rules out a cut in the global total, while the Russian one is too wide to settle it (Table 8). What remains of a global effect is the intensity gap between the displaced producer and its replacement (Meng et al., 2023), and that gap runs the wrong way for policy: the redirected supply carries 27% more carbon per dollar for Russia, 33% for China. It is far from the cut that policy assumes.

This reconciles the two literatures. Trade lowers emissions when it routes demand to cleaner producers (Shapiro, 2021; Le Moigne et al., 2024; Wang et al., 2026). Forced reshuffling does the reverse and relocates carbon. Our two-directional evidence shows both faces of one mechanism: the carbon map follows the barriers.

The policy reading is direct. First, metrics built on national or bloc footprints, consumption-based accounts and the carbon numbers behind climate-finance disclosure (supply-chain and scope-3 reporting, science-based targets), count relocation as reduction. A bloc that cleans its import basket while the carbon resurfaces elsewhere has not abated; it has relocated. Second, the instrument reaches only part of the problem by construction: as legislated it covers a sixth of the carbon the bloc consumes through these sectors, so even a fully effective border price leaves

five sixths untouched, and the standard calibration overstates even the covered effect (Larch and Wanner, 2017; Bellora and Fontagné, 2023). Third, sanctions are a cautionary case for climate. Cutting trade with a carbon-intensive producer relocated its output rather than ending it, and the destinations that absorbed it buy at a higher carbon content per dollar, though part of that gap is the discount Russia now grants its new buyers rather than a difference in how the goods are made (Section 5.4).

The estimates have limits. The CBAM counterfactual is partial-equilibrium; a general-equilibrium version would add income feedbacks, but with an estimated elasticity below standard calibrations it would reinforce the small bloc effect. The generalised fragmentation result rests on nine multilateral, comprehensive episodes selected on the criteria of Section 6; a broader definition that included targeted or arms-only measures would add episodes with no measurable trade leg and attenuate the average effect toward zero. And the measure captures carbon exposure in trade rather than consumption responsibility, a distinction Section 2 draws and this paper keeps.

10 Conclusion

Three decades of bilateral trade at the product level, run through two opposite kinds of shock, give one answer. Integration pulls carbon-intensive production toward the acceding country over a decade; fragmentation pushes it out within a year; and the displaced carbon reappears, at a retention this paper estimates at complete for Russia and above complete for China, in a channel that is if anything more carbon-intensive per dollar than the one it replaced. The geography of embodied carbon follows the barriers. Its total does not follow them down.

That has a direct consequence for how carbon policy is measured and priced. Any account that stops at a national or bloc boundary, whether a consumption-based inventory or the scope-3 figure behind a corporate target, will read a relocation as an abatement, because within its frame it is one. And a border adjustment priced with a calibrated trade elasticity will be expected to do several times what an elasticity estimated from an actual tariff shock says it can do: 2 to 4 percent of the embodied carbon of the sectors it covers at \$100 per tonne, of which between a third and all leaks, rather than the 8 percent the calibration implies. Only the border leg alone is an import cut, and that one is larger, 9 percent.

Two things would sharpen this. A general-equilibrium closure would let prices and income adjust, which the partial-equilibrium counterfactual holds fixed, and would test whether the small bloc effect survives. And a measure on physical quantities throughout, rather than one that meets a price at the handful of points named in Section 8, would settle whether the intensity gap between displaced and replacement supply is a difference in technology or in the terms of trade. Neither changes the sign of what is reported here. In a fragmenting world, trade policy redraws the carbon map faster than climate policy shrinks it.

Declarations

Competing interests. The author has no relevant financial or non-financial interests to disclose.

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Data availability. The bilateral carbon panel, every analysis script and the provenance record are deposited at 10.5281/zenodo.21889661, a concept identifier that resolves to the latest version. The underlying trade and life-cycle sources are third-party and are not redistributed there; Table 1 names each one.

Code availability. The analysis code is part of the same deposit and carries an MIT licence; the derived data carry their own terms, stated in the archive.

Use of large language models. Beyond copy-editing, a large language model was used to write and refactor the code that produces the figures and tables. Every figure and table is generated by the deposited code from the data described above. The research question, the designs, the estimation and the interpretation are the author’s own, and the author takes full responsibility for the content.

Author contributions. Sole author: the author designed the study, built the data, carried out the analysis and wrote the manuscript.

Ethics approval. Not applicable. The study uses aggregate trade statistics and life-cycle inventories, with no human participants, no animals and no personal data.

Consent to participate. Not applicable.

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References

- ADEME. AGRIBALYSE: the French life-cycle inventory database for agricultural and food products. Agence de la transition écologique, via Base Empreinte, 2023. URL <https://base-empreinte.ademe.fr>.
- Rahel Aichele and Gabriel Felbermayr. Kyoto and carbon leakage: An empirical analysis of the carbon content of bilateral trade. *Review of Economics and Statistics*, 97(1):104–115, 2015.
- Laura Alfaro and Davin Chor. Global supply chains: the looming “great reallocation”. Working Paper 31661, National Bureau of Economic Research, 2023.
- Mary Amiti, Stephen J. Redding, and David E. Weinstein. The impact of the 2018 tariffs on prices and welfare. *Journal of Economic Perspectives*, 33(4):187–210, 2019. doi: 10.1257/jep.33.4.187.
- Werner Antweiler, Brian R. Copeland, and M. Scott Taylor. Is free trade good for the environment? *American Economic Review*, 91(4):877–908, 2001. doi: 10.1257/aer.91.4.877.

Geoffrey Barrows and Hélène Ollivier. Foreign demand, developing country exports, and CO₂ emissions: Firm-level evidence from India. *Journal of Development Economics*, 149:102587, 2021. doi: 10.1016/j.jdeveco.2020.102587.

Cecilia Bellora and Lionel Fontagné. EU in search of a carbon border adjustment mechanism. *Energy Economics*, 123:106673, 2023.

Christoph Böhringer, Edward J. Balistreri, and Thomas F. Rutherford. The role of border carbon adjustment in unilateral climate policy: overview of an Energy Modeling Forum study (EMF 29). *Energy Economics*, 34:S97–S110, 2012. doi: 10.1016/j.eneco.2012.10.003.

Kirill Borusyak, Xavier Jaravel, and Jann Spiess. Revisiting event-study designs: robust and efficient estimation. *Review of Economic Studies*, 91(6):3253–3285, 2024. doi: 10.1093/restud/rdae007.

Maaïke C. Bouwmeester and Jan Oosterhaven. Specification and aggregation errors in environmentally extended input–output models. *Environmental and Resource Economics*, 56(3):307–335, 2013. doi: 10.1007/s10640-013-9649-8.

Frédéric Branger and Philippe Quirion. Would border carbon adjustments prevent carbon leakage and heavy industry competitiveness losses? insights from a meta-analysis of recent economic studies. *Ecological Economics*, 99:29–39, 2014. doi: 10.1016/j.ecolecon.2013.12.010.

Brantly Callaway and Pedro H. C. Sant’Anna. Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230, 2021.

Maddalena Conte, Pierre Cotterlaz, and Thierry Mayer. The CEPII gravity database. Centre d’Études Prospectives et d’Informations Internationales, Paris, 2022. URL http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele.asp.

B. R. Copeland and M. S. Taylor. Trade, growth, and the environment. *Journal of Economic Literature*, 42(1):7–71, 2004.

S. J. Davis and K. Caldeira. Consumption-based accounting of CO₂ emissions. *Proceedings of the National Academy of Sciences*, 107(12):5687–5692, 2010. doi: 10.1073/pnas.0906974107.

Clément de Chaisemartin and Xavier D’Haultfœuille. Two-way fixed effects estimators with heterogeneous treatment effects. *American Economic Review*, 110(9):2964–2996, 2020. doi: 10.1257/aer.20181169.

Pablo D. Fajgelbaum, Pinelopi K. Goldberg, Patrick J. Kennedy, and Amit K. Khandelwal. The return to protectionism. *Quarterly Journal of Economics*, 135(1):1–55, 2020.

Gabriel Felbermayr, Aleksandra Kirilakha, Constantinos Syropoulos, Erdal Yalcin, and Yoto V. Yotov. The global sanctions data base. *European Economic Review*, 129:103561, 2020.

Meredith Fowlie and Mar Reguant. Challenges in the measurement of leakage risk. *AEA Papers and Proceedings*, 108:124–129, 2018. doi: 10.1257/pandp.20181087.

- P. Friedlingstein, M. O’Sullivan, M. W. Jones, et al. Global carbon budget 2023. *Earth System Science Data*, 15:5301–5369, 2023.
- Guillaume Gaulier and Soledad Zignago. BACI: International Trade Database at the Product-Level. The 1994–2007 Version. *CEPII Working Paper*, (2010-23), 2010. doi: 10.2139/ssrn.1994500. URL <http://www.cepii.fr/CEPII/en/publications/wp/abstract.asp?NoDoc=2726>.
- Andrew Goodman-Bacon. Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277, 2021. doi: 10.1016/j.jeconom.2021.03.014.
- G. P. Hammond and C. I. Jones. Embodied energy and carbon in construction materials. *Proceedings of the Institution of Civil Engineers – Energy*, 161(2):87–98, 2008. doi: 10.1680/ener.2008.161.2.87.
- Maia King, Bassel Tarbush, and Alexander Teytelboym. Targeted carbon tax reforms. *European Economic Review*, 119:526–547, 2019. doi: 10.1016/j.euroecorev.2019.08.001.
- Mario Larch and Joschka Wanner. Carbon tariffs: An analysis of the trade, welfare, and emission effects. *Journal of International Economics*, 109:195–213, 2017.
- Mathilde Le Moigne, Simon Lepot, Ralph Ossa, Marcos Ritel, and Dora Simon. Greening Ricardo: Environmental comparative advantage and the environmental gains from trade. Technical report, WTO Staff Working Paper ERSD-2024-07, 2024.
- Jing Meng, Jingwen Huo, Zengkai Zhang, Yu Liu, Zhifu Mi, Dabo Guan, and Kuishuang Feng. The narrowing gap in developed and developing country emission intensities reduces global trade’s carbon leakage. *Nature Communications*, 14(1):3775, 2023. doi: 10.1038/s41467-023-39449-7.
- Office of the United States Trade Representative. Section 301 tariff actions on imports from China: product exclusion lists and tariff schedules. USTR, Washington, DC, 2018. URL <https://ustr.gov/issue-areas/enforcement/section-301-investigations>.
- G. P. Peters, J. C. Minx, C. L. Weber, and O. Edenhofer. Growth in emission transfers via international trade from 1990 to 2008. *Proceedings of the National Academy of Sciences*, 108(21):8903–8908, 2011. doi: 10.1073/pnas.1006388108.
- Jordi Planelles and María-Eugenia Sanin. Carbon taxation in a global production network. *European Economic Review*, 172:104938, 2025. doi: 10.1016/j.euroecorev.2024.104938.
- Florian Pothin. A product-level Trade-LCA framework for embodied carbon accounting in global trade. Preprint, Research Square; under review at the *Journal of Industrial Ecology*. Code, derived data, blind-audit workbooks and audit trail: Zenodo, <https://doi.org/10.5281/zenodo.20719018>, 2026. URL <https://doi.org/10.21203/rs.3.rs-10627706/v1>.
- Ashesh Rambachan and Jonathan Roth. A more credible approach to parallel trends. *Review of Economic Studies*, 90(5):2555–2591, 2023. doi: 10.1093/restud/rdad018.

- Jonathan Roth, Pedro H. C. Sant’Anna, Alyssa Bilinski, and John Poe. What’s trending in difference-in-differences? a synthesis of the recent econometrics literature. *Journal of Econometrics*, 235(2):2218–2244, 2023. doi: 10.1016/j.jeconom.2023.03.008.
- J. M. C. Santos Silva and Silvana Tenreyro. The log of gravity. *Review of Economics and Statistics*, 88(4):641–658, 2006.
- Joseph S. Shapiro. The environmental bias of trade policy. *Quarterly Journal of Economics*, 136(2):831–886, 2021.
- Konstantin Stadler, Richard Wood, Tatyana Buber, Moana Kondo, José Acosta-Fernández, et al. EXIOBASE 3: Developing a time series of detailed environmentally extended multi-regional input-output tables. *Journal of Industrial Ecology*, 22(3):502–515, 2018. doi: 10.1111/jiec.12715.
- Kjartan Steen-Olsen, Anne Owen, Edgar G. Hertwich, and Manfred Lenzen. Effects of sector aggregation on CO2 multipliers in multiregional input–output analyses. *Economic Systems Research*, 26(3):284–302, 2014. doi: 10.1080/09535314.2014.934325.
- Liyang Sun and Sarah Abraham. Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199, 2021. doi: 10.1016/j.jeconom.2020.09.006.
- Jiaming Wang, Peng Wang, Shu-Chien Hsu, Pan He, Yangyang Wu, Futian Ren, Yiyi Wang, Wenhai Chu, Jun Bi, Lei Huang, and Yuli Shan. International trade reduces emissions through technology transfer led by key emitters. *Nature Climate Change*, 16(4):451–459, 2026.
- Gregor Wernet, Christian Bauer, Bernhard Steubing, Jürgen Reinhard, Emilia Moreno-Ruiz, and Bo Weidema. The ecoinvent database version 3 (part I): overview and methodology. *International Journal of Life Cycle Assessment*, 21:1218–1230, 2016.
- World Bank. *World Development Indicators*. World Bank Group, Washington, D.C., 2024.

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