The Environmental Costs of Sanctions: Flaring, Venting, and Biodiversity in Venezuela*

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Abstract

Economic sanctions on oil-producing autocracies reduce not only how much oil is produced but also how each remaining barrel is produced. Combining field-level production data, satellite measurements of gas flaring and atmospheric methane, and citizen-science records of bird abundance as a proxy for local biodiversity across six Latin American countries from 2012 to 2024, we study the US sanctions on Venezuela. Per-barrel gas flaring at heavy Venezuelan fields roughly tripled relative to unsanctioned neighbours even as production fell by two-thirds, so post-period environmental damage is about three times what proportional decline would predict. Three reinforcing channels generate this gap: small clean fields exit first; surviving fields cut maintenance budgets; and surviving infrastructure runs past design capacity. Bird abundance falls in the affected cells, consistent with pollution-driven ecological harm. A November 2022 US Treasury licence that let Chevron alone resume operations at four Venezuelan fields provides a unique quasi-experimental laboratory for the maintenance channel: per-barrel pollution falls sharply at those fields, and bird abundance recovers in tandem. The same pattern of rising per-barrel emissions despite falling output appears in sanctions on Russia (post-2014/2022) and Iran (post-2018).

JEL Classification: F51, Q53, Q35, L71

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"Telegram from Walter Saxer in Iquitos. Apparently things are looking very good, except that the whole situation might collapse from one moment to the next."
Werner Herzog, *Conquest of the Useless*, 2004

1 Introduction

Economic sanctions are among the most widely deployed instruments of foreign policy, yet their environmental consequences remain poorly understood. When sanctions target oil-producing states, the standard policy calculus weighs geopolitical objectives against humanitarian costs. What it typically omits is that oil extraction is infrastructure-intensive: wells, pipelines, gas-handling plants, and processing facilities all require sustained investment, imported equipment, and technical expertise to operate within environmental norms. When sanctions sever the channels that sustain this infrastructure, the result may not be a clean reduction in output but a degradation of the production process itself, making each remaining barrel dirtier rather than just scarcer.

Whether sanctions raise or lower the environmental damage from oil extraction is theoretically ambiguous. Sanctions reduce the volume of oil produced, which by itself would proportionately reduce the total damage. But they may also raise the pollution generated per barrel, and if pollution per barrel rises enough, total damage need not fall and may even rise. Three forces can drive pollution per barrel up. First, the carbon intensity of crude oil production varies enormously across fields, and how production is reallocated when fields exit matters (Masnadi et al., 2018; Coulomb et al., 2026; Asker et al., 2024): when sanctions raise the cost of operating, marginal small fields shut down first and surviving production concentrates on the larger fields, which may be cleaner or dirtier per barrel depending on the cross-sectional intensity gradient: this is the *composition* channel. Second, sanctions cut the maintenance budgets at the fields that keep producing; deteriorating equipment captures less of the gas that comes up with crude oil, so more of it leaks or has to be burned off, the *maintenance* channel. Third, surviving fields are pushed harder against the limits of their gas-handling infrastructure, and more gas escapes through leaks or flaring as those limits are approached, the *strain* channel.

Each channel responds to a different sanctions-design choice, and the three map onto a menu of three currently-deployed instruments. The first instrument is *targeted carve-outs* like the November 2022 US Treasury licence for Chevron in Venezuela, which restored operational inputs that sanctions had cut (spare parts, foreign expertise, banking services, and the imported diluents that the thickest crude needs to flow through pipelines) and so acted on both the maintenance and the strain channels at once. The second is *price caps that target revenue rather than the production process*, such as the G7 oil price cap on Russia, which addresses the composition channel by making the dirtiest high-marginal-cost fields unprofitable first. The third is *buyer-side standards* like the EU's 2024 Methane Regulation, which leans on the same composition margin from the demand side by conditioning import access on per-barrel methane intensity. What is new here is that we introduce this three-channel framework, measure each channel separately, recover an underlying damage

function that links operating decisions to per-barrel pollution, and trace its consequences through to local biodiversity.

Venezuela now flares about 8 billion cubic metres of associated natural gas a year (World Bank, 2024). That is worth around $1.4 billion at Henry-Hub prices, and is enough gas to cover the entire annual demand of neighbouring Colombia. It makes Venezuela the world's fifth-largest flarer, even though the country now produces only about a tenth as much oil as the top extractors do. What we can do in Venezuela that we cannot do elsewhere is identify where the anomaly comes from. The country holds the world's largest proven oil reserves, concentrated in extra-heavy crude deposits in the Orinoco Belt that require continuous investment, imported inputs and technical expertise to keep flowing (U.S. Energy Information Administration, 2024; Rodríguez, 2022b). The sanctions we study are public: explicit US Treasury restrictions, distinct from the private sanctions through which firms voluntarily disengage from a jurisdiction (Hart et al., 2024; Fioretti et al., 2026b). The international joint-venture partners covered by these sanctions did not expressly choose to withdraw from Venezuela and could consider re-entry, but the 2007 nationalisation of upstream JV assets creates a sovereign hold-up precedent that conditions any future investment decision (Fioretti et al., 2026a).

US sanctions came in two waves with different identifying content. The first, between 2017 and 2019, severed financing (Congressional Research Service, 2024) and access to the imported naphtha diluent that heavy crude requires to flow through pipelines, generating extensive year-to-year variation in maintenance budgets and production at each Venezuelan field. The second, in November 2022, was a US Treasury licence that allowed Chevron alone to resume operations at four Venezuelan joint-ventures while sanctions remained in place at every neighbouring field. This licence is the key identifying shock: it raised maintenance spending and restored access to imported parts and foreign expertise specifically at the four covered fields, so its differential effect on pollution there separates the maintenance mechanism from any sanctions-driven co-movement of spending and pollution. Russia and Iran exhibit the qualitative three-channel pattern under their own sanctions episodes but lack a within-firm licence shock and therefore cannot recover the underlying damage function.

We link field-level production and expenditure data to satellite measures of gas flaring, atmospheric methane, and avian biodiversity. The cross-country dimension is asymmetric across outcomes: flaring and operating expenditure use the full six-country LATAM panel; methane uses Venezuelan TROPOMI cells (with a six-country robustness check in the appendix); and the biodiversity regressions use Venezuelan eBird checklists, with Colombian checklists added as a placebo control for the bird-relocation test. Venezuelan production fell to roughly one-third of its pre-sanctions level over the sanctions period, but the decline was sharply uneven: production concentrated on the largest fields in the Orinoco extra-heavy belt, whose resources are more polluting, while smaller fields and the conventional Maracaibo Basin contracted sharply across the board. Because PDVSA owns or operates most Venezuelan fields, the reshuffling happens largely within a single multi-asset firm choosing across its heterogeneous portfolio rather than between firms

exiting and entering (Fioretti et al., 2025). This is the *composition channel*, the across-field margin: sanctions reshaped which fields keep producing.

The other two channels operate within fields. The *maintenance* channel: holding production fixed, the average within-Venezuela elasticity of flaring volume to per-barrel operating expenditure is small, on the order of a 3% reduction when OPEX per barrel doubles, and the post-2017 within-field slope flattens close to zero, consistent with sanctions-driven binding constraints overwhelming the pre-sanctions maintenance margin. The November 2022 US Treasury licence sharpens this within-field test: at the four Chevron joint-ventures during the licence period, doubling maintenance spending cuts flaring per barrel by roughly 25%, an order of magnitude steeper than the average Venezuelan field, because each restored dollar buys real gas-handling parts that secondary sanctions block elsewhere.

The *strain* channel operates through a different lever. When small Venezuelan fields shut down, the surviving big heavy-oil fields had to make up the lost production. They now waste about three times as much gas per barrel as comparable heavy-oil fields in countries without sanctions. Venezuela's lighter-oil fields show no such jump. The asymmetry tracks the underlying physics: only operations whose gas handling depends on imported diluent (itself in chronically short supply since the 2019 embargo) respond to the supply-chain shock, and only in fields where post-sanctions production was sustained near pre-sanctions throughput.

The three-channel decomposition, applied to the observed surge in maintenance spending and production at Chevron fields, predicts pollution per barrel roughly halving at the four licence fields. Flaring damages local populations in two ways. Directly, through respiratory and other health effects from chronic exposure to combustion pollutants (Blundell and Kokoza, 2022). Indirectly, through degradation of surrounding ecosystems. We test this prediction on local avian biodiversity. Birds are widely used as indicators of broader ecosystem health: they sit high in the food web and integrate effects on insects, plants, and small vertebrates that they consume; they are sensitive to temperature, air quality, and habitat disturbance; and their mobility means local declines reflect local conditions rather than slow demographic inertia (Şekercioğlu, 2006; Gregory and Van Strien, 2010; Eglington et al., 2012).

Bird abundance near the four Chevron fields recovers post-licence by approximately 53%, against the framework's predicted 51% decline in per-barrel pollution. The implied elasticity of bird abundance to local pollution is substantial and in the order of magnitude estimated by Liang et al. (2020) for US bird populations under the NO_x Budget Trading Program, though somewhat larger. This is consistent with higher baseline pollution at sanctioned Venezuelan oil sites, the simultaneous decline of multiple flaring co-pollutants, and the habitat sensitivity of tropical forest insectivores.

Combining the three channel-specific estimates, total environmental damage from Venezuelan oil extraction in 2022 to 2024 is approximately three times what the proportional decline of output alone would predict. The maintenance and strain channels together contribute essentially all of the gap (the composition channel does less than one percent of the work numerically), but composition

determines where the maintenance–strain damage lands. The cross-country comparison with operating heavy-oil regions in Mexico, Ecuador, and Colombia, which face no diluent shortage and exhibit no comparable methane trend at pipeline-vicinity grid cells, confirms that the within-Venezuela pattern is sanctions-specific rather than generic to heavy-oil extraction.

The same qualitative pattern appears in Russia and Iran. We do not run our own field-level decomposition for either case; the overlapping sanctions waves on Russia and the opacity of post-2018 Iranian production data both go beyond the scope of this paper. External evidence on production composition and methane emissions, however, is consistent with the qualitative pattern we document for Venezuela: pooling Russia's 2014, 2017–2018, and February 2022 sanctions episodes, satellite and industry sources point to flaring intensity at sanctioned Russian fields rising sharply against unsanctioned analogues. In Iran, post-2018 maximum-pressure sanctions roughly halved production at the 2020 trough, with partial recovery as dark-shipping networks routed crude to non-cooperating buyers (Fernández-Villaverde et al., 2025); satellite reanalysis by the International Energy Agency shows Iranian oil-and-gas methane emissions rising despite falling output. In all three cases, total output falls or stagnates, production concentrates on the largest dirtiest fields, and per-barrel emissions rise. What does not travel is the structural identification: only Venezuela has the within-firm licence carve-out that decomposes the regime differential into maintenance and strain.

These findings have direct implications for the design of sanctions targeting petrostates. The decomposition implies that sanctions design has two distinct objectives, not one: maximising coercive impact on the regime, and minimising the environmental damage that production reshuffling induces. The three channels map onto three policy instruments (targeted carve-outs, price caps that target revenue rather than the production process, and buyer-side standards), so the two objectives are not always in conflict. A package that combines a Chevron-style carve-out (which restores maintenance inputs and diluent supply at heavy fields) with a methane-indexed price cap or an MRV-style import standard hits the regime's revenue base hard while leaving the maintenance and strain channels quiet and tilting composition away from the dirtiest fields. The Chevron carve-out demonstrates one side of this directly; the G7 oil price cap on Russia is a partial implementation of the second; and the EU's 2024 Methane Regulation is an emerging implementation of the third. Our framework suggests how to combine them. The environmental costs we document are absent from the standard sanctions calculus, and the structural decomposition we recover names the policy instruments that can blunt the environmental cost without compromising the coercive one.

Related literature. The paper sits at the intersection of work on the economic consequences of sanctions, the environmental externalities of oil and gas extraction, and the misallocation literature. The Venezuelan case has attracted considerable attention. Rodríguez (2022a), exploiting credit-access heterogeneity across Orinoco joint ventures, finds large output losses attributable to financial and oil-sector sanctions; Bahar et al. (2019) argue that aggregate counterfactuals for this idiosyncratic case are infeasible. The broader sanctions literature documents trade reductions

(Afesorgbor, 2019), GDP losses through disrupted capital flows (Gutmann et al., 2023), and evasion through opaque shipping networks (Fernández-Villaverde et al., 2025); in an oil sector dependent on imported services and diluent, these channels supply the macro background to the field-level effects we document.[1] We move from aggregate output to field-level environmental performance and decompose the response into three separately identified channels rather than a single volume-or-intensity effect.

A growing body of work, building on Madani (2020), documents environmental degradation in sanctioned countries and attributes it to constrained maintenance and increased reliance on inefficient production (Fu et al., 2020; Sun and Wang, 2025; Khalid et al., 2024; Afesorgbor and Steinbach, 2024; Madani, 2021). None of these papers separates composition, maintenance, and strain; none identifies the maintenance channel quasi-experimentally. We do both, and we tie the result to ecological outcomes in the same panel. Our biodiversity analysis sits in a complementary literature that uses avian data to recover environmental costs of human activity (Liang et al., 2020, 2025; Katovich, 2023; Hogan et al., 2025) and that treats bird populations as integrating indicators of ecosystem health (Eglington et al., 2012; Gregory and Van Strien, 2010). Field-level production shocks have, to our knowledge, not been linked to satellite pollutants and ecological outcomes within a single decomposition.

The infrastructure-and-composition view of oil-sector externalities has clear antecedents. Coulomb et al. (2026) show that crude carbon intensity varies sharply across fields, that historical extraction patterns embody large-scale carbon misallocation, and that small policy shifts can reshape which barrels are produced. Asker et al. (2024) decompose OPEC's environmental effects into a volume effect (fewer barrels) and a composition effect (dirtier barrels at high-cost producers). Covert and Kellogg (2025) show that pipeline and processing constraints push operators toward dirtier extraction methods. We extend this perspective by identifying sanctions as another institutional shock that reshapes extraction composition, and by separating composition from maintenance (within-field operating-budget collapse) and strain (within-field capacity-constraint binding).[2]

The misallocation literature provides the conceptual frame (Restuccia and Rogerson, 2008; Hsieh and Klenow, 2009; Bartelsman et al., 2013; Asker et al., 2014), including a recent strand that treats the depreciation rate of capital as itself endogenous to the supply of repair, parts, and expertise (Graff, 2026). An environmental strand has applied the lens to pollution: Shapiro and Walker (2018) decompose the US manufacturing pollution decline into composition, technique, and scale and find that composition does relatively little while technique change drives most of the result; Tombe and Winter (2015) show how intensity-based environmental standards themselves distort

[1] On the humanitarian costs of Venezuelan sanctions, see Weisbrot and Sachs (2019) and the response in Hausmann and Muci (2019). The paper also speaks to the political economy of sanctions (Egorov et al., 2025; Itskhoki and Ribakova, 2024).

[2] A related supply-side literature studies deliberate restrictions on extraction (Harstad, 2012; Ahlvik et al., 2026; Kellogg, 2024); sanctions differ in that they restrict extraction involuntarily and without environmental intent, worsening outcomes by degrading the infrastructure that contains emissions. The flaring and methane mechanisms themselves have been studied extensively (Agerton et al., 2023; Lade and Rudik, 2020; Marks, 2022; Nathan et al., 2024; Hancock et al., 2025), and a parallel literature in finance examines how credit constraints affect pollution control (Xu and Kim, 2022; Lanteri and Rampini, 2025; Singer, 2026). Both feed directly into the maintenance channel we identify.

allocation across heterogeneous firms; Fowlie et al. (2012) study how emissions markets reallocate abatement across plants. We add a sanctions-driven misallocation along the environmental margin: the production base reallocates toward fields with sharply higher per-barrel pollution, and the welfare loss runs through external damage rather than through measured TFP. The Chevron quasi-experiment recovers the marginal product of the maintenance input directly, supplying an elasticity that misallocation models typically calibrate from aggregate moments, and the three-channel framework separates what the literature usually treats as a single composition wedge into a survival margin, an input-spending margin, and a capacity-constraint margin, each mapped to a distinct policy lever.

The remainder of the paper proceeds as follows. Section 2 states the conceptual framework and its three predictions. Section 3 provides the institutional and engineering context: the chronology of sanctions, the physics of extra-heavy oil, and the gas-handling chain that links naphtha supply to flaring outcomes. Section 4 describes the data sources and identification strategy. Sections 5, 6, and 7 present the empirical evidence on each channel in turn. Section 8 quantifies the combined damage ratio R, extends the analysis to Russia and Iran, and draws implications for sanctions design. Section 9 concludes. Appendix A formalises the two-field reallocation model underlying the framework; the remaining appendices document data sources, matching procedures, and robustness specifications.

2 Conceptual framework

A natural benchmark is *proportional decline*: if production falls x%, extractive damage falls x%. The benchmark holds when sanctions leave technology, the set of operating fields, per-barrel intensity, and capacity utilisation unchanged. Whether it holds is the empirical question of this paper.

Three margins move outcomes away from the benchmark.

Composition. Sanctions raise the fixed cost of operating any field: evasion infrastructure, lost foreign expertise, premium pricing on sanctioned counterparties, deferred replacement of expatriate staff. Small fields with low marginal cost are also small in capacity, so they cross the new break-even threshold first. Surviving production reconcentrates on the larger fields. Whether aggregate intensity rises or falls then turns on the per-barrel emissions gap between exiting and surviving fields. In Venezuela that gap is small. Large fields are extra-heavy but operate at the flat part of the gas-to-oil-ratio curve, with fixed gas-handling capacity amortised over many barrels; large fields are if anything mildly *cleaner* per barrel than the small fields that exit. Composition therefore contributes little to aggregate intensity directly: damage loads onto the next two channels.

Maintenance. Per-barrel emission intensity is not a fixed engineering constant. It falls in operating expenditure on leak repair, equipment turnover, gas capture, and the labour and contracted services that move with maintenance. Sanctions cut these budgets through restricted access to spare parts,

capital, and foreign service contractors, raising intensity *wherever production continues*, including at fields whose total output is unchanged. Section 7 proxies the maintenance budget with per-barrel OPEX, which absorbs maintenance spending and the correlated operating inputs.

Strain. Each field is built for a planned output. Pipes, compressors, and gas-handling equipment have a fixed capacity, with a safety margin for surges and breakdowns. As exiting small fields throw production onto surviving large ones, the survivors approach their design margin and a rising share of associated gas ends up vented or flared rather than captured. In Venezuela the binding constraint is an imported-input bottleneck: the 2019 naphtha embargo piles up extra-heavy crude at wellheads, stalls sales pipelines, and forces the gas-handling chain past its operating margin even when nominal output has fallen. Damage per barrel rises faster than field output: the damage function is convex in q_i.[3]

Decomposition. These three margins are exhaustive. They correspond, respectively, to *which* fields operate, *how* each operates, and *how much* each produces. Appendix A formalises the channels in a two-field model and derives the threshold at which surviving production concentrates entirely on the dirty field. Total damage is

$$D = \underbrace{\sum_{i \in \text{operating}}}_{\text{(i) composition}} \Big[\underbrace{\alpha_i(m_i)}_{\text{(ii) maintenance}} \cdot q_i + \underbrace{\frac{\beta_i}{2} q_i^2}_{\text{(iii) strain}} \Big], \tag{1}$$

with $\beta_i \geq 0$. The proportional-decline benchmark obtains if and only if sanctions leave the operating set, the intensity $\alpha_i(m_i)$, and field utilisation q_i relative to capacity all unchanged. Any deviation runs through one of the three.

Section 3 sets out the institutions, engineering, and data. Sections 5, 6, and 7 identify the three channels with designs that hold the other two fixed. Section 8 aggregates them and quantifies how far Venezuela departs from the proportional benchmark. Section 8.4 draws the implications for sanctions design.

3 Background: sanctions and the physics of extra-heavy oil

This section provides two pieces of context the empirical analysis will draw on. Subsection 3.1 summarises the sanctions chronology in Venezuela and the analogous episodes in Russia and Iran. Subsection 3.2 describes what the proportional-decline counterfactual looks like in a well-functioning oil field, so the deviations we measure later have a baseline to be measured against, and

[3] Maintenance is about *how* a barrel is produced; strain is about *how much*. The two are conceptually distinct but quantitatively correlated in any outcome (methane, biodiversity) that responds to both, so separating them requires designs that hold one fixed while varying the other. We exploit such designs: the Chevron licence (Section 7) shifts the maintenance budget at approximately fixed production; the production-share shock (Section 6) raises strain at approximately fixed maintenance.

walks through the physical steps by which a cut in imported diluent supply translates into flaring and methane releases at Venezuelan extra-heavy oil fields. This second subsection is essential because the sanctions–environment link runs through a specific physical mechanism that is not generic to oil extraction; understanding it clarifies why our channel decomposition has the shape it does and why Venezuela is, in this respect, a particularly informative case.

3.1 Sanctions chronology

Venezuela holds the world's largest proven oil reserves and produces from two main regions with distinct crude characteristics. The *Maracaibo Basin*, in the country's west, produces conventional medium-density crude that flows through pipelines without modification. The *Orinoco Belt*, in the country's east, produces extra-heavy crude so viscous at surface temperatures that it cannot move through pipelines without first being blended with imported light hydrocarbons (most commonly naphtha). Smaller volumes come from Barinas in the south-west, eastern conventional fields, and a thin offshore base. Before the 2017–2019 sanctions, Orinoco accounted for roughly 51 % of national crude output and Maracaibo for roughly 30 % (U.S. Energy Information Administration, 2024; Monaldi et al., 2021). The asymmetry in crude characteristics, and in particular the Orinoco Belt's dependence on imported diluent, is the physical reason for the sanctions-impact patterns this paper documents.

The United States imposed sectoral financial sanctions on Venezuela in August 2017 (Executive Order 13808), restricting US-person dealings in new debt and equity issued by the Government of Venezuela and PDVSA. In January 2019 the Treasury's Office of Foreign Assets Control (OFAC) designated PDVSA itself as a Specially Designated National, severing PDVSA from the US dollar clearing system and from US-sourced inputs, most consequentially, naphtha and other light hydrocarbon diluents that Orinoco extra-heavy crude requires for transport. A series of secondary sanctions in 2020 expanded the perimeter to non-US counterparties dealing in Venezuelan crude. Aggregate Venezuelan production fell from a 2016 peak of 2.28 million barrels per day (Rystad UCube) to a 2020 trough of 0.58 before stabilising near 0.78 in 2023–24.[4] Within-country, the decline was heterogeneous: Maracaibo Basin output (medium-API conventional crude, 11–19° API) collapsed across all field-size classes to 15–30% of 2016 levels, while Orinoco extra-heavy production (8–10° API) was retained much more at the largest fields (46% of 2016 output) and collapsed at the small and medium fields (7–8%). In November 2022 OFAC issued General Licence 41, permitting Chevron specifically to resume operations at four Venezuelan joint-ventures (PetroBoscan, PetroIndependencia, PetroIndependiente, and PetroPiar) under restrictions on revenue distribution to PDVSA. This license is the source of the quasi-experimental variation we use in Section 7.[5]

[4]Mexican production also declines over 2012–2024, driven by Cantarell-led depletion and chronic Pemex underinvestment; per-barrel flaring rises mechanically as gas-to-oil ratios climb at depleting fields without offsetting capex. The Mexican trajectory is smooth, pre-dates 2017, and is not accompanied by rising pipeline-vicinity methane (Section 6); the joint flaring+methane signature is sanctions-specific.

[5]Russia and Iran have undergone broadly similar sanctions episodes, with qualitatively similar production-composition and methane patterns, which we discuss as external-validity checks in Section 8.3.

3.2 The proportional-decline benchmark and why Venezuela violates it

What should environmental outcomes do when production falls in a well-managed oil field? Two facts pin down the benchmark. First, flaring is engineered to be small or zero in steady state: associated gas is captured for sales, reinjected, or used as on-site fuel, and flared only as a safety relief (World Bank, 2024, 2025). In our LATAM panel, pre-sanctions flaring intensity at non-Venezuelan fields ranges from 14 to 52 m^3/bbl across countries against a Venezuelan pre-sanctions mean of $\sim$196 m^3/bbl (Table 1, computed from Rystad UCube and World Bank VIIRS, 15 km flare-allocation radius); the World Bank Global Gas Flaring Reduction Partnership's global inventory shows best-in-class producers operate well below 5 m^3/bbl (Agerton et al., 2023; International Energy Agency, 2024). Second, methane leakage scales roughly proportionally with the amount of equipment in service and its age and maintenance status (Marks, 2022; Plant et al., 2022).[6] Under proportional decline, flaring intensity stays near its pre-period level and methane falls in line with activity.

This benchmark fails in Venezuela because of how extra-heavy crude is produced. Orinoco crude is too viscous to flow through pipelines without 20–40 % blending with imported naphtha or other light hydrocarbons (Monaldi et al., 2021; U.S. Energy Information Administration, 2024); the January 2019 PDVSA designation severed the US naphtha supply, and each lifted barrel now has to wait for thinning at the gathering centre. Compounding this, heavy-oil wells using cyclic steam stimulation or electric submersible pumping cannot be cleanly throttled without permanent damage from wax and asphaltene precipitation and pump seizure. The associated gas, produced at near-fixed gas-oil ratios with the crude, has nowhere to go when diluent supply collapses: sales pipelines require diluted crude flowing through them, reinjection compressors require parts, and upgraders require crude feed. The only remaining gas sinks are the flare and the vent. The asymmetry is operationally clean: Maracaibo conventional grades flow without diluent and can be shut down cleanly; Orinoco extra-heavy fields cannot, and continue producing under sanctions only with deteriorated operations. The full five-step physical chain is in Appendix B; the three channels of Section 2 (composition, maintenance, strain) are all consequences of this physical structure.

4 Data and identification strategy

4.1 Motivating fact

Two datasets frame the per-barrel pollution puzzle: a field-level production panel and a satellite flaring product, joined by spatial matching.

[6] The clearest empirical test of this proportionality is the COVID-19 oil-price shock: when US oil-and-gas activity contracted in spring 2020, satellite-observed methane emissions fell by a roughly proportional amount, with the shock fully reversing as activity recovered (Lyon et al., 2021).

Field-level production (Rystad UCube). The Rystad UCube provides field-level monthly observations on crude production, capital expenditure, operating expenditure, ownership shares, crude grade, reservoir type, and operational status. We restrict to the six-country Latin American panel (Argentina, Brazil onshore, Colombia, Ecuador, Mexico, Venezuela), 2012–2024, yielding 1,874 fields and 11,983 field-year observations; 236 Venezuelan fields are tracked. Reporting density on tracked Venezuelan fields is 97–100% post-2017, indistinguishable from the other five countries, and the field count drifts from 223 in 2016 to 160 in 2024: decommissioning, not reporting attrition. Rystad triangulates sanctioned-jurisdiction data across OPEC secondary-source figures, joint-venture-partner disclosures (Chevron, Repsol, Eni), tanker tracking, and refinery throughput; we treat the panel as the closest available approximation to a complete frame of upstream Venezuelan operations (Appendix C.2).

Satellite flaring (World Bank VIIRS). VIIRS night-time fire detections identify high-temperature combustion at roughly 750 m resolution; the World Bank Global Gas Flaring Reduction Partnership processes them into annual flare-volume estimates by site.[7] We allocate site volumes to Rystad fields in two stages: Stage 1 fuzzy Jaro–Winkler name matching, Stage 2 a production-weighted inverse-distance gravity scheme within a candidate radius of 7.5, 10, or 15 km. The 15 km headline radius accommodates the spatial extent of oil-field infrastructure: the Yucal Placer flare site sits 14.8 km from its Rystad centroid yet fuzzy name matching confirms a single field (Online Appendix Figure C1). At 15 km the procedure allocates 91.4% of total LATAM flaring volume and exceeds 90% in every country except Brazil, whose offshore concentration depresses the onshore rate (Online Appendix Table C1; Appendix C details the algorithm). Flaring intensity is the field-allocated annual volume divided by the field's Rystad annual production.

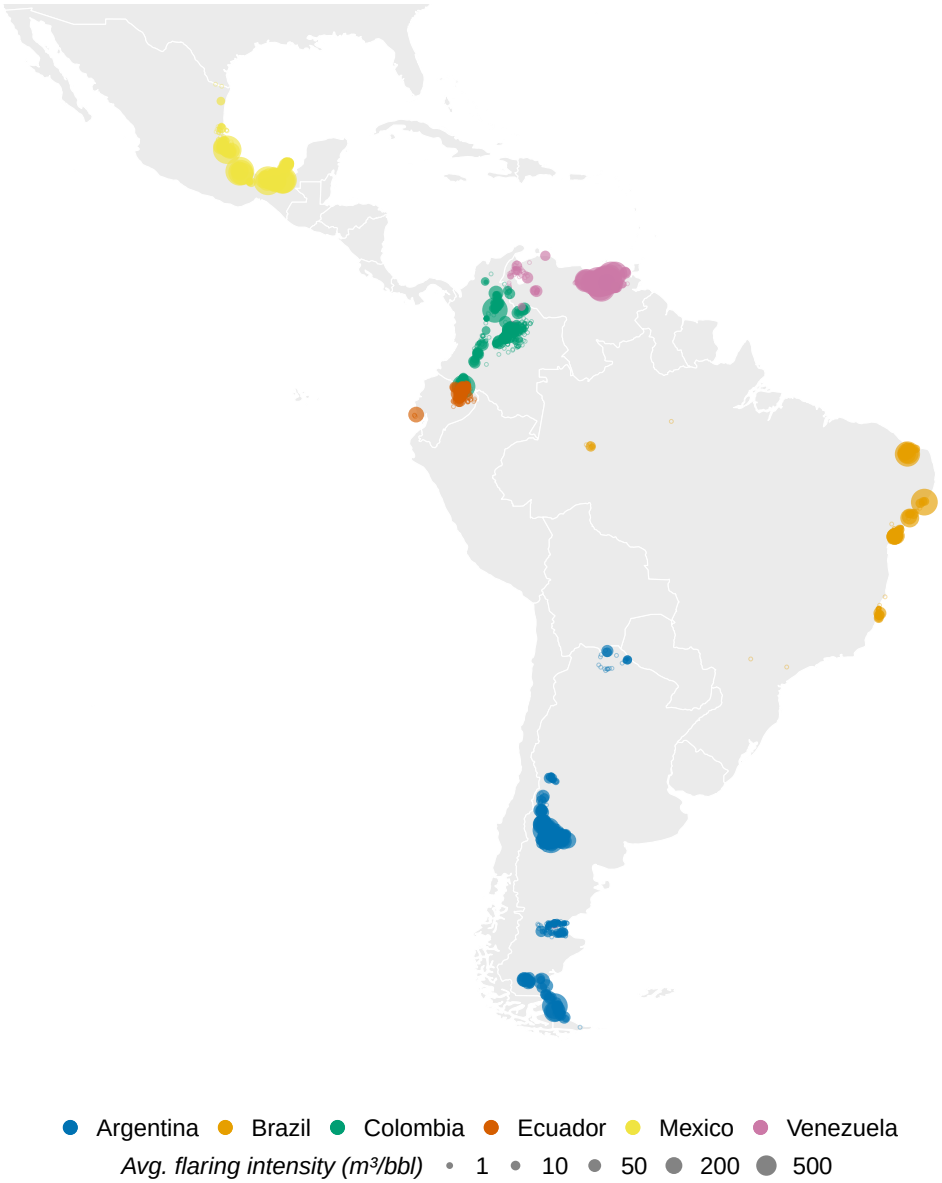
Where the fields are. Figure 1 maps the 1,874 Rystad-tracked fields across the six-country panel, coloured by their average 2012–2024 flaring intensity. Heavy-oil clusters in eastern Venezuela (the Orinoco Belt), the Mexican Maya basin, and the Ecuadorean Oriente stand out; conventional fields in Argentina, Brazil onshore, and Colombia flare comparatively little per barrel.

Descriptive statistics. Table 1 reports country-level pre-period flaring intensities, production volumes, and ownership composition.

The puzzle. Per-barrel flaring intensity at Venezuelan fields rose roughly threefold between 2012–2016 and 2017–2024 while average annual production over the same windows fell 48% (the peak-to-trough decline from the 2016 peak to the 2022–2024 mean is 66%; we use the latter as the headline production-loss number in the quantification of Section 8). Figure 2 traces flaring, flaring-

[7] We use the file `2012-2024 Flare Volume Estimates by Individual Flare Location` from the GGFR data portal (https://www.worldbank.org/en/programs/gasflaringreduction), which yields approximately 10,200 flare-site-year observations across the six sample countries.

Figure 1: Oil Fields and Flaring Intensity in Latin America

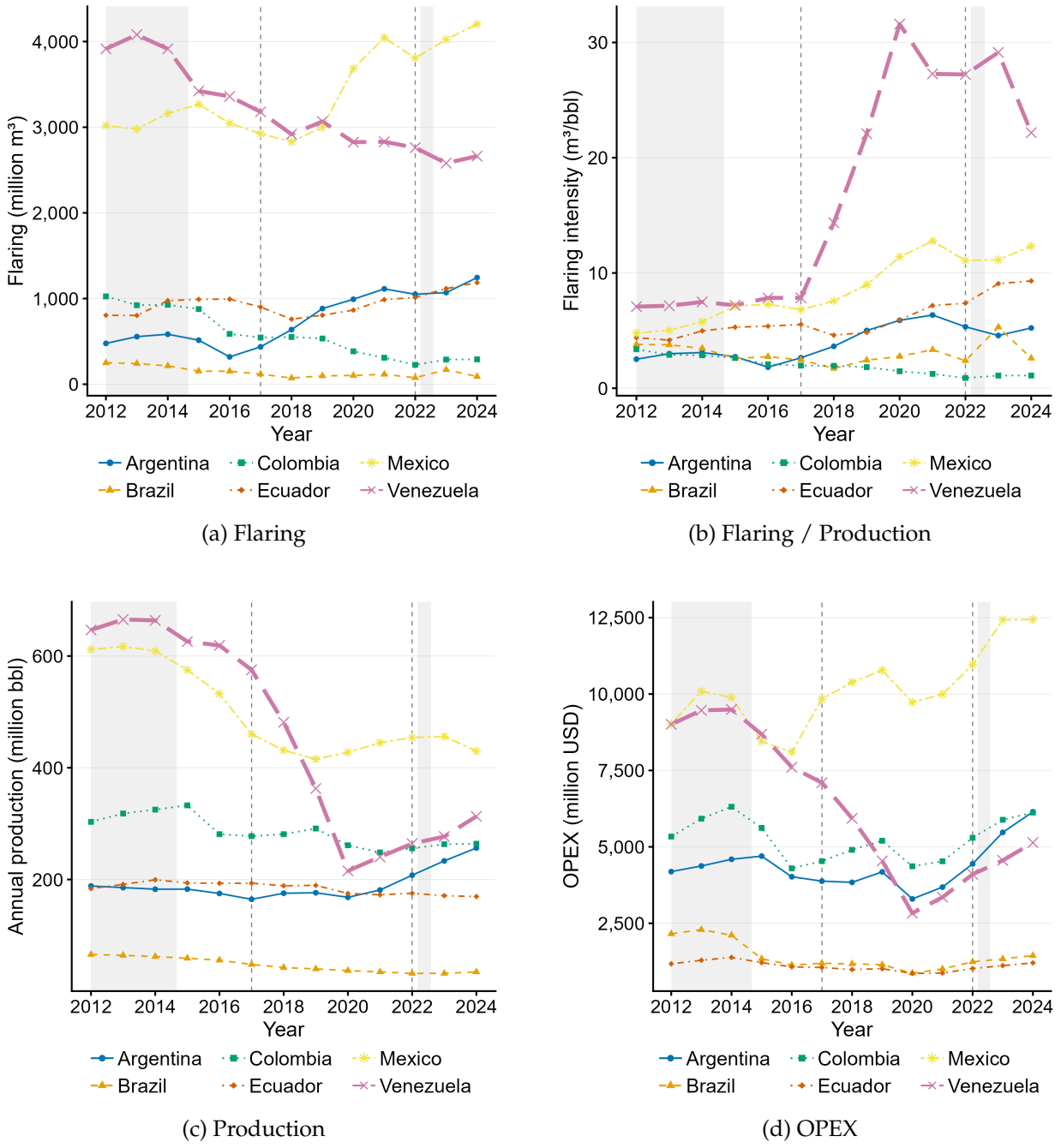


Notes: Each marker represents a Rystad Energy oil field in one of the six sample countries (Argentina, Brazil onshore, Colombia, Ecuador, Mexico, Venezuela). Marker color indicates the field's average annual flaring intensity (m^3/bbl), averaged over all field-years in 2012–2024, computed as allocated VIIRS flaring volume divided by annual crude oil production (15 km allocation radius). Source: Rystad Energy UCube; World Bank VIIRS Global Gas Flaring Tracker.

intensity, production, and OPEX by country: Venezuelan per-barrel intensity tripled, production collapsed, OPEX collapsed, and the pattern is unique to Venezuela.[8]

[8]Our six-country LATAM panel is approximately representative of the world's unsanctioned heavy-oil operating environments outside the Middle East: it includes the Mexican Maya basin, the Ecuadorean Oriente, and the Colombian Llanos. It does not cover Canadian oil sands, where the production process is very different, or Middle Eastern conventional crude.

Figure 2: Evolution of Flaring, Production, and Investment by Country



(a) Flaring

(b) Flaring / Production

(c) Production

(d) OPEX

Notes: Raw country-level aggregates (not regression-based) for the six sample countries, 2012–2024. Panel (a): total VIIRS flaring volume allocated to Rystad fields within a 15 km radius (million m^3). Panel (b): production-weighted mean flaring intensity (m^3/bbl, 15 km radius), winsorised at the 99.5th percentile. Panel (c): total annual crude oil production (million bbl). Panel (d): total annual operational expenditure (million USD). Brazil restricted to onshore fields. Vertical dashed lines indicate 2018 (first full year of financial sanctions) and 2022 (OFAC General Licence 41 granted to Chevron). Gray shaded bars indicate periods when the Brent crude oil price exceeds $100/barrel. Source: Rystad Energy UCube; World Bank VIIRS Global Gas Flaring Tracker.

Table 1: Descriptive Statistics

	Argentina	Brazil	Colombia	Ecuador	Mexico	Venezuela
Panel (a): Geology & Reservoir						
Water depth (m)	520.8 (540.3)	134.0 (161.6)	410.3 (829.1)	336.8 (388.5)	-146.1 (808.3)	111.0 (173.4)
Reservoir depth (m)	1872.1 (767.7)	1427.8 (736.8)	2446.3 (1235.9)	2572.5 (650.7)	3219.1 (1902.0)	2293.2 (1137.6)
Porosity (%)	7.6 (8.6)	2.8 (6.4)	6.5 (8.8)	18.2 (3.2)	4.2 (7.0)	9.8 (12.7)
Temperature (°C)	60.4 (19.2)	50.3 (18.5)	74.2 (27.2)	78.9 (16.7)	88.1 (37.5)	72.3 (36.1)
OOIP (million bbl)	106.9 (529.5)	14.7 (127.7)	63.8 (460.8)	224.8 (764.0)	130.8 (840.6)	1016.6 (5248.7)
Recovery factor (%)	35.1 (13.9)	31.7 (20.5)	28.5 (12.3)	24.7 (7.8)	45.7 (236.3)	32.1 (14.7)
Panel (b): Production & Economics (pre-period mean)						
Production (kbbl/d)	0.4 (1.7)	0.1 (0.9)	0.6 (5.7)	2.0 (7.1)	1.1 (12.3)	3.9 (20.3)
OPEX (M USD)	4.8 (21.2)	1.3 (10.8)	4.8 (42.3)	4.7 (16.2)	6.0 (52.4)	18.2 (87.8)
CAPEX (M USD)	6.9 (32.6)	1.0 (6.3)	5.0 (35.2)	9.1 (34.9)	6.1 (45.5)	14.0 (62.9)
NOC ownership share (%)	25.1 (40.8)	23.9 (42.0)	20.4 (36.7)	38.8 (47.7)	24.7 (42.7)	51.5 (41.3)
Panel (c): Field Counts						
Number of fields	1,313	1,502	1,455	265	2,132	666
Share onshore (%)	91.2%	100.0%	95.3%	95.8%	66.5%	79.9%
Panel (d): Flaring (pre-period mean, matched fields)						
Flaring intensity, 7.5 km (m^3/bbl)	48.2 (209.6)	15.3 (32.7)	25.2 (116.6)	19.3 (142.6)	63.8 (263.3)	310.8 (633.6)
Flaring intensity, 15 km (m^3/bbl)	36.3 (192.4)	28.8 (64.0)	17.6 (97.6)	14.5 (120.8)	52.3 (235.7)	195.6 (548.1)
Flaring volume, 7.5 km (M m^3)	3.4 (8.9)	6.4 (17.9)	9.9 (14.9)	22.0 (40.1)	41.8 (106.4)	110.6 (277.4)
Flaring volume, 15 km (M m^3)	2.3 (7.0)	4.5 (14.2)	7.0 (13.4)	15.8 (35.9)	30.7 (90.8)	85.7 (274.2)

Notes: Panel (a) reports field-level geological characteristics from Rystad Energy. Panel (b) reports pre-period (2012–2016) field-year averages. Standard deviations in parentheses. NOC ownership share is the top-owner share when the top owner is the national oil company (PDVSA, YPF, Petrobras, Ecopetrol, EP Petroecuador, Pemex), zero otherwise. Panel (c) counts all fields in the Rystad upstream database for each country. Panel (d) conditions on fields with positive flaring (matched subsample) during the pre-period. Brazil includes onshore fields only; Mexico includes all fields.

Where the rise concentrates. Table 2 sharpens the picture with a Venezuela × Post difference-in-differences run separately on heavy and non-heavy fields against the five LATAM controls. At heavy fields, per-barrel flaring rises by $+125.1$ m^3/bbl on a pre-period mean of 56.5 ($p < 0.01$, col. 4): roughly a tripling. Production falls 48% and OPEX falls 46% (cols. 5–6, both $p < 0.01$). At non-heavy fields the flaring-intensity coefficient is indistinguishable from zero. The per-barrel pollution rise sits *inside* the heavy operations, at the fields where production is collapsing and operating spend is being cut. What drives it? The rest of the paper decomposes this gap into three channels: which fields keep operating (*composition*), how they are run (*maintenance*), and how hard each is pushed relative to its design capacity (*strain*).

What drives this rise? The rest of the paper decomposes it into three channels: composition, strain, and maintenance.

4.2 Other data sources

Atmospheric methane (TROPOMI). Sentinel-5P TROPOMI provides daily column-averaged dry-air methane mixing ratios (XCH_4) at native pixels of $\approx 5.5 \times 7$ km (Lorente et al., 2021). We use the operational bias-corrected gridded product, aggregated to monthly L3 composites at 0.05° resolution and projected to a regular 10×10 km analysis grid covering November 2018 through

Table 2: Sanctions Effects by Crude Oil Heaviness

Dependent Vars:	Flaring Vol. 7.5km (1)	Flaring Vol. 15km (2)	Flaring Int. 7.5km (3)	Flaring Int. 15km (4)	Prod. (log) (5)	OPEX (log) (6)	CAPEX (log) (7)	Cum. CAPEX (log) (8)
Heavy oil (Venezuela) × Post	-5.9228	-2.0061	176.6656***	125.0990***	-0.6578***	-0.6130***	-0.4037	-0.4008***
	(10.9280)	(6.8320)	(59.0852)	(47.0277)	(0.1463)	(0.1482)	(0.3240)	(0.1541)
Non-heavy oil (Venezuela) × Post	-35.3138**	-19.8566	-37.5629	-0.8748	-0.7207	-0.4529	-0.4993	-0.5664***
	(16.8961)	(18.7968)	(46.5616)	(11.9262)	(0.5139)	(0.3739)	(1.0925)	(0.1145)
Fixed effects								
Asset	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Mean dept. var.	29.8540	22.0782	76.9685	55.9316	12.0406	14.9673	12.7102	14.8554
Observations	5,023	7,795	5,023	7,795	11,983	11,983	11,983	11,983
Fields	772	1,097	772	1,097	1,097	1,097	1,097	1,097
R^2	0.90678	0.93667	0.68533	0.67789	0.86183	0.83241	0.65119	0.91986

Notes: This table tests heterogeneity in the sanctions effect by crude oil heaviness, interacting Post with indicators for heavy and non-heavy Venezuelan fields (regression (3)). Sample: six LATAM countries (Argentina, Brazil onshore, Colombia, Ecuador, Mexico, Venezuela), 2012–2024, field-year level. Post $= \mathbb{1}\{\text{year} \geq 2017\}$. VEN Heavy: fields in the Orinoco Belt (East Venezuela Basin or Llanos) or with heavy crude share $> 50\%$ (Extra Heavy, Heavy 15–19, Heavy 20–22, Bitumen). VEN Non-Heavy: remaining Venezuelan fields. Reference group: non-Venezuelan LATAM fields. Cols (1)–(2): allocated flaring volume (million m^3). Cols (3)–(4): flaring intensity (m^3/bbl), winsorized at the 99.5th percentile. Col (5): log(1 + crude production in bbl). Col (6): log(1 + OPEX in USD). Cols (7)–(8): log(1 + CAPEX in USD) and log(1 + cumulative CAPEX in USD). Cols (1) and (3) restrict to field-years with positive flaring at 7.5 km; Cols (2) and (4) at 15 km; Cols (5)–(8) use the full sample. All models include field and year fixed effects. Standard errors clustered at the asset level in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. Source: Rystad Energy; World Bank VIIRS.

December 2024. The body strain regression (eq. 5) is run on the 1,280 Venezuelan cells with a Rystad field within 15 km of the cell centroid; the appendix extends to the full six-country grid (2,588,253 cell-months, 72,439 cells). We use L3 rather than L2 to obtain a complete monthly cell-level panel; Online Appendix E documents the choice, and Appendix E.6 compares our reduced-form approach with the atmospheric-inversion methodology of Nathan et al. (2024) and replicates their three central patterns in our L3 panel.

Biodiversity outcomes (eBird). We obtain $\approx$ 134,000 Venezuelan eBird checklists covering $\approx$ 1,500 analysis cells over 2012–2024, plus the broader LATAM panel for cross-country work. Each checklist supplies species richness, total abundance, and effort attributes (duration, distance, traveling indicator) that are used as controls. The citizen-science nature of eBird makes effort-control essential; observer fixed effects absorb cross-observer heterogeneity, with $\geq$2-checklist observers accounting for 99.8% of the OOIP-gradient sample and 98.9% of the Chevron sample (Appendix H).

Pipeline network (OSM + GEM). We union OpenStreetMap and Global Energy Monitor pipeline layers, deduplicating overlapping segments within 200 m. Venezuelan onshore oil pipelines total $\approx$ 3,400 km after restricting to crude service, matching the EIA benchmark; six-country combined coverage ranges from two-thirds to one-and-a-third of the CIA World Factbook total in each country, with Brazil's high ratio reflecting OSM's inclusion of gas-distribution networks the Factbook treats separately.

Spatial matching and identification overview. Each VIIRS flare detection is allocated to nearby Rystad fields by the two-stage algorithm above. TROPOMI cells and eBird checklists carry NearWell_d and NearPipe_d indicators for distance bands $d \in \{10, 20, 50, 100\}$ km, with the 20 km band as headline. The composition channel (Section 5) is a field-level difference-in-differences against the five-country LATAM control with field and year fixed effects, exploiting the within-Venezuela regional (Orinoco East / Maracaibo / Barinas / Other; the cell-level methane analysis in Appendix E.2 collapses Barinas into Other because of cell-count sparsity) and OOIP-tercile partitions. The strain channel (Section 6) is a within-Venezuela cell + year-month fixed-effects regression of log XCH_4 on log naphtha price interacted with NearPipe_d. The maintenance channel (Section 7) exploits the November 2022 Chevron OFAC General Licence 41 as a within-Venezuela between-operator event study on cells near Chevron versus other-Western-JV fields.

Ownership and operator categories. Venezuelan fields are partitioned by 2012–2016 baseline participation into six operator bins: Chevron joint-ventures (4 fields: PetroBoscan, PetroIndependencia, PetroIndependiente, PetroPiar), other Western majors (5), Chinese state operators (8: CNPC and Sinopec), Russian operators (11, primarily Rosneft), PDVSA full ownership (78), and other operators (38).

5 The composition channel

The composition channel predicts that when sanctions raise the fixed cost of operating, the surviving production base concentrates on assets that can absorb those fixed costs: large fields, heavy crude operations whose gas-handling equipment cannot easily be turned down, and operators with international maintenance access. We test the three margins in turn against the cross-country LATAM panel, using Argentina, Brazil onshore, Colombia, Ecuador, and Mexico as unsanctioned controls. Each margin uses the same Venezuela $\times$ Post difference-in-differences design as Table D1 (equations (2) and (3)) but varies the dependent variable to isolate the relevant compositional shift. The three subsections below cover (i) reallocation toward larger fields, (ii) reallocation toward heavier crude, and (iii) reallocation across operators.

5.1 Reallocation toward larger fields

The first composition margin is asset size. When fixed operating costs jump, small fields whose pre-sanctions margins barely covered flat costs exit first, while large fields can spread the same flat-cost burden across more barrels and remain profitable. The clean way to test this within Venezuela is to ask whether, after 2017, the producing-rate of small fields fell by more than the producing-rate of large fields. We estimate

$$\mathbb{1}\{\text{prod}_{it} > 0\} \;=\; \alpha_i + \tau_t + \beta\,(\text{Post}_t \cdot \text{Large}_i^s) + \varepsilon_{it}, \tag{2}$$

where i indexes Venezuelan fields, t calendar years over 2012–2024, $\text{Post}_t = \mathbb{1}\{t \geq 2017\}$, and Large_i^s is a time-invariant indicator that field i's pre-period (2012–2016) value of size measure s exceeds the Venezuelan pre-period median. We use two size measures $s \in \{\text{OOIP, mean pre-period production}\}$, and run each on three samples: the full Venezuelan ever-producing panel, the heavy-field subsample (Orinoco Belt or heavy-crude share above 50%), and the non-heavy subsample. Field fixed effects α_i absorb time-invariant heterogeneity (including Large_i^s itself); year fixed effects τ_t absorb common shocks (including Post_t and the 2014–2016 oil-price collapse). A field that exits contributes its post-period zeros and identifies β through the within-field producing-rate change. Standard errors are clustered at the asset level. The composition prediction is $\beta > 0$: large fields keep producing more often than small fields after sanctions.

Table 3 reports the estimates. The size-survival effect is concentrated in heavy fields: a 23 pp differential at heavy fields (col. 3, $\hat{\beta} = +0.234^{***}$), essentially zero at non-heavy fields (col. 5, $\hat{\beta} = +0.043$, n.s.). The fixed-cost shock that small fields cannot absorb operates only where production requires imported diluent. But heavy and non-heavy fields had similar pre-period flaring intensities (12.9 vs. 7.8 m^3/bbl), so this composition shift contributes negligibly to the per-barrel pollution rise. We show this formally in Section 8 (Figure 8): the composition channel adds $+0.004$ R-units against an observed $R \approx 3$.

Appendix Figure D1 reports the event-study version with year-by-year Post $\times$ Large coefficients

Table 3: Composition Channel within Venezuela: Producing-rate Change, Large vs. Small Fields, by Heaviness

	Full VEN		Heavy fields		Non-heavy fields	
Dependent variable: $\mathbb{1}\{\text{producing}\}$	Large by OOIP (1)	Large by pre-prod (2)	Large by OOIP (3)	Large by pre-prod (4)	Large by OOIP (5)	Large by pre-prod (6)
Post × Large (β)	0.203***	0.147***	0.234***	0.153***	0.043	0.021
	(0.041)	(0.042)	(0.047)	(0.048)	(0.053)	(0.053)
Mean dept. var.	0.821	0.821	0.807	0.807	0.893	0.893
Pre-flaring intensity (m^3/bbl)	12.5	12.5	12.9	12.9	7.8	7.8
Fixed effects						
Asset	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Observations	3,042	3,042	2,535	2,535	507	507

Notes: This table tests the composition channel within Venezuela, separately by crude heaviness. The specification is $\mathbb{1}\{\text{prod}_{it} > 0\} = \alpha_i + \tau_t + \beta\,(\text{Post}_t \cdot \text{Large}_i^s) + \varepsilon_{it}$ (equation (2)). Sample: ever-producing Venezuelan fields, 2012–2024. $\text{Post}_t = \mathbb{1}\{t \geq 2017\}$. Large_i^s is a time-invariant indicator that field i's pre-period (2012–2016) value of size measure s exceeds the Venezuelan pre-period median: OOIP (original-oil-in-place, MMbbl) for odd columns; mean pre-period annual crude production (bbl) for even columns. Cols (1)–(2): full Venezuelan ever-producing panel. Cols (3)–(4): restricted to heavy fields (Orinoco Belt or fields with heavy-crude share > 50%). Cols (5)–(6): restricted to non-heavy Venezuelan fields. Field fixed effects α_i absorb time-invariant heterogeneity (including Large_i^s); year fixed effects τ_t absorb common time shocks (including Post_t and the 2014–2016 oil-price collapse). *Mean dep. var.* is the panel proportion of field-years with positive production. *Pre-flaring intensity* is the production-weighted mean pre-period (2012–2016) flaring intensity in m^3/bbl, conditional on positive flaring. Standard errors clustered at the asset level in parentheses. ***p<0.01, **p<0.05, *p<0.1. Source: Rystad Energy UCube; World Bank VIIRS.

normalised to zero in 2016: the gap opens at 2017–2019 and widens through 2024, with no parallel-trends violation in the pre-period.

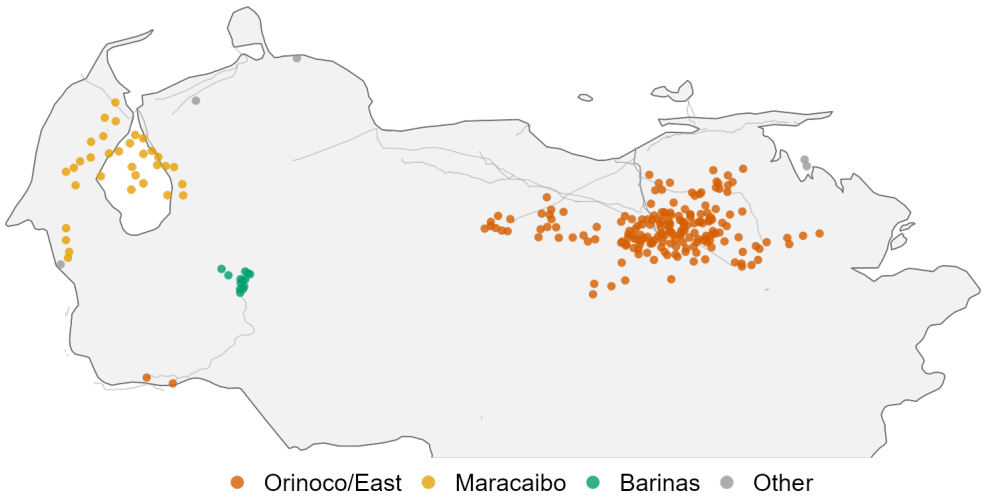
5.2 Reallocation toward heavier crude

The second composition margin is crude heaviness. Venezuelan upstream operations split into two very different gas-handling setups: the Orinoco Belt's 8–10° API extra-heavy crude must be blended with imported naphtha (a light hydrocarbon diluent) to flow through the pipelines and through the equipment that recovers the diluent for re-use, while the Maracaibo basin's medium-API operations need none of that machinery (Section 3). Sanctions cut the naphtha import flow, so the heavy operations should adjust much more sharply than the lighter ones.

In 2016, Venezuelan crude production was approximately 2.28 mbbl/d (Rystad UCube), distributed across the Orinoco extra-heavy belt, the Maracaibo medium-API basin, and a smaller residual of Barinas, eastern, and offshore fields. EIA / Monaldi et al. (2021) attribute roughly 51% of crude output to Orinoco, 30% to Maracaibo, and 19% to the residual at this peak; the Rystad panel we use throughout the regressions allocates production somewhat differently across regions, but the qualitative ordering (Orinoco largest, Maracaibo second, residual smallest) is the same.

By 2023, total production had fallen to approximately 0.78 mbbl/d, a $\approx$ 66% decline. Within Venezuela, the post-period reallocation favoured Orinoco: its share of the (smaller) total rose, while Maracaibo's share fell and the residual held roughly flat. The cross-region asymmetry is consistent with the heaviness-channel prediction: the basin hosting large high-cost fields whose gas-handling equipment cannot easily be turned down retained a disproportionate share, while the basin with smaller conventional fields cut production cleanly. Figure 3 maps the four Venezuelan regions used below.

Figure 3: Venezuelan Oil Fields by Geographic Region



Notes: Each marker represents a Venezuelan oil field with strictly positive crude production in at least one year of the 2012–2024 panel ($n = 234$ fields); fields that did not produce during the sample period are not shown. Fields are classified into four geographic regions based on the Rystad basin assignment: Orinoco/East (East Venezuela Basin and Llanos), Barinas, Maracaibo, and Other. Grey lines show oil and gas pipeline infrastructure from OpenStreetMap and the Global Energy Monitor. Source: Rystad Energy UCube; OpenStreetMap; Global Energy Monitor.

The cross-country regression test interacts Post with indicators for VEN-Heavy and VEN-Non-Heavy fields, where VEN-Heavy is defined as the Orinoco Belt or any Venezuelan field with heavy-crude share $> 50\%$:

$$Y_{ift} = \alpha_i + \tau_t + \beta_h(\text{VEN}_i^{\text{Heavy}} \times \text{Post}_t) + \beta_n(\text{VEN}_i^{\text{Non-Heavy}} \times \text{Post}_t) + \varepsilon_{ift}, \tag{3}$$

with reference category the non-Venezuelan LATAM control fields. The outcome Y_{ift} varies across the eight columns of Table 2: flaring volume at 7.5 km and 15 km, flaring intensity (m^3/bbl) at 7.5 km and 15 km, $\log(1 + \text{production})$, $\log(1 + \text{OPEX})$, $\log(1 + \text{CAPEX})$, and $\log(1 + \text{cumulative CAPEX})$. Field and year fixed effects and asset-clustered standard errors match equation (2); the sample is the six-country LATAM panel restricted to ever-flaring fields, with the per-DV

refinement that the flaring-volume and flaring-intensity columns are restricted to field-years with positive flaring at the relevant radius and the production / OPEX / CAPEX columns use the full ever-flaring sample.

Table 2 (Section 4.1) reports the heavy-vs-non-heavy difference-in-differences on flaring intensity, production, OPEX, and CAPEX. The heavy-vs-non-heavy asymmetry is sharp. At the 15 km flare-allocation radius, $\hat{\beta}_h = +125.1$ m^3/bbl ($p < 0.01$) at heavy Venezuelan fields against a pre-period mean of 56.5 m^3/bbl, roughly a tripling of per-barrel flaring; the non-heavy coefficient is statistically indistinguishable from zero ($\hat{\beta}_n = -0.87$, n.s.). Production and OPEX both fall by $\approx$ 46–48% at heavy fields; CAPEX shows a similar ordering but with wider standard errors. This is the empirical counterpart of the naphtha story laid out in Section 3: only fields whose gas-handling depends on imported naphtha are sharply affected.[9] Appendix Figure D2 reports the flaring-intensity event-study by Venezuelan geographic region together with the unsanctioned controls (Mexican Maya basin, Brazilian onshore): the Orinoco intensity break appears at 2017–2019; the Mexican Maya declines smoothly throughout under Cantarell reservoir maturation, a profile predicted by geology rather than by any policy shock; Brazilian onshore is approximately flat. Neither control replicates the Venezuelan break.

5.3 Reallocation across operators

The third composition margin is across operators. Venezuelan upstream operations are organised through joint ventures between PDVSA and international partners. International partners hold maintenance and procurement networks that PDVSA-only operations lack, and the value of those networks rises sharply when sanctions cut PDVSA's direct procurement access.

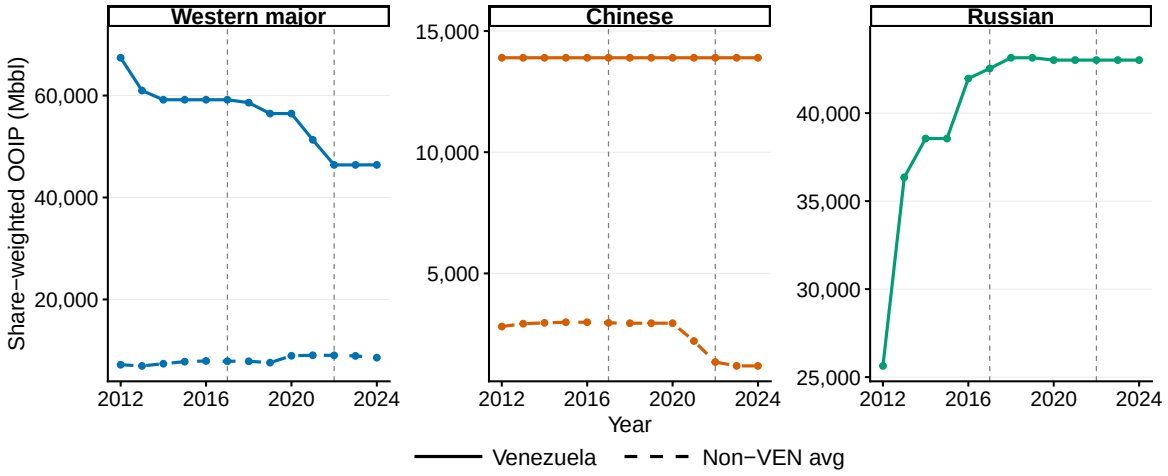
We allocate each field-year's oil-in-place and flaring volume to operators in proportion to their equity share, then sum within international-partner group. So a field that is 40% Rosneft and 60% PDVSA contributes 40% of its OOIP and 40% of its allocated VIIRS flaring to the Russian-partnered series each year. This avoids reclassification artefacts (e.g. a partner exit shifting a field's entire reserve base to a different bin overnight) and produces series that respond *discretely* to the named policy events (August 2017, E.O. 13808; and November 2022, OFAC General Licence 41 to Chevron), not gradually. Both figures restrict to the three international-partner groups (Western including Chevron, Chinese, Russian); the residual is held by PDVSA directly.

Figure 4 traces the share-weighted oil-in-place. Inside Venezuela, the Western-partnered reserve base falls steeply at 2017–2019 (the OFAC Section 5(b) wind-down that removes ConocoPhillips, ExxonMobil, and others) and only partially recovers from late 2022 with OFAC General Licence 41 to Chevron; the Russian-partnered reserve base rises smoothly from 2017 onward; and the Chinese-

[9] The unconditional Venezuela $\times$ Post DiD on the same outcomes, without the heavy/non-heavy split, is reported in Online Appendix Table D1. We use the heavy/non-heavy specification of equation (3) as the main-text table because the unconditional version pools two production regimes that respond very differently to the same policy shock. Inverse-probability-weighted versions of the heavy/non-heavy (Table F2) and ownership-group (Table F3) regressions, balancing Venezuelan fields against control-country fields on pre-period geological covariates, are reported in Appendix F; the estimates are qualitatively unchanged.

partnered reserve base is essentially *flat* throughout. The cross-country contrast is what stands out. Chinese-partnered reserves in the non-VEN LATAM controls (dashed line) decline visibly post-2017 as Chinese majors trim their LATAM exposure, while their Venezuelan reserves stay put. Russian-partnered fields are essentially absent from the non-VEN controls throughout the panel, so the entire Russian series is a within-Venezuela phenomenon. Together: Chinese partners did not exit Venezuela the way they exited the rest of LATAM, and Russian partners stepped into the equity gaps left by the Western wind-down.

Figure 4: Oil-in-Place by Ownership Group



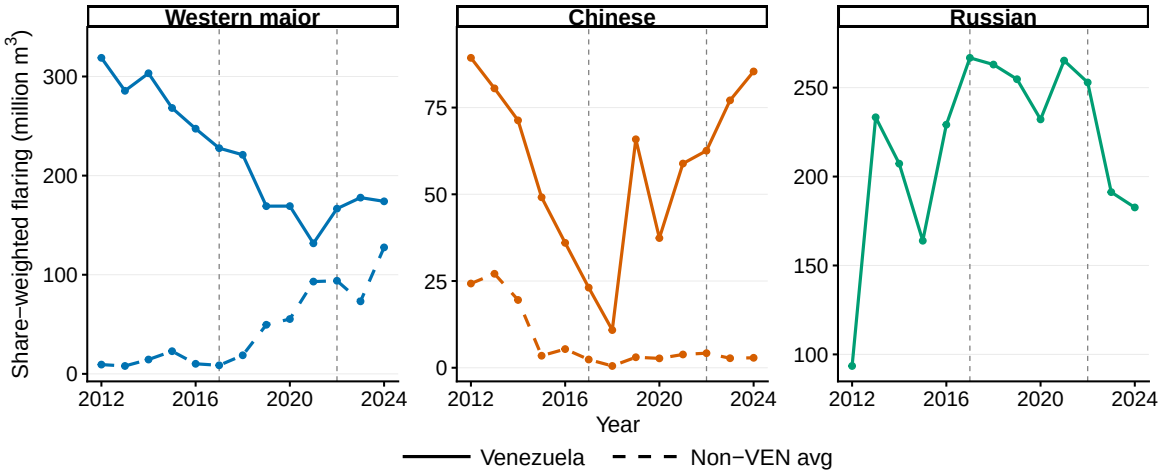
Notes: Share-weighted original oil-in-place (MMboe) attributed to each international-partner group, by year: Western majors (including Chevron, ExxonMobil, Shell, BP, Total, Eni, Equinor, ConocoPhillips, Repsol), Chinese (CNPC, CNOOC, Sinopec, PetroChina), and Russian (Rosneft, Gazprom, Lukoil). Solid lines: Venezuela; dashed lines: average across Argentina, Colombia, and Ecuador. The reserve base is apportioned in proportion to each operator's equity stake in each field-year, avoiding reclassification artifacts from discrete ownership changes. Vertical dashed lines indicate August 2017 (E.O. 13808) and November 2022 (OFAC General Licence 41 to Chevron). Source: Rystad Energy UCube.

Figure 5 repeats the share-weighting exercise for allocated VIIRS flaring volumes. The same equity-share rule applies: a field that is 40% Rosneft contributes 40% of its flaring to the Russian-partnered series each year. The patterns mirror Figure 4 on the equity side and amplify them on the emissions side. Russian-partnered flaring in Venezuela rises from $\approx$ 94 Mm^3 in 2012 to $\approx$ 183 Mm^3 by 2024, roughly doubling. Two forces compound to produce that doubling: the Russian-partnered *share* of Venezuelan reserves rises (Figure 4) through the post-2017 equity transfers as Western majors withdraw, and the Russian-partnered fields are heavily concentrated in the Orinoco Belt's extra-heavy operations (Petromonagas in particular), where per-barrel flaring intensity is high in absolute terms and rises sharply post-sanctions (Section 5.2). Russian-partnered flaring therefore rises through both the size and the heaviness margins already documented.[10] Chinese-partnered

[10]The geographic-clustering pattern behind these dynamics is sharp: among the 233 Venezuelan fields in the analysis sample, 91% of Russian-partnered fields, 100% of Chinese-partnered, 92% of Other-JV, 67% of Chevron, and 60% of Western-Major fields lie in the Orinoco extra-heavy region, against 95% for PDVSA-only fields. International JVs also concentrate among the largest, most capital-intensive heavy fields. Online Appendix Figure G1 maps each Venezuelan analysis-sample field by ownership bin and heavy-crude status. The collinearity between ownership, location, size,

Venezuelan flaring is roughly flat throughout. Western-partnered Venezuelan flaring falls during the 2017–2019 wind-down and recovers partially from late 2022 with Chevron's licence restoration. Outside Venezuela, the dashed lines tell their own stories that are unrelated to sanctions: Chinese-partnered flaring in the LATAM controls collapses (the same exit pattern visible in the OOIP figure), and Russian-partnered flaring is essentially zero throughout (no Russian joint ventures in the LATAM control countries).

Figure 5: Allocated Flaring Volume by Ownership Group



Notes: Share-weighted allocated VIIRS flaring volume (million m^3) attributed to each international-partner group, by year. The flaring volume of each field-year is allocated to operators in proportion to their equity stake (the same rule as Figure 4 applied to flaring instead of oil-in-place). Field-level flaring is the World Bank VIIRS allocation at the 15 km radius, restricted to Onshore fields and to the six LATAM countries. Solid lines: Venezuela; dashed lines: average across Argentina, Colombia, and Ecuador. Vertical dashed lines: August 2017 (E.O. 13808) and November 2022 (OFAC General Licence 41 to Chevron). Source: Rystad Energy UCube; World Bank VIIRS Global Gas Flaring Tracker. The corresponding flaring-intensity-by-owner panel (which divides through by share-weighted production) is reported in Online Appendix D.

The cross-country regression test interacts Post with each of four ownership-group indicators applied to Venezuelan fields:

$$Y_{ift} = \alpha_i + \tau_t + \sum_g \beta_g (\text{VEN}_i^g \times \text{Post}_t) + \varepsilon_{ift}, \tag{4}$$

with $g \in \{$PDVSA-only, Russian, Chinese, Chevron, Western Majors, Other (Venezuela)$\}$, ownership bins assigned using 2012–2016 baseline participation shares with the precedence rule of Table 4, and reference category the non-VEN LATAM fields. Field and year fixed effects and asset-clustered standard errors match equation (2); the sample is the ever-flaring six-country panel of equation (3) intersected with the geo-classification sample used to define the ownership bins.

Table 4 reports the estimates. The flaring-intensity rise and production decline concentrate at PDVSA-only fields and at Western-partnered fields during the 2017–2019 wind-down; Russian

and heaviness motivates the size-by-ownership decomposition in Online Appendix G, which holds size fixed and asks whether joint-venture giants behave differently from PDVSA-sole giants.

Table 4: Sanctions Effects by Ownership Group

Dependent Vars:	Flaring Vol. 7.5km (1)	Flaring Vol. 15km (2)	Flaring Int. 7.5km (3)	Flaring Int. 15km (4)	Prod. (log) (5)	OPEX (log) (6)	CAPEX (log) (7)	Cum. CAPEX (log) (8)
PDVSA × Post	-5.1397	8.3450	133.9061**	89.4193	0.0023	0.1308	0.4462	-0.5996***
	(17.0493)	(9.6604)	(67.8889)	(56.0294)	(0.0748)	(0.0987)	(0.3084)	(0.0971)
Russia × Post	2.5803	-5.9854	248.0255**	265.8159**	-0.8476**	-1.3402***	0.8826***	-0.8511***
	(21.9990)	(13.2023)	(116.6912)	(128.9822)	(0.3644)	(0.3659)	(0.2981)	(0.1626)
China × Post	-6.0258	-6.0490	1.8926	-13.7759	-2.5627**	-2.3789**	-3.0399	0.7171
	(6.8535)	(3.7854)	(25.1289)	(9.7026)	(1.1600)	(1.0289)	(2.0415)	(0.8311)
Chevron × Post	-0.2433	-76.1697	-21.4096**	-22.5433***	0.2548	0.0594	0.1413	-0.3162
	(2.6263)	(55.2103)	(9.0177)	(6.7081)	(0.4019)	(0.4070)	(0.2855)	(0.2019)
Western Majors × Post	-13.3526	-11.8381	350.2150	290.0557	-0.4529	-0.5995*	-3.4294**	-0.4695***
	(30.0468)	(24.3866)	(304.5394)	(261.8658)	(0.4289)	(0.3210)	(1.6041)	(0.0841)
Other (Venezuela) × Post	-30.0564**	-17.2802**	152.9799	130.4584	-1.9304***	-1.8506***	-1.8807**	-0.1400
	(11.8059)	(6.8386)	(148.7432)	(107.2288)	(0.3620)	(0.3302)	(0.7387)	(0.4645)
Fixed effects								
Asset	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Mean dept. var.	29.8540	22.0782	76.9685	55.9316	12.0406	14.9673	12.7102	14.8554
Observations	5,023	7,795	5,023	7,795	11,983	11,983	11,983	11,983
Fields	772	1,097	772	1,097	1,097	1,097	1,097	1,097
R^2	0.90686	0.93713	0.68611	0.67933	0.86573	0.83661	0.65263	0.92003

Notes: This table tests heterogeneity in the sanctions effect by ownership group, interacting Post with indicators for six Venezuelan ownership bins (regression (3)). Sample: six LATAM countries (Argentina, Brazil onshore, Colombia, Ecuador, Mexico, Venezuela), 2012–2024, field-year level. Post $= \mathbb{1}\{\text{year} \geq 2017\}$. Ownership bins are assigned using pre-2017 baseline participation shares with the following precedence: PDVSA ($\geq$ 99% PDVSA participation), Russia, China, Chevron, Western Majors, Other (any firm from each group $>$ 0%). Reference group: non-Venezuelan LATAM fields. Cols (1)–(2): allocated flaring volume (million m^3). Cols (3)–(4): flaring intensity (m^3/bbl), winsorized at the 99.5th percentile. Col (5): log(1 + crude production in bbl). Col (6): log(1 + OPEX in USD). Cols (7)–(8): log(1 + CAPEX in USD) and log(1 + cumulative CAPEX in USD). Cols (1) and (3) restrict to field-years with positive flaring at 7.5 km; Cols (2) and (4) at 15 km; Cols (5)–(8) use the full sample. All models include field and year fixed effects. Standard errors clustered at the asset level in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. Source: Rystad Energy; World Bank VIIRS.

and Chinese partnered fields show smaller production declines, consistent with their international partners maintaining procurement access. The Chevron license restoration in November 2022 reverses the Western-partnered decline at the four Chevron joint ventures (PetroPiar, PetroBoscan, PetroIndependiente, PetroIndependencia). We exploit this November 2022 shock as a within-Venezuelan, within-firm quasi-experiment in Section 7. Appendix Figure D3 reports the event-study dynamics by ownership group, showing the same ordering and confirming flat pre-trends.

6 The strain channel: methane and biodiversity

The strain channel predicts that surviving fields, pushed closer to the maximum throughput their gas-handling equipment was designed for, vent and leak more gas per barrel. The diagnostic is *atmospheric methane*: when a heavy-oil gathering system overloads, gas that the system can no longer route to a sales pipeline, reinjection compressor, or upgrader feed escapes through flange leaks, vapour-recovery bypasses, and emergency vents (Marks, 2022). Methane is the right outcome for two reasons. First, venting produces no thermal anomaly, so VIIRS flare-detection (the central outcome of Section 5) *misses* it; only the column-averaged atmospheric concentration shows it. Second, methane is the proximate non-CO_2 greenhouse gas in the social cost of carbon literature (International Energy Agency, 2024; Plant et al., 2022), so the magnitude maps directly into externality-equivalent dollars.

We measure methane with TROPOMI, using the same 10×10 km analysis grid and pipeline-distance classification defined in Section 4.2. Restricted to Venezuela, the regression sample comprises 25,520 cell-months spanning 1,280 analysis cells over November 2018 through December 2024 (Veefkind et al., 2012).[11]

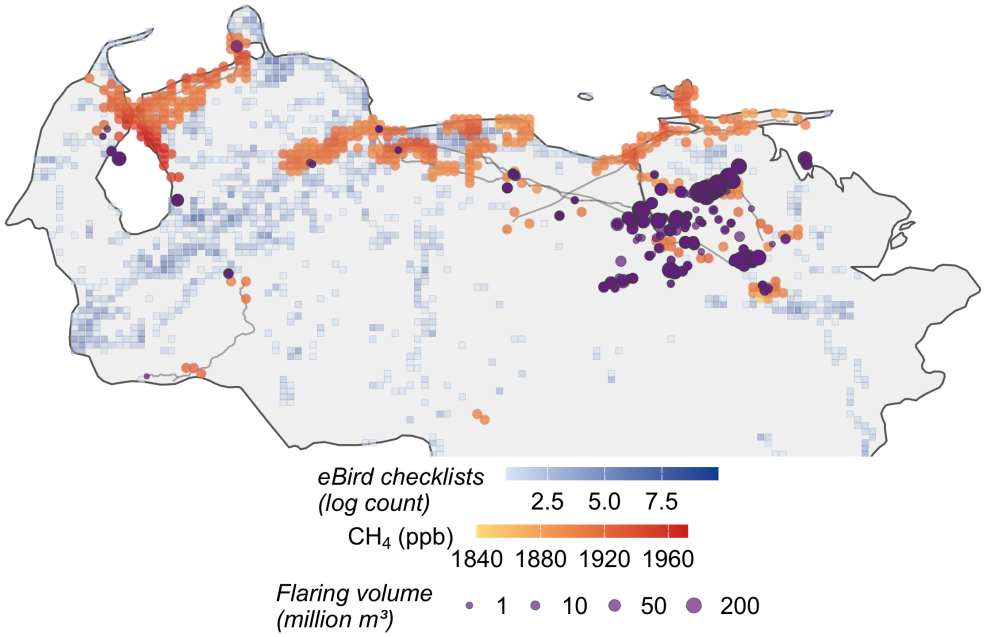
Figure 6 shows the geography on which the analysis runs. The black lines are oil and gas pipelines, the yellow-to-red circles are mean cell-level XCH_4 over 2018–2024 (brighter shades = higher concentrations), and the purple circles are NASA FIRMS VIIRS active-fire detections (the flare sites). The pipeline corridors trace the path between Maracaibo oilfields, the Orinoco Belt heavy-oil operations, refineries, and export terminals; methane hotspots co-locate with the corridors and especially with wellhead clusters in the Orinoco Belt and around Lake Maracaibo. The biodiversity sample we use later in this section (Venezuelan eBird checklists; sample statistics in Online Appendix H, Table H1) is concentrated in the populated north and along the same pipeline corridors, so cell-level pollution exposure varies sharply across cells while ecological observations are dense enough to support cell-month identification.

6.1 Exploiting high-frequency response to naphtha-price shocks

To identify the diluent channel cleanly, we use the spot price of naphtha on the US Gulf Coast (Venezuela's pre-sanctions diluent supplier) as a high-frequency, exogenous proxy for diluent

[11] Online Appendix E documents the L2-versus-L3 choice, the cell-grid construction, our use of the bias-corrected product, and a side-by-side comparison with the atmospheric-inversion methodology of Nathan et al. (2024).

Figure 6: Pipelines, methane, and flare detections in Venezuela



Notes: Black lines: oil and gas pipelines from the combined OSM+GEM network. Yellow-to-red circles: cell-level mean TROPOMI XCH_4 (column-averaged dry-air methane) over 2018–2024, brighter shades indicating higher concentrations. Purple circles: NASA FIRMS VIIRS S-NPP active-fire detections retained as flare sites (types 2 and 3). Source: ESA Sentinel-5P TROPOMI; NASA FIRMS; OpenStreetMap; Global Energy Monitor.

scarcity. If diluent dependence is the channel through which sanctions raise methane, Orinoco pipeline-vicinity methane should respond month-to-month to naphtha-price shocks, and Maracaibo methane should not.

We estimate, on the Venezuelan Orinoco cell-month sample, the contemporaneous-elasticity specification

$$\log \mathrm{XCH}_{4ct} \;=\; \alpha_c + \tau_t + \theta_0 \, \log \mathrm{NaphthaPrice}_t \cdot \mathrm{NearPipe}_c + \varepsilon_{ct}, \tag{5}$$

with cell and year-month fixed effects, which gives $\hat{\theta}_0 = +3.05$ ($p = 0.001$): a one-log-point rise in the spot price of naphtha is associated with a 3-log-point rise in Orinoco pipeline-vicinity methane in the same month. A lag-extended version that re-estimates the regression at each of the 1-, 2-, and 3-month lags of log naphtha price (reported in Online Appendix Table E2) yields positive and statistically significant coefficients at every horizon (between +2.1 and +3.1, all $p < 0.05$), so the contemporaneous elasticity is not driven by single-month timing.

In Maracaibo, where conventional crude does not require naphtha blending, the same interaction is negative at short radii and unstable across distance bands. We interpret this placebo pattern as evidence that the Orinoco response is not a generic hydrocarbon-price effect: conditional on common monthly shocks, higher naphtha prices raise methane only where naphtha is a binding physical input. In conventional Maracaibo operations, higher naphtha prices instead appear to

coincide with lower relative pipeline activity, consistent with production being easier to scale down without overloading the gas-handling chain. The full basin-by-distance results are in Table 5.

Table 5: TROPOMI CH_4: naphtha price × pipeline proximity

	(1) $d = 10$ km	(2) $d = 20$ km	(3) $d = 50$ km	(4) $d = 100$ km
Panel A: Naphtha price × pipeline proximity (all Venezuela)				
log(Naphtha) × NearPipe	0.5427	0.5974	0.2182	-0.4255
	(0.7463)	(0.6140)	(0.5159)	(0.6446)
Observations	25,520	25,520	25,520	25,520
Panel B: Naphtha price × pipeline proximity (Orinoco only)				
log(Naphtha) × NearPipe	2.6774**	3.0533***	2.5254***	0.0002
	(1.1093)	(0.9072)	(0.8361)	(0.9557)
Observations	9,124	9,124	9,124	9,124
Panel C: Naphtha price × pipeline proximity (Maracaibo only)				
log(Naphtha) × NearPipe	-2.5638*	-3.6105**	0.0145	-1.3035
	(1.4016)	(1.5284)	(1.3425)	(1.5904)
Observations	4,218	4,218	4,218	4,218
Cell FE	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓

Notes: This table tests whether global naphtha prices differentially affect methane concentrations near pipeline infrastructure. Sample: Venezuelan 10 km grid cells, 2018–2024, cell-month level. The dependent variable is $\log(\mathrm{XCH_4})$, where $\mathrm{XCH_4}$ is the column-averaged dry-air methane mole fraction (ppb) from TROPOMI; all estimates and standard errors are multiplied by 1,000 for readability. Each column corresponds to a different pipeline proximity threshold d. Panel A estimates the pooled naphtha–proximity interaction across all Venezuelan cells. Panel B restricts the sample to the Orinoco Belt, where extra-heavy crude requires naphtha diluent. Panel C restricts to the Maracaibo Basin, which produces lighter crude that does not require naphtha blending. Naphtha: NAF-C-NWE CIF NW Europe spot ($/tonne, monthly average from Refinitiv). All specifications include cell and year-month fixed effects. Standard errors clustered at the cell level in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. Source: ESA Sentinel-5P TROPOMI; Refinitiv; OpenStreetMap.

The naphtha-price test sharpens the trend regression in two ways. First, naphtha prices vary at monthly frequency for reasons orthogonal to Venezuelan oil policy (US Gulf refining, global naphtha demand), so the elasticity is identified off variation that is plausibly exogenous to Venezuela. Second, the prediction is sign-asymmetric across regions in exactly the way the diluent-dependence physics implies: Orinoco responds, Maracaibo does not. Cumulating the elasticity over the post-2018 sanctions window implies a $\approx 0.8\%$ uplift in atmospheric methane near Venezuelan pipelines by 2024 (a year-by-year event-study version of equation (5) yields the same total at calendar-year, semi-annual, and quarterly aggregations). The methane magnitude is reported alongside R in Section 8 as a direction-of-effect confirmation rather than folded into R numerically: the TROPOMI record begins only in November 2018, so there is no clean pre-sanctions methane baseline against

which to scale the post-sanctions level, and R is consequently quantified on flaring intensity alone.

6.2 Biodiversity outcomes

To check whether the methane signal we just documented translates into ecological damage at the spatial scale at which households live, we use citizen-science bird observations from eBird, the Cornell Lab of Ornithology platform whose Venezuelan coverage runs to $\approx$ 134,000 checklists across 1,508 unique 10 km grid cells over 2012–2024 (Sullivan et al., 2014).[12] For each checklist we record *species richness* (count of unique species) and *log abundance* (log 1 + total individuals).

The natural test runs a horse race between the two pollutants that the conceptual framework predicts should drive ecological damage. Composition (Section 5) operates through field-level flaring, which is observable from VIIRS as fire radiative power. Strain (this section) operates through methane and the volatile organics that co-emit with it, observable from TROPOMI as XCH_4. The two pollutants are imperfectly correlated within Venezuela because they map to different stages of gas-handling failure: VIIRS picks up flare-stack combustion; TROPOMI integrates flare incompleteness, venting, and pipeline leakage. Running both on bird outcomes simultaneously isolates which margin matters at which spatial scale.

We estimate, on Venezuelan eBird checklists 2018–2024,

$$Y_{ict} \;=\; \alpha_i + \tau_t + \mu_{b(i),t} + \beta_{\mathrm{CH_4}}\, \log(1+\mathrm{CH_4})_{i,R} + \beta_{\mathrm{F}}\, \log(1+\mathrm{Flare})_{i,R} + \mathbf{X}'_{ict}\boldsymbol{\delta} + \varepsilon_{ict}, \tag{6}$$

where Y_{ict} is log(1 + abundance) (cols 1–3) or species richness (cols 4–6); $\log(1+\mathrm{CH_4})$ and $\log(1+\mathrm{Flare})$ are z-standardised within sample; $\mathrm{CH_4}$ and Flare are aggregated within radius $R \in \{25, 50, 75\}$ km of cell i; α_i is a cell fixed effect, τ_t a year-month fixed effect, and $\mu_{b(i),t}$ a basin-by-year-month fixed effect that absorbs basin-specific seasonal and trend variation. The controls $\mathbf{X}_{ict}$ collect checklist-level effort variables (log duration, log distance, number of observers, traveling indicator, hour and hour^2) together with the cell's proximity to Lake Maracaibo, $-\log(1+$ distance to Lake Maracaibo$)$, interacted with year and month indicators (a wetland control). Standard errors clustered at the cell level. A basin-interacted version of the same specification reports implied basin-specific slopes (Other / Orinoco / Maracaibo).

Table H3 (Appendix H) reports the estimates. The two pollutants act on different spatial scales.[13]

[12] Online Appendix H (Table H1) reports sample statistics: mean richness 13.7 species per checklist, median 11; mean log abundance 3.4. Checklist density is highest in the populated north and along the pipeline corridors mapped in Figure 6, providing the spatial overlap with TROPOMI and VIIRS that the regression below exploits. A natural concern with citizen-science data is that observer effort might covary with pollution exposure: if birders avoid (or seek) methane- or flare-heavy cells, the estimated pollution effect on biodiversity would be a selection artefact. We rule this out directly: regressing six standardised effort and coverage outcomes on $\log(1+\mathrm{CH_4})$ and $\log(1+\mathrm{VIIRS\ flare})$ at the $R = 50$ km buffer used below, with cell and year-month fixed effects, all twelve coefficients are individually insignificant (largest $|t| = 1.22$). Pollution exposure does not predict observer effort, so the richness and abundance results below are not selection-driven (Online Appendix Table H6).

[13] Methane is a long-lived gas (lasting approximately 12 years in the atmosphere) that mixes regionally, so its impact on birds shows up out to 75 km from the source. The other pollutants released by flaring — smoke particles (specks of black carbon from incomplete burning), reactive nitrogen compounds (formed at the high flame temperatures), and unburnt hydrocarbon vapours — react quickly and settle out of the air within hours to days, so the bird damage they

VIIRS flaring matters most at $R = 25$ km, the close radius where direct flare-stack disturbance localises: a one-standard-deviation rise in log VIIRS flare is associated with 0.05 log units lower abundance ($p < 0.05$) and roughly three-quarters of a species fewer ($p < 0.01$). At $R = 50$ km the VIIRS signal attenuates and the methane signal takes over: a one-standard-deviation rise in log CH_4 is associated with 0.030 log units lower abundance ($p < 0.01$) and roughly a third of a species fewer ($p < 0.01$); at $R = 75$ km the CH_4 abundance effect attenuates further (-0.021, $p < 0.10$) while the richness effect remains (-0.334, $p < 0.05$). Both effects concentrate in the Orinoco basin (Panel B): Orinoco-specific slopes are uniformly negative across radii, with the CH_4 coefficients on richness and abundance significant at $p < 0.05$ at every R and the VIIRS coefficients significant at the close $R = 25$ radius where flare-stack disturbance localises. The horse race therefore reads as complementary rather than substitute: the composition channel of Section 5 appears in the close-radius VIIRS effect, and the strain channel of this section appears in the larger-radius CH_4 effect, and both bite hardest at the heavy operations in Orinoco where the mechanisms come together.

Bird-relocation test. A second concern is whether the pollution-biodiversity association reflects birds physically relocating away from polluted cells rather than dying or failing to recruit. To distinguish the two we estimate a triple-difference of cell-year mean richness on POST × VEN × FAR using Colombia as the placebo country.[14] Under the relocation hypothesis the triple should be *positive and large*: displaced birds in Venezuela should crowd into far-from-oil cells, raising richness there relative to the corresponding far-from-oil cells in Colombia. We find $\hat{\beta}_3 = +0.39$ (SE $= 2.14$, $p = 0.85$), statistically indistinguishable from zero. The data therefore reject pure spatial relocation: there is no measurable net flow of birds from polluted to unpolluted Venezuelan cells over the post-sanctions period. The biodiversity reduction we estimate is consistent with population loss, not with birds moving next door.[15]

cause is concentrated within about 25 km of the flame.

[14]The estimating equation is

$$\overline{\text{richness}}_{cyt} = \alpha_c + \tau_y + \beta_1 (\text{POST}_y \cdot \text{VEN}_c) + \beta_2 (\text{POST}_y \cdot \text{FAR}_c) + \beta_3 (\text{POST}_y \cdot \text{VEN}_c \cdot \text{FAR}_c) + \varepsilon_{cy},$$

with $\overline{\text{richness}}_{cyt}$ = mean checklist species richness in cell c, year y; cell (α_c) and year (τ_y) fixed effects; $\text{POST}_y = \mathbb{1}\{y \geq 2017\}$; $\text{VEN}_c = \mathbb{1}\{\text{cell in Venezuela}\}$ (with Colombian cells as the placebo control); $\text{FAR}_c = \mathbb{1}\{\text{cell more than 10 km from any Rystad oil field}\}$. The coefficient of interest is the triple β_3. Standard errors clustered at the cell level. Under the relocation hypothesis $\beta_3 > 0$: displaced Venezuelan birds crowd into Venezuelan FAR cells, raising richness there relative to Colombian FAR cells.

[15]The triple-difference panel is restricted to Venezuela and Colombia, so it does not directly test long-haul overwater emigration to the Caribbean islands, Trinidad and Tobago, Guyana, or Brazil. We do not regard this as a serious alternative for our setting because the guilds that drive the Chevron-licence abundance gain (Section 7.2) are forest insectivores, granivores, and frugivores, mostly sedentary tropical residents whose flight stamina and behavioural repertoire do not include sustained overwater crossings. The one guild that does cross open water seasonally, waterbirds, shows small and statistically insignificant Chevron-licence coefficients. A complementary diagnostic using vegetation and land-cover controls (Hansen tree-cover loss; GHSL built-up indicators), reported in Online Appendix H, shows that the pollution-biodiversity association is not driven by differential habitat conversion. Together these diagnostics rule out the leading non-pollution explanations: local relocation, long-haul overwater emigration for the relevant species, and habitat conversion.

Strain at large fields: a complementary OOIP gradient. A third probe asks whether bird abundance is depressed near the largest surviving fields, where post-sanctions production concentrates and gas-handling runs closest to capacity. Regressing checklist-level log abundance on $\log(\text{OOIP})$ within 50 km, with observer fixed effects and the same effort controls as Table H3, the Orinoco-OOIP interaction is -0.054 ($p < 0.01$): a one-standard-deviation increase in $\log(\text{OOIP})$ corresponds to roughly 5% fewer birds. The Maracaibo gradient is similarly negative (-0.033, $p < 0.05$) but if anything attenuates over time as production at that basin collapses. Within-post-period trend tests are imprecise (pre-2020 eBird coverage is thin), so we treat this gradient as suggestive support for the strain channel rather than identifying evidence; full estimates appear in Online Appendix Table H2.

7 The maintenance channel: the Chevron license

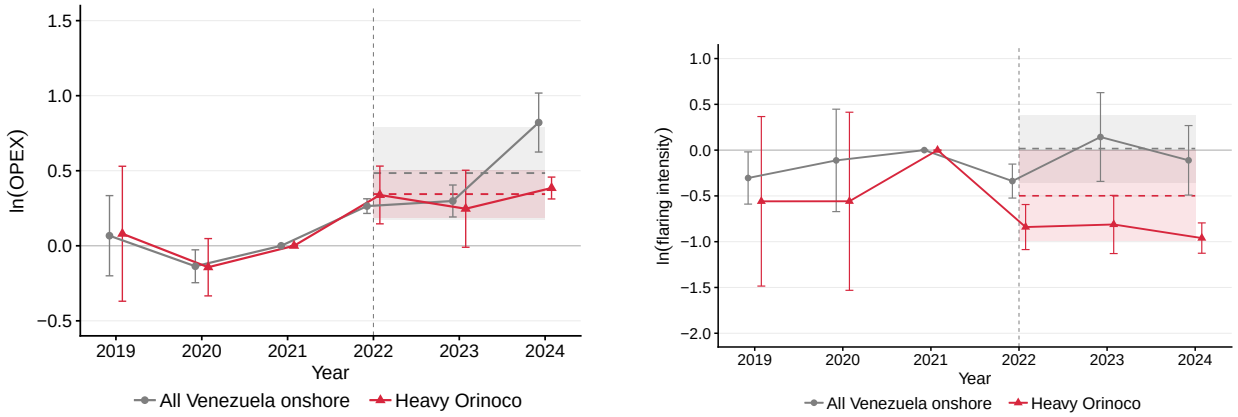
The maintenance channel predicts that sanctions raise per-barrel emissions at fields whose total production is unchanged or modestly changed, because operating expenditure on leak prevention, gas reinjection, and equipment turnover falls. We exploit one sharply dated relaxation of the maintenance constraint to identify this channel: OFAC General Licence 41, issued on 26 November 2022, which authorised Chevron specifically to resume operations and maintenance at four Venezuelan joint-ventures (PetroBoscan, PetroIndependencia, PetroIndependiente, and PetroPiar).[16] The licence reset Chevron's per-barrel OPEX to roughly its pre-sanctions level (Figure 7, Panel (a)) while sanctions remained in place at all other Venezuelan fields, generating quasi-experimental variation in maintenance spending that is not also variation in production volume.

We use *per-barrel* OPEX, $\log(1 + \text{OPEX}_{ft}/\text{Production}_{ft})$, as the maintenance regressor, scaled this way for two reasons. First, dollar OPEX correlates mechanically with field size; scaling by production isolates the per-barrel maintenance *intensity* that the channel is supposed to operate through. Second, because flaring and bird outcomes are also per-barrel objects, the elasticity η on $\log(\text{OPEX}/\text{prod})$ has a direct maintenance-channel interpretation. We saturate the specification with indicators for the two policy shocks, $\text{Post}\,2017_t = \mathbb{1}\{t \geq 2017\}$ (broad sanctions) and $\text{Post}\,2022_t = \mathbb{1}\{t \geq 2023\}$ (Chevron licence; we date Post 2022 to 2023 because the licence took effect in late November of that year), and a Chevron joint-venture indicator:

$$\begin{aligned} Y_{it} \;=\; & \alpha_i + \tau_t + \eta_0\, X_{it} + \eta_1\, X_{it} \cdot \text{Post}\,2017_t \\ & + \eta_2\, X_{it} \cdot \text{Post}\,2022_t + \eta_3\, X_{it} \cdot \text{Chevron}_i + \eta_4\, \text{Post}\,2022_t \cdot \text{Chevron}_i \\ & + \eta_5\, X_{it} \cdot \text{Post}\,2022_t \cdot \text{Chevron}_i + \varepsilon_{it}, \end{aligned} \tag{7}$$

[16] The body specification identifies η_5 off three of the four GL-41 joint-ventures, all operating heavy crude with vulnerable gas-handling chains: PetroPiar (VEF0028, Hamaca, Orinoco extra-heavy), PetroIndependencia (represented by VEF0466, Carabobo 5 Early, Orinoco extra-heavy), and PetroBoscan (VEF0082, Boscan, Maracaibo heavy with API around 10°). The fourth GL-41 partner, PetroIndependiente, appears in Rystad as the conventional medium-API Lake Maracaibo asset LL-652, classified as offshore; the diluent-strain mechanism the licence is supposed to relax does not operate at conventional fields (Section 6). Pooling PetroIndependiente into the treatment group nonetheless delivers a similar but smaller elasticity, as expected: $\eta_5 = -0.30$ instead of -0.42 (both $p < 0.001$).

Figure 7: Event Studies at Chevron Fields around the Nov 2022 Licence: OPEX and Flaring Intensity



(a) OPEX (ln)

(b) Flaring intensity (ln)

Notes: Event-study coefficients β_k from the field-year regression $Y_{ft} = \alpha_f + \tau_t + \sum_{k \neq -1} \beta_k \mathbb{1}\{t - 2022 = k\} \cdot \text{Chevron}_f + \varepsilon_{ft}$ on Venezuelan onshore field-years, 2017–2024. Reference year $k = -1$ (2021); vertical line marks the Nov 2022 Chevron licence. Field and year fixed effects throughout. **Panel (a):** dependent variable is log(OPEX in million USD); sample restricted to field-years with positive OPEX (N = 1,297 for All Venezuela onshore with 3 Chevron fields; N = 273 for Heavy Orinoco peers with 2 Chevron fields); standard errors clustered at the field level. **Panel (b):** dependent variable is log of winsorised flaring intensity (flaring vol./production); sample restricted to producing field-years (N = 1,318 for All Venezuela onshore with 3 Chevron fields; N = 278 for Heavy Orinoco peers with 2 Chevron fields); standard errors two-way clustered at the field and year level. In both panels, grey circles trace the All Venezuela onshore counterfactual and red triangles trace the Heavy Orinoco peer counterfactual; shaded bands report the pooled post-2022 ($k \geq 0$) Chevron × post effect with 95% CI. Source: Rystad Energy UCube; World Bank VIIRS.

where $X = \log(1 + \text{OPEX/prod})$, α_i is a field fixed effect, τ_t a year fixed effect, and Chevron = 1 at the GL-41 covered fields (PetroPiar, PetroBoscan, and PetroIndependencia). The maintenance coefficient is η_0 (the average within-field elasticity over 2012–2024); η_5 is the Chevron-licence-specific differential after November 2022. Standard errors are two-way clustered at the field and year level throughout the Chevron analysis.

7.1 OPEX intensity and flaring

Table 6 reports the saturated specification on flaring across four fixed-effect structures. Column (1) is the baseline field-plus-year FE specification. Column (2) adds a heavy-share×year linear trend that lets fields with higher heavy-oil content follow their own time path, addressing the concern that heavy and non-heavy fields might be drifting differentially. Column (3) replaces the heavy trend with an Orinoco-East×year linear trend, controlling for any basin-specific time trajectory at the Chevron-relevant geography. Column (4) substitutes operator fixed effects for field fixed effects, so that identification runs off within-year cross-operator variation rather than within-field within-time variation.

The headline coefficient is remarkably stable across the four specifications: $\eta_5 = -0.417^{***}$ (Col 1), $\eta_5 = -0.420^{**}$ (Col 2), $\eta_5 = -0.429^{***}$ (Col 3), $\eta_5 = -0.418^{***}$ (Col 4). At the covered fields,

Table 6: Maintenance Channel: Per-Barrel OPEX and Flaring Volume

	(1)	(2)	(3)	(4)
$\log(1 + \text{OPEX/prod})$ (η_0)	-0.0462*	-0.0459	-0.0430	-0.0296
	(0.0248)	(0.0259)	(0.0248)	(0.0578)
$\times$ Post2017 (η_1)	+0.0577*	+0.0552*	+0.0529*	+0.0058
	(0.0267)	(0.0277)	(0.0283)	(0.0160)
$\times$ Post2022 (η_2)	-0.0202***	-0.0154***	-0.0173***	-0.0685***
	(0.0043)	(0.0024)	(0.0037)	(0.0117)
$\times$ Chevron (η_3)	-0.8184	-0.9289	-0.8786	-0.1931
	(2.1854)	(2.1961)	(2.2128)	(1.8210)
$\times$ Post2022 $\times$ Chevron (η_5)	-0.4170***	-0.4196**	-0.4287***	-0.3115***
	(0.1274)	(0.1389)	(0.1289)	(0.0657)
Post2022 $\times$ Chevron (δ_2)	+1.5960***	+1.5583***	+1.6401***	+0.9537***
	(0.1013)	(0.0978)	(0.1029)	(0.1776)
Field FE	Yes	Yes	Yes	—
Owner-group FE	—	—	—	Yes
Year FE	Yes	Yes	Yes	Yes
Heavy share $\times$ Year	—	Yes	—	—
Orinoco-East $\times$ Year	—	—	Yes	—
Observations	2,344	2,344	2,344	2,332

Notes: Saturated triple-difference test of the maintenance channel on flaring volume. Dependent variable: $\log(1 + \text{flaring volume in million m}^3)$ at the field-year level. Sample: Venezuelan onshore field-years with positive production, 2012–2024. The four columns vary the fixed-effect structure: (1) field + year FE (baseline); (2) field + year FE + heavy-share$\times$year linear trend to allow heavy fields to follow a separate time path; (3) field + year FE + Orinoco-East$\times$year linear trend, controlling for Orinoco-specific time path; (4) owner-group FE rather than field FE, identifying off cross-owner-group within-year variation. The owner-group classification (Chevron, other-JV, PDVSA-sole, Russo–Chinese, Western Majors) is from the field-level ownership data and reflects equity stakes rather than the JV operator name. Chevron = 1 if the field is one of the GL-41 Chevron JVs (PetroPiar, PetroBoscan, PetroIndependencia). Standard errors two-way clustered at the field and year level. ***p<0.01, **p<0.05, *p<0.1. Source: Rystad Energy UCube; World Bank VIIRS Global Gas Flaring Tracker.

a one-log-point rise in per-barrel OPEX in the post-licence period reduces flaring volume by an additional $1 - \exp(\eta_5) \approx 34\%$, a doubling of OPEX ($\Delta \log = \log 2$) cuts flaring by approximately 25%, and the more easily interpretable 10 % increase in per-barrel OPEX ($\Delta \log \approx 0.095$) cuts flaring by about 4 %. The licence sharpens the maintenance-channel response at the very fields that received the maintenance-spending shock.

The within-field maintenance elasticity on flaring volume ($\eta_0 \approx -0.05$, marginal across columns) is negative and small, consistent with a Venezuela-wide baseline elasticity that is swamped by the licence-specific gain at Chevron fields.

Event study of flaring intensity at Chevron fields. The Chevron coefficient is identified off three GL-41 joint-ventures (two of them in the Orinoco extra-heavy belt: PetroPiar in Ameriven and PetroIndependencia in Carabobo 5; one in the Maracaibo basin: PetroBoscan). Because Orinoco fields are operationally distinct from Maracaibo fields (extra-heavy syncrude, high gas-oil-ratio,

infrastructure-intensive maintenance), we report an event-study analog of η_5 that traces log(flaring intensity) year-by-year at Chevron joint-ventures relative to two control sets: (i) heavy Orinoco peers operationally similar to PetroPiar and PetroIndependencia, and (ii) all Venezuelan onshore producing fields. The sample is restricted to producing field-years (production > 0) and outcomes are evaluated against the year immediately pre-licence ($k = -1, 2021$).

Panel (b) of Figure 7 reports the intensity result. Against heavy Orinoco peers (red), Chevron's flaring intensity drops by $\approx$ 0.8–0.9 log points (corresponding to a roughly 60% reduction in flaring per barrel) within the licence year and stays at that level through 2024. Against the All Venezuela counterfactual (blue), the gap is essentially zero on average post-licence, because the all-Venezuela control pool mixes operationally heterogeneous fields and dilutes the heavy-oil maintenance margin where the licence bites. The size of the licence-period gap in red, and its near-immediate appearance in 2022 (suggestive of pre-licence anticipation as government–Chevron talks advanced through 2022), is the event-time analog of the maintenance elasticity η_5 in Table 6.

Bird abundance and species richness. The maintenance shock at Chevron fields also propagates to local biodiversity outcomes. The bird-side counterpart of Table 6, reported in Online Appendix Table H4, runs the same triple-interaction specification on log abundance and log richness at eBird checklists within 30 km of a Chevron JV. The post-2022$\times$Chevron coefficient on abundance is positive, stable across three FE structures ($+1.64$ Cell+YM, $+1.44$ Cell+YM+Obs, $+1.64$ Cell+YM+Obs$\times$Yr) and significant ($p \leq 0.06$); the corresponding richness coefficients are directionally positive but not statistically significant under any FE structure. The pattern is consistent with how bird communities recover: individuals return immediately when habitat quality improves, but new species require time to disperse in and establish. Our results thus track biodiversity more broadly than the headline flaring elasticity suggests.

Event study evidence. A field-level event study tracing flaring, OPEX, CAPEX, and production at Chevron joint-ventures around the licence date is reported in Online Appendix Table D2; a companion event study replacing flaring volume with per-barrel flaring intensity is reported in Online Appendix Table D3. The bird abundance/richness event study at Chevron-near cells is reported in Online Appendix Figure H1.

7.2 Guild-level decomposition

To probe which trophic guilds drive the abundance recovery, we estimate a static Chevron-vs-Western-JV difference-in-differences on each guild's log abundance,

$$\log(1 + Y_{g,ict}) \;=\; \alpha_i + \tau_t + \beta_g \,(\text{NearChev}_i \cdot \text{Post}_t) + \mathbf{X}'_{ict}\boldsymbol{\delta} + \varepsilon_{ict}, \tag{8}$$

on the $\pm$24-month window around the licence date, restricted to cells with at least one Chevron or Western JV field within 30 km. Treatment cells are those near a Chevron joint-venture; controls

are cells near other Western JVs (which lacked the licence). Effort controls $\mathbf{X}_{ict}$ are checklist-level (duration, distance, observers, hour, traveling).

Online Appendix Table H5 reports estimates across three fixed-effect structures. Forest insectivores show the clearest post-licence gain ($+0.60^{***}$ under Cell+YM, $+0.51^{***}$ under Cell+YM+Obs), consistent with their canopy and understory foraging niches being sensitive to local air-quality and gas-flaring disturbance. Frugivores and granivores show smaller, directionally positive coefficients but never reach conventional significance. Waterbirds show small negative coefficients in the first two specifications and zero under the most demanding observer×year FE; their pre-trends are also the cleanest of the four guilds, so the licence shock plausibly does not move their abundance much. The pattern is consistent with the eBird-based evidence in the existing literature (Liang et al., 2020): pollution remediation moves abundance most for guilds whose foraging niches overlap most directly with the local pollutant.[17]

8 Quantification, generalisation, and policy implications

The framework in Section 2 predicts that sanctions-induced environmental damage exceeds what aggregate-output reduction alone would imply, with the gap given by the sum of three channel-specific contributions. This section quantifies that gap for the Venezuelan case from 2017 to 2024, extends the qualitative pattern to Russia (post-2014, 2017–2018, and post-2022 sanctions waves) and Iran after 2018, and draws design implications for sanctions architecture.

8.1 Constructing the counterfactual

Let D_{pre} denote total environmental damage in the pre-sanctions baseline year (2016), and D_{post} the damage observed in the post-sanctions period (we use the 2022–2024 average to smooth short-run volatility). Aggregate output fell from $Q_{\text{pre}} \approx 2.28$ mbbl/d to $Q_{\text{post}} \approx 0.78$ mbbl/d over this window, a reduction of $\rho \equiv 1 - Q_{\text{post}}/Q_{\text{pre}} \approx 66\%$.

Under the proportional-decline benchmark of Section 2,

$$D^{\text{ctf}}_{\text{post}} \;\equiv\; (1-\rho)\, D_{\text{pre}} \;=\; \tfrac{Q_{\text{post}}}{Q_{\text{pre}}}\, D_{\text{pre}}, \tag{9}$$

holding per-barrel intensity, the set of operating fields, and proximity to capacity all fixed at their pre-sanctions values. The empirical question is whether $D_{\text{post}} > D^{\text{ctf}}_{\text{post}}$, and by how much.

We construct the ratio

$$R \;\equiv\; \frac{D_{\text{post}}}{D^{\text{ctf}}_{\text{post}}} \;=\; \frac{D_{\text{post}}}{D_{\text{pre}}} \cdot \frac{Q_{\text{pre}}}{Q_{\text{post}}} \tag{10}$$

[17] A species-level decomposition addresses the concern that the guild-level effects might be driven by a small number of species. Of 265 species with at least five checklist detections in the sample, 172 have positive (Chevron × Post) coefficients and 92 have negative; the binomial sign test rejects equal shares at $p < 10^{-6}$, and the sum of point estimates is +4.53 species, in line with the net guild-level gain. Individual-species significance is low (17% of positive and 14% of negative species at the 5% level), reflecting limited power at the species level given the 2,600-checklist sample, so the guild-level result is best read as a direction-of-effect finding.

where $R = 1$ means proportional decline holds and $R > 1$ means damage outruns the output reduction.

8.2 Channel-by-channel decomposition

The outcome we quantify is gas-flaring intensity: the total m^3 flared per barrel of crude lifted. Production-weighted mean intensity in Venezuela is $\bar{\alpha}_{\text{pre}} = 12.6$ m^3/bbl in the pre-period (2012–2016) and $\bar{\alpha}_{\text{post}} = 38.0$ m^3/bbl in the post-period (2022–2024), so directly from the data

$$R = \frac{\bar{\alpha}_{\text{post}}}{\bar{\alpha}_{\text{pre}}} = \frac{38.0}{12.6} = 3.0. \tag{11}$$

Equivalently, $R = F_{\text{post}}/F^{\text{ctf}}_{\text{post}}$, where $F^{\text{ctf}}_{\text{post}} \equiv F_{\text{pre}}\,(Q_{\text{post}}/Q_{\text{pre}})$ is the proportional-decline counterfactual on total flaring volume; simple cancellations turn the volume ratio in equation (10) into the intensity ratio in equation (11). Empirically, total Venezuelan flaring volume is roughly constant between the pre- and post-periods while production fell by 66%, which is the same fact as a tripling of per-barrel intensity. We work with the per-barrel ratio, as defined in equation (10), because it isolates the degradation of the production *process* from the output decline from sanctions.

Venezuelan flaring damage in 2022–2024 is three times what the proportional-decline benchmark would predict. We now decompose the change in flaring $\frac{\bar{\alpha}_{\text{post}} - \bar{\alpha}_{\text{pre}}}{\bar{\alpha}_{\text{pre}}} = R - 1$ into the three channels of Section 2, with each component anchored to a specific coefficient already estimated in Sections 5–7. Methane (Section 6) and biodiversity (Sections 6.2, 7) confirm the channel-specific signs but are not folded into R numerically since we lack their pre-sanction values; we report them as direction-of-effect confirmations and quantify R on flaring intensity alone.[18]

The standard Oaxaca decomposition of the change in production-weighted mean intensity, with H for heavy fields (Orinoco East or heavy-crude share above 50%) and NH for non-heavy, is

$$\underbrace{\bar{\alpha}_{\text{post}} - \bar{\alpha}_{\text{pre}}}_{\text{numerator of } R-1} = \underbrace{\Delta s_H\,(\bar{\alpha}_{H,\text{pre}} - \bar{\alpha}_{NH,\text{pre}})}_{\text{composition}} + \underbrace{s_{H,\text{post}}\,\Delta\bar{\alpha}_H + (1 - s_{H,\text{post}})\,\Delta\bar{\alpha}_{NH}}_{\text{within-field intensity change}}, \tag{12}$$

where s_H is the heavy share of Venezuelan production. The four production-weighted intensities and the heavy share are reported in Table 7.
Two implications follow immediately:

Composition. Most Venezuelan production was already at heavy fields before sanctions (94% of barrels), so the within-VEN heavy-share shift is small: $\Delta s_H = +0.01$. The within-Venezuela survival result, that small fields exit and large fields keep producing, is identified by the Post × Large coefficient in Table 3 (+0.15 to +0.24, all $p < 0.001$), but because the surviving large fields are essentially all heavy already, this within-VEN selection does not move the heavy share much. The

[18] Ideally R would combine flaring CO_2 with vented CH_4 on a common global warming potential scale, but the TROPOMI methane record begins only in November 2018.

Table 7: Inputs to the R decomposition.

	Pre (2012–2016)	Post (2022–2024)	Δ	Source
Panel A: Production-weighted aggregates from raw data				
Heavy intensity $\bar{\alpha}_H$ (m^3/bbl)	12.9	39.6	+26.7	—
Non-heavy intensity $\bar{\alpha}_{NH}$ (m^3/bbl)	8.1	6.7	-1.4	—
Overall intensity $\bar{\alpha}$ (m^3/bbl)	12.6	38.0	+25.4	—
Heavy share of production s_H	0.94	0.95	+0.01	—
Panel B: Structural coefficients from earlier regressions				
	Value			Source
Chevron OPEX–flaring elasticity η_5	−0.42			Table 6
Heavy-VEN log-OPEX shock β_h^{OPEX}	−0.61			Table 2

Notes: Panel A reports production-weighted means computed as $\sum_i F_{it} / \sum_i Q_{it}$ over Venezuelan field-years with positive flaring and positive production. Heavy = Orinoco East geographic region or heavy-crude share above 50%. Sample windows: 2012–2016 (pre) and 2022–2024 (post). F in cubic metres, Q in barrels of crude. Source: VIIRS Global Gas Flaring Tracker (allocated within 15 km of each field); Rystad Energy UCube. Panel B reports the two structural coefficients used to split the within-heavy intensity rise into maintenance and strain contributions: η_5 is the Post-2022 × Chevron × log(1 + OPEX/prod) triple interaction on log(1 + flaring volume) (column 1 of Table 6); β_h^{OPEX} is the Heavy × Post coefficient on log(1 + OPEX) (Table 2).

resulting contribution to $R - 1$ is

$$r_{\text{comp}} = \frac{\Delta s_H \left(\bar{\alpha}_{H,\text{pre}} - \bar{\alpha}_{NH,\text{pre}}\right)}{\bar{\alpha}_{\text{pre}}} = \frac{0.01 \cdot (12.9 - 8.1)}{12.6} \approx 0.004,$$

essentially zero. The composition channel does very little numerical work in this case because there is no clean-versus-dirty margin to shift along inside Venezuela: the country's pre-sanctions production base was already concentrated on heavy crude.

Maintenance and strain (joint). The remaining $R - 1 \approx 2.0$ is the within-heavy intensity rise. Empirically, $\bar{\alpha}_H$ tripled from 12.9 to 39.6 m^3/bbl ($\Delta\bar{\alpha}_H \approx +26.7$ m^3/bbl). This is consistent with the differential Heavy × Post coefficient on flaring intensity reported in Table 2: $\hat{\beta}_h = +125.1^{***}$ m^3/bbl at the 15 km radius; the production-weighted analogue recovers the same direction at smaller magnitude because most heavy production sits at large fields with lower per-barrel intensity. Weighted by post-period heavy share, the within-heavy intensity rise contributes

$$r_{\text{maint+strain}} = \frac{s_{H,\text{post}}\, \Delta\bar{\alpha}_H + (1 - s_{H,\text{post}})\, \Delta\bar{\alpha}_{NH}}{\bar{\alpha}_{\text{pre}}} = \frac{0.95 \cdot 26.7 + 0.05 \cdot (-1.4)}{12.6} \approx 2.01,$$

which matches $R - 1 = 2.01$ to two decimal places. The within-heavy intensity rise is the entirety of the damage multiplier; non-heavy intensity is essentially flat, consistent with the regression coefficient $\beta_n \approx 0$ on flaring intensity in column (4) of Table 2.

Splitting maintenance from strain. The heavy-field intensity rise bundles two sub-channels in equilibrium because sanctions cut both maintenance budgets and diluent imports simultaneously at the same fields. The coefficients from Sections 6.1 and 7 let us identify each sub-channel.

The within-Chevron OPEX elasticity of flaring volume from Table 6 is $\eta_5 = -0.42^{***}$ (column 1): a one-log-point rise in OPEX per barrel reduces flaring volume by about 42%. The Heavy $\times$ Post coefficient on $\log(\text{OPEX})$ in Table 2 (column 6) is -0.61^{***}, a 46% post-period drop in heavy-field OPEX. Multiplying gives the maintenance-induced rise in heavy flaring volume: $\eta_5 \cdot \beta_h^{\text{OPEX}} = (-0.42) \cdot (-0.61) = +0.2562$ log units, or about $\exp(0.2562) - 1 \approx +29\%$ on flaring volume from maintenance alone. This calculation assumes the Chevron-licence elasticity η_5, identified at the four GL-41 fields, is the relevant maintenance-elasticity for all heavy Venezuelan fields when maintenance is suppressed by sanctions.

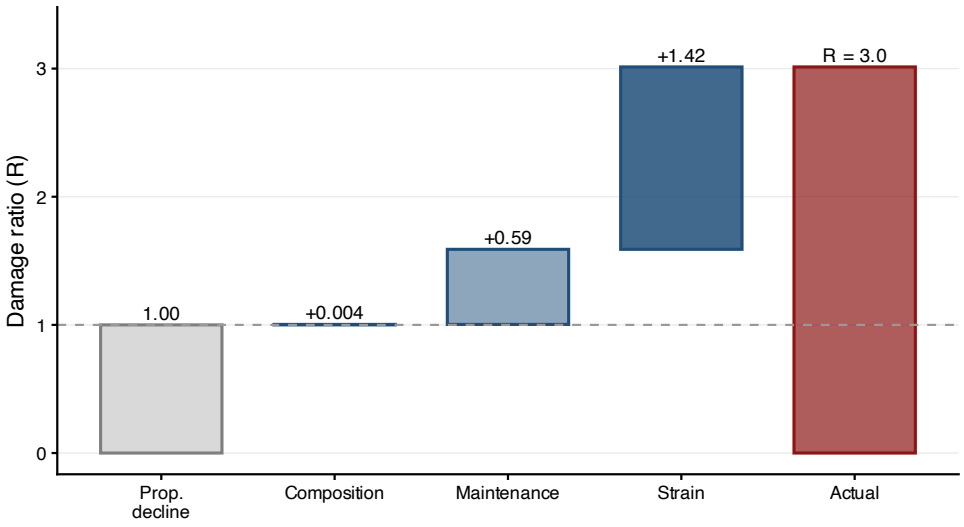
The strain component is then obtained as the residual: the within-heavy rise that remains after the maintenance contribution has been subtracted. Combining, maintenance accounts for roughly 29% of the heavy-field flaring rise and strain for the remaining 71%. Both channels are sanctions-specific: the cross-country comparison (Online Appendix Table D4) shows Mexican Maya and Colombian Llanos wellhead-pipeline trends *fall* at -2.51 and -0.81 per year respectively; only the Venezuelan Orinoco shows the trend rise.

The damage multiplier. Figure 8 visualises the decomposition: the three channel contributions ($r_{\text{comp}} = +0.004$, $r_{\text{maint}} = +0.59$, $r_{\text{strain}} = +1.42$) add to $R \approx 3.0$. Sensitivity bounds across the 7.5 km versus 15 km flare-allocation radii (which produce a Heavy $\times$ Post coefficient of $+176.7$ versus $+125.1$, Table 2 cols (3)–(4)) and across the post-period definition (2022 alone vs. 2022–2024 average) give $R \in [2.5, 3.5]$. Composition does very little work; maintenance and strain together do almost everything.

Population-weighted multiplier. Weighting each field's damage contribution by the population within a 30 km buffer (GHS-POP 2020) raises the multiplier from a field-equal-weighted analogue of $R = 2.72$ to $R^{\text{pop}} = 2.93$, with $R^{\text{pop}} \in [2.86, 3.25]$ across 10–50 km buffers. The surviving heavy operations sit near populated cities at the northern margin of the Orinoco belt and around Lake Maracaibo, so the exposure-weighted welfare loss exceeds the field-equal aggregate.

A note on conservatism. The attribution above treats the within-Heavy intensity change as a single block. A finer two-way Oaxaca decomposition by Heavy $\times$ Size shows that 97% of the per-barrel rise comes from within-cell intensity change at the surviving large heavy fields (Heavy $\times$ Large goes from 9.94 to 22.77 m^3/bbl), and that the size-survival channel *inside* Heavy contributes only -0.004 R-units: that is, it is *negative* (small heavy fields exit, mechanically lowering the average) but quantitatively negligible because small heavy fields are only 0.6% of pre-period production. The strain and maintenance channels would therefore be slightly larger than the headline if isolated from this small cleaner-survivor offset; we report the conservative attribution.

Figure 8: Decomposition of the damage ratio R into three sanctions-driven channels



Notes: The grey bar marks the counterfactual baseline $R = 1$ that would prevail if per-barrel pollution had simply scaled with the proportional output decline. The three blue bars are the additive contributions to R: composition ($+0.004$, the share-weighted reallocation toward heavy fields), maintenance ($+0.59$, from the OPEX-restoration elasticity $\eta_5 = -0.42$ and the 0.61 log-unit drop in per-barrel OPEX at heavy fields), and strain ($+1.42$, the residual within-heavy intensity rise after subtracting maintenance, anchored by the naphtha-price elasticity $\theta_0 = +3.05$). The red bar at the right is the empirically observed ratio $R \approx 3$. Composition is environmentally negligible because 94% of pre-sanctions production was already heavy; the post-sanctions environmental cost is built almost entirely from maintenance and strain.

8.3 Cross-country generalisation

The same three-channel structure should hold under any large sanctions-driven reallocation of oil-and-gas production. Russia post-2014 and Iran post-2018 are the natural external-validity checks. We do not run our own field-level decomposition for either case; the multiple overlapping sanctions waves in Russia and the opacity of Iranian post-2018 production data both require treatment that goes beyond the scope of this paper. External evidence on production composition and methane emissions is consistent with the qualitative pattern we document for Venezuela.

Russia. Russia has been subject to three successive sanctions waves: 2014 (Crimea/Donbass financing and technology restrictions), 2017–2018 (CAATSA), and the most severe in February 2022 (G7+EU oil price cap, EU embargo on seaborne crude, and broadened US restrictions on Russian financial institutions and oil-trade intermediaries). Aggregate Russian crude production fell modestly, from 10.7 to 9.5 million barrels per day between 2021 and 2023 (-11%). The composition signature parallels Venezuela: surviving output has concentrated on the Western Siberian super-giants of the Yamal Peninsula, where state-owned Gazprom and Rosneft retain the technical capacity that European-financed mid-tier fields could not sustain after the 2022 import controls. Russia is already the world's largest oil-and-gas methane emitter at roughly 10–14 Mt per year (International Energy Agency, 2024), and post-2022 evidence points to deterioration: documented flaring spikes accompanied the suspension of Nord Stream exports in mid-2022 (notably at the Portovaya loading

station near the Finnish border), and sanctions on imported methane-detection sensors, drones, and gas-handling equipment have constrained the routine repair work that contained Russian leaks pre-invasion (Center on Global Energy Policy, Columbia SIPA, 2023).

Iran. The May 2018 US withdrawal from the Joint Comprehensive Plan of Action and the subsequent maximum-pressure campaign reduced Iranian production from 3.8 to 1.9 million barrels per day at the 2020 trough; partial recovery to 3.2 by 2023–24 has been routed through dark-shipping networks (Fernández-Villaverde et al., 2025). The composition signature parallels Venezuela: surviving production has concentrated at the South Pars condensate field (the world's largest gas-condensate field, shared with Qatar) and at the heavy-oil clusters of Ahvaz and Marun in Khuzestan province. Iranian oil-and-gas methane emissions rose 10% to 15% between 2018 and 2024 even as production fell (International Energy Agency, 2024).

Cross-country contrast: sanctioned vs. operating heavy-oil regions. A natural concern is that what we attribute to sanctions might be a generic feature of heavy-oil extraction. To separate the two, we estimate the same pipeline-vicinity methane trend in unsanctioned heavy-oil regions of Latin America and compare to the Venezuelan estimate. The differential per-year trend in pipeline methane (relative to the Latin American mean) is $+1.30^{**}$ in the Venezuelan Orinoco Belt; -2.51^{***} in the Mexican Maya basin; $+1.52^{***}$ in the Ecuadorean Oriente; and -0.81^{***} in the Colombian Llanos (Online Appendix Table D4 reports all four coefficients under three fixed-effect structures). The two cleanly comparable unsanctioned regions, Mexico and Colombia, decline; only the sanctioned region, Venezuela, shows the near-pipeline methane rise that the diluent-dependence physics predicts. The Ecuadorean Oriente also trends upward but follows a different profile (steady operational expansion, not a sanctions shock) and shows clean pre-trends, so it does not act as a heavy-oil-extraction baseline that rationalises the Venezuelan rise. This cross-country difference is the sharpest evidence that the within-Venezuela strain pattern is sanctions-driven rather than crude-type-driven.

8.4 Policy implications

The three-channel decomposition turns the headline ratio R into a quantitative menu. Each channel maps to a distinct policy lever, and the lever's effect on R is what falls out when we set the relevant r_x to zero in the waterfall of Figure 8. We organise the discussion around three instruments that are actively in use or under regulatory development: targeted carve-outs, price caps that target revenue, and buyer-side standards. For each one we map the channels it addresses and the empirical anchor that calibrates its bite.

1. Targeted carve-outs. OFAC General Licence 41, issued on 26 November 2022, is the operational template. The licence names a single firm (Chevron) at four heavy-oil joint ventures and restores the operational inputs that sanctions had cut: spare parts, foreign expertise, banking services, and

crucially the diluent (naphtha) imports required to move heavy crude through pipelines. Financial sanctions on the rest of the sector remained in place. Because the licence simultaneously restored maintenance spending *and* the diluent supply, it acts on both the maintenance and the strain channels.

The decomposition lets us trace the licence's potential bite. The OPEX-restoration elasticity from the Chevron license is $\eta_5 = -0.42$ (Table 6, column 1). Applied to the -0.61 log-unit OPEX shock at heavy fields (Table 2, column 6), this removes the $r_{\text{maint}} \approx 0.59$ contribution.[19] The naphtha-price elasticity $\theta_0 = +3.05$ (Table 5) is the structural anchor for the strain channel: restoring diluent supply at the wellhead sets $r_{\text{strain}} = 0$. Diluent licensing alone is the single most consequential sub-lever in our setting, because heavy crude cannot move through pipelines without it. It delivers $R \approx 1.6$, which is roughly a halving of the damage multiplier. A general-purpose carve-out at all heavy fields, modelled on the Chevron template and combining diluent with the maintenance restoration, brings R back to roughly the proportional-decline benchmark of 1.0.

Carve-outs are coercive-compatible only if the licence severs the link between operations and state revenue. The Chevron template illustrates how this is done. The licence permits the firm to import operational inputs at the four covered joint-ventures, but it explicitly prohibits payment of taxes, royalties, or dividends to the Venezuelan state. The proceeds of Chevron's oil sales are routed toward settlement of pre-existing PDVSA debt to Chevron rather than to the Venezuelan treasury. Even when output at the covered fields rises modestly post-licence, the regime sees no new revenue from those additional barrels. A general-purpose carve-out would have to inherit this same revenue-routing design: license inputs, not outputs, and keep export and financial sanctions in place. Under that design the carve-out is a Pareto improvement over unconditional sanctions, because R falls to 1 while the coercive bite is preserved.

2. Price caps that target revenue, not the production process. The G7 cap on Russian Urals (Crozet and Hinz, 2020) is the second instrument. It was set initially at \$60/bbl in December 2022 and lowered to \$47.60 in September 2025. The mechanism is interesting. G7-domiciled shipping and insurance services are made conditional on the per-barrel sale price being below the cap, so the cap binds on every Russian barrel that uses G7 logistics. The cap reduces per-barrel revenue without restricting volume. As currently designed, it is pollution-neutral.

Tying the cap to each field's methane intensity (tighter for the dirty fields, looser for the cleaner ones) converts the instrument into a composition-steering lever. The high-marginal-cost legacy fields, which are also the dirtiest per barrel, become unprofitable first, and surviving production concentrates on cleaner tiers. The lever has bite where the within-country intensity gradient is

[19] The counterfactual here holds heavy-field production at observed post-sanctions levels and restores total OPEX to pre-sanctions levels. This is consistent with the Chevron quasi-experiment, in which the licence restored OPEX (from \$753M in 2020 to over \$2B in 2024) while production stayed approximately flat at the four covered joint-ventures; the analogue regression with $\log(1 + \text{production})$ as the outcome gives a triple-interaction coefficient of -0.515 (s.e. 0.103), of which a mechanical -1 is the denominator effect of per-barrel OPEX. Under this convention, $\Delta \log(\text{OPEX}/Q)_H = \Delta \log \text{OPEX}_H = -0.61$. Without the fixed-production convention, total OPEX and production at heavy fields fell together, so $\Delta \log(\text{OPEX}/Q)_H \approx +0.05$, r_{maint} is near zero, and strain absorbs essentially the entire within-field rise.

steep. In Russia it does, because the Western-Siberian super-giants run substantially cleaner per barrel than the legacy basins. In Venezuela it does almost no environmental work, because 94% of pre-sanctions production was already at heavy fields, the production-weighted gap between heavy and non-heavy Venezuelan fields is modest (12.9 vs. 8.1 m^3/bbl, Table 7), and the surviving large heavy fields are mildly cleaner per barrel than the small fields that exited (Section 5.1). There is no large clean tier inside Venezuela to preserve.

3. Buyer-side standards. The EU's 2024 Methane Regulation imposes methane-intensity monitoring, reporting and verification (MRV) thresholds on imported natural gas, with the oil side under regulatory development. This is a third implementation. The instrument works on the demand side rather than the supply side. Importers must verify the methane content of what they buy, and producers with cleaner fields become preferred suppliers. The lever bites under the same heterogeneity condition as the price cap: Russia qualifies, Venezuela does not, for the same composition reason. Field-named sanctions are a fourth implementation in the same family. They are practical when the dirty tier is concentrated in a small number of named assets, and impractical when it is hundreds of legacy fields spread across a basin.

Coercive equivalence and additivity. The three instruments are environmentally additive. The carve-out addresses strain and maintenance directly, and the price-cap and MRV instruments address composition where the within-country intensity gradient permits. Combining a Chevron-style carve-out with a methane-indexed price cap brings R back to 1 in Venezuela and, qualitatively, further below the proportional-decline benchmark in heterogeneous settings like Russia. The bundle is also coercive-equivalent to unconditional sanctions. The revenue-routing design feature documented above means that the input-side carve-outs leave state-level revenue unaffected, and the price-cap and MRV instruments reduce it directly. The Venezuelan pattern that motivates this policy menu is not unique to one country; we discuss the Russian and Iranian counterparts in Section 8.3.

A measurement template. Aggregate flaring volumes are useful but insufficient for calibrating any of these instruments. Methane concentrations capture leakage that flaring data miss, and biodiversity outcomes integrate flaring, methane, and the co-emitted local pollutants at the spatial scale at which households actually live. The Chevron event study and the methane analysis in this paper together provide a template that can be applied to other sanctioned jurisdictions where production-side data are sparse and satellite remote sensing is the only credible source of variation. Without the three-channel framework, R is just a number. With it, R is the sum of three margins, each of which can be targeted by a different policy lever.

9 Conclusion

Sanctions on resource-rich autocracies are widely understood to reduce aggregate output, but less commonly understood to reshape *how* the surviving output is produced. We document three reinforcing channels in the Venezuelan case, composition, maintenance, and strain, and identify each through a distinct research design, with the November 2022 Chevron licence carve-out providing the within-country, within-firm variation that recovers the structural responsiveness of pollution per barrel to the maintenance budget. Combining the channel-specific estimates, total environmental damage from Venezuelan oil extraction in 2022 to 2024 is approximately three times what the proportional decline of output alone would predict, with the maintenance and strain channels at heavy-oil fields carrying essentially all of the gap and the composition channel determining where that damage lands. The same qualitative pattern, falling or stagnating output, surviving production concentrating on the largest dirtiest fields, rising per-barrel emissions, appears in Russia after the 2014, 2017–2018, and 2022 sanctions waves and in Iran after 2018, though only Venezuela offers the within-firm licence shock that makes the structural identification possible.

The decomposition has direct implications for sanctions design. It implies that sanctions design has two distinct objectives, not one: maximising coercive impact on the regime, and minimising the environmental damage that the production reshuffling sanctions induce. The three channels map onto three currently-deployed policy instruments (targeted carve-outs, price caps that target revenue rather than the production process, and buyer-side methane-intensity standards), so the two objectives are not always in conflict. A package that combines a Chevron-style carve-out (which restores maintenance inputs and diluent supply at covered heavy fields, addressing both the maintenance and strain channels) with a methane-indexed price cap or an MRV-style import standard (addressing composition) hits the regime's revenue base hard while leaving the maintenance and strain channels quiet and tilting composition away from the dirtiest fields. The Chevron carve-out shows the design feature that makes the first instrument work in practice. The licence covers operational inputs but explicitly bars payment of taxes, royalties, or dividends to the Venezuelan state, and it routes oil-sale proceeds toward settlement of pre-existing PDVSA debt to Chevron, so any incremental production at the covered fields generates no new state revenue. The G7 oil price cap on Russia is a partial implementation of the second instrument, and the EU's 2024 Methane Regulation is an emerging implementation of the third. The Chevron license identifies the maintenance channel responding quickly to budget restoration, with biodiversity recovery of a magnitude consistent with the predicted pollution decline. The strain channel runs through physical bottlenecks like diluent supply for Venezuelan extra-heavy crude, so sanctions designs that interfere with these bottlenecks activate strain damage directly while designs that leave them alone do not. The wider takeaway is that the environmental costs of sanctions are first-order, predictable from the structure of extraction technology, and amenable to design through policy instruments already in the sanctions toolkit.

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Online Appendix

The Environmental Costs of Sanctions: Flaring, Venting, and Biodiversity in Venezuela

A A stylised two-field model of reallocation under sanctions

This appendix formalises the three-channel framework introduced in Section 2. The setup is the simplest two-field model in which a sanctions-induced rise in per-field fixed costs endogenously concentrates surviving production on the larger field; on top of the resulting composition wedge we layer a maintenance channel and a convex-damage strain channel, giving the damage decomposition $D = \sum_i \alpha_i(m_i)\, q_i + (\beta_i/2)\, q_i^2 + F\,\mathbb{1}\{q_i > 0\}$ used in the body.

A.1 Setup

A regime controls two heterogeneous fields $i \in \{S, L\}$: field S (small, low-cost, clean) has capacity Q_S, marginal cost c_S, and per-barrel external damage α_S; field L (large, high-cost, dirty) has capacity Q_L, marginal cost $c_L > c_S$, and damage $\alpha_L > \alpha_S$. Each operating field carries a per-period fixed cost F (overhead, sanctions-evasion infrastructure, foreign expertise). The regime takes the world price p as given, must meet a revenue target G (so total production $q_S + q_L \geq q^* \equiv G/p$), ignores externalities, and chooses production to minimise operating cost:

$$\min_{q_S, q_L \in [0, Q_i]} \quad c_S q_S + c_L q_L + F \cdot \mathbb{1}\{q_S > 0\} + F \cdot \mathbb{1}\{q_L > 0\} \quad \text{s.t.} \quad q_S + q_L \geq q^*. \tag{A1}$$

We assume $Q_S < q^* < Q_L$, so the small field alone cannot meet the target while the large field alone can.

A.2 The reallocation threshold

Two solutions satisfy the constraint: Option A operates both fields ($q_S = Q_S$, $q_L = q^* - Q_S$) at total cost $c_S Q_S + c_L(q^* - Q_S) + 2F$; Option B operates only the large field ($q_S = 0$, $q_L = q^*$) at cost $c_L q^* + F$. Option A is cheaper iff

$$F \;<\; (c_L - c_S)\, Q_S, \tag{A2}$$

i.e., when the per-field fixed cost is below the variable-cost penalty of routing Q_S barrels through the expensive field.

We model sanctions as a multiplicative shock to the per-field fixed cost, $F \mapsto \lambda F$ with $\lambda > 1$ (extra overhead from sanctions-evasion banking, parts substitution, security, foreign- expertise sourcing). After the shock, Option B beats Option A iff $\lambda F > (c_L - c_S) Q_S$. Combining,

$$F \;<\; (c_L - c_S)\, Q_S \;<\; \lambda F \tag{A3}$$

gives an interior range of parameters in which the regime *endogenously reallocates*: both fields operate pre-sanctions, only the large field operates post-sanctions. Equivalently, the sanctions multiplier must exceed $\lambda^* \equiv (c_L - c_S)Q_S/F$ for the small field to exit. λ^* falls when fixed costs are large relative to the marginal-cost gap, when the small field is small, or when the two fields have similar marginal costs; in the Venezuelan context, mature small fields with declining yields exhibit large F/Q_S ratios, so λ^* is modest.

A.3 Three reinforcing channels of damage

When the reallocation condition (A3) binds, total external damage rises through three reinforcing channels.

Composition. Reassigning Q_S barrels from S to L under constant per-barrel intensities raises damage by $(\alpha_L - \alpha_S)Q_S$.

Maintenance. Per-barrel intensity at field i depends on maintenance spending m_i: $\alpha_i(m_i) = \alpha_i^0\, g(m_i)$ with $g(0) = 1$, $g'(m_i) < 0$, $g''(m_i) > 0$. Sanctions block the imported parts and foreign expertise that maintenance requires, forcing m_i down at every operating field; the channel applies to both surviving fields, not only to those receiving reallocated volume.

Strain (convex damage). Replacing the linear L-segment $\alpha_L q_L$ with $\alpha_L^0 q_L + (\beta_L/2)\, q_L^2$ for $\beta_L > 0$ captures convex damage from gas-handling capacity binding at high throughput. Pushing q_L from $q^* - Q_S$ to q^* raises damage by $(\beta_L/2)Q_S\,(q_L^{\text{post}} + q_L^{\text{pre}})$.

Combining,

$$\Delta D \;=\; \underbrace{(\alpha_L - \alpha_S)\, Q_S}_{\text{composition}} \;+\; \underbrace{\alpha_L^0 \left[g(m_L^{\text{post}}) - g(m_L^{\text{pre}})\right] q^*}_{\text{maintenance}} \;+\; \underbrace{\tfrac{\beta_L}{2}\, Q_S\, (q_L^{\text{post}} + q_L^{\text{pre}})}_{\text{strain}}. \tag{A4}$$

Each term is positive under sanctions; an aggregate-output analysis that reports only "production fell by X%" captures none of them. The biodiversity outcomes used in Section 6.2 integrate the three channels at the local ecological scale.

B Heavy-oil gas-handling mechanism

This appendix expands the five-step physical chain summarised in Section 3.2 of the body, with the petroleum-engineering references and numerical ranges that establish each step.

Gas-oil ratio and diluent dependence. Published industry-standard gas-oil ratios for extra-heavy Orinoco crude are on the order of 30–80 standard cubic feet of associated gas per barrel of crude lifted (Monaldi et al., 2021); the ratio is a thermodynamic co-product of the lift process, not an

operator choice. At surface conditions, the crude has a viscosity on the order of 10^4 centipoise at 30°C, functionally a solid for pipeline purposes, so it must be blended with 20–40% by volume of light hydrocarbons (naphtha, condensate, or upgraded synthetic crude) at the wellhead or at a local gathering centre (U.S. Energy Information Administration, 2024). Naphtha imports were the largest single category of US-sourced petroleum exports to Venezuela before the January 2019 PDVSA designation severed that supply channel and forced PDVSA to source smaller volumes through intermediary networks at premium prices (Fernández-Villaverde et al., 2025).

Throttle constraints on heavy-oil wells. Orinoco production uses cyclic steam stimulation, steam-assisted gravity drainage, or electric submersible pumping. Once these systems are running, they cannot be paused for short periods without risk of permanent damage: wax and asphaltene precipitation in the wellbore, sand bridging, pump seizure, and ultimately well loss. The operator faces a binary choice when diluent runs short: continue lifting crude that cannot be moved (and stockpiling it), or shut the well permanently. Both choices break the gas-handling chain.

Storage asymmetry. When operators continue producing without sufficient diluent, the heavy crude accumulates in tank farms at the upgrader feed (PetroPiar, PetroMonagas, PetroCedeño, PetroSan Felix). Crude has a marginal cost of storage near zero per barrel; gas does not. Associated gas exits the separator at low pressure (5–50 psi), is uneconomical to compress for storage, and must be moved or burned within minutes of separation. The gas sinks are: sales-gas pipeline (capped by pipeline capacity and downstream demand); reinjection into the reservoir (requires functioning compressors and dedicated injection wells); feedstock for the upgrader's hydrogen-production unit and on-site power generation (requires the upgrader to be running). When the upgrader is starved of crude because the diluent-deficient gathering system cannot move it, all three sinks collapse simultaneously.

Flare and vent as residual sinks. Once the upstream sinks fail, the only ways to relieve pressure in the gathering system are to flare the gas (the safer choice) or to vent it (the cheaper choice when the flare stack itself has deteriorated). This is the physical reason for the asymmetric flaring-vs-venting shares we observe in the strain-channel results (Section 6): flare events spike during periods of acute diluent stress (high naphtha price), while venting (which generates the methane signal but no thermal anomaly visible to VIIRS) rises more steadily as overall maintenance degrades.

Why this physics is Orinoco-specific. Conventional medium-API Maracaibo crude (11–19° API) flows through pipelines without naphtha blending. Maracaibo gas-handling does not depend on diluent imports; its environmental degradation under sanctions runs through aging-pipeline leakage rather than the flare-substitution episodes documented for Orinoco. The asymmetry between the two basins is the physical counterpart of the asymmetry our model formalises: small clean fields can be cleanly shut down, large dirty ones cannot be.

C Flaring Data and Matching Procedure

This appendix describes the two-stage procedure used to link World Bank VIIRS flare-site detections to Rystad Energy oil fields, producing the field-level flaring variables used throughout the paper.

C.1 Two-Stage Matching Algorithm

Stage 1: Fuzzy Name Matching. Many World Bank flare-site records carry a location name that corresponds, sometimes imprecisely, to a Rystad field name. We compute Jaro–Winkler string distances between every (WB flare-site name, Rystad field name) pair within the same country.[20] A match is accepted if and only if three conditions hold simultaneously:

1. *Distance threshold:* The Jaro–Winkler distance between the best-matching pair is ≤ 0.12 (on a 0–1 scale where 0 is an exact match).
2. *Gap requirement:* The best match beats the second-best match by at least 0.03, ensuring that the assignment is unambiguous.
3. *Mutual best match:* The WB field's best Rystad match and the Rystad field's best WB match agree, i.e., the mapping is bijective.

Of 721 candidate pairs evaluated across the six countries, 472 satisfy all three criteria. Name-matched flare-site-years are directly linked to the corresponding Rystad field, consuming approximately 3,975 flare-site-years and accounting for 44.5% of the total World Bank flaring volume in the sample.

Stage 2: Geographic Allocation. Flare-site-years *not* consumed by Stage 1 are allocated to nearby Rystad fields using a production-weighted inverse-distance gravity model. For each remaining flare-site-year, we identify all Rystad fields within a specified radius r whose annual production is strictly positive and compute allocation weights:

$$w_i = \frac{\text{Production}_i}{(d_i + d_0)^2},$$

where d_i is the great-circle (Haversine) distance in metres between the flare site and field i, and $d_0 = 100$ m is a small floor that prevents singularity when satellite and field coordinates coincide. This production-weighted inverse-squared-distance (PW-IDW) scheme assigns most of the flaring volume to the nearest and most productive fields while allowing smaller neighbours within the radius to receive a share. When all candidate fields within the radius have zero or missing production in a given year, the scheme falls back to pure inverse-squared distance ($1/(d_i + d_0)^2$). Weights are normalized within each flare-site-year so that $\sum_i w_i = 1$, ensuring that the allocated volume

[20] We normalize names before comparison: lowercasing, stripping accents and generic suffixes (e.g., "field," "area"), and collapsing whitespace. Candidate pairs are restricted to those sharing at least one token (word) to reduce computation.

exactly equals the World Bank observation. Each flare-site-year is assigned exactly one disposition (name-matched, geo-allocated, or unallocated), so the total World Bank volume decomposes without double-counting; at the 15 km radius the procedure captures 91.5% of total World Bank flaring volume (Table C1).

C.2 Matching Coverage

Table C1 reports coverage of the satellite-to-field flaring allocation procedure at 7.5 km and 15 km matching radii, evaluated from the perspective of World Bank VIIRS satellite flare detections over 2012–2024. At 15 km, the volume allocation rate exceeds 90% for all countries except Brazil (onshore), where the low match rate reflects the predominantly offshore orientation of Brazil's flaring activity.

Table C1: Satellite Flaring Coverage by Country and Matching Radius

Country	Radius	WB flare sites	Matched sites	Match rate (%)	WB volume (Mm^3)	Allocated volume	Vol. alloc. rate (%)
Argentina	7.5 km	2,499	1,707	68.3	11,194.5	7,823.3	69.9
Argentina	15 km	2,499	2,231	89.3	11,194.5	10,105.2	90.3
Brazil	7.5 km	1,552	234	15.1	15,117.2	1,459.6	9.7
Brazil	15 km	1,552	288	18.6	15,117.2	1,852.1	12.3
Colombia	7.5 km	847	759	89.6	7,374.5	7,186.7	97.5
Colombia	15 km	847	782	92.3	7,374.5	7,213.6	97.8
Ecuador	7.5 km	998	975	97.7	14,383.7	14,338.1	99.7
Ecuador	15 km	998	998	100.0	14,383.7	14,383.7	100.0
Mexico	7.5 km	2,223	1,884	84.8	64,326.3	59,341.0	92.3
Mexico	15 km	2,223	1,979	89.0	64,326.3	61,593.5	95.8
Venezuela	7.5 km	2,057	1,443	70.2	101,701.8	76,523.9	75.2
Venezuela	15 km	2,057	1,895	92.1	101,701.8	100,438.7	98.8
Total	7.5 km	10,176	7,002	68.8	214,098.0	166,672.6	77.8
Total	15 km	10,176	8,173	80.3	214,098.0	195,586.8	91.4

Notes: Coverage is evaluated from the perspective of World Bank VIIRS satellite flare detections. A flare site is matched if it is allocated to at least one Rystad field via the two-step procedure (Jaro–Winkler name match plus production-weighted inverse-distance gravity). Volume allocation rates exceed site-count rates because large, high-volume flare sites near major fields are easier to match; unallocated sites are predominantly small or remote. Brazil includes onshore fields only; Mexico includes all fields.

C.3 Sensitivity of Matching to Radius Choice

A key consideration in the geographic allocation stage is the choice of matching radius. Oil fields can have irregular shapes extending several kilometres from the Rystad-reported centroid, and the World Bank's satellite-detected flare coordinates need not coincide with the centroid of the field to which the flare belongs. To quantify this discrepancy, we exploit the name-matched pairs from Stage 1 as a validation set: because fuzzy string matching independently confirms that both the World Bank flare site and the Rystad field refer to the same physical asset, the great-circle distance

between their respective coordinates provides a direct measure of the geographic offset for known matches.

Table C2 reports the distribution of these offsets for the 51 Venezuelan name-matched pairs. Over 43% of pairs have a flare-to-centroid distance exceeding 5 km, and one quarter exceed 7.5 km. At a 7.5 km matching radius, 13 confirmed matches, including fields such as Yucal Placer (14.8 km), Acema A (14.6 km), and Miga (12.1 km), would fall outside the radius and be excluded from the purely distance-based allocation. The 15 km radius recovers nine of these, reducing the miss rate from 25.5% to 7.8%.

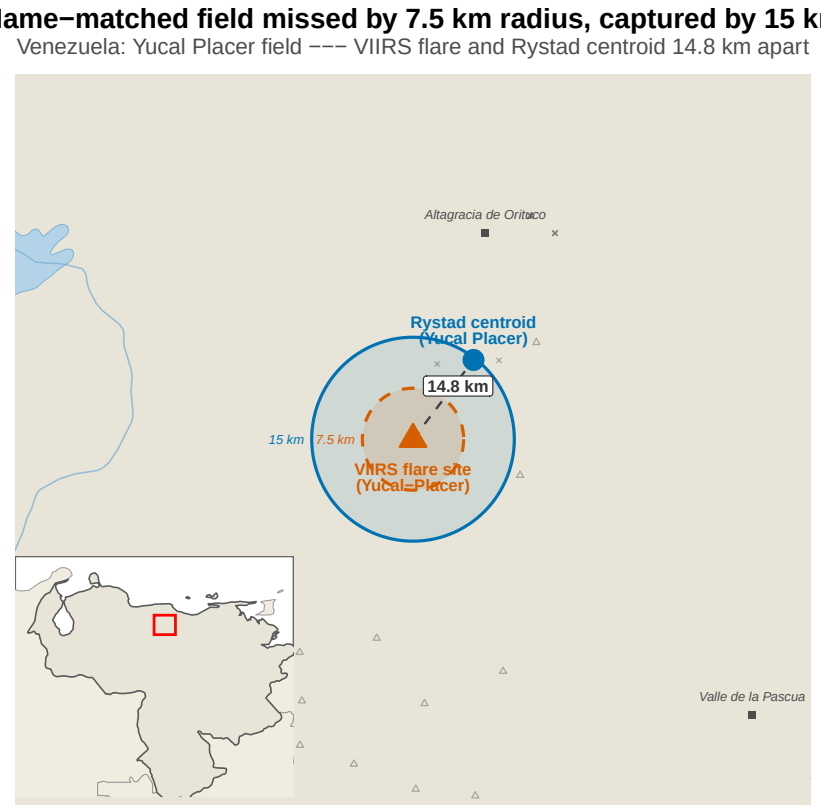
Figure C1 illustrates this pattern for the Yucal Placer field, where the World Bank flare site and the Rystad centroid are 14.8 km apart. The orange dashed circle (7.5 km) fails to reach the Rystad centroid, while the blue solid circle (15 km) comfortably encompasses it. This example is representative: oil-field infrastructure is spatially extended, and a radius that is too restrictive systematically excludes valid matches.

Table C2: Geographic Distance Between Name-Matched Flare Sites and Rystad Field Centroids: Venezuela

Distance band	Pairs	Share (%)
0–5 km	29	56.9
5–7.5 km	9	17.6
7.5–10 km	6	11.8
10–15 km	3	5.9
$>$15 km	4	7.8
Total	51	100.0

Notes: Distribution of great-circle distances between World Bank VIIRS flare-site coordinates and Rystad field centroids for the 51 accepted name-matched pairs in Venezuela. Name-matched pairs are confirmed by fuzzy string matching (Jaro–Winkler distance $\leq$ 0.12, mutual best match), so both sources identify the same physical field despite the coordinate discrepancy. Pairs in the upper distance bands would be missed by a purely distance-based approach at the corresponding radius threshold.

Figure C1: Name-Matched Field Missed at 7.5 km Radius, Captured at 15 km: Yucal Placer, Venezuela

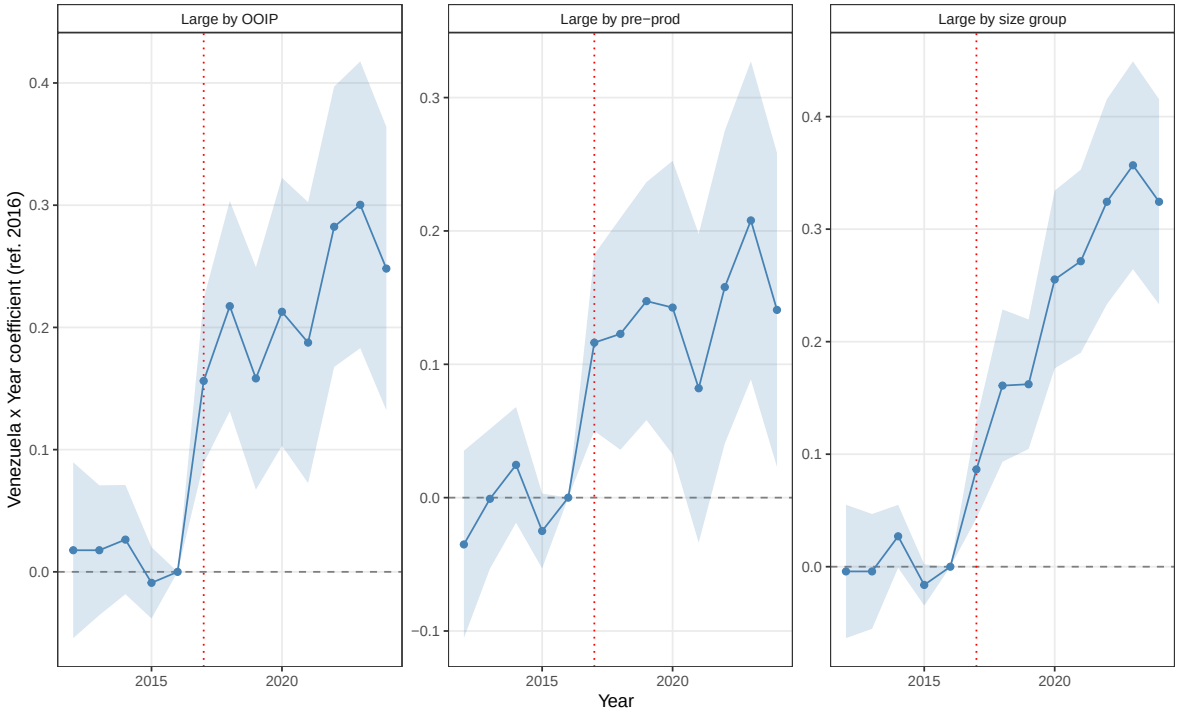


Notes: The orange triangle marks the World Bank VIIRS flare-site location ("Yucal-Placer"); the blue circle marks the Rystad Energy field centroid ("Yucal Placer, VE"). The dashed orange circle shows a 7.5 km matching radius around the flare site; the solid blue circle shows a 15 km radius. Fuzzy name matching confirms both sources refer to the same field, yet their coordinates are 14.8 km apart. At 7.5 km the field centroid falls outside the matching radius and would be excluded from geographic allocation. Small grey symbols show other nearby VIIRS flare sites ($\times$) and Rystad field centroids ($\triangle$). The inset locates the area within Venezuela. Basemap from Natural Earth.

D Additional Exhibits

This appendix collects the baseline difference-in-differences table that underlies the central results in Sections 5–6, the event-study counterparts of the composition, geography, and ownership pooled estimates, and a field-level event study around the November 2022 OFAC Licence 41 that traces the dynamics of flaring, OPEX, CAPEX, and production at Chevron joint-ventures relative to the rest of the Venezuelan onshore panel (Table D2), together with a companion table that replaces flaring volume with per-barrel flaring intensity to isolate the maintenance margin from any contemporaneous production response (Table D3).

Figure D1: Composition Channel: Event-Study Estimates of the Producing-and-Large Share



Notes: Per-year coefficients from a Venezuela-by-year event study of equation (2), with the omitted year set to 2016. Outcomes match the columns of Table 3: in the first three panels, $Y_{ift} = \mathbb{1}\{\text{prod}_{ift} > 0\} \cdot \text{Large}_i$ where Large is defined respectively by OOIP, pre-period mean production, and Rystad field-size group; the fourth panel uses heavy-oil indicator; the fifth panel is the unconditional $\mathbb{1}\{\text{prod}_{ift} > 0\}$ benchmark. Field and year fixed effects; standard errors clustered at the asset level. Shaded bands are 95% confidence intervals. Vertical dotted line at 2017 marks E.O. 13808. The producing-and-large coefficients are flat through 2016 and break at 2017–2019 in the size measures, consistent with the composition channel.

Cross-country wellhead-pipeline trends by basin. Table D4 reports the country–basin breakdown of the per-year wellhead-pipeline methane trend referenced in the body strain section, under three increasingly demanding fixed-effect structures. Only the Venezuelan Orinoco/East row shows a positive differential trend that survives all three; the Mexican Maya and Colombian Llanos rows are negative throughout. This rules out a generic heavy-oil-extraction story for the

Table D1: Effect of Sanctions on Flaring, Production, and Investment

Dependent Vars:	Flaring Vol. 7.5km (1)	Flaring Vol. 15km (2)	Flaring Int. 7.5km (3)	Flaring Int. 15km (4)	Prod. (log) (5)	OPEX (log) (6)	CAPEX (log) (7)	Cum. CAPEX (log) (8)
Venezuela × Post	-7.8181	-2.9685	162.8513***	118.3075***	-0.6618***	-0.6029***	-0.4098	-0.4113***
	(10.3728)	(6.5629)	(56.0808)	(44.7596)	(0.1412)	(0.1412)	(0.3145)	(0.1464)
Fixed effects								
Asset	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Mean dept. var.	29.8540	22.0782	76.9685	55.9316	12.0406	14.9673	12.7102	14.8554
Observations	5,023	7,795	5,023	7,795	11,983	11,983	11,983	11,983
Fields	772	1,097	772	1,097	1,097	1,097	1,097	1,097
R^2	0.90670	0.93664	0.68477	0.67769	0.86183	0.83240	0.65119	0.91985

Notes: This table reports difference-in-differences estimates of the effect of US sanctions on Venezuelan oil fields (regression (6)). Sample: six LATAM countries (Argentina, Brazil onshore, Colombia, Ecuador, Mexico, Venezuela), 2012–2024, field-year level. Post $= \mathbb{1}\{\text{year} \geq 2017\}$. Cols (1)–(2): allocated flaring volume (million m^3). Cols (3)–(4): flaring intensity (m^3/bbl), winsorized at the 99.5th percentile. Col (5): log(1 + crude production in bbl). Col (6): log(1 + OPEX in USD). Cols (7)–(8): log(1 + CAPEX in USD) and log(1 + cumulative CAPEX in USD). Cols (1) and (3) restrict to field-years with positive flaring at 7.5 km allocation radius; Cols (2) and (4) at 15 km; Cols (5)–(8) use the full sample. All models include field and year fixed effects. Standard errors clustered at the asset level in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. Source: Rystad Energy; World Bank VIIRS.

Table D2: Event study around OFAC General Licence 41 (November 2022)

Event time (year)	$\log(1+\text{flaring})$ (1)	$\log(1+\text{flaring int.})$ (2)	$\log(1+\text{flaring/OPEX})$ (3)	$\log(1+\text{OPEX})$ (4)	$\log(1+\text{CAPEX})$ (5)
β_{-5} (2017)	$+0.358$	$+0.259$	$+0.190$	$+0.101$	$+1.683^{***}$
	(0.266)	(0.301)	(0.147)	(0.137)	(0.319)
β_{-4} (2018)	$+0.270$	$+0.366$	$+0.221$	$+0.037$	$+1.525^{***}$
	(0.390)	(0.303)	(0.144)	(0.146)	(0.453)
β_{-3} (2019)	-0.025	$+0.141$	$+0.136$	$+0.140$	$+1.480^{***}$
	(0.334)	(0.269)	(0.136)	(0.201)	(0.531)
β_{-2} (2020)	-0.232	-0.021	-0.020	-0.128	$+1.011^{*}$
	(0.323)	(0.291)	(0.136)	(0.098)	(0.540)
β_{+0} (2022)	-0.130	$+0.000$	-0.090	$+0.193^{**}$	$+0.541^{**}$
	(0.214)	(0.264)	(0.156)	(0.076)	(0.228)
β_{+1} (2023)	$+0.061$	$+0.141$	-0.008	$+0.197^{**}$	$+0.556^{**}$
	(0.304)	(0.277)	(0.152)	(0.092)	(0.222)
β_{+2} (2024)	$+0.495^{***}$	$+0.087$	-0.012	$+0.696^{***}$	$+1.007^{***}$
	(0.179)	(0.263)	(0.123)	(0.175)	(0.283)
Field FE / Year FE	✓ / ✓	✓ / ✓	✓ / ✓	✓ / ✓	✓ / ✓
SE clustered at field	✓	✓	✓	✓	✓
Observations	359	359	359	359	359
Fields	56	56	56	56	56

Notes: Event-study estimates of $Y_{it} = \alpha_i + \tau_t + \sum_{k \neq -1} \beta_k \mathbb{1}\{t = 2022 + k\}\,\text{Chev}_i + \varepsilon_{it}$. The omitted year ($k = -1$, i.e. 2021) is the reference GL-41 Chevron joint-ventures (PetroBoscan, PetroIndependencia, PetroIndependiente, PetroPiar). Sample: **heavy** Venezuelan onshore field heavy-crude share $> 50\%$); restricting to heavy fields holds crude type fixed and avoids contaminating the comparison with the faster-co Outcomes are field-year $\log(1+\cdot)$ of: flaring volume (million m^3, VIIRS allocated within 15 km); operating expenditure (million USD, (million USD, Rystad); and crude oil production (barrels, Rystad). Standard errors clustered at the field level in parentheses. $^{***}p<0.01$, *

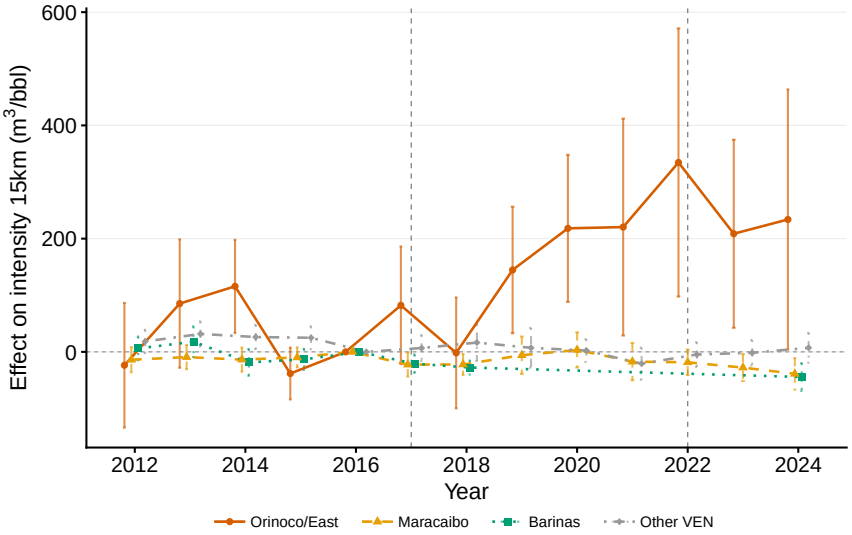
wellhead-elevation pattern observed in Venezuela.

Table D3: Event study around OFAC General Licence 41 (intensity, November 2022)

Event time (year)	$\log(1+\text{flaring int.})$ (1)	$\log(1+\text{OPEX})$ (2)	$\log(1+\text{CAPEX})$ (3)	$\log(1+\text{production})$ (4)
β_{-5} (2017)	$+0.248$	$+0.101$	$+1.683^{***}$	-0.387^{*}
	(0.299)	(0.137)	(0.319)	(0.230)
β_{-4} (2018)	$+0.355$	$+0.037$	$+1.525^{***}$	-0.393
	(0.295)	(0.146)	(0.453)	(0.242)
β_{-3} (2019)	$+0.130$	$+0.140$	$+1.480^{***}$	$+0.260$
	(0.261)	(0.201)	(0.531)	(0.380)
β_{-2} (2020)	-0.032	-0.128	$+1.011^{*}$	$+0.126$
	(0.285)	(0.098)	(0.540)	(0.284)
β_{+0} (2022)	$+0.008$	$+0.193^{**}$	$+0.541^{**}$	$+0.252^{***}$
	(0.263)	(0.076)	(0.228)	(0.082)
β_{+1} (2023)	$+0.154$	$+0.197^{**}$	$+0.556^{**}$	$+0.324^{***}$
	(0.275)	(0.092)	(0.222)	(0.102)
β_{+2} (2024)	$+0.107$	$+0.696^{***}$	$+1.007^{***}$	$+0.742^{***}$
	(0.262)	(0.175)	(0.283)	(0.165)
Field FE / Year FE	✓ / ✓	✓ / ✓	✓ / ✓	✓ / ✓
SE clustered at field	✓	✓	✓	✓
Observations	359	359	359	359
Fields	56	56	56	56

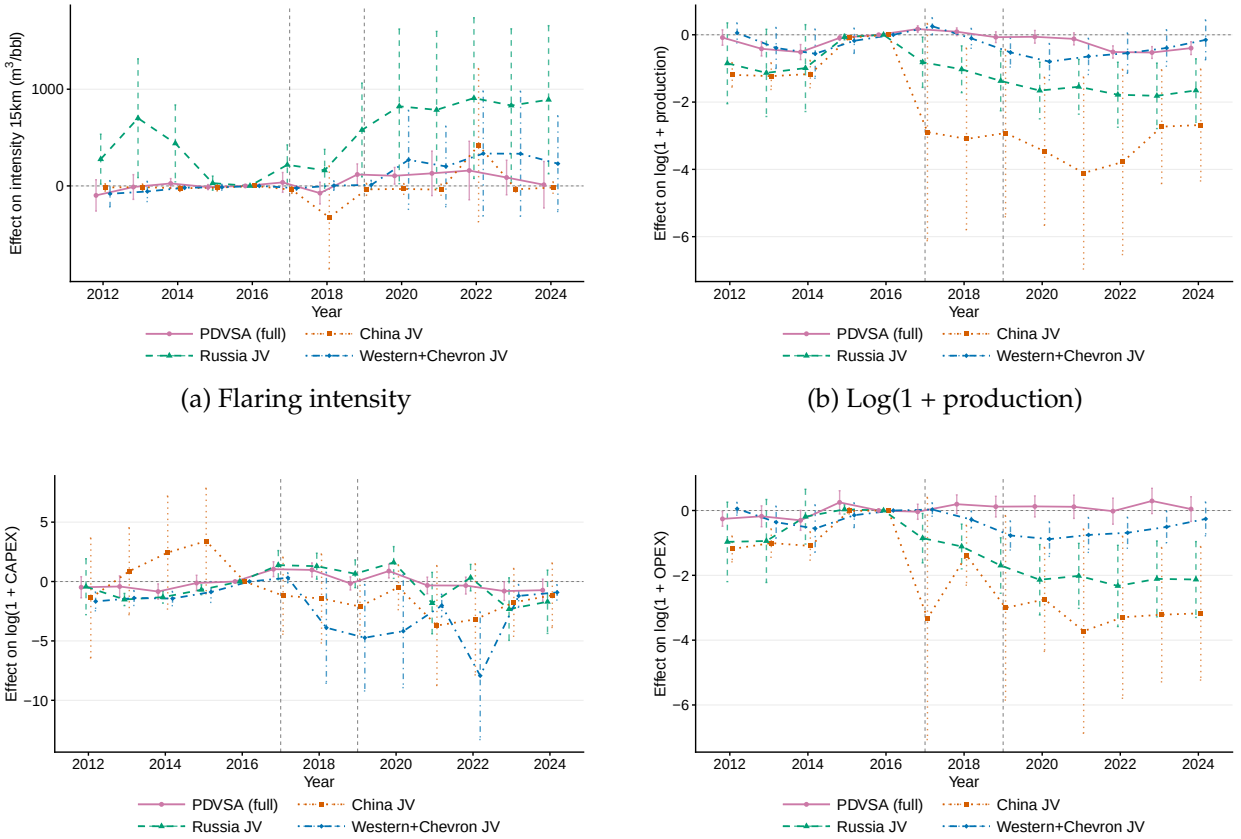
Notes: Event-study estimates of $Y_{it} = \alpha_i + \tau_t + \sum_{k \neq -1} \beta_k \mathbb{1}\{t = 2022 + k\}\,\text{Chev}_i + \varepsilon_{it}$. The omitted year ($k = -1$, i.e. 2021) is the reference. *Chev* $= 1$ for the three OFAC GL-41 Chevron joint-ventures in the heavy onshore panel (PetroBoscan, PetroIndependencia, PetroPiar). Sample: **heavy** Venezuelan onshore fields, 2017–2024 (is_heavy $= 1$ or heavy-crude share $> 50\%$); restricting to heavy fields holds crude type fixed and avoids contaminating the comparison with the faster-collapsing non-heavy trajectory. Outcomes are field-year $\log(1+\cdot)$ of: flaring intensity (m^3/bbl, VIIRS flare volume allocated within 15 km divided by Rystad crude production, winsorised at the 99th percentile of the heavy 2017–2024 sample to suppress the tiny-production-denominator tail; cap $= 8009.9$ m^3/bbl); operating expenditure (million USD, Rystad); capital expenditure (million USD, Rystad); and crude oil production (barrels, Rystad). Standard errors clustered at the field level in parentheses. ***p$<$0.01, **p$<$0.05, *p$<$0.1.

Figure D2: Flaring Intensity by Geographic Region: Event-Study



Notes: Event-study estimates of equation (3) (heavy/non-heavy DiD) interacted with geographic region indicators, normalised to zero in 2016. Outcome: flaring intensity (m^3/bbl) at the 15 km flare-allocation radius, winsorised at the 99.5th percentile. Geographic regions plotted: Venezuelan Orinoco/East, Venezuelan Maracaibo, the Mexican Maya basin, and Brazilian onshore. Reference: remaining LATAM fields. Field and year fixed effects; standard errors clustered at the asset level. Shaded bands are 95% confidence intervals. The intensity break in Venezuelan Orinoco appears at 2017–2019; Mexican Maya declines smoothly under Cantarell maturation; Brazilian onshore is approximately flat. Source: Rystad Energy UCube; World Bank VIIRS.

Figure D3: Event-Study Estimates by Ownership Group



(a) Flaring intensity

(b) Log(1 + production)

(c) Log(1 + CAPEX)

(d) Log(1 + OPEX)

Notes: Event-study estimates from equation (4) interacted with four ownership-group indicators: PDVSA-only (≥99% PDVSA equity), Russian, Chinese, and Western (including Chevron, collapsed). Ownership bins assigned using 2012–2016 baseline participation shares. Sample: six LATAM countries, 2012–2024, field-year level. Reference: non-Venezuelan LATAM fields, normalised to zero in 2016. Source: Rystad Energy UCube; World Bank VIIRS.

Table D4: Per-year log-XCH_4 trend at wellhead-and-pipeline cells, by country and basin.

Per-year trend ($\times$1,000)	(1)	(2)	(3)
LATAM baseline (pipe + well)	-0.92^{***} (0.03)	-0.54^{***} (0.03)	-0.54^{***} (0.03)
Venezuela — Orinoco/East	$+1.30^{***}$ (0.44)	$+1.51^{***}$ (0.40)	$+1.50^{***}$ (0.36)
Venezuela — Maracaibo	$+0.90^{***}$ (0.27)	$+1.32^{***}$ (0.27)	$+1.19^{***}$ (0.28)
Venezuela — Barinas	$+0.31^{***}$ (0.04)	$+0.82^{***}$ (0.08)	$+0.84^{***}$ (0.10)
Venezuela — Other	$+1.15^{***}$ (0.29)	$+1.44^{***}$ (0.33)	$+1.18^{***}$ (0.34)
Mexico — Maya basin	-2.51^{***} (0.15)	-2.14^{***} (0.12)	-2.13^{***} (0.10)
Ecuador — Oriente	$+1.51^{***}$ (0.17)	$+0.49^{***}$ (0.18)	$+0.67^{***}$ (0.15)
Colombia — Llanos	-0.81^{***} (0.14)	$+0.82^{***}$ (0.13)	$+0.98^{***}$ (0.14)
Cell FE	✓	✓	✓
Year-month FE	✓	✓	
Country $\times$ Year FE		✓	
Country $\times$ Year-month FE			✓
SE clustered at cell	✓	✓	✓
Cell-month observations	2,587,874	2,587,874	2,587,873

Specification. Each column is a separate regression of $\log \mathrm{XCH}_4$ on the time index t (years since 2018) interacted with a wellhead-and-pipeline indicator (cells within 20 km of an OSM+GEM pipeline *and* within 10 km of any oil-or-gas wellhead), with that interaction further interacted with seven country–basin indicators:

$$\log \mathrm{XCH}_{4ict} = \alpha_i + \tau_t + \phi\,(t \cdot \mathrm{PipeWell}_i) + \sum_g \psi_g\,(t \cdot \mathrm{PipeWell}_i \cdot \mathbb{1}\{i \in g\}) + \varepsilon_{ict},$$

where i indexes a 10×10 km TROPOMI cell, c its country, t calendar time in years from 2018, and $g \in \{\text{VEN Orinoco/East, VEN Maracaibo, VEN Barinas, VEN Other, MEX Maya, ECU Oriente, COL Llanos}\}$ are the country–basin indicators (LATAM Other is the omitted reference). *Reference category.* LATAM Other comprises pipe+well cells in the 6-country panel (Argentina, Brazil-onshore, Colombia, Ecuador, Mexico, Venezuela) that fall outside the seven named basins above. In practice this is dominated by Argentina (Vaca Muerta and the Neuquén/Mendoza fields) and includes the non-Maya regions of Mexico (Burgos, Veracruz, Chicontepec), the non-Llanos regions of Colombia (Catatumbo, Magdalena Medio, Putumayo), and Brazil's onshore pipe+well cells; Ecuadorean cells outside Oriente are negligible, and the residual Venezuelan cells are absorbed by *VEN Other*. Because Vaca Muerta dominates the reference and is in a rapid-development phase (high flaring during the unconventional ramp), the baseline trend ϕ is biased upward by Argentina; this makes the Mexican Maya and Colombian Llanos negative differentials *larger in magnitude* and the Venezuelan positive differentials a more conservative comparison. Coefficients are reported as the per-year change in $\log \mathrm{XCH}_4$ multiplied by 1,000 to ease reading. The row labelled *LATAM baseline* is ϕ (the trend in the omitted reference); each subsequent row is the corresponding ψ_g (the differential trend in basin g, on top of the baseline). *Fixed effects.* Column (1) is the baseline specification used in the body: cell and year-month fixed effects, with cell-clustered standard errors. Column (2) adds country $\times$ year fixed effects, absorbing country-specific yearly shocks. Column (3) replaces year-month with country $\times$ year-month fixed effects, fully saturating country-by-time variation. *Reading.* Only the Venezuelan Orinoco/East row shows a sustained *positive* differential trend across all three specifications, consistent with the corridor-suppression-and-wellhead-elevation pattern that the diluent-dependence physics predicts. The Mexican Maya and Colombian Llanos rows are robustly *negative*, ruling out a generic heavy-oil-extraction explanation. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Source: ESA Sentinel-5P TROPOMI L3; OpenStreetMap + Global Energy Monitor pipelines.

E TROPOMI Methane Data and Pipeline Proximity

This appendix describes the TROPOMI satellite data used in Section 6, explains the distinction between Level 2 and Level 3 data products and why we use the latter, documents the construction of the cell-level methane panel and pipeline proximity measures, and compares our reduced-form approach with the atmospheric inversion methodology of Nathan et al. (2024).

E.1 Level 2 versus Level 3 Data Products

TROPOMI data are disseminated at two processing levels that differ fundamentally in their granularity:

- *Level 2 (L2):* Individual satellite overpasses, with one observation per pixel per overpass. Each L2 pixel carries rich quality-assurance (QA) metadata (quality-value flags, aerosol optical depth in the near-infrared (NIR) and short-wave infrared (SWIR) bands, SWIR surface albedo, cloud radiance fraction, and retrieval uncertainty), enabling the analyst to apply custom, pixel-level filters. L2 data must be downloaded from Copernicus or SRON archives as individual orbit files.
- *Level 3 (L3):* Pre-aggregated composites (typically monthly) produced by applying the operational processor's standard QA filters and averaging surviving pixels onto a regular grid. L3 products are available via the Google Earth Engine (GEE) catalogue and are convenient for large-scale analysis. However, because pixel-level QA metadata are lost during aggregation, custom post-hoc filters, such as those in Nathan et al. (2024), cannot be applied retroactively.

Scale of the L2 data. With approximately 33,000 pixels per daily overpass covering Venezuela, a six-year panel (2019–2024) would require processing roughly $33{,}000 \times 365 \times 6 \approx 72$ million raw pixel observations, before any quality filtering. Even after applying standard QA thresholds (which eliminate most tropical pixels due to cloud cover), the filtered dataset would contain several million pixel-level records, each requiring individual retrieval-quality decisions. Downloading and processing this volume of L2 data represents a substantial data-engineering task that is beyond the scope of this study. Applying the full Nathan et al. methodology would also require coupling L2 retrievals with an atmospheric transport model (GEOS-Chem or WRF-Chem) to invert observed concentrations into emission fluxes, a specialised atmospheric chemistry exercise rather than a reduced-form econometric analysis.

Why L3 suffices for our purpose. Our empirical design does not require pixel-level QA decisions. We exploit *within-cell temporal variation* via cell and year-month fixed effects, so any systematic filtering difference between L2 and L3 that affects the level of XCH_4 in a cell is absorbed by the cell fixed effect. Any common temporal trend in data quality is absorbed by the year-month fixed effect. The coefficient of interest, the *differential* time trend near pipelines, is identified from variation that is orthogonal to both dimensions. To verify this, we conduct sensitivity analyses (reported below

in Section E.7) showing that stricter QA filtering within the L3 product *strengthens* rather than attenuates our coefficients. Monthly aggregated data also fits our biodiversity analyses better, as daily methane spikes are less likely to affect bird richness and abundance metrics.

E.2 Data Acquisition and Grid Construction

Data Acquisition. Level 3 monthly composites of bias-corrected XCH_4 are retrieved via the Google Earth Engine (GEE) Python API. For each 10 km grid cell covering Venezuela, we extract the monthly mean of all quality-filtered TROPOMI pixels whose centroids fall within the cell boundary. Following the quality-assurance approach in Nathan et al. (2024), we retain only pixels with aerosol optical depth < 0.3, a threshold that improves retrieval accuracy in the tropics at the cost of reduced coverage during hazy periods, and discard retrievals flagged as low quality by the operational processor. Values outside the physically plausible range of 1,700–2,100 ppb are excluded as artifacts.

Spatial Grid. The regression grid consists of 10 km $\times$ 10 km cells covering Venezuela, defined on a UTM projection and reprojected to WGS 84 (EPSG:4326) for centroid extraction. The same grid is used for both the methane panel and the biodiversity analysis in Section 6. Cell centroids are computed as the geometric centre of each grid polygon. The final regression sample comprises 25,520 cell-months spanning 1,280 cells over 2018–2024, with a mean XCH_4 of 1,908 ppb and a standard deviation of 28.8 ppb.

Temporal Coverage and Limitations. The GEE Level 3 product provides consistent coverage from November 2018 onward. The first US sanctions Executive Order constraining PDVSA's access to US capital markets (E.O. 13808) was already in force from August 2017, the first asset-blocking designation against PDVSA officials (E.O. 13850) followed in November 2018, and the comprehensive embargo (E.O. 13857) was imposed in January 2019; TROPOMI coverage therefore begins after the financial-sanctions wave but immediately before the asset-blocking and embargo waves. There is no clean pre-sanctions TROPOMI baseline, which motivates the time-trend specification used in Section 6.

E.3 Within-Venezuela near-pipeline trend

The body strain regression of equation (5) uses naphtha-price variation to identify the diluent channel at near-pipeline cells. As a complement, a pooled within-Venezuela specification fixes location at the cell level and asks whether methane rose *faster* near pipelines than far from them, without the naphtha interaction:

$$\log \mathrm{XCH}_{4ct} \;=\; \alpha_c + \tau_t + \phi\,(t \cdot \mathrm{NearPipe}_{d,c}) + \varepsilon_{ct}, \tag{E1}$$

where t is a linear time index, $\mathrm{NearPipe}_{d,c}$ is the indicator that cell c falls within distance d of a pipeline, and α_c, τ_t are cell and year-month fixed effects. ϕ is the differential per-year trend in

pipeline-vicinity methane. The same specification can be enriched with regional indicators (Other / Maracaibo / Orinoco) to test which Venezuelan region drives the trend.

Table E1 reports the estimates at $d \in \{10, 20, 50, 100\}$ km. Panel A gives the pooled trend; Panel B decomposes by Venezuelan region. Coefficients are multiplied by 1,000 for readability. The pooled trend is positive at every distance band ($+0.95$ at $d = 10$ km, falling monotonically to $+0.57$ at $d = 100$ km, all $p < 0.001$). The regional decomposition shows that Other-region cells (no Orinoco, no Maracaibo) drive most of the level signal, while Maracaibo shows a positive differential and Orinoco shows a near-pipeline trend with a negative differential at moderate distance bands. The cell fixed effect absorbs all time-invariant differences between cells, so the identifying variation is the within-cell rise in methane over the post-2018 window relative to the year-month average.

Table E1: TROPOMI CH_4: pipeline proximity and time trend

	(1) $d = 10$ km	(2) $d = 20$ km	(3) $d = 50$ km	(4) $d = 100$ km
Panel A: Near pipeline × time trend				
NearPipe × trend	0.9490***	0.7951***	0.6039***	0.5715***
	(0.1500)	(0.1288)	(0.1153)	(0.1269)
Panel B: Regional heterogeneity (Near pipeline × time trend)				
NearPipe × trend (Other)	1.2918***	1.0075***	0.6866***	0.5075***
	(0.2192)	(0.1801)	(0.1361)	(0.1410)
× Maracaibo (diff.)	0.1646	0.1776	0.5016**	0.8479***
	(0.3652)	(0.2859)	(0.1952)	(0.1780)
× Orinoco (diff.)	-0.8526***	-0.5557**	-0.4248**	-0.2237
	(0.2943)	(0.2418)	(0.1695)	(0.1417)
Observations	25,520	25,520	25,520	25,520
Cell FE	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓

Notes: This table estimates the differential methane trend near pipeline infrastructure using TROPOMI satellite data (regression 6 and 5). Sample: 1,280 Venezuelan 10 km grid cells, 2018–2024, cell-month level. The dependent variable is $\log(XCH_4)$, where XCH_4 is the column-averaged dry-air methane mole fraction (ppb) from TROPOMI; all estimates and standard errors are multiplied by 1,000 for readability. Each column corresponds to a different pipeline proximity threshold d. Panel A reports the pooled near-pipeline time-trend coefficient $\hat{\phi}$, where $t = \text{year} + (\text{month} - 1)/12 - 2018$ is a linear time trend. Panel B decomposes the trend by region: Row 1 reports the Other-region baseline ($\hat{\phi}_1$), Rows 2–3 report the Maracaibo ($\hat{\phi}_2$) and Orinoco ($\hat{\phi}_3$) differentials relative to this baseline. All specifications include cell and year-month fixed effects. Standard errors clustered at the cell level in parentheses. ***p<0.01, **p<0.05, *p<0.1. Source: ESA Sentinel-5P TROPOMI; OpenStreetMap.

E.4 Naphtha-price lag structure

Table E2 reports the lag-extended version of the naphtha-price regression in body Table 5, with the contemporaneous coefficient and the four-month-lag structure estimated jointly on the Venezuelan Orinoco cell-month sample.

Table E2: Naphtha-Price Lag Structure in the Orinoco Methane Panel

	(1) Contemp.	(2) Lag-1	(3) Lag-2	(4) Lag-3
$\log(\text{Naphtha}_t) \times \text{NearPipe}_{20}$	+3.053*** (0.907)			
$\log(\text{Naphtha}_{t-1}) \times \text{NearPipe}_{20}$		+2.235** (1.092)		
$\log(\text{Naphtha}_{t-2}) \times \text{NearPipe}_{20}$			+2.136** (1.019)	
$\log(\text{Naphtha}_{t-3}) \times \text{NearPipe}_{20}$				+2.882*** (1.067)
Cell FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Cell-month obs	9,138	9,138	9,138	9,138

Notes: Coefficients are the per-(log naphtha) change in $\log(\text{XCH}_4)$ in cells within 20 km of a pipeline, multiplied by 1,000. Sample is restricted to Venezuelan grid cells in the Orinoco Belt. Each column enters a single lag of the naphtha price interacted with NearPipe_{20} into the regression in isolation; the joint specification with all four lags entered together is omitted because the price series is highly autocorrelated, so the joint coefficients are unstable and individually uninterpretable. All specifications include cell and year-month fixed effects; standard errors clustered at the cell level in parentheses. The sample is the same 9,138 cell-months across 589 Orinoco cells in all four columns. *p<0.10, **p<0.05, ***p<0.01.

E.5 Cross-country LATAM extension

The within-Venezuela trend regression of equation (E1) can be extended to a six-country LATAM cell-month panel (Argentina, Brazil onshore, Colombia, Ecuador, Mexico, and Venezuela) to confirm that the Venezuelan near-pipe methane rise documented in the body is sanctions-specific rather than a global near-pipe drift. We use a balanced-cell sub-sample of 3,183 cells observed in both pre-July 2021 and post-July 2021 ($n = 158{,}484$ cell-months), because the LATAM-wide TROPOMI download was first run on a 2,500-centroid sub-sample before being extended to the full $\sim 72{,}000$-cell grid; the balanced restriction guarantees that the same set of cells contributes to both pre- and post-period identification of the trend. The pooled regression is

$$\log \text{XCH}_{4ict} \;=\; \alpha_i + \tau_t + \phi_1 \left(t \cdot \text{NearPipe}_{d,i} \cdot \text{VEN}_c\right) + \phi_2 \left(t \cdot \text{NearPipe}_{d,i}\right) + \delta \left(t \cdot \text{VEN}_c\right) + \varepsilon_{ict}, \quad \text{(E2)}$$

estimated separately at $d \in \{10, 20, 50, 100\}$ km, with cell α_i and year-month τ_t fixed effects, where $\text{NearPipe}_{d,i} = \mathbb{1}\{\text{cell } i \text{ within } d \text{ km of a pipeline}\}$ and $\text{VEN}_c = \mathbb{1}\{\text{cell } i \text{ in Venezuela}\}$. The three coefficients of interest trace four combinations of (country, pipeline-proximity) cells over time: ϕ_2 is the LATAM-wide pipeline-vicinity time trend (the non-Venezuela baseline near-pipe effect); δ is the Venezuela-wide trend differential vs LATAM (whether average Venezuelan methane rises faster than average LATAM methane, regardless of pipeline proximity); and ϕ_1 is the triple-interaction, the Venezuelan near-pipe trend differential relative to the LATAM-wide near-pipe trend.

Table E3 reports two summaries. Row 1 is the within-Venezuela near-pipe trend $\phi = \phi_1 + \phi_2$ from the Venezuela-only specification, the same object as in Table E1 once the units are aligned: it is positive and statistically significant at every distance band (+0.00047 to +0.00078 per year, equivalent to +0.47–0.78 in the per-mille convention used elsewhere in the appendix). Row 2 is δ, the Venezuela-vs-LATAM *country-wide* trend differential: negative at every distance band and

significant at $d \leq 50$ km. The two rows pin down the spatial pattern. Venezuelan near-pipeline cells rise faster than their LATAM analogues, but Venezuelan territory *as a whole* rises more slowly than LATAM. The only configuration consistent with both signs is that Venezuelan cells *far from pipelines* are trending sharply down while *near-pipeline* cells trend up, consistent with the near-pipeline naphtha-price response documented in Section 6.1.

Table E3: Methane Trend in Venezuela versus LATAM Controls

	$d = 10$ km (1)	$d = 20$ km (2)	$d = 50$ km (3)
VEN × NearPipe × t $(\hat{\phi}_1)$	+0.00103***	+0.00088***	+0.00072***
	(0.00017)	(0.00014)	(0.00012)
NearPipe × t $(\hat{\phi}_2)$	-0.00032***	-0.00029***	-0.00026***
	(0.00002)	(0.00001)	(0.00001)
VEN × t $(\hat{\delta})$	-0.00081***	-0.00089***	-0.00106***
	(0.00007)	(0.00007)	(0.00009)
Within-VEN near-pipe trend $\hat{\phi} = \hat{\phi}_1 + \hat{\phi}_2$	+0.00078***	+0.00067***	+0.00047***
	(0.00015)	(0.00012)	(0.00011)
Cell-month observations	2,588,253	2,588,253	2,588,253

Notes: Specification:

$$\log \mathrm{XCH}_{4ict} = \alpha_i + \tau_t + \phi_1(t \cdot \mathrm{NearPipe}_{d,i} \cdot \mathrm{VEN}_c) + \phi_2(t \cdot \mathrm{NearPipe}_{d,i}) + \delta(t \cdot \mathrm{VEN}_c) + \varepsilon_{ict},$$

where i indexes a 10×10 km cell, c its country, t calendar time in years from 2018, α_i a cell fixed effect, τ_t a year-month fixed effect, $\mathrm{NearPipe}_{d,i}$ the indicator that cell i lies within d km of an OSM+GEM combined pipeline, and VEN_c the indicator that cell i is in Venezuela. $\hat{\phi}_1$ is the triple-interaction Venezuela-near-pipe trend differential vs LATAM-near-pipe (the headline); $\hat{\phi}_2$ is the LATAM near-pipe-vs-far time-trend differential (non-Venezuela baseline pipeline effect); $\hat{\delta}$ is the Venezuela-overall trend differential vs LATAM (the country-wide shift, not pipeline-specific). The last row reports $\hat{\phi} = \hat{\phi}_1 + \hat{\phi}_2$ from a Venezuela-only specification (the within-Venezuela near-pipe trend, identical in interpretation to equation (E1)); the Venezuela-only value differs slightly from the joint-spec sum because of differences in fixed-effect support and clustering. Sample: cell-month TROPOMI $\log \mathrm{XCH}_4$ panel for the six-country LATAM grid (Argentina, Brazil onshore, Colombia, Ecuador, Mexico, Venezuela), 2018–2024, restricted to the balanced-cell subsample of 3,183 cells (of $\sim$ 71,000) observed both pre- and post-July 2021. Coefficients are reported in their native log-XCH_4-per-year units and are not multiplied by 1,000 (unlike Table E1); to compare with the body, multiply by 1,000. Each column is a separate NearPipe threshold d. Standard errors clustered at the cell level in parentheses. ***p<0.01, **p<0.05, *p<0.1. Source: ESA Sentinel-5P TROPOMI; OpenStreetMap + Global Energy Monitor combined pipelines.

E.6 Comparison with and replication of Nathan et al. (2024)

Nathan et al. (2024) study methane emissions from Venezuelan oil infrastructure using a fundamentally different methodology. Where we use TROPOMI Level 3 monthly composites (10 km grid, Nov 2018–2024) and run a reduced-form cell+year-month panel regression to test whether methane concentration trends differ near pipelines after sanctions, Nathan et al. use TROPOMI Level 2 daily retrievals ($\sim$5.5×7 km native pixels, 2018–2020) and atmospheric inversion models (GEOS-Chem, WRF-Chem) to recover emission fluxes (Tg/year) by basin. The two approaches

are complementary: ours asks whether methane rose faster near pipelines under sanctions; theirs asks how much methane Venezuela's oil sector emits in total. Nathan et al. quantify Venezuela's total methane budget at 7.5 Tg per year, with Lake Maracaibo alone contributing 1.2 Tg (16% of the national total), and document that methane emission intensity approximately doubled, from 11% to 23%, even as production collapsed.

To validate that our L3 data capture the same empirical patterns, we test three of their central findings in our concentration panel. (i) *Maracaibo is the methane hotspot.* Classifying cells by oil basin, mean XCH_4 is highest in the Maracaibo region (1,925 ppb) versus the Orinoco Belt (1,902 ppb) and the rest of Venezuela (1,907 ppb), and cells within 20 km of pipelines in Maracaibo average 1,951 ppb, the highest of any subgroup. (ii) *Methane rose while production collapsed.* Indexing both near-pipeline mean XCH_4 and national crude production to 2018 = 100, by 2020 the methane index reached 100.2 against a production index of 39.4, and by 2023 the methane index reached 102.8 against 51.9. (iii) *Methane intensity increased.* The concentration-based intensity proxy (near-pipeline mean XCH_4 divided by total Venezuelan production, indexed to 2018 = 100) peaked at 254.6 in 2020, a 2.5-fold increase, before partially recovering as production stabilised. While concentration-to-production ratios are not directly comparable to emission-based intensities, the direction and order of magnitude are consistent with Nathan et al.'s inversion results, suggesting that the L3 product is adequate for detecting the spatial and temporal signatures of infrastructure-related methane emissions.

E.7 Sensitivity to QA Filtering

A potential concern with using L3 data is that the pre-aggregated composites may include lower-quality pixels that would be discarded under the stricter L2 filters applied by Nathan et al. (2024). To address this, we re-estimate the main methane regressions (Tables E1 and 5) under two alternative specifications that approximate stricter QA filtering within the L3 framework:

1. *Low-uncertainty filter (B):* The L3 product includes a retrieval precision band (`XCH4_S5P_L3_CH4_uncertainty`), which reports the posterior uncertainty (in ppb) of each pixel's column-averaged methane estimate from the operational TROPOMI algorithm. We average this band to the cell-month level and drop cell-months with mean retrieval uncertainty above the 75th percentile (3.35 ppb), retaining 19,107 of 25,520 cell-months. This removes observations where the composite is likely dominated by hazy or marginal-quality retrievals.

2. *20-km aggregation (E):* We aggregate the 10 km grid to ∼20 km resolution, closer to the effective resolution of Nathan et al.'s analysis, yielding 14,482 cell-months.

Results. Under the low-uncertainty filter, the pooled time-trend coefficient $\hat{\phi}$ (multiplied by 1,000) *increases* from 0.95 to 1.08 at $d = 10$ km and from 0.80 to 0.94 at $d = 20$ km, with stronger statistical significance throughout. The Orinoco differential remains negative and significant (-0.48 vs. -0.56 at $d = 20$ km). The naphtha–Orinoco interaction remains stable (3.04 vs. 3.05 at $d = 20$ km). Stricter

filtering thus *strengthens* the time-trend results: any noise introduced by marginal pixels in the L3 product attenuates rather than inflates our estimates.

Under 20-km aggregation, the pooled coefficient weakens (0.53 at $d = 10$ km, versus 0.95 at baseline), consistent with spatial dilution: aggregating to coarser cells blends near-pipeline and far-from-pipeline pixels, attenuating the localised signal. The regional decomposition retains the same qualitative pattern (the Orinoco differential remains negative and significant at all distances), confirming that the spatial structure of the results is robust.

Table E4: Sensitivity of TROPOMI Results to QA Filtering

		Variant		
Table	**Coefficient**	**(A) Baseline**	**(B) Low uncertainty**	**(E) 20-km aggregation**
Panel A: Pooled time trend (Table E1, Panel A)				
	$\hat{\phi}$ at $d = 10$ km	0.95^{***}	1.08^{***}	0.53^{***}
		(0.15)	(0.15)	(0.15)
	$\hat{\phi}$ at $d = 20$ km	0.80^{***}	0.94^{***}	0.64^{***}
		(0.13)	(0.13)	(0.17)
	$\hat{\phi}$ at $d = 50$ km	0.60^{***}	0.84^{***}	0.44^{***}
		(0.12)	(0.12)	(0.14)
	$\hat{\phi}$ at $d = 100$ km	0.57^{***}	0.94^{***}	0.55^{***}
		(0.13)	(0.13)	(0.15)
Panel B: Regional decomposition (Table E1, Panel B)				
	Other baseline at $d = 20$ km	1.01^{***}	1.14^{***}	0.93^{***}
		(0.18)	(0.17)	(0.23)
	Maracaibo Δ at $d = 20$ km	0.18	-0.09	0.31
		(0.29)	(0.28)	(0.37)
	Orinoco Δ at $d = 20$ km	-0.56^{**}	-0.48^{**}	-0.74^{***}
		(0.24)	(0.23)	(0.26)
Panel C: Naphtha price × Orinoco (Table 5, Panel B)				
	$\widehat{\text{Naphtha} \times \text{NearPipe}}$ at $d = 10$ km	2.68^{**}	2.08^{*}	-0.06
		(1.11)	(1.15)	(0.22)
	$\widehat{\text{Naphtha} \times \text{NearPipe}}$ at $d = 20$ km	3.05^{***}	3.04^{***}	-0.31
		(0.91)	(0.94)	(0.34)
Cell-months		25,520	19,107	14,482

Notes: All coefficients multiplied by 1,000. Standard errors (clustered at cell level) in parentheses. Variant (A) reproduces the baseline estimates from Tables E1 and 5. Variant (B) drops cell-months with TROPOMI retrieval uncertainty above the 75th percentile (3.35 ppb). Variant (E) aggregates the 10 km grid to ∼20 km resolution. Pipeline geometries combine OpenStreetMap and Global Energy Monitor (GOIT/GGIT) data. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

E.8 Pipeline Proximity Measures

Pipeline Data Sources. We combine pipeline geometries from two open sources. OpenStreetMap (OSM), obtained via the Overpass API, provides 404 pipeline segments (≈1,440 km) after excluding non-hydrocarbon features; its volunteer-contributed coverage is concentrated along major trunk corridors. We supplement OSM with curated transmission-level routes from the Global Energy Monitor's Global Oil Infrastructure Tracker (GOIT) and Global Gas Infrastructure Tracker (GGIT),

which add 23 segments (≈2,670 km) after clipping to Venezuela's national boundary.[21] The combined dataset contains 427 features totalling approximately 4,110 km.

Coverage Benchmarking. The EIA estimates that Venezuela has 25 operational crude-oil pipeline systems totalling 2,139 miles (3,442 km), drawing on Global Energy Monitor data (U.S. Energy Information Administration, 2024). Our combined dataset slightly exceeds this figure because it also includes gas pipelines (≈679 km from five GEM gas projects), refined-product lines, and segments that may no longer be operational. After excluding GEM gas projects, the oil-only component of our dataset (≈3,430 km) is consistent with the EIA benchmark.

Deduplication. Because GEM analysts use OSM as a spatial reference but independently retrace pipeline geometries from aerial imagery, the same physical pipeline can appear in both datasets with slightly offset line strings. A naive union would double-count these segments. We address this by (i) projecting all OSM features to UTM Zone 20N and creating a 1 km buffer around their union, (ii) computing the fraction of each GEM segment's length that falls inside this buffer, and (iii) dropping any GEM segment with more than 80% overlap. At a 1 km buffer, 13 of the 23 GEM segments have zero overlap with OSM, and the maximum overlap fraction is 7.5% (a single liquid-pipeline segment). The two sources thus cover largely distinct portions of the network, and no segment approaches the 80% removal threshold.

Alternative Sources. The Oil and Gas Infrastructure Mapping database (OGIM; Omara et al., 2023) provides an alternative global pipeline dataset. However, its Venezuela coverage is limited: the OGIM v2.7 Data Source References list only two ArcGIS Online maps (from 2017 and 2021) as Venezuela-specific pipeline sources, whereas countries such as Argentina and Brazil draw on eight or more official government datasets. We downloaded OGIM v2.7 and found 108 Venezuelan pipeline segments totalling approximately 16,000 km, of which 6,300 km are classified as oil, nearly twice the EIA's 3,442 km benchmark for operational crude-oil trunk lines. All segments lack facility names, operator information, and operational status, suggesting the underlying sources may include decommissioned, planned, or duplicate lines. By contrast, our OSM + GEM oil-only total (≈3,430 km) closely matches the EIA figure. We therefore retain the OSM + GEM combination as our pipeline source.

Distance Computation. For each 10 km grid cell, we compute the minimum geodesic distance (using the S2 geometry library) from the cell centroid to the nearest pipeline segment. We define a binary proximity indicator:

$$\text{NearPipe}_{d,i} = \mathbb{1}\{\text{distance from cell } i \text{ to nearest pipeline} \leq d \text{ km}\},$$

[21] Global Energy Monitor, GOIT/GGIT Pipeline Routes: https://github.com/GlobalEnergyMonitor/GOIT-GGIT-pipeline-routes. License: Creative Commons CC BY 4.0.

with distance thresholds $d \in \{10, 20, 50, 100\}$ km. The indicator is time-invariant (pipeline geometry is fixed to the OSM download date) and enters the regression specifications as an interaction with the time trend or post-period indicator. Cell fixed effects absorb the level of the indicator itself, so identification comes from the *differential temporal evolution* of methane concentrations in near-pipeline versus far-from-pipeline cells.

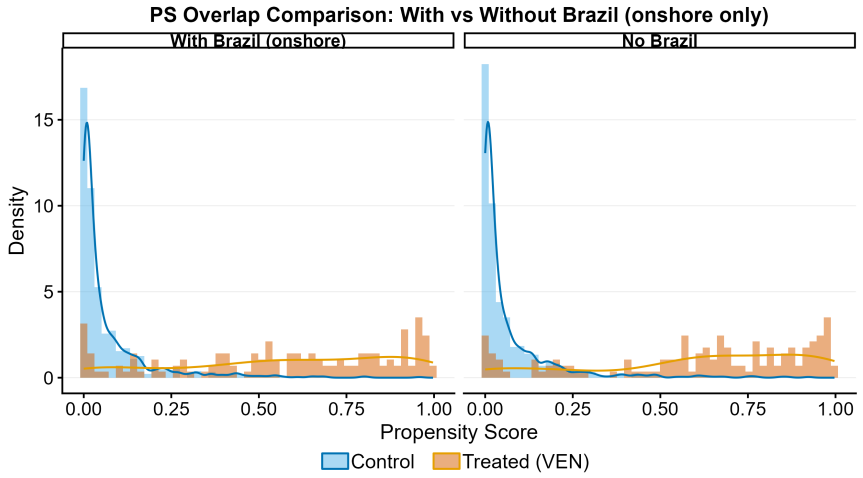
Regional Classification. To decompose the methane signal by oil-producing region, we assign grid cells to the Maracaibo Basin, Orinoco Belt, or Other category based on their geographic overlap with field-level region assignments from Rystad Energy. The regional interaction terms $\text{NearMara}_{d,i}$ and $\text{NearOrinoco}_{d,i}$ in regression (5) are the product of $\text{NearPipe}_{d,i}$ and the corresponding regional indicator.

F Inverse Probability Weighting

The baseline difference-in-differences in Table D1 relies on the parallel-trends assumption for identification. A potential concern is that Venezuelan fields differ systematically from control-country fields along observable geological dimensions (reservoir depth, porosity, temperature, API gravity) and that these differences could generate divergent trajectories even absent sanctions. To address this, we re-estimate the main specifications using stabilised inverse probability weights (IPW) derived from a logistic propensity-score model. The propensity score is estimated using pre-period (2012–2016) field-level covariates: geological characteristics (water depth, reservoir depth, porosity, temperature), baseline production volumes, and an onshore/offshore indicator. The resulting weights upweight control fields that are observationally similar to Venezuelan fields and downweight those that are dissimilar, producing a pseudo-population in which the covariate distributions are balanced.

Figure F1 displays the propensity-score distributions for Venezuelan and non-Venezuelan fields. There is substantial overlap across most of the support, though the treated distribution has a concentration at higher propensity scores reflecting Venezuela's distinctive geology (Orinoco Belt extra-heavy deposits have few direct analogues elsewhere). We trim the propensity scores at the 2nd and 98th percentiles and cap the resulting weights at the 99th percentile to mitigate the influence of extreme scores.

Figure F1: Propensity-Score Distributions: Venezuela vs. Control Countries



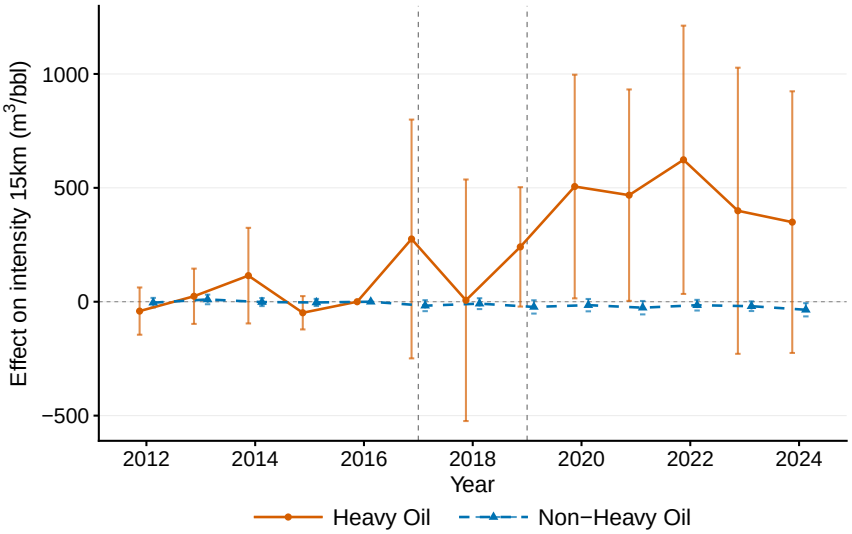
Notes: Kernel density plots of estimated propensity scores for Venezuelan (treated) and non-Venezuelan (control) fields. Propensity scores are estimated via logistic regression of a Venezuela indicator on pre-period (2012–2016) field-level covariates: water depth (m), reservoir depth (m), porosity (%), reservoir temperature (°C), mean baseline crude oil production (bbl/day), and an onshore indicator. The propensity score is used to construct stabilised inverse probability weights (IPW) for the reweighted estimates in Tables F1, F2, and F3. Propensity scores are trimmed at the 2nd and 98th percentiles, and resulting weights are capped at the 99th percentile, to limit the influence of extreme scores. Source: Rystad Energy UCube.

Table F1 reports the corresponding pooled estimates. The production coefficient implies a decline of approximately 42% ($\exp(-0.537) - 1 \approx -0.42$), comparable to the unweighted baseline,

and cumulative CAPEX declines by approximately 44% ($\exp(-0.573) - 1 \approx -0.44$). Flaring intensity at the 15 km radius rises substantially under IPW ($+259.8$ m^3/bbl, $p < 0.10$, larger than the unweighted estimate), consistent with the reweighting placing more emphasis on observationally similar control fields. Reweighting to balance observable covariates does not materially alter the main findings: the sanctions-induced production collapse, investment decline, and flaring intensity increase are robust to IPW adjustment.

Figure F2 and Table F2 present the IPW-weighted heavy-oil heterogeneity results, confirming that the heaviness channel is robust to propensity-score reweighting.

Figure F2: IPW Event-Study Estimates: Flaring Intensity by Crude Oil Heaviness



Notes: IPW-weighted event-study estimates from regression (3) (heavy/non-heavy DiD) with stabilised inverse probability weights. Heavy: fields in the Orinoco Belt (East Venezuela Basin or Llanos) or with heavy crude share >50% (extra heavy, heavy 15–22° API, bitumen). Sample: six LATAM countries (Argentina, Brazil onshore, Colombia, Ecuador, Mexico, Venezuela), 2012–2024, field-year level. Each coefficient $\hat{\beta}_k$ measures the year-k differential between heavy (or non-heavy) Venezuelan fields and non-Venezuelan LATAM fields, normalised to zero in 2016. Outcome: flaring intensity in m^3/bbl (allocated at 15 km radius, winsorized at the 99.5th percentile, restricted to field-years with positive flaring). Pooled production, CAPEX, and OPEX coefficients are reported in Table F2. Shaded areas show 95% confidence intervals. Standard errors clustered at the asset level. All models include field and year fixed effects. Stabilised inverse probability weights estimated from a logistic propensity-score model on pre-period geological and production covariates, propensity scores trimmed at the 2nd and 98th percentiles; weights capped at the 99th percentile. Source: Rystad Energy UCube; World Bank VIIRS Global Gas Flaring Tracker.

Figure F3 presents the IPW-weighted ownership group event studies, and Table F3 reports the corresponding pooled estimates, confirming the robustness of the six-group heterogeneity results.

Table F1: Effect of Sanctions: Inverse Probability Weighting

Dependent Vars:	Flaring Vol. 7.5km (1)	Flaring Vol. 15km (2)	Flaring Int. 7.5km (3)	Flaring Int. 15km (4)	Prod. (log) (5)	OPEX (log) (6)	CAPEX (log) (7)	Cum. CAPEX (log) (8)
Venezuela × Post	-13.3773	-5.9391	314.9786	259.2161*	-0.5400***	-0.4660**	-0.8036	-0.5830***
	(22.7235)	(13.4226)	(234.9367)	(154.8156)	(0.2090)	(0.2361)	(0.6229)	(0.1098)
Fixed effects								
Asset	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Mean dept. var.	29.8540	22.0782	76.9685	55.9316	12.0406	14.9673	12.7102	14.8554
Observations	4,820	7,459	4,820	7,459	11,567	11,567	11,567	11,567
Fields	700	997	700	997	997	997	997	997
R^2	0.85670	0.87990	0.61712	0.64530	0.87689	0.85131	0.65467	0.91666

Notes: This table replicates Table D1 using inverse probability weighting (IPW) to improve covariate balance between Venezuelan and non-Venezuelan fields (regression (6)). Propensity scores are estimated via logit on pre-period geology and production characteristics; stabilised weights are trimmed at the 2nd and 98th percentiles and capped at the 99th percentile. Sample: six LATAM countries (Argentina, Brazil onshore, Colombia, Ecuador, Mexico, Venezuela), 2012–2024, field-year level. Post $= \mathbb{1}\{\text{year} \geq 2017\}$. Cols (1)–(2): allocated flaring volume (million m^3). Cols (3)–(4): flaring intensity (m^3/bbl), winsorized at the 99.5th percentile. Col (5): log(1 + crude production in bbl). Col (6): log(1 + OPEX in USD). Cols (7)–(8): log(1 + CAPEX in USD) and log(1 + cumulative CAPEX in USD). Cols (1) and (3) restrict to field-years with positive flaring at 7.5 km; Cols (2) and (4) at 15 km; Cols (5)–(8) use the full sample. All models include field and year fixed effects. Standard errors clustered at the asset level in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. Source: Rystad Energy; World Bank VIIRS.

Table F2: Crude Oil Heaviness: Inverse Probability Weighting

Dependent Vars:	Flaring Vol. 7.5km (1)	Flaring Vol. 15km (2)	Flaring Int. 7.5km (3)	Flaring Int. 15km (4)	Prod. (log) (5)	OPEX (log) (6)	CAPEX (log) (7)	Cum. CAPEX (log) (8)
Heavy oil (Venezuela) × Post	-0.1973	-0.0148	374.1344	334.9423*	-0.5752**	-0.5462**	-1.0594	-0.6114***
	(22.2379)	(13.1766)	(263.5776)	(181.1025)	(0.2500)	(0.2725)	(0.7285)	(0.1153)
Non-heavy oil (Venezuela) × Post	-79.2304***	-27.2070	19.4102	-12.6349	-0.3711**	-0.0819	0.4227	-0.4466**
	(14.3418)	(37.6271)	(24.1966)	(14.2755)	(0.1619)	(0.3242)	(0.2949)	(0.1745)
Fixed effects								
Asset	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Mean dept. var.	29.8540	22.0782	76.9685	55.9316	12.0406	14.9673	12.7102	14.8554
Observations	4,820	7,459	4,820	7,459	11,567	11,567	11,567	11,567
Fields	700	997	700	997	997	997	997	997
R^2	0.85851	0.88026	0.62088	0.64973	0.87692	0.85146	0.65493	0.91666

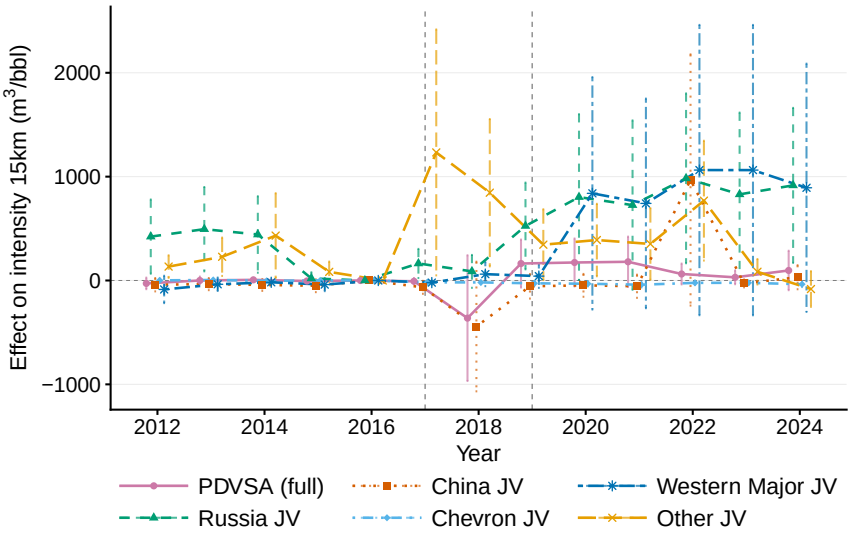
Notes: This table replicates Table 2 using inverse probability weighting (IPW) to improve covariate balance between Venezuelan and non-Venezuelan fields (regression (3)). Propensity scores are estimated via logit on pre-period geology and production characteristics; stabilised weights are trimmed at the 2nd and 98th percentiles and capped at the 99th percentile. Sample: six LATAM countries (Argentina, Brazil onshore, Colombia, Ecuador, Mexico, Venezuela), 2012–2024, field-year level. Post $= \mathbb{1}\{\text{year} \geq 2017\}$. VEN Heavy: fields in the Orinoco Belt (East Venezuela Basin or Llanos) or with heavy crude share $> 50\%$ (Extra Heavy, Heavy 15–19, Heavy 20–22, Bitumen). VEN Non-Heavy: remaining Venezuelan fields. Reference group: non-Venezuelan LATAM fields. Cols (1)–(2): allocated flaring volume (million m^3). Cols (3)–(4): flaring intensity (m^3/bbl), winsorized at the 99.5th percentile. Col (5): log(1 + crude production in bbl). Col (6): log(1 + OPEX in USD). Cols (7)–(8): log(1 + CAPEX in USD) and log(1 + cumulative CAPEX in USD). Cols (1) and (3) restrict to field-years with positive flaring at 7.5 km; Cols (2) and (4) at 15 km; Cols (5)–(8) use the full sample. All models include field and year fixed effects. Standard errors clustered at the asset level in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. Source: Rystad Energy; World Bank VIIRS.

Table F3: Ownership Heterogeneity: Inverse Probability Weighting

Dependent Vars:	Flaring Vol. 7.5km (1)	Flaring Vol. 15km (2)	Flaring Int. 7.5km (3)	Flaring Int. 15km (4)	Prod. (log) (5)	OPEX (log) (6)	CAPEX (log) (7)	Cum. CAPEX (log) (8)
PDVSA × Post	-3.5715	6.2079	92.5588*	38.9608	-0.0788	0.0709	0.5049**	-0.5531***
	(9.7142)	(6.1075)	(47.5696)	(30.1079)	(0.0836)	(0.1903)	(0.2563)	(0.1296)
Russia × Post	0.9189	-6.3144	221.3453*	221.5442*	0.2895	-0.2061	0.2249	-0.8987**
	(20.4375)	(11.9722)	(113.6451)	(118.8860)	(0.5572)	(0.3250)	(0.4874)	(0.3485)
China × Post	-4.2421	-5.3910	16.5598	-14.7370	-4.0276***	-3.3403***	-5.1437**	0.1027
	(7.2843)	(4.4765)	(30.1969)	(15.6290)	(1.5007)	(1.1473)	(2.0338)	(0.6196)
Chevron × Post	-0.9653	-17.9461	-25.8149***	-29.2706***	0.7133	0.5168	-0.0492	-0.1663
	(4.1166)	(26.5897)	(9.6118)	(10.0618)	(0.5589)	(0.5635)	(0.2166)	(0.2719)
Western Majors × Post	-16.6493	-18.1082	478.5744	494.3365	-0.8775***	-0.7275**	-2.6241	-0.5274***
	(38.1416)	(39.1401)	(361.6821)	(377.9493)	(0.1863)	(0.2913)	(2.0364)	(0.0859)
Other (Venezuela) × Post	-34.8135***	-13.1930*	45.3420	407.4666**	-1.5718**	-1.4230*	-2.5159	-0.6044***
	(8.3049)	(7.8101)	(65.2520)	(191.0140)	(0.6425)	(0.8450)	(1.6524)	(0.1631)
Fixed effects								
Asset	✓	✓	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓	✓	✓
Mean dept. var.	29.8540	22.0782	76.9685	55.9316	12.0406	14.9673	12.7102	14.8554
Observations	4,820	7,459	4,820	7,459	11,567	11,567	11,567	11,567
Fields	700	997	700	997	997	997	997	997
R^2	0.85693	0.88027	0.62553	0.65519	0.88010	0.85388	0.65675	0.91670

Notes: This table replicates Table 4 using inverse probability weighting (IPW) to improve covariate balance between Venezuelan and non-Venezuelan fields (regression (3)). Propensity scores are estimated via logit on pre-period geology and production characteristics; stabilised weights are trimmed at the 2nd and 98th percentiles and capped at the 99th percentile. Sample: six LATAM countries (Argentina, Brazil onshore, Colombia, Ecuador, Mexico, Venezuela), 2012–2024, field-year level. Post $= \mathbb{1}\{\text{year} \geq 2017\}$. Ownership bins are assigned using pre-2017 baseline participation shares with the following precedence: PDVSA ($\geq$ 99% PDVSA participation), Russia, China, Chevron, Western Majors, Other (any firm from each group $>$ 0%). Reference group: non-Venezuelan LATAM fields. Cols (1)–(2): allocated flaring volume (million m^3). Cols (3)–(4): flaring intensity (m^3/bbl), winsorized at the 99.5th percentile. Col (5): log(1 + crude production in bbl). Col (6): log(1 + OPEX in USD). Cols (7)–(8): log(1 + CAPEX in USD) and log(1 + cumulative CAPEX in USD). Cols (1) and (3) restrict to field-years with positive flaring at 7.5 km; Cols (2) and (4) at 15 km; Cols (5)–(8) use the full sample. All models include field and year fixed effects. Standard errors clustered at the asset level in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. Source: Rystad Energy; World Bank VIIRS.

Figure F3: IPW Event-Study Estimates: Flaring Intensity by Ownership Group



Notes: IPW-weighted event-study estimates from regression (4) interacted with six ownership-group indicators. Ownership bins assigned using 2012–2016 baseline participation shares (see Table 4 notes for precedence rule). Sample: six LATAM countries (Argentina, Brazil onshore, Colombia, Ecuador, Mexico, Venezuela), 2012–2024, field-year level. Each coefficient $\hat{\beta}_k$ measures the year-k differential between a Venezuelan ownership group and non-Venezuelan LATAM fields, normalised to zero in 2016. Outcome: flaring intensity in m^3/bbl (allocated at 15 km radius, winsorized at the 99.5th percentile, restricted to field-years with positive flaring). Pooled production, CAPEX, and OPEX coefficients are reported in Table F3. Shaded areas show 95% confidence intervals. Standard errors clustered at the asset level. All models include field and year fixed effects. Stabilised inverse probability weights estimated from a logistic propensity-score model on pre-period geological and production covariates, propensity scores trimmed at the 2nd and 98th percentiles; weights capped at the 99th percentile. Source: Rystad Energy UCube; World Bank VIIRS Global Gas Flaring Tracker.

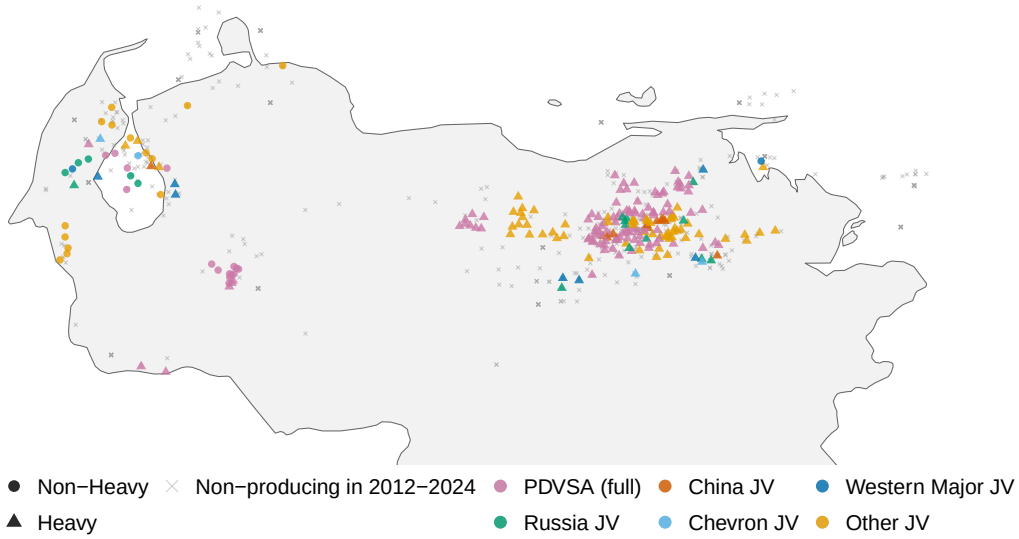
G Ownership and Size Heterogeneity

This appendix provides the size-by-ownership decomposition that underlies the within-Venezuela ownership discussion in Section 5.3 and the size-survival discussion in Section 5.1. The central question is whether the post-2017 reallocation toward giant fields reflects firm capacity (international joint ventures sustaining the plants they operate) or pure scale (any owner can keep the largest fields running).

Figure G1 maps Venezuelan fields in the analysis sample by ownership bin and heavy-crude status. Analysis-sample counts differ slightly from the baseline-partnership totals reported in Section 4: PetroIndependiente (Chevron, offshore conventional) and two Other-JV offshore conventional fields are excluded by the diluent-strain sample restriction (see the footnote in Section 7). Three patterns of geographic clustering stand out. First, the international joint ventures concentrate sharply in the Orinoco Belt extra-heavy region: 8/8 Chinese-partnered fields (100%), 10/11 Russian-partnered (91%), 33/36 Other-JV (92%), 2/3 Chevron, and 3/5 Western-Major fields lie in Orinoco East, versus 74/78 (95%) of PDVSA-only fields. Second, by crude type the partnership pattern flips: Chevron fields are uniformly heavy (3/3), Western Majors mostly heavy (4/5, 80%), but Chinese (1/8, 13%) and PDVSA-only (12/78, 15%) fields are predominantly non-heavy. Third, the geographic concentration in Orinoco is not a coincidence with size: the international JVs are also concentrated among the largest, most capital-intensive fields, which are the ones whose gas-handling chains are most exposed to the diluent shortage. The body-text ownership coefficients in Section 5.3 therefore mix three collinear margins (location, crude type, size); the size-by-ownership breakdown below isolates the size-versus-firm dimension.

Table G1 breaks each Venezuelan field-size bin into PDVSA sole-ownership (100% equity) versus joint ventures (PDVSA typically holding 60–80% with a minority international partner). Among giant fields, the divergence is pronounced: PDVSA-sole giants *increased* flaring by 7.6% (from 5,192 to 5,584 million m^3/year) while their production fell by 68%, so per-barrel flaring intensity roughly tripled. Joint-venture giants, in contrast, reduced flaring by 23% alongside a 59% production decline, consistent with international partners maintaining some degree of operational discipline. The divergence is concentrated in the giant-field bin: at smaller sizes, PDVSA-sole and joint-venture trajectories track each other closely. The reallocation toward giants is therefore not a pure scale story; it is a scale-and-firm story, in which the surviving giants are disproportionately the ones with foreign technical partners. Figure G2 extends this by region and OOIP tercile and shows that the same composition shift, large fields surviving while small ones exit, holds within Orinoco and Maracaibo separately.

Figure G1: Venezuelan Oil Fields by Ownership Group and Heaviness



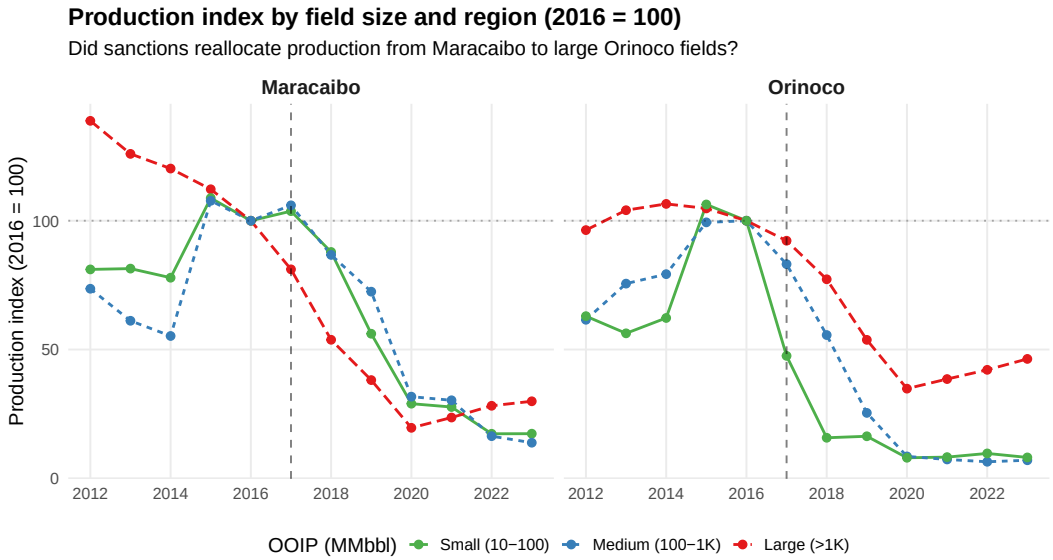
Notes: Each marker represents a Venezuelan oil field in the analysis sample ($n = 233$ producing fields with valid coordinates and ownership-bin assignment, 2012–2024). Marker colour indicates the field's pre-period ownership bin (Chevron JV, Western Major JV, Chinese JV, Russian JV, PDVSA full ownership, Other JV); marker shape indicates crude heaviness (triangle = heavy, defined as Orinoco location or heavy-crude share above 50%; circle = non-heavy). Grey lines: oil-and-gas pipelines from the OSM + GEM combined network. Source: Rystad Energy UCube; OpenStreetMap; Global Energy Monitor.

Table G1: Flaring and Production by Field Size and Ownership — Venezuela

		Flaring (M m^3/yr)			Production (M bbl/yr)			
Size	Owner	Pre	Post	Δ%	Pre	Post	Δ%	Fields
Small (<30)	Joint venture	40	9	-78.4	8	2	-77.0	45/33
	PDVSA sole	25	25	+2.2	1	1	-41.9	50/49
Medium (30-300)	Joint venture	920	352	-61.7	89	27	-69.1	46/46
	PDVSA sole	155	79	-49.3	14	6	-57.1	41/41
Large (300-1k)	Joint venture	432	367	-15.1	80	52	-34.7	12/12
	PDVSA sole	483	467	-3.4	33	23	-29.5	13/14
Giant (>1000)	Joint venture	830	638	-23.1	366	152	-58.6	13/13
	PDVSA sole	5,192	5,584	+7.6	358	116	-67.6	11/12

Notes: "PDVSA sole" denotes fields where PDVSA holds 100% of equity; "Joint venture" includes all fields with minority partners (PDVSA typically holds 60–80%) as well as non-PDVSA operators (8 fields). Pre: 2012–2016, post: 2017–2024. Fields column shows pre/post count. Flaring: VIIRS-allocated volume at 15 km. Production from Rystad.

Figure G2: Production Index by Region and Field Size



Notes: Production indexed to 2016 = 100, by Venezuelan oil-producing region and OOIP tercile. Large Orinoco fields retained roughly 46% of 2016 output through 2023; small and medium Orinoco fields collapsed to 7–8%. Maracaibo large fields retained only 30%. Source: Rystad Energy UCube.

H Biodiversity Appendix

eBird Sample. We use complete Venezuelan eBird checklists over 2012–2024 with duration 5–300 minutes, distance $\leq$ 5 km, and at least one species reported. The cleaned panel comprises 133,673 checklists across 1,508 unique 10 km grid cells. Species are matched to trophic guilds using EltonTraits 1.0 with a deterministic priority rule (91% match rate). Table H1 reports summary statistics for the panel; the spatial overlap of checklist locations with pipelines, TROPOMI methane, and VIIRS flare detections is shown in Figure 6 of the body.

Table H1: Summary Statistics: eBird Checklists in Venezuela, 2012–2024

	N	Mean	SD	P10	P25	P50	P75	P90
Panel A: Biodiversity outcomes								
Species richness	133,673	13.66	11.49	3.00	6.00	11.00	18.00	28.00
Shannon entropy	116,552	2.02	0.81	0.95	1.52	2.10	2.58	3.00
Gini–Simpson index	116,552	0.77	0.21	0.50	0.72	0.84	0.90	0.94
Log abundance	116,552	3.40	1.19	1.95	2.71	3.47	4.16	4.79
Pielou's evenness	113,026	0.86	0.13	0.69	0.82	0.91	0.95	0.97
Panel B: Effort variables								
Duration (minutes)	133,673	32.36	43.18	5.00	9.00	15.00	36.00	75.00
Distance (km)	133,673	0.63	1.29	0.00	0.00	0.10	0.69	1.84
Number of observers	133,673	1.59	1.22	1.00	1.00	1.00	2.00	3.00

Notes: This table reports summary statistics for the Venezuelan eBird sample used in the biodiversity analysis. Sample: complete eBird checklists from Venezuela, 2012–2024, assigned to 10 km grid cells, with duration between 5 and 300 minutes and distance $\leq$ 10 km for traveling protocols. Panel A: species richness is the number of unique species per checklist; abundance is the total number of individual birds counted per checklist. Panel B: effortcovariates used as controls in biodiversity regressions; traveling protocol equals 1 if the observer moved during the count, 0 if stationary. Source: eBird Basic Dataset (Cornell Lab of Ornithology); EltonTraits 1.0.

Robustness to Land-Cover and Built-Up Confounds. A natural concern is that the pollution-biodiversity association might be confounded with tree-cover loss or with urban build-up; both would mechanically suppress local bird abundance through habitat-loss channels independent of pollution. We address the concern with two diagnostics. First, augmenting the pollution-richness regression with Hansen tree-cover loss (2001–2023) and its post-period interaction leaves the CH_4 coefficient essentially unchanged while the tree-cover-loss interaction is itself approximately zero ($+0.0018$, $p = 0.95$). The pollution effect is therefore not driven by differential tree-cover dynamics. Second, GHSL built-up data show no asymmetric urbanisation pattern across cell pollution quartiles (built-up share of grid loss roughly equal across quartiles). Both diagnostics support reading the pollution-biodiversity association as a pollution effect, not a habitat-conversion artifact.

Strain Channel: OOIP Gradient. Table H2 reports the cross-sectional gradient of bird abundance and species richness against $\log(\text{OOIP})$ within 50 km of each cell, interacted with basin indicators,

on the post-2017 Venezuelan eBird sample restricted to cells near at least one field with positive OOIP. All specifications include year-month fixed effects and effort controls (log duration, log distance, number of observers, traveling indicator, hour-of-day quadratic); columns (2) and (5) add observer fixed effects, and columns (3) and (6) replace them with observer×year fixed effects to absorb birder learning (Madhok, 2025). Standard errors are clustered at the cell level. The Orinoco log(OOIP) interaction is negative across all columns and significant on log abundance with observer fixed effects (column 5: -0.054, $p < 0.01$); the Maracaibo interaction is similarly negative (-0.033, $p < 0.05$). Species richness loads with the same sign but is imprecise once observer effects are absorbed, consistent with the extensive margin having already adjusted to chronic exposure.

Table H2: Oil Reserves and Bird Abundance

	Total Richness			log(1+Abundance)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(OOIP) × Orinoco	−0.886***	−0.025	−0.125	−0.102***	−0.053***	−0.046**
	(0.201)	(0.131)	(0.142)	(0.025)	(0.018)	(0.021)
log(OOIP) × Maracaibo	−0.526***	0.088	0.028	−0.169***	−0.033**	−0.035**
	(0.178)	(0.119)	(0.112)	(0.043)	(0.013)	(0.014)
Year-month FE	✓	✓	✓	✓	✓	✓
Observer FE	No	✓	No	No	✓	No
Observer × Year FE	No	No	✓	No	No	✓
Effort controls	✓	✓	✓	✓	✓	✓
Observations	40,481	40,418	40,336	40,481	40,418	40,336

Notes: Dependent variables: total species richness (columns 1–3) and log of 1 plus total individual abundance (columns 4–6). Sample: post-2017 Venezuelan eBird checklists within 50 km of an oil field with positive OOIP. log(OOIP) is the log of cumulative Original Oil In Place (million barrels) of fields within 50 km, included as a control in all specifications. Coefficients report the differential association of log(OOIP) with biodiversity in each basin relative to the rest of Venezuela. Effort controls: log duration, log distance, number of observers, protocol indicator, hour-of-day quadratic. Columns (3) and (6) include observer×year fixed effects to account for birder learning (Madhok, 2025). Standard errors clustered at cell level. ***p<0.01, **p<0.05, *p<0.1.

Pollution and biodiversity: the methane/flaring horse race. Table H3 reports the horse-race specification of equation (6) that pits VIIRS flaring against TROPOMI methane on log abundance and species richness at three buffer radii. Flaring bites at the close radius ($R = 25$ km) and methane takes over at the larger radii ($R = 50$–75 km); both effects concentrate in the Orinoco basin (Panel B). See Section 6 for discussion.

Maintenance Channel: Bird Abundance and Species Richness. Bird-side counterpart to Table 6. Columns (1)–(3) report $\log(1 + \text{abundance})$ as the dependent variable; columns (4)–(6) report $\log(1 + \text{richness})$. Abundance recovers strongly and significantly at Chevron-near cells after the licence; richness moves in the same direction but the coefficient is not significant under any FE structure (slower extensive-margin recovery).

Table H3: Atmospheric Pollution, Bird Abundance, and Species Richness

	log(1 + abundance)			Species richness		
	$R = 25$ km	$R = 50$ km	$R = 75$ km	$R = 25$ km	$R = 50$ km	$R = 75$ km
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Pooled specification						
$\log(1 + CH_4)$ (std)	-0.026**	-0.030***	-0.021*	-0.109	-0.329***	-0.334**
	(0.010)	(0.011)	(0.011)	(0.123)	(0.109)	(0.129)
$\log(1 +$ VIIRS flare) (std)	-0.051**	0.001	0.005	-0.748***	-0.050	-0.249
	(0.023)	(0.019)	(0.022)	(0.211)	(0.194)	(0.259)
Panel B: Implied basin-specific slopes						
Other region						
CH_4 (std)	0.027	-0.021	0.001	0.436	0.149	0.335
	(0.027)	(0.025)	(0.025)	(0.326)	(0.301)	(0.284)
VIIRS flare (std)	-0.022	0.028	0.013	-0.749**	0.104	-0.105
	(0.040)	(0.032)	(0.043)	(0.371)	(0.355)	(0.400)
Orinoco basin						
CH_4 (std)	-0.038***	-0.040***	-0.031**	-0.273**	-0.553***	-0.545***
	(0.013)	(0.013)	(0.016)	(0.114)	(0.147)	(0.184)
VIIRS flare (std)	-0.050*	-0.031	-0.009	-0.651**	-0.415	-0.432
	(0.030)	(0.026)	(0.025)	(0.282)	(0.281)	(0.323)
Maracaibo basin						
CH_4 (std)	-0.028	0.002	0.008	0.124	0.088	-0.010
	(0.042)	(0.030)	(0.046)	(0.631)	(0.231)	(0.375)
VIIRS flare (std)	-0.104**	0.102	0.126	-1.029	1.614*	1.773*
	(0.046)	(0.072)	(0.087)	(0.710)	(0.925)	(0.981)
Effort controls	✓	✓	✓	✓	✓	✓
Cell FE	✓	✓	✓	✓	✓	✓
Year-month FE	✓	✓	✓	✓	✓	✓
Basin × month FE	✓	✓	✓	✓	✓	✓
Lake prox. × year, month	✓	✓	✓	✓	✓	✓
Observations	49,851	80,094	93,884	49,851	80,094	93,884
Mean dept. var.	3.54	3.49	3.47	14.92	14.44	14.34

Notes: Joint test of pollution exposure on bird outcomes in the post-sanctions period. Outcomes are $\log(1 + \text{abundance})$ in cols (1)–(3) and species richness (number of unique species per checklist) in cols (4)–(6). Sample: Venezuelan eBird checklists 2018–2024 with non-missing biodiversity outcomes. Both exposure variables are standardised (z-scored) within each radius-specific regression sample. CH_4 is the mean TROPOMI column-averaged dry-air methane mixing ratio (ppb) across 10 km cells within radius R; VIIRS flare is the sum of fire radiative power (MW) from NASA FIRMS active-fire detections within radius R. Panel A reports the pooled specification. Panel B reports implied basin-specific slopes from an interaction specification where each exposure is interacted with basin indicators (Other = baseline; Orinoco and Maracaibo = baseline + interaction). All regressions include cell, year-month, and basin×month fixed effects, log-distance to Lake Maracaibo interacted with year and month dummies, and checklist-level effort controls (log duration, log distance, number of observers, traveling indicator, hour-of-day quadratic). Standard errors clustered at the cell level in parentheses. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. Source: eBird; Sentinel-5P TROPOMI; NASA FIRMS VIIRS.

Table H4: Maintenance Channel: Per-Barrel OPEX, Bird Abundance, and Species Richness

	log(1 + abundance)			log(1 + richness)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(1 + OPEX/prod) (η_0)	-0.1588	-0.4389	+0.1279	+0.0138	-0.1279	-0.1736
	(0.3731)	(0.3657)	(0.2286)	(0.1291)	(0.1015)	(0.1831)
× Post2017 (η_1)	+0.2261	+0.5052	-0.0665	+0.0329	+0.1644*	+0.2007
	(0.3688)	(0.3629)	(0.2212)	(0.1217)	(0.0965)	(0.1801)
× Post2022 (η_2)	-0.0675	-0.0218	-0.1471	-0.0689*	-0.0357	-0.1050
	(0.0471)	(0.0477)	(0.1224)	(0.0366)	(0.0314)	(0.0720)
× Chevron (η_3)	-2.2792***	-2.1356***	-1.4534***	-0.3118***	-0.2801	+0.0628
	(0.3506)	(0.3680)	(0.3180)	(0.1130)	(0.2082)	(0.1828)
× Post2022 × Chevron (η_5)	+1.6407**	+1.4437**	+1.6382*	+0.2037	+0.1022	+0.0070
	(0.7845)	(0.5947)	(0.8477)	(0.2317)	(0.2744)	(0.5012)
Post2022 × Chevron (δ_2)	-2.3427	-1.8200	-2.7721	-0.2755	+0.1015	+0.1648
	(1.9741)	(1.4607)	(2.1272)	(0.6003)	(0.6600)	(1.2210)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observer FE	No	Yes	—	No	Yes	—
Observer × Year FE	No	No	Yes	No	No	Yes
Observations	7,565	7,522	7,457	7,565	7,522	7,457

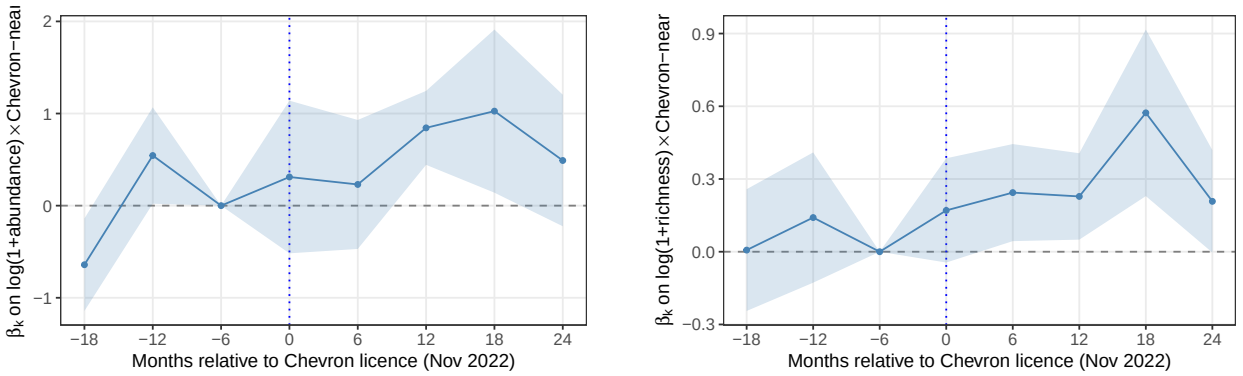
Notes: Bird-side counterpart of Table 6. Dependent variable: log(1 + bird abundance per checklist) in columns (1)–(3), and log(1 + checklist species richness) in columns (4)–(6), both at the cell-checklist level. Sample: Venezuelan eBird checklists in cells with at least one Venezuelan onshore field within 30 km, 2012–2024. Chevron = 1 if any GL-41 Chevron JV field lies within 30 km of the cell, and OPEX/production is the cell-year mean of log(1 + OPEX/prod) over fields within 30 km. Checklist-level effort controls (log duration, log distance travelled, number of observers, hour started, traveling indicator) included throughout. Standard errors clustered at the cell level. ***p<0.01, **p<0.05, *p<0.1. Source: Rystad Energy UCube; World Bank VIIRS Global Gas Flaring Tracker; eBird.

Maintenance Channel: Bird Event Study Dynamics. Figure H1 reports the dynamic counterpart of Table H4: per-bin coefficients on NearChevron × bin, in 6-month windows ±24 months around 26 November 2022, for log abundance (panel (a)) and log richness (panel (b)). Abundance builds gradually post-licence, peaking at +1.03 at +18 months ($p = 0.025$). Richness rises at roughly half that magnitude, peaking at +0.57 at +18 months ($p < 0.01$). Pre-period coefficients on richness are near zero, consistent with parallel trends. The lag profile is consistent with the mechanics of clearing a maintenance backlog (parts ordered, equipment swapped, leaks sealed, gas-reinjection capacity restored), with the abundance–richness wedge reflecting the slower extensive margin (individuals return before new species disperse in and establish).

Maintenance Channel: Guild-Level Decomposition. Counterpart to the saturated specification in Table 6, with log(1 + abundance) broken out by trophic guild and using the Chevron-vs-Western-JV ±24-month window of equation (8).

Pollution–Effort Selection at $R = 50$ km. Table H6 tests whether satellite-measured pollution predicts eBird effort or coverage outcomes at the radius where the main CH_4–richness specification is most significant. Six standardised effort outcomes are regressed on standardised log(1 + CH_4)

Figure H1: Bird Abundance and Species Richness at Chevron Cells around the Licence Date



(a) $\log(1 + \text{abundance})$ (b) $\log(1 + \text{richness})$

Notes: Per-bin coefficients β_k from $Y_{ict} = \alpha_i + \tau_t + \sum_{k \neq -6\text{m}} \beta_k \mathbb{1}\{\text{bin}_t = k\} \cdot \text{NearChev}_i + \mathbf{X}'\delta + \varepsilon$, with $Y = \log(1 + \text{abundance})$ in panel (a) and $Y = \log(1 + \text{richness})$ in panel (b). Estimated on Venezuelan eBird checklists in cells with at least one field within 30 km, ±24 months around 26 November 2022, with 6-month bins. Cell, year-month, and observer fixed effects; effort controls. Reference bin: −6 to 0 months pre-licence. Vertical blue line at the licence date. Shaded band: 95% confidence interval. Source: eBird; Rystad Energy UCube; World Bank VIIRS.

Table H5: Chevron Licence and Bird Abundance by Trophic Guild

	NearChev × Post: β_g on $\log(1 + \text{abund}_g)$		
	Cell+YM	Cell+YM+Obs	Cell+YM+Obs×Yr
	(1)	(2)	(3)
Forest insectivores	+0.6041***	+0.5085***	+0.0373
	(0.1771)	(0.1720)	(0.3081)
Frugivores	+0.2863	+0.2031	+0.3470
	(0.2422)	(0.2187)	(0.3276)
Granivores	+0.2596	+0.2529	+0.6338
	(0.1951)	(0.2170)	(0.3916)
Waterbirds	-0.2643	-0.1808	+0.0544
	(0.2187)	(0.1524)	(0.3708)
Cell + Year-Month FE	Yes	Yes	Yes
Observer FE	No	Yes	—
Observer × Year FE	No	No	Yes
Observations	2,584	2,579	2,573

Notes: Guild-level Chevron-license event around 26 November 2022, using the specification of equation (8): $\log(1 + \text{abund}_g)_{ict} = \alpha_i + \tau_t + \beta_g (\text{NearChev}_i \cdot \text{Post}_t) + \mathbf{X}'_{ict}\delta + \varepsilon_{ict}$. Sample: cells within 30 km of a Chevron joint-venture (PetroPiar, PetroBoscan, PetroIndependencia) or another Western JV, observed within ±24 months of the licence date. Treatment is NearChev × Post; the reference group is Western-JV cells without a Chevron field nearby. All columns include cell and year-month fixed effects and checklist-level effort controls; columns (2)–(3) add observer fixed effects; column (3) uses observer × year fixed effects. Standard errors clustered at the cell level. ***p<0.01, **p<0.05, *p<0.1. Source: eBird; EltonTraits; Rystad Energy UCube.

and $\log(1 + \text{VIIRS flare})$ at $R = 50$ km, with cell and year-month fixed effects and cell-clustered standard errors. All twelve coefficients are individually insignificant (largest $|t| = 1.22$), confirming that the richness results at this radius are not artefacts of differential observer behaviour.

Table H6: Selection Diagnostic: Pollution Exposure and Birding Effort ($R = 50$ km)

	log(1 + CH_4)		log(1 + VIIRS flare)	
Dependent variable	Coef.	(SE)	Coef.	(SE)
log(1 + # checklists)	−0.016	(0.015)	−0.021	(0.031)
Mean log(duration)	−0.007	(0.018)	−0.011	(0.030)
Mean distance (km)	0.018	(0.016)	−0.017	(0.032)
Mean # observers	0.020	(0.017)	0.008	(0.035)
Traveling share	−0.022	(0.018)	−0.045	(0.038)
Mean start hour	0.000	(0.020)	0.017	(0.037)
Cell FE	✓			
Year-month FE	✓			
SE clustering	Cell			
N (cell-months)	7,239			

Notes: This table tests whether pollution exposure predicts birding effort or coverage, as a selection diagnostic. Each row reports a separate regression of a standardised (z-scored) effort or coverage outcome on standardised log(1 + CH_4) and log(1 + VIIRS flare) at $R = 50$ km. Sample: post-period Venezuelan cell-months with non-missing TROPOMI methane data (2018–2024). All specifications include cell and year-month fixed effects. Coefficients are in standard-deviation units: a one-standard-deviation increase in the exposure is associated with a β-standard-deviation change in the outcome. No coefficient is significant at conventional levels, indicating that methane and flaring do not predict birding effort or coverage at this radius. Standard errors clustered at the cell level. ***p<0.01, **p<0.05, *p<0.1. Source: eBird; Sentinel-5P TROPOMI; NASA FIRMS VIIRS.