The Environmental Cost of Sanctions

Gas Flaring in Venezuela's Oil Sector*

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Abstract

This study examines the environmental consequences of the 2017 U.S. financial sanctions imposed on Venezuela, focusing on natural gas flaring intensity as well as production, capital expenditures (CAPEX), and operating expenditures (OPEX) at the oil asset level. Using a panel dataset combining satellite-detected flaring with field-level production and expenditure data, we implement a difference-in-differences and triple-difference strategy with oil fields in Argentina, Brazil, Colombia, and Ecuador as the control group. The results show that sanctions significantly increased flaring intensity and caused sharp declines in production, CAPEX, and OPEX, but these effects were mitigated for assets with higher national oil company (NOC) ownership shares. The findings suggest that Petróleos de Venezuela, Venezuela's state-owned oil company, strategically concentrated scarce resources in majority state-owned assets during the sanctions period, limiting the decline in production and investment for these fields. These results highlight the importance of the unintended consequence of sanctions and underscore the need for policymakers to consider the environmental externalities of economic statecraft.

Future analysis plan: Building on these findings, we plan to deepen the analysis by explicitly accounting for the role of *ownership* and *operatorship* in shaping environmental outcomes. The results so far indicate that ownership structure fundamentally mediates how sanctions affect flaring. To further unpack this mechanism, we will explore heterogeneity across operators based on nationality and corporate affiliation.

Specifically, we will investigate whether firms with operational or investment exposure to the United States—particularly those headquartered in the U.S. or Europe—behaved differently in their flaring responses after 2017. On one hand, these firms may have maintained lower flaring intensities because of stronger internal environmental standards and greater regulatory scrutiny in their home jurisdictions. On the other hand, they may have reduced technology transfer and operational support to Venezuelan fields to comply with U.S. sanctions, effectively limiting the diffusion of cleaner production practices.

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By combining field-level operational data with information on firm nationality, operatorship, and ownership shares, we will assess whether these dual incentives—corporate environmental responsibility versus geopolitical compliance—produced divergent flaring behaviors across operator types. This extension will clarify how sanctions interact with the political economy of field ownership and the global structure of the oil industry.

Ultimately, the expanded analysis will shed light on how ownership nationality and the strategic incentives of multinational operators shape environmental performance under geopolitical pressure. Understanding these mechanisms is crucial for designing both sanctions and environmental policies that account for firm-level incentives to flare.

1 Introduction

Oil and gas still power the world. Together they supply about half of global primary energy (International Energy Agency, 2024). Extraction produces a costly byproduct: routine flaring of associated gas. Flaring wastes fuel and increases greenhouse gases. It is concentrated in a small number of producers, which makes it a tractable policy target (World Bank, 2025).

Sanctions are a core tool of economic statecraft. They aim to change behavior without resorting to force. Their macroeconomic and political effects are well studied. Their environmental consequences are not. We ask whether sanctions change how oil is produced and whether those changes raise the emissions intensity of each barrel.

Venezuela is a natural case. It is a major flarer and a petrostate. PdVSA dominates production and operations. Since 2017, the United States has imposed financial measures that limited access to capital, equipment, and markets (Seelke, 2025). We ask a simple question with broad implications: did the 2017 sanctions worsen gas flaring in Venezuela's oil sector?

We find that they did. Using asset-level data, we estimate that sanctions increased flaring intensity—gas flared per barrel—by 58% in Venezuelan fields relative to comparable fields in Argentina, Brazil, Colombia, and Ecuador. Over the same period, production, capital spending (CAPEX), and operating spending (OPEX) fell. Ownership matters. Relative to similarly owned fields outside Venezuela, fields with 60% or less national oil company (NOC) ownership increased flaring intensity by 88%. Fully state-owned fields increased by 56%. Within Venezuela, differences by ownership are smaller. The core message is clear. Sanctions reduced output but raised emissions per barrel.

These findings matter for policy. Flaring abatement is among the cheapest ways to cut oil-sector emissions. Sanctions that disrupt funding and technology for gas capture can raise flaring intensity even as output falls. Sanctions design should account for this trade-off. Licensing and exemptions should cover gas capture, compression, maintenance, and monitoring equipment. Otherwise, foreign policy may carry hidden climate costs that run against the Zero Routine Flaring by 2030 goal (Elvidge et al., 2018).

We build a new field-level panel. We link satellite detections of flares to producing assets. We use a production-weighted inverse-distance rule to assign flares to fields. This approach is transparent and replicable. It limits spurious matches while preserving the spatial signal from satellites (Zhang et al., 2021).

The panel merges flaring assignments with field-year production and spending. We track oil output, CAPEX, and OPEX. We observe ownership shares and group assets by PdVSA participation. We form two groups: full state ownership and mixed ownership with NOC share at or below 60%. This split is salient for exposure to financing constraints and managerial attention.

We focus on 2012–2024. This window brackets the 2017 sanctions and aligns with high-quality flaring measures. Treatment is at the country level. All Venezuelan fields are exposed after 2017. The control group consists of Argentina, Brazil, Colombia, and Ecuador. These countries have large NOCs, similar technologies, and face the same regional shocks. None was subject to the U.S. measures in 2017.

Measurement follows best practice. We convert night-time radiance to gas volumes using established algorithms. We validate country-year sums against the Global Gas Flaring Tracker (World Bank, 2025). We harmonize production and spending, deflate to constant dollars, and winsorize outliers at the field-year level. Ownership is time-invariant over the main window.

Our empirical design is a difference-in-differences at the field level. We compare changes in Venezuelan fields before and after 2017 to changes in the control fields over the same period. We include field fixed effects to absorb geology and infrastructure. We include year fixed effects to absorb global oil cycles and common shocks. We then extend to a triple-difference that interacts treatment with ownership groups to study mechanisms and distributional effects. We report robust variance estimates and extensive sensitivity checks.

Identification rests on parallel trends. Event-study plots show flat pre-trends for Venezuela relative to the control group. Placebo treatments dated before 2017 yield null effects. Results are robust to dropping each control country in turn. They are also robust to adding country-specific linear trends, allowing the post-shock effect to vary with world oil prices, and re-estimating on a balanced panel of continuously operating fields.

Mechanisms align with common-sense constraints. Sanctions restrict access to finance, parts, and partners. Operators defer maintenance and gas-capture upgrades. Unplanned outages in gathering and processing increase. With weak local gas markets, producers flare more. Ownership mediates exposure. Assets with deeper state support and access to PdVSA's scarce resources show smaller increases in flaring intensity.

Our work connects several literatures. In research on sanctions, recent syntheses show that their reach and externalities have grown well beyond trade and finance, affecting growth, human welfare, and institutional quality (Drezner, 2024, Morgan et al., 2023, Fioretti et al., 2021). We add an environmental dimension, measuring how sanctions alter the emissions intensity of production at the operational level. In doing so, we link macroeconomic statecraft to micro-level efficiency and show how ownership structure mediates the transmission of shocks.

We also speak to work on financial sanctions and payment systems, which highlights how constraints on finance and technology spread through global value chains (Cipriani et al., 2023). Our evidence shows that these channels extend to energy operations: limits on credit, equipment, and service contracts reshape maintenance and gas-handling practices in oil fields. The result is an unintended environmental cost of financial coercion.

A growing literature examines the environmental consequences of sanctions and other geopolitical disruptions, often documenting shifts toward dirtier production or weaker enforcement (Madani, 2020, 2021, Hatipoglu et al., 2023, Le and Hoang, 2022). We contribute finer evidence by tracing how flaring intensity—emissions per barrel—responds to sanctions, complementing national or sectoral studies. This focus clarifies how geopolitical frictions affect firm behavior and climate outcomes.

We also connect to a literature analyzing flaring drivers. Infrastructure constraints, mid-stream congestion, and regulatory design are first-order factors (Lade and Rudik, 2020, Agerton et al., 2024). We identify a new, policy-relevant driver: financing and technology frictions induced by sanctions. The pattern fits the narrative. Where gathering and processing are brittle and funding is tight, flaring rises even as production falls. We also show how ownership attenuates the shock by reallocating scarce resources toward majority state-owned assets. Recent work further highlights how firms' accumulated know-how and technology transfer shape their performance in upstream oil & gas fields (Fioretti et al., 2025).

Methodologically, we build on recent advances in satellite measurement of flaring (Zhang et al., 2021), integrating spatial detections with field-level operational data to enable causal inference. Substantively, we complement work on Venezuela's oil sector and its above-ground risks, which document chronic underinvestment and institutional decay even before sanctions (Monaldi et al., 2021). Our micro evidence shows how sanctions compounded these dynamics and reinforced PdVSA's focus on majority-owned assets.

Together, these connections highlight a central message: understanding the incentives to flare requires understanding who owns and operates the field and the political constraints they face. Future work will exploit heterogeneity by operatorship and nationality. Firms with U.S. or European exposure may have faced competing pressures—on one hand, stricter environmental standards; on the other, compliance with U.S. embargoes that discouraged technology transfer. Disentangling these motives will clarify how global political economy shapes the environmental footprint of oil production.

Our findings carry direct policy implications. Sanctions that lower output can still raise emissions. Carve-outs and licenses should include gas capture, compression, and flare-monitoring equipment to prevent collateral climate damage. Verification is feasible: satellites now allow independent monitoring of flaring reductions. International coordination through the Global Gas Flaring Reduction Partnership could align sanctions policy with global mitigation goals. Domestically, producer governments should secure maintenance budgets and price flaring directly through royalties or taxes, which evidence suggests are more cost-effective than rigid technology mandates (Lade and Rudik, 2020).

The rest of the paper proceeds as follows. We describe the institutional setting and the data, including the construction and validation of the flaring measures. We then present the empirical strategy and identification tests. We report the main effects and the het-

erogeneity by ownership, and we discuss mechanisms. We close with policy implications for sanctions design and domestic regulation.

Next Steps These results open a broader research agenda on how ownership and political incentives shape environmental performance in the oil sector. The next step is to examine heterogeneity by operatorship and ownership nationality. We will investigate whether firms with exposure to the United States—particularly U.S. and European multinationals—behaved differently after 2017. Such firms may have lower flaring intensities due to stricter environmental standards, but they may also have curtailed technology transfer to comply with U.S. sanctions, limiting the diffusion of cleaner practices. By combining field-level operational data with firm-level nationality and exposure, we will identify how geopolitical ties and corporate incentives interact to determine environmental outcomes. Understanding these mechanisms will help explain the political economy of flaring and inform the design of sanctions and environmental policy in resource-dependent states.

2 Data

2.1 Data Sources

The empirical analysis relies on two primary data sources: asset-level data from Rystad Energy and flaring data from the World Bank's Global Gas Flaring and Methane Reduction (GFMR) Partnership. The first data source is Rystad Energy's UCube database, an extensive global upstream oil and gas database widely used in both academia and industry. Rystad Energy defines each producing or discovered hydrocarbon accumulation as an asset, which is the unit of observation used throughout this study. The dataset provides annual asset-level information on production volumes, reserves, start-up and discovery years, operating and capital expenditures, geographic coordinates, and company-level ownership shares. These data allow for precise linking of production, costs, and ownership structures across time and assets.

The second data source is the World Bank's GFMR flaring dataset, which is derived from satellite observations of flare combustion sites captured by the U.S. National Oceanic and Atmospheric Administration (NOAA). The raw night-time light detections are processed by the Payne Institute for Public Policy at the Colorado School of Mines to identify persistent flare locations and to estimate flared gas volumes at each site. The dataset provides annual flare volumes and latitude–longitude coordinates for all observed sites worldwide from 2012 onward.

Flaring sites are not always observed at the exact same latitude–longitude coordinates or in the same number each year because both the underlying flaring activity and the

detection process vary over time. First, flaring is not constant, as some facilities may start or stop production, experience outages, or change operational practices that affect whether and how much they flare gas. Second, satellite detection of flares is imperfect and can be influenced by atmospheric conditions, sensor coverage, and cloud cover, meaning that a flare may be intermittently observed or measured at slightly different locations due to geolocation uncertainty. Together, these factors lead to year-to-year variation in the apparent number and location of flaring sites.

Figure 1: Flaring sites by country



Note: Flaring sites shown for the five countries in the panel in South America. Sites in Argentina are in blue, Brazil in green, Colombia in purple, Ecuador in orange, and Venezuela in red.

Figure 1 shows the flaring sites in each country in the sample in 2019. Flaring sites, along with oil production, are typically highly concentrated within the sample countries, reflecting the geographic clustering of petroleum reserves and infrastructure.

Argentina, whose flaring sites are shown in blue, has on average 192 flaring sites per year. Argentina's oil production, and thus its flaring activity, is largely concentrated in the Neuquén Basin located in the country's west-central region, with some additional flaring sites sporadically situated along its eastern coast, particularly near smaller producing fields.

Brazil is unique in the data in that most of its flaring sites are located offshore. Its flaring sites are depicted in green. Brazil has an average of 119 flaring sites per year, with approximately 59% of those sites offshore. These offshore flaring sites are clustered along Brazil's southeastern coast in the Santos and Campos Basins, which are responsible for a significant share of Brazil's oil production and associated flaring.

With flaring sites mapped in orange, Ecuador has an average annual flaring site count of 77. These sites are highly concentrated in the northwestern section of Ecuador in the Oriente Basin, where most of the country's upstream oil production takes place.

Colombia has the lowest average annual flaring site count, shown in purple, with roughly 65 sites per year. Many of the sites in Colombia are located along the central vein of the Middle Magdalena Valley Basin, which extends from north to south through Colombia, though some flaring also occurs in the Llanos Basin to the east.

Finally, Venezuela, whose flaring sites are shown in red, has 158 flaring sites per year on average. Venezuela's flaring sites are mostly located in the northern and northwestern parts of the country, as production is heavily concentrated in the prolific Orinoco Belt and in the Maracaibo Basin near Lake Maracaibo.

Overall, there are an average of 611 flaring sites per year across all five countries in the data.

For consistency, the Rystad Energy data are restricted to the period 2012–2024 to match the temporal coverage of the GFMR data. The resulting panel includes producing assets in Venezuela and in the comparison countries of Argentina, Brazil, Colombia, and Ecuador over a twelve-year horizon, forming a balanced panel of asset-year observations suitable for difference-in-differences analysis.

2.2 Flaring Volume Allocation

The Rystad Energy data are organized at the asset level while the GFMR data are organized at the site level, necessitating an allocation strategy to match flaring sites to producing assets. We use a two-step strategy to allocate the flaring volumes to the assets in the Rystad Energy data. At the first level, we use a direct matching strategy, allocating flaring sites to assets based on a matching between the Rystad Energy asset name and the GFMR Field Name. If the asset name and the field names match, the flaring volumes from the GFMR fields are directly allocated to the associated Rystad Energy assets.

For the assets and fields that remained unmatched after the direct allocation method, we use a production-weighted inverse distance weighting formula, a form of the gravity model to assign the remaining flaring volumes algorithmically.

For each flare site f with flaring volume F_f, we identify candidate assets $i \in \mathcal{N}(f)$ within a search radius R km and compute an asset weight

$$\tilde{w}_{fi} = \frac{1}{d_{fi}^{p}} \cdot P_i^{\alpha},$$

where d_{fi} is the great-circle distance between flare f and asset i, $p > 0$ is the inverse distance power, P_i is annual production for asset i, and α is the production weighting power. In the final formula, the radius R is set to 15km and $p = \alpha = 1$, but other values were tested for these parameters yielding no difference in the allocations.

Weights are then normalized:

$$w_{fi} = \frac{\tilde{w}_{fi}}{\sum_{j \in \mathcal{N}(f)} \tilde{w}_{fj}},$$

ensuring that $\sum_{i \in \mathcal{N}(f)} w_{fi} = 1$. Each flare's allocated volume to asset i is

$$\widehat{F}_{fi} = w_{fi} \cdot F_f,$$

and the asset-year allocation is given by

$$\widehat{F}_i = \sum_{f \in \mathcal{F}(i)} \widehat{F}_{fi}.$$

This approach proportionally allocates flare volumes according to both proximity and production scale, preventing double-counting by excluding directly matched assets from the candidate set.

2.3 Outcome Variable

The main outcome variable is flaring intensity, defined as cubic meters of gas flared per barrel of oil produced at the asset-year level:

$$\text{Flaring Intensity}_{jt} = \frac{\widehat{F}_{jt}}{\text{Production}_{jt}}$$

where $\widehat{F}_{jt}$ is the allocated flaring volume in and Production is measured in barrels of oil per year.

This variable captures the operational efficiency of each asset in managing associated gas. It is preferred over absolute flaring volume because it normalizes for differences in production scale across assets, allowing for meaningful comparison over time and between treatment and control groups. Because flaring intensity is highly right-skewed, a small number of extreme outliers can exert disproportionate influence on regression estimates. To mitigate this issue, the flaring intensity variable is winsorized at the 99th percentile of its distribution. This procedure preserves nearly all of the information in the original

variable while reducing the leverage of extreme observations, resulting in more robust and stable estimates of treatment effects.

2.4 Descriptive Statistics

2.4.1 Flaring Intensity

Table 1: Descriptive statistics for flaring intensity by country. 'Overall' aggregates across all countries.

Country	n	Mean	p25	Median	p75	p95	SD
Argentina	2394	35.49	0.29	2.12	11.94	98.69	188.06
Brazil	1231	56.80	0.33	1.06	3.40	59.86	312.51
Colombia	1431	12.78	0.41	1.57	6.27	33.99	100.06
Ecuador	1075	7.94	0.97	3.37	8.49	21.12	36.32
Venezuela	1045	338.16	3.45	15.72	170.01	2820.12	755.85
Overall	7176	74.56	0.50	2.37	10.74	214.53	354.92

Table 1 reports descriptive statistics for flaring intensity, measured in cubic meters of gas flared per barrel of oil produced, across the five countries included in the sample. There is substantial heterogeneity in both the central tendency and the dispersion of flaring intensity across countries. Venezuela stands out with an average flaring intensity of roughly 338 m^3/bbl, nearly an order of magnitude higher than the other countries. Venezuela also displays the largest variance, with a standard deviation of over 750 m^3/bbl and a 95th percentile value exceeding 2,800 m^3/bbl, reflecting the presence of extremely high-intensity outliers.

By contrast, Argentina, Brazil, Colombia, and Ecuador all show considerably lower average flaring intensities. Colombia and Ecuador have the lowest means of 12.8 and 7.9 m^3/bbl, respectively, with tight distributions and relatively small dispersion, as indicated by their standard deviations. Argentina and Brazil have somewhat higher average intensities of 35.5 and 56.8 m^3/bbl, but still far below Venezuela.

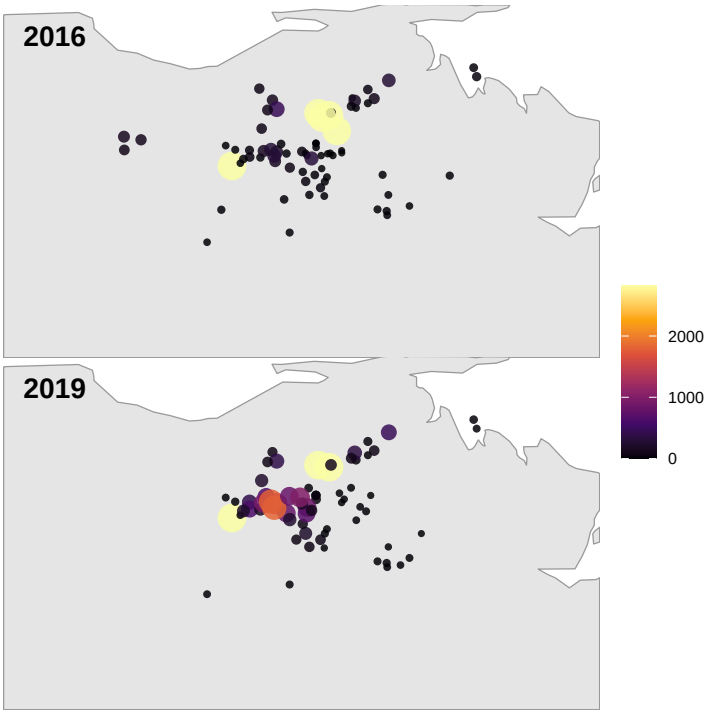
Across all countries, the median flaring intensity is only 2.4 m^3/bbl, highlighting the highly skewed nature of the distribution. Most asset-years experience low or moderate flaring intensity, while a small subset of asset-years accounts for extremely high values. This skewness justifies the winsorization of the outcome variable at the 99th percentile used in the main regressions to mitigate the influence of outliers.

2.4.2 Descriptive Analysis of Flaring Allocation: Orinoco Belt

Table 2 and Figure 2 document the evolution of flaring intensity in Venezuela's Orinoco Belt before and after 2017. Flaring activity in this region dominates the national picture:

on average, about 99% of all gas flared in Venezuela is concentrated within this belt. All units in Table 2 and Figure X are in m^3/bbl. The descriptive statistics show that mean flaring intensity rose from 321 m^3/bbl in the pre-2017 period to over 407 m^3/bbl in the post-2017 period, with the median more than doubling (from 14.5 m^3/bbl to 32.4 m^3/bbl). The upper tail of the distribution remains heavy, suggesting that very high-intensity flaring sites persisted into the post-2017 period.

Figure 2: Flaring intensities in the Orinoco Belt area



Note: Flaring intensities (in m^3/bbl) are shown for assets located in the Orinoco Belt area in Venezuela for 2016 and 2019. Larger, lighter colored dots indicate larger flaring intensities.

Table 2: Descriptive Statistics for Flaring Intensity in the Orinoco Belt

Period	n	Mean	p25	Median	p75	p95	SD
Pre-2017	415	321.44	3.54	14.50	105.73	2820.12	768.92
Post-2017	538	407.41	4.35	32.40	303.17	2820.12	794.49

The maps of 2016 and 2019 visually reinforce this pattern. Not only are flaring sites highly clustered in the Orinoco Belt, but post-2017 higher intensities appear more spatially widespread and severe across assets. Larger and lighter markers in 2019 highlight that a greater share of assets are flaring at elevated levels compared to the pre-treatment period. Together, these results point to a general intensification of flaring in the Orinoco Belt after 2017, consistent with a deterioration of gas capture or reinjection capacity during this period.

2.4.3 Other Descriptive Statistics

Table 3: Descriptive statistics by country for key asset-level variables

Variable	n	Mean	p25	Median	p75	p95	SD
Argentina							
Cumulative Capex	2394	243.17	13.28	77.89	281.57	1075.70	410.81
Total Opex	2394	7.41	0.32	1.59	6.55	32.42	16.76
Annual Production	2394	620.74	21.56	118.45	510.93	2940.05	1602.41
NOC Participation	2394	43.99	0.00	35.00	100.00	100.00	43.61
Brazil							
Cumulative Capex	1229	2071.31	103.42	800.21	2808.62	7796.64	3101.27
Total Opex	1229	146.77	2.14	25.90	179.08	661.49	270.76
Annual Production	1231	7387.80	80.54	888.70	6509.30	45192.95	14170.90
NOC Participation	1231	70.49	43.29	100.00	100.00	100.00	41.57
Colombia							
Cumulative Capex	1430	322.44	53.25	144.06	344.46	1228.63	521.67
Total Opex	1430	22.35	1.00	3.98	14.99	118.82	53.83
Annual Production	1431	1465.11	83.95	333.40	1107.83	6868.75	3438.30
NOC Participation	1431	59.32	25.00	66.12	100.00	100.00	41.46
Ecuador							
Cumulative Capex	1075	290.97	59.39	178.08	303.94	947.82	475.47
Total Opex	1075	9.88	0.78	3.08	8.04	48.06	22.36
Annual Production	1075	1697.57	131.90	482.40	1383.85	8115.20	3970.58
NOC Participation	1075	16.37	0.00	0.00	0.00	100.00	35.88
Venezuela							
Cumulative Capex	1044	784.74	22.78	147.01	544.64	3880.26	1770.80
Total Opex	1044	53.82	0.04	1.13	14.96	386.92	151.38
Annual Production	1045	4972.08	4.79	99.63	2076.20	35141.16	13025.11
NOC Participation	1045	83.62	60.00	100.00	100.00	100.00	19.54
Overall							
Cumulative Capex	7172	658.24	33.35	149.16	473.21	3531.26	1640.81
Total Opex	7172	41.39	0.48	2.98	14.70	229.78	138.44
Annual Production	7176	2744.94	38.67	250.41	1270.42	15293.59	8432.11
NOC Participation	7176	53.23	0.00	60.00	100.00	100.00	44.12

Table 3 presents descriptive statistics for key asset-level variables across the five countries in the sample. These statistics provide a detailed picture of the production scale, investment intensity, operating costs, and state participation that characterize each country's oil fields.

Cumulative capital expenditure (CAPEX), expressed in millions of U.S. dollars, varies widely across countries. Brazil's assets are, on average, the most capital-intensive, with a mean cumulative CAPEX of roughly 2,070 million USD, compared to less than 800 million USD in Venezuela and under 350 million USD in Argentina, Colombia, and Ecuador. This reflects the prevalence of large offshore projects in Brazil, which require substantial

upfront investment.

Operating expenditures (OPEX), also displayed in millions of U.S. dollars, display similar heterogeneity. Brazil again leads with the highest total and OPEX per asset, followed by Venezuela. In contrast, Argentina and Ecuador have much lower levels of operating expenditure, consistent with smaller production scales and lower-cost operations.

Annual production volumes, expressed in thousand barrels, also show substantial dispersion. Brazilian assets are, on average, the largest producers in the sample, followed by Venezuela. Argentina, Colombia, and Ecuador all have median annual production levels below 500 kbbl, consistent with their generally smaller, more mature fields. The right-skewed distributions, indicated by the high 95th-percentile values relative to the medians, suggest that production is concentrated in a relatively small number of very large fields.

National Oil Company (NOC) participation rates reveal sharp institutional differences. Venezuelan assets are, as expected, overwhelmingly controlled by PdVSA, with mean participation exceeding 80%. Brazil's NOC participation averages about 70%, reflecting Petrobras' dominant but not exclusive role. Argentina and Colombia exhibit more mixed ownership structures, with median participation well below 100%, while Ecuador's average NOC share is low, with many assets fully privately operated. Overall, these statistics highlight the heterogeneity of the sample and underscore the importance of controlling for differences in production scale, cost structure, and institutional ownership when estimating the effects of sanctions on flaring behavior.

3 Methodology

3.1 Motivation and Conceptual Framework

Flaring intensity in Venezuelan oil fields is not random and is likely correlated with both observed and unobserved characteristics of the fields and the firms operating them. Fields that are larger, older, or more technologically sophisticated may have different gas-to-oil ratios, associated infrastructure, and production planning horizons, all of which could systematically affect their flaring behavior. For example, mature fields with declining production may operate with outdated gathering systems and be less likely to invest in new gas capture equipment, leading to persistently higher flaring intensity. Conversely, newly developed fields may be built with more modern facilities that incorporate gas processing from the outset, reducing routine flaring. A simple before–after comparison of flaring intensity within Venezuela, or a basic cross-country comparison between Venezuelan and non-Venezuelan fields, would therefore risk conflating the effects of sanctions with these underlying differences in asset characteristics and with trends unrelated to sanctions.

To address these concerns, this study adopts a difference-in-differences (DiD) framework that exploits the sharp change in Venezuela's external economic environment triggered by the imposition of U.S. financial sanctions targeting the state-owned oil company PdVSA. These sanctions, issued by the U.S. Treasury's Office of Foreign Assets Control beginning in August 2017 under Executive Order 13808, prohibited transactions in certain new debt and equity issued by the Government of Venezuela, including PdVSA, and barred dividend payments to the government from subsidiaries operating abroad. The sanctions effectively shut Venezuela and PdVSA out of U.S. financial markets, substantially restricting their ability to raise capital, refinance existing debt, or import critical technologies. Later measures, including Executive Order 13850 in 2019, escalated these restrictions by authorizing sanctions on any person determined to have materially assisted PdVSA, tightening international compliance and reducing Venezuelan crude exports to the U.S. Taken together, these measures represent a major, plausibly exogenous shock to the operating environment for Venezuelan oil assets, one that was not anticipated by firms and could not be influenced at the asset level.

The sanctions' intended economic consequences are well documented. Sanctions were designed to constrain access to financing, impair the ability to import machinery and spare parts, and increase the transaction costs of marketing Venezuelan crude internationally. These constraints likely translated into increased operational stress, deferred maintenance, and disruptions to gas capture and flaring mitigation systems. From a theoretical perspective, sanctions can affect flaring intensity through several channels: by reducing investment in gas infrastructure, raising flaring in the medium run, by curtailing oil production, which may lower total flaring but may increase flaring per barrel if gas capture capacity deteriorates, and by changing incentives within PdVSA to prioritize short-run revenue generation over environmental performance. This study focuses on the net effect of these channels on flaring intensity. Because of these potential channels that sanctions can affect flaring, the other variables included in the analysis are measure of production and investment. These variables begin to give some insights into the mechanisms through which sanctions can cause higher flaring intensities across assets in Venezuela. Change in production is measured in the DiD setting, as are changes in cumulative CAPEX—the sum of capital expenditures since an asset began production—and changes in annual OPEX—the annual operating expenditures of an asset. Cumulative CAPEX is favored to annual CAPEX as capital remains in place over time and capital expenditures may not occur in every period. Cumulative CAPEX therefore captures the overall expenditures that have gone into lasting investments like infrastructure or explorations.

The identifying assumption of the DiD approach is that, absent sanctions, the evolution of flaring intensity in Venezuelan assets would have followed a parallel trajectory to that of assets in an appropriate control group. To construct this counterfactual, we lever-

age asset-level data from four major Latin American oil producers: Argentina, Brazil, Colombia, and Ecuador. These countries are well suited as a control group because they share important structural similarities with Venezuela, as all are significant crude producers, all have a strong presence of national oil companies, and all are subject to broadly similar global price cycles and market conditions. Crucially, none of these countries were subject to comparable oil-sector-specific financial sanctions during the study period. This makes them a credible benchmark for the evolution of flaring intensity in a no-sanctions scenario.

Figure 3 depicts the aggregate flaring intensity trends for Venezuela compared with each individual country in the set of control countries. As can be seen in the graph, the pre-2017 trends for all countries are relatively flat and constant. Venezuela, shown in black, clearly has a higher baseline intensity than every other country, which aggregate flaring intensity typically between 10 and 15 m^3/bbl between 2012 and 2016 before a rapid increase beginning in 2017. Nevertheless, the overall pre-trend is similar. Argentina (red), Brazil (green), Colombia (Blue), and Ecuador(purple), all show similar trends to one another, with flaring intensities typically between 3 and 8 m^3/bbl. After 2017, however, there is a sharp divergence in the trends of Venezuela and the control countries, as Venezuela'a aggregate flaring intensity increases dramatically while the other countries' trends remain stable. The graph shows that the parallel trends assumption holds and that we can assume that, in the absence of sanctions, the trends for all countries, including Venezuela, would have remained on their flat and stable path. As such, the use of a DiD framework is justified in this situation and the coefficients from the regression results can be interpreted as the causal effects of sanctions on flaring intensities for assets in Venezuela.

One caveat to note about Figure 3 is that the trends presented are country-wide aggregate trends. This means that overall flaring volumes are weighted by production so that asset-level outliers do not substantially impact the overall trends. While this aggregation helps smooth idiosyncratic noise from individual assets, it also masks within-country heterogeneity in flaring behavior. It is possible that some subset of assets in Venezuela or in the control countries experienced different pre-2017 dynamics, even if the country-level average trend is parallel. If the composition of production shifted substantially over time then the aggregate series might fail to reflect the true counterfactual path of the average asset.

Nevertheless, there are several reasons to believe that this concern is limited in this setting. First, flaring intensity tends to be relatively persistent at the asset level because it is tied to physical infrastructure such as gathering systems and gas processing capacity, which does not fluctuate dramatically year to year. As a result, the distribution of asset-level flaring intensities within a country is unlikely to change drastically absent major policy or technological shocks. Second, the use of aggregates means that the series reflects

the performance of the dominant producing assets in each country, which together account for the overwhelming majority of observed flaring. If the largest contributors to flaring exhibit parallel trends, then the average asset-level counterfactual path is likely to do so as well.

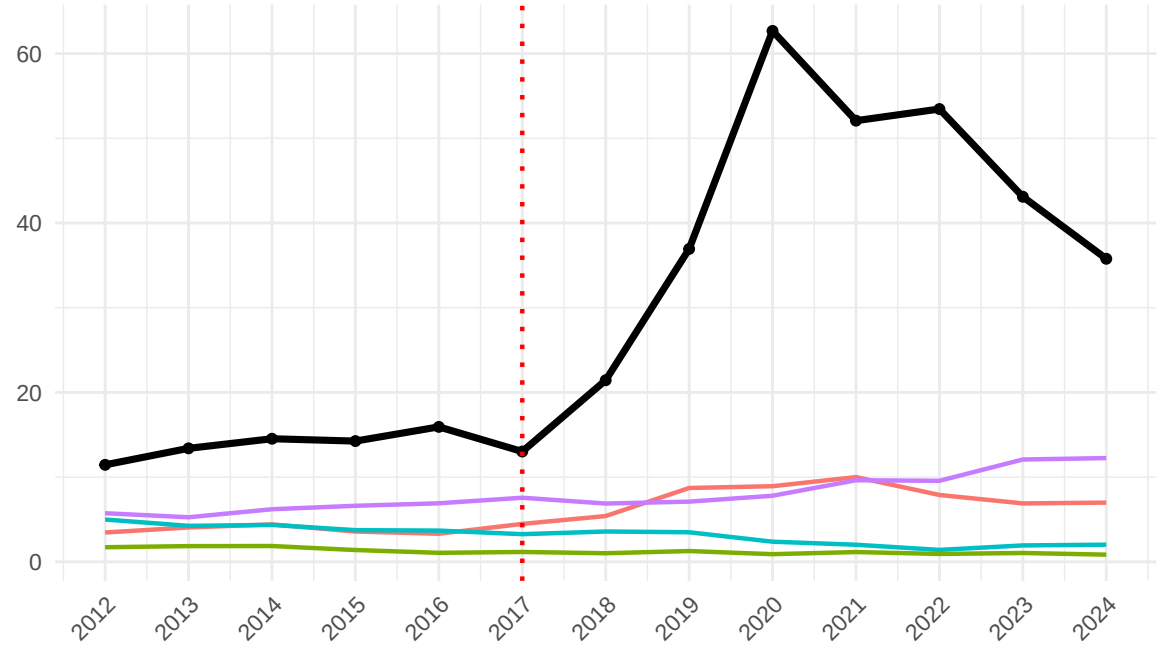
Moreover, the parallel-trends assumption in a DiD framework is fundamentally an assumption about mean counterfactual outcomes rather than about every individual unit. What is required for identification is that the average untreated outcome trajectory of Venezuelan assets would have been parallel to that of the control group in the absence of treatment. Given that the aggregate country-level flaring intensity is simply the production-weighted average of untreated outcomes, observing parallel trends at the aggregate level provides direct evidence that the average untreated trajectory is similar. In other words, if the average aggregate flaring intensity is evolving in parallel prior to treatment, there is no strong theoretical reason to believe that the cross-sectional distribution of flaring intensities is shifting in a way that would undermine identification.

Finally, the asset-level regressions include both country and year fixed effects, which absorb permanent country-level differences and common shocks affecting all assets simultaneously. The DiD estimator is therefore identified based on of differential changes relative to the country-level mean within each year. Combined with the evidence of parallel pre-trends in the aggregate, this structure supports the validity of the identification strategy and suggests that unobservable time-varying factors are unlikely to systematically bias the estimated treatment effects.

Figure 4 graphically represents the trends for the other outcome variables of interest: production, cumulative CAPEX, and OPEX at the asset level. Each outcome variable's asset level average is shown by country, with Venezuela depicted in black, Argentina in red, Brazil in green, Colombia in blue, and Ecuador in purple. Production is shown in thousands of barrels per year while cumulative CAPEX and OPEX are shown in millions of U.S. dollars.

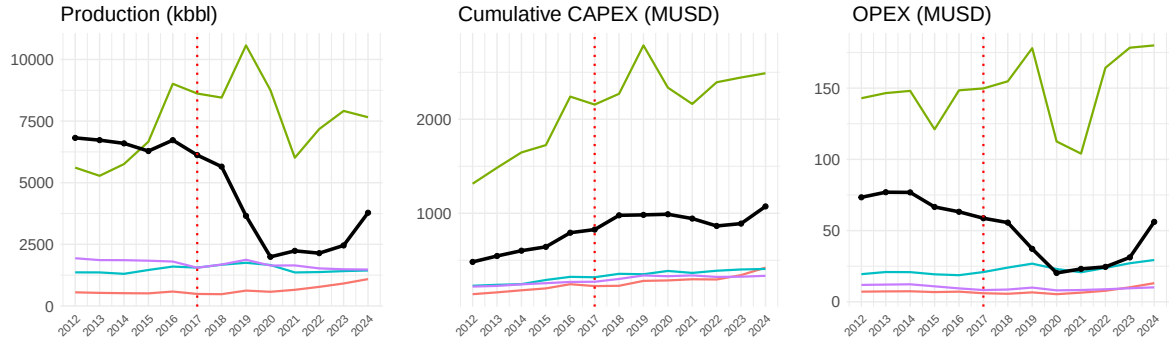
The first panel of Figure 4 shows that the trends for production between Venezuela, Argentina, Colombia, and Ecuador are all parallel in the pre-sanctions period and that the trends in Argentina, Colombia, and Ecuador continue even after sanctions were imposed on Venezuela. Venezuela diverges from the trends of the three aforementioned countries substantially after the 2017 imposition of U.S. financial sanctions. The trend for production in Brazil is clearly abnormal compared to the other regional countries, increasing rapidly toward the end of the pre-sanctions period. Due to the abnormality of the trend and the lack of parallel trends between assets in Venezuela and assets in Brazil, Brazil is excluded from the regressions with production as an outcome variable since the main assumption of the identification strategy does not hold. Thus, when production is the outcome variable, assets in Argentina, Colombia, and Ecuador form the control group while Venezuela is the treated group.

Figure 3: Aggregate Flaring Intensity by Country



Note: Flaring intensity is in(m^3/bbl). The red dotted line indicates the 2017 sanctions cutoff. Venezuela is in black, Argentina in red, Brazil in green, Colombia in blue, and Ecuador in purple.

Figure 4: Average Asset-Level Outcome Trends



Note: Production is in kbbl and cumulative CAPEX and OPEX are in MUSD. The red dotted line indicates the 2017 sanctions cutoff. Venezuela is in black, Argentina in red, Brazil in green, Colombia in blue, and Ecuador in purple.

In the second panel of Figure 4, trends for cumulative CAPEX are shown. Brazil clearly has higher levels of cumulative CAPEX, on average, than all the other countries in the panel, but countries share similar slightly upward sloping trends in the pre-sanctions period. Although the divergence of Venezuela is not as clear as in the case for production, Venezuela's cumulative CAPEX trend stagnates and even decreases after sanctions while the other countries' trends continue to rise.

The final panel in Figure 4 shows asset averages by country for OPEX. Here, once again, the trends for Argentina, Ecuador, and Colombia are stable and relatively flat throughout the entire timeframe of the panel. Similarly to its trend in production, Brazil has some abnormalities and is therefore excluded from calculations when OPEX is an outcome variable. The trend for Venezuela shows a modest decline in OPEX during the pre-treatment period, falling from approximately 75 million USD in 2012 to roughly 55 million USD by 2017. While this suggests that the strict parallel trends assumption may not hold perfectly for OPEX, the divergence is relatively gradual and does not suggest a structural break prior to sanctions. Additionally, OPEX is included as a secondary outcome, so the results should be interpreted as descriptive evidence of how sanctions may have affected operating costs rather than as a precise causal estimate.

Including OPEX as an outcome remains informative for two reasons. First, changes in OPEX may reflect assets' operational adjustments to sanctions, such as reductions in maintenance, workforce, or gas-handling expenditures, all of which may mediate the impact on flaring intensity. Second, large post-sanction shifts in OPEX can help shed light on potential mechanisms underlying the main results, such as whether increases in flaring intensity are driven by investment-cutting behavior or by other constraints such as access to equipment and spare parts.

Because the sanctions were imposed at the national level and affected all PdVSA operations simultaneously, treatment assignment is not a choice variable at the asset level. No single asset could opt in or out of the sanctions regime. This feature strengthens the causal interpretation of the DiD design because it eliminates concerns about self-selection into treatment. The variation exploited is thus a combination of temporal variation, comparing assets before versus after 2017, and cross-sectional variation, comparing Venezuelan assets to assets in the control countries. The coefficient on the interaction between treatment status and post-sanctions period captures the average treatment effect on the treated (ATT), or the average change in flaring intensity, production, cumulative CAPEX, or OPEX among Venezuelan assets attributable to the sanctions, netting out time-invariant differences between countries and common shocks affecting all producers.

3.2 Empirical Specifications

This section describes the four main empirical specifications used to estimate the effect of U.S. financial sanctions targeting Venezuela's oil sector and PdVSA on gas flaring and related outcomes. In all cases, the outcome variable of interest is flaring intensity, defined as flaring volume per barrel of oil produced at the asset-year level, though we also report estimates using ln(Production), ln(Opex), and ln(Cumulative Capex) as outcomes to explore production and cost channels.

3.2.1 Specification 1: Baseline Difference-in-Differences

The first specification uses a standard two-way fixed effects DiD model, comparing Venezuelan oil and gas assets to assets in Argentina, Brazil, Colombia, and Ecuador before and after the imposition of U.S. financial sanctions on the oil sector in 2017. The estimating equation is:

$$y_{it} = \alpha_i + \gamma_t + \beta\big(\text{Venezuela}_i \times \text{Post}_t\big) + \varepsilon_{it} \tag{1}$$

where y_{it} is the outcome variable for asset i in year t, α_i are asset fixed effects controlling for time-invariant differences across assets, γ_t are year fixed effects capturing common time shocks, Venezuela_i is an indicator equal to 1 if asset i is located in Venezuela, and Post_t is an indicator equal to 1 in the post-sanction period. The coefficient of interest is β, which measures the ATT, the average treatment effect of sanctions on Venezuelan assets relative to the control countries. ε_{it} is the error term.

The inclusion of asset and year fixed effects ensures that β is identified from within-asset changes over time relative to contemporaneous changes in untreated assets. Standard errors are clustered at the asset level to allow for arbitrary serial correlation within assets.

Each of flaring intensity, production, cumulative CAPEX, and OPEX are evaluated as outcome variables y_{it}. Each is transformed with a $\log(y_{it} + 1)$ transformation in order to accommodate zero values in the data. The distribution for flaring intensity is very left skewed, so other transformations of the variables were also tested to ensure robustness of the estimates (see Appendix). Since all outcome variables are under a log transformation, the coefficient β must be exponentiated to determine the percent change in flaring intensity for Venezuelan assets after sanctions.

3.2.2 Specification 2: Triple-Differences with Ownership Heterogeneity

The second specification extends the baseline model by introducing a third difference based on asset-level ownership composition. This is to evaluate the potential heterogeneity that may exist in the impacts of sanctions depending on the share of ownership

held by the NOC for a given asset. To estimate this, we interact the treatment indicator with a measure of national oil company (NOC) ownership share averaged over the pre-treatment period, between 2012 and 2016. This measure is importantly averaged over the pre-treatment period to avoid endogeneity concerns. Sanctions could impact the degree to which the state is involved in a given asset, so it is important to evaluate the ownership share pre-sanctions for this specification. We implement two versions of this model.

First, we use a binary indicator for whether an asset had greater than 60% NOC participation in the pre-period. This threshold was selected because the Venezuelan Hydrocarbons Act of 2006 necessitates at least a 60% share of ownership of any given asset be controlled by PdVSA. As such, all assets in Venezuela have at least 60% NOC participation. The 60% threshold indicates the lower bound and gives insights into the heterogeneity that may exist at the extremes of the extent of state ownership in Venezuela. The estimation equation using the binary indicator is:

$$y_{it} = \alpha_i + \gamma_t + \beta_1(\text{Venezuela}_i \times \text{Post}_t) + \beta_2(\text{HighNOC}_i \times \text{Post}_t) + \delta\big(\text{Venezuela}_i \times \text{Post}_t \times \text{HighNOC}_i\big) + \varepsilon_{it}$$

where HighNOC_i equals 1 if asset i had >60% NOC ownership in the pre-period. β_1 is the DiD estimator for low-NOC assets. We expect this estimator to still show an increase in flaring intensity after sanctions compared to the control group for low-NOC assets. The coefficient δ is the triple-difference parameter of interest, capturing the differential effect of sanctions on highly state-owned assets in Venezuela relative to Venezuelan assets with lower state participation and highly state-owned assets in the control countries.

Second, we replace HighNOC_i with the continuous measure of average pre-period NOC ownership share:

$$y_{it} = \alpha_i + \gamma_t + \beta_1(\text{Venezuela}_i \times \text{Post}_t) + \beta_2(\text{NOCShare}_i \times \text{Post}_t) + \delta\big(\text{Venezuela}_i \times \text{Post}_t \times \text{NOCShare}_i\big) + \varepsilon_{it}$$

where NOCShare_i is the average percent ownership held by the NOC between 2012 and 2016, the pre-treatment period. Here, δ measures how the treatment effect varies with the extent of state ownership. δ gives the change in outcome for a 1% increase in NOC participation in the pre-sanction period for Venezuelan assets after sanctions.

These two specifications are both used to evaluate all the same outcome variables as the initial DiD specification: flaring intensity, production, cumulative CAPEX and OPEX. Once again, all outcomes are transformed with a $\log(y_{it} + 1)$ tranformation, meaning the coefficient must be exponentiated as before for easiest interpretation. As in the baseline DiD specification, versions of these specifications using untransformed outcomes and outcomes transformed using the inverse hyperbolic sine function were tested for robustness (see Appendix).

3.2.3 Specification 3: Split-Sample Difference-in-Differences by Ownership

The third specification returns to the simple DiD framework but re-defines the treatment and control groups. This specification creates three treatment and control groups to be compared to one another based on average NOC ownership share in the pre-sanction period. The first group are assets with less than or equal to 60% average NOC share between 2012 and 2016. Assets with less than or equal to 60% ownership share in Venezuela are the treated group and assets with less than or equal to 60% average NOC share in Argentina, Brazil, Colombia, and Ecuador are the control group. The next group are those with average pre-treatment ownership shares greater than 60% but less than 100%. The assets in this category in Venezuela are again compared to the assets in the same category in the control countries. Finally, the last panel group is made up of assets that are fully state owned between 2012 and 2016. Fully state owned assets in Venezuela, the treated country, are compared to fully state owned assets in the control countries. The estimating equation for this specification is:

$$y_{it} = \alpha_i + \gamma_t + \beta_g\big(\text{Treat}_{i,g} \times \text{Post}_t\big) + \varepsilon_{it} \tag{2}$$

where $g \in \{\text{HighNOC}, \text{LowNOC}, \text{FullState}\}$ denotes the relevant subgroup. Comparing β_{HighNOC}, β_{LowNOC}, and $\beta_{\text{FullState}}$ allows me to assess whether the effect of sanctions differs systematically by ownership composition.

This specification is only used to evaluate flaring intensity for the various ownership subgroups, once again under a $\log(y_{it} + 1)$ transformation. Other transformations of the outcome variable using this specification can be found in the Appendix.

3.2.4 Specification 4: Within-Venezuela Difference-in-Differences

Finally, we implement a within-Venezuela DiD design, comparing fully state-owned assets to partially state owned assets within the same country. This is to further evaluate if there is heterogeneity in the exposure to sanctions based on asset ownership structure within Venezuela. All assets in this new panel are impacted by the sanctions, but here, fully state-owned assets in the pre-sanction period serve as the treated group while assets with some ownership by a company other than PdVSA are the control group. The estimating equation is:

$$y_{it} = \alpha_i + \gamma_t + \beta\big(\text{FullState}_i \times \text{Post}_t\big) + \varepsilon_{it} \tag{3}$$

where $\text{FullState}_i = 1$ for assets that were 100% NOC-owned on average during 2012–2016. This specification holds constant country-level shocks that could confound the baseline model and focuses exclusively on differential effects within Venezuela.

This specification is also used to test each outcome variable: flaring intensity, produc-

tion, cumulative CAPEX, and OPEX. Once again, each is transformed with a $\log(y_{it}+1)$ transformation in order to accommodate zero values in the data. The coefficient β can be evaluated similarly to the first DiD specification, but this time it gives the average treatment effect of sanctions on fully state-owned assets compared to joint ventures.

4 Results

This section presents the results for the various econometric specifications detailed in the methodology section. First, we will present the main results from the baseline difference-in-differences (DiD) specification, followed by the results for the estimates from the two triple-difference specifications found in Equations 3.2.2 and 3.2.2. Next we will outline the heterogeneity from the DiD by national oil company (NOC) ownership group, followed by the final results from Specification 4, the within Venezuela DiD comparing 100% state owned assets to joint ventures.

Table 4 presents the results for the main DiD specification outlined in Equation 1. The main finding can be found in the first column of the table, coefficient of 0.456 on log(Flaring Intensity), significant at the 1% level. When exponentiates for interpretation, this coefficient represents about a 57.7% increase in flaring intensity for assets in Venezuela after sanctions compared to assets in the control countries. This finding is consistent with the notion that sanctions have a causal and economically meaningful impact on flaring intensity and thus on upstream emissions in the oil industry in Venezuela.

The subsequent results presented in Table 4 help to shed further light on the potential factors that may have influenced the substantial and significant impact that sanctions had upon flaring intensity of Venezuelan assets after sanctions. The second column gives the DiD estimate for the change in production of Venezuelan assets compared to the control countries' assets after sanctions. This result shows that production dropped by approximately 55% in Venezuelan assets after sanctions compared to the counterfactual, based on a coefficient of -0.807, which is also significant at the 1% level. This outcome exemplifies the juxtaposition between outcomes in the panel: even with production cut in half, Venezuelan assets still increased their flaring intensities considerably. This is indicative of a material decrease in efficiency in dealing with associated gas in Venezuela under sanctions.

The inefficiency caused by sanctions in Venezuela may be further explained by the changed in cumulative capital expenditures (CAPEX) and operating expenditures (OPEX). The DiD coefficients for these outcomes are -0.114 and -0.856, both with p-values less than 0.01. These correspond to decreases in cumulative CAPEX of 10.8% and in OPEX of 42.5% compared to the control assets' baseline. These drops in expenditures are substantial and are consistent with the constrained access to financial assets and services faced by PdVSA and other firms operating in Venezuela in the wake of sanctions.

Table 4: Baseline DiD: Flaring Intensity, Production, and Costs by Asset

Dependent Vars:	Flaring Intensity (log)	Prod. (log)	Cum. CAPEX (log)	OPEX (log)
Model:	(1)	(2)	(3)	(4)
Variables				
Venezuela × Post	0.4560***	-0.8068***	-0.1135***	-0.8557***
	(0.1607)	(0.1679)	(0.0226)	(0.1631)
Fixed-effects				
RE.ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	7,176	5,945	7,172	5,943
R^2	0.77144	0.86618	0.99588	0.84398

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

Lower cumulative OPEX means that investments in gas capture technology could have stalled and investments in infrastructure project, such as the construction of liquid natural gas terminals for the export of natural gas came to a halt. Similarly, the reduction in OPEX may reflect less emphasis on maintenance of existing gas capture infrastructure, worsening environmental performance.

Overall, the results indicate a large increase in gas flaring intensity compared to the baseline coupled with a drop in efficiency that was likely fueled by reductions in investment and spending. Altogether, the results strengthen the notion that sanctions worsened environmental performance rather than merely reducing output.

The next tables present the results for the triple-difference specifications. First, Table 5 presents the results for the estimates based on Equation 3.2.2 and subsequently Table 6 presents the estimates for the specification given by Equation 3.2.2. The first specification uses an indicator to denote high NOC ownership shares while the second uses a continuous measure of pre-treatment average NOC ownership.

The first column of Table 5 shows the results for log(Flaring Intensity) as the outcome variable. Here, the triple-difference coefficient is negative, but not significant. The sign, however, is indicative of the fact that having a higher state ownership share may actually mitigate the effects of sanctions on flaring. This could indicate that assets with higher degrees of state ownership were prioritized by PdVSA as their stakes in assets with greater state control are higher.

This idea is further evidenced by the fact that the triple-difference coefficient for production, cumulative CAPEX, and OPEX are all positive and significant, meaning that higher state ownership in an asset mitigates the decreases in these outcomes as caused by sanctions. This means that compared to assets with smaller NOC ownership

Table 5: Triple Difference: Flaring Intensity, Production, and Costs by Asset

Dependent Vars:	Flaring Intensity (log)	Prod. (log)	Cum. CAPEX (log)	OPEX (log)
Model:	(1)	(2)	(3)	(4)
Variables				
Treated × Post	0.6327**	-1.397***	-0.1492***	-1.374***
	(0.3092)	(0.3449)	(0.0350)	(0.2713)
Post × High NOC	-0.0841	-0.2045**	-0.1117***	-0.1001
	(0.0766)	(0.0984)	(0.0294)	(0.0940)
Treated × Post	-0.2210	0.9461**	0.0905**	0.7936**
× High NOC	(0.3597)	(0.3920)	(0.0432)	(0.3370)
Fixed-effects				
RE.ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	6,433	5,370	6,430	5,369
R^2	0.77122	0.87891	0.99607	0.86711

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

shares, assets with high NOC ownership had smaller decreases in production, cumulative CAPEX, and OPEX. PdVSA may have chosen to prioritize assets that it had more control of in order to receive the largest returns from investments and from production. Conversely, these results could also indicate that firms in joint ventures with PdVSA as various assets scaled back their investments and production as they were aware of the overall consequences that the financial sanctions would cause. Firms in joint ventures may have quickly understood that sanctions likely would become more severe and impact trade and exports from Venezuela, causing them to invest their money into assets in countries that were not under sanctions.

Table 6 further solidifies this analysis. In this specification, none of the coefficients in the first column for flaring intensity are statistically significant. The signs on all the coefficients are the same as in Table 5, but the standard errors are very large, likely due to the fact that the smallest ownership share in Venezuela is 60% NOC ownership and the baseline for Treated × Post assumes a baseline of no state ownership.

The other columns in Table 6 are more revealing. Once again, the triple-difference coefficients are significant for production and OPEX, but in the continuous specification, none of the coefficients for the model with cumulative CAPEX are significant. Nevertheless, the triple-difference coefficients for log(production) and log(OPEX) help to convey the degree to which state ownership mitigates the decreases in production and OPEX as caused by sanctions in Venezuela.

For every one percentage-point increase in average state ownership share in the pre-

treatment period, the production decline due to sanctions is mitigated by roughly 2.3%. Similarly, for every one percentage-point increase in average state ownership before sanctions, the decline in OPEX is attenuated by approximately 2.2%. This further reinforces the idea that the larger the ownership share of the state in an asset, the more of a priority the asset seems to be in terms of production and investment. Once again, the attenuating nature of state ownership share is not apparent from the results shown in column 1 of the table, but the sign continues to indicate that the environmental inefficiency caused by the imposition of sanctions on Venezuela may have been made less severe by higher degrees of state ownership.

Table 6: Continuous Triple Difference: Flaring Intensity, Production, and Costs by Asset

Dependent Vars:	Flaring Intensity (log)	Prod. (log)	Cum. CAPEX (log)	OPEX (log)
Model:	(1)	(2)	(3)	(4)
Variables				
Treated × Post	1.182	-2.619***	-0.0097	-2.636***
	(0.7213)	(0.8130)	(0.0741)	(0.6932)
Post	-0.0005	-0.0020*	-0.0009***	-0.0010
× Avg NOC Part.	(0.0009)	(0.0011)	(0.0003)	(0.0010)
Treated × Post	-0.0083	0.0223***	-0.0009	0.0215***
× Avg NOC Part.	(0.0083)	(0.0086)	(0.0008)	(0.0076)
Fixed-effects				
RE.ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	6,433	5,370	6,430	5,369
R^2	0.77122	0.87902	0.99605	0.86737

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

Table 7 presents the estimated coefficients for the DiD specification in Equation 2. These three sets of results show the coefficients for the impact of sanctions on flaring for various degrees of NOC concentration for assets in Venezuela compared to assets with similar degrees of NOC concentration in the control countries. The first column gives the estimates for assets that have the lowest degree of state ownership. Once again, Venezuelan law necessitates a majority stake in all Venezuelan assets by PdVSA, so these assets represent the lower bound of state control for the treated group. The coefficient for the regression over the lowest NOC ownership group is 0.6327, which is statistically significant at the 5% level. This can be interpreted as about an 88.3% increase in flaring intensity for assets in Venezuela with less than or equal to a 60% NOC ownership share compared to assets in the control countries in the same bracket of NOC ownership share.

The second column of Table 7 shows the DiD estimates for the middle ownership group, with average NOC ownership shares greater than 60% but less than 100% for the period between 2012 and 2016 before sanctions. The coefficient for DiD interaction term is 0.441, but the standard error for this estimate is very large, making it statistically insignificant. Nevertheless, the sign and magnitude of the coefficient are somewhat informative. The positive sign of the coefficient indicates that this ownership group, like the other two groups, also experienced an increase in flaring intensity in Venezuela after sanctions. The magnitude is also smaller than that of the low NOC ownership share group and similar to the magnitude of the estimator for the fully state-owned asset group.

Table 7: DiD by NOC Participation Group: Flaring Intensity

Dependent Variable:	log(Flaring Intensity)		
	≤60%	>60–<100%	100%
Model:	(1)	(2)	(3)
Variables			
Treated × Post	0.6327**	0.4414	0.4471**
	(0.3106)	(0.3862)	(0.2128)
Fixed-effects			
RE.ID	Yes	Yes	Yes
Year	Yes	Yes	Yes
Fit statistics			
Observations	3,320	1,123	1,990
R^2	0.75936	0.70372	0.81052

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

The final column in Table 7 shows the DiD results for assets that were fully state-owned in Venezuela in the pre-treatment period compared to assets that were fully state-owned in the control countries in the pre-treatment period. The $\beta_{\text{FullState}}$ estimate for this regression is 0.447, and, like the result for the low NOC ownership group, this result is significant at the 5% level. This coefficient corresponds to an average increase in flaring intensity of about 56.4% for the treatment group after sanctions. Notably, this effect is smaller than that of the low NOC ownership group.

The results from the ownership group DiD regressions reinforce the idea that the Venezuelan state and PdVSA likely prioritized the assets where their interest share was higher. PdVSA has limited capital and operational capacity, which became extremely constrained after sanctions restricted access to U.S. financing and technology. As such, assets where PdVSA holds a large, and particularly a full stake, are likely to be prioritized for the scarce investment and maintenance that existed after the imposition of sanctions. This is due to the fact that the state captures the full value of production in assets they

fully own.

As aforementioned, the estimated coefficient for the 60% to 100% NOC ownership group is positive but not statistically significant. This lack of significance could be caused by a couple of factors. First, this could reflect the mixed nature of incentives within this group, since PdVSA, as the majority owner, may have sought to maintain production and limit flaring, but minority private partners may have scaled back investment in response to sanctions. This results in greater heterogeneity within this group, with some assets exhibiting higher flaring than others, leading to greater variance and wider confidence intervals. Secondly, this could be due to the smaller sample size of this group relative to the others that contributes to the lack of statistical power. With a greater number of observations in this group, the true relationship may become more apparent.

The final table, Table 8 present the results for the specification detailed in Equation 3. This specification treats fully state-owned assets in Venezuela as the treatment group and joint ventures in Venezuela as the control group. Although all assets in Venezuela have some state ownership and all assets in Venezuela are impacted by sanctions for 2017 and beyond, this specification seeks to explain the exposure to sanctions may cause heterogeneous outcomes within Venezuelan assets.

Table 8: DiD: Venezuela Only — Flaring Intensity, Production, and Costs

Dependent Vars:	Flaring Intensity (log)	Prod. (log)	Cum. CAPEX (log)	OPEX (log)
Model:	(1)	(2)	(3)	(4)
Variables				
100% State-Owned	-0.2865	1.318***	-0.0691**	1.399***
× Post	(0.3148)	(0.3285)	(0.0323)	(0.3065)
Fixed-effects				
RE.ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	957	957	957	957
R^2	0.73291	0.89710	0.99908	0.87024

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

As with the other results, the primary outcome of interest for this specification is flaring intensity. However, the results in column 1 of the table show that, although negatively signed and economically large, the effect of sanctions on fully state owned assets in Venezuela compared to Venezuelan joint ventures is not statistically significant. The sign does indicate, however, that full state-ownership of an asset may mitigate its reduction in efficiency as onset by the imposition of financial sanctions.

Moving on to the results for the other outcomes—production, cumulative CAPEX,

and OPEX—all of the other coefficients are statistically significant, at least at the 5% level. The coefficients for production and OPEX both have p-values less than 0.01. The associated coefficients for both production and OPEX are both very economically large. These coefficients indicate that there is substantial heterogeneity in the way that sanctions have impacted production and OPEX for fully Venezuelan state-owned assets in comparison to Venezuelan joint ventures.

These results reiterates the dynamics that arise when countries fall under sanctions. These effects are likely driven by two forces that both move outcomes higher for fully state-owned assets when compared to joint ventures. The first force is the emphasis that PdVSA put on the assets that were under its full control when Venezuela fell under sanctions. Again, these assets are those for for which the returns to PdVSA, and thus the state, are highest. It is sensible for PdVSA to invest the most in the assets for which it will see the highest returns on investment. Secondly, there is the effect of firms operating in joint ventures pulling back investment and scaling back production in the wake of sanctions. This would decrease production and investment from the unsanctioned baseline and further drive the post-sanctions differences between fully state-owned Venezuelan assets and Venezuelan assets operating as joint ventures.

Interestingly, the coefficient for cumulative CAPEX is negative for the Venezuela-only DiD, indicating that fully state-owned assets in Venezuela invested less in capital expenditures than did assets operating as joint ventures in Venezuela. This could be because fully state-owned assets were prioritized for production, with the limited available financing after sanctions allocated to maintaining operations, even if at a scaled-down level. Thus, there was a lack of remaining financing for capital expenditures, such as the expansion of production or the purchase of new technology within fully state-owned assets. Overall, sanctions created an environment under which PdVSA prioritized short-term revenue extraction over long-term capacity-building.

In a similar manner to the results for flaring intensity presented in Table 7, the results for flaring intensity in the Venezuela-only DiD are lacking observations that could provide greater statistical power. Despite the lack of statistical significance, the coefficient for the DiD with flaring intensity as the outcome still may show that sanctions may not have exacerbated the inefficiency of flaring intensity as much in fully state-owned assets. This result is also consistent with the fact that, given their smaller reduction in production compared to Venezuelan joint ventures under sanctions, fully state-owned assets likely needed to reinject more gas to continue extracting oil at the desired rates. In contrast, joint ventures with more reduced production after sanctions still had associated gas as waste, but did not require the same quantities of gas for reinjection in order to maintain their post-sanction production rates.

Overall, the results provide evidence that flaring intensity was substantially and significantly increased by sanctions for the average Venezuelan asset. Additionally, expendi-

tures and production both decreased, meaning that the increase in flaring intensity also represents a decrease in efficiency in the oil sector in Venezuela. Importantly, further results show how state ownership played an important role in mitigating some of the impact of U.S. sanctions on Venezuelan oil sector outcomes. Assets with higher state participation experienced significantly smaller declines in production and operating expenditures following the 2017 sanctions. These findings suggest that PdVSA may have deliberately prioritized its wholly owned assets in the wake of sanctions, likely to concentrate limited financial and technical resources on operations that maximized returns to the state.

5 Discussion

This study investigates the effects of the 2017 U.S. financial sanctions on Venezuela's oil sector, focusing on natural gas flaring intensity and related outcomes at the asset level. Sanctions substantially increased flaring intensity relative to neighboring producers while sharply reducing production, CAPEX, and OPEX. These effects were mitigated for assets with higher national oil company (NOC) ownership, suggesting that PdVSA concentrated scarce resources in majority state-owned ventures.

Several mechanisms explain why sanctions worsen flaring. First, financial restrictions reduce access to credit and equipment, leading to underinvestment in gas-capture infrastructure such as compressors and gathering lines. Flaring then becomes the lowest-cost disposal method for associated gas (Beltrán-Jiménez et al., 2018). Empirical studies show that higher investment improves firms' environmental performance (Alam et al., 2019), implying that reduced CAPEX and OPEX translate into higher emissions. Our results echo prior work documenting how sanctions constrained Venezuela's oil industry and financing capacity (Rodríguez, 2022).

Second, lower production can itself raise flaring intensity. In heavy-oil regions like the Orinoco Belt, gas is reinjected to maintain reservoir pressure. When output declines, reinjection needs fall while gas output remains, leaving excess gas to be flared (Archer and Wall, 1986). This mechanism is consistent with the production declines observed in our baseline estimates.

Third, sanctions may weaken environmental oversight. When state revenues collapse, governments prioritize short-term extraction over environmental protection, as argued by Madani (2020). PdVSA's revenue constraints likely shifted attention away from emission mitigation toward maintaining cash flow. Although our data cannot test this mechanism directly, it aligns with broader evidence of regulatory slack under sanctions.

We also find heterogeneity by ownership. Assets with higher PdVSA control show smaller output and investment declines, suggesting that the firm prioritized operations where its fiscal returns were greatest. Similar patterns are observed elsewhere: sanctioned or state-linked firms often receive preferential support from their governments (Nigmat-

ulina, 2023). This behavior reflects both political incentives and financial dependence. State-owned firms generally enjoy better credit access and implicit guarantees (Gao et al., 2023, Geng and Pan, 2021), though the efficiency of such support can vary (Dong et al., 2016).

Our findings complement a growing literature on the macroeconomic and environmental effects of sanctions. Whang et al. (2013) and Walentek et al. (2021) show that sanctions are more effective when targets rely on the sender state, a condition clearly met by Venezuela's dependence on U.S. markets. More broadly, Hatipoglu et al. (2023) and Balali et al. (2024) demonstrate that sanctions can push countries toward more carbon-intensive energy paths by raising capital costs and limiting clean technology transfer. We provide micro evidence of the same mechanism: financing constraints increase flaring per barrel even as production falls. This mirrors findings from Iran and Russia, where sanctions increased emissions despite declining output (Liu et al., 2023).

Our results also connect to research on the environmental performance of national oil companies. Studies show that governance, ownership, and financial autonomy strongly influence operational efficiency (Monaldi et al., 2021). By quantifying how PdVSA's ownership share shapes emissions intensity, we highlight the need to integrate ownership structure into analyses of energy and climate policy.

Future analysis plan. Next, we plan to explore heterogeneity by operatorship and firm nationality. In particular, we will examine whether firms with exposure to the United States—especially U.S. and European multinationals—behaved differently after 2017. These firms may have maintained lower flaring due to stricter home-country environmental standards, or conversely curtailed technology transfer to comply with sanctions. Combining field-level operations with firm-level ownership and nationality data will allow us to test these channels directly. This extension will clarify how global political incentives interact with corporate governance to shape emissions outcomes in sanctioned states.

6 Conclusion

This paper quantifies the environmental consequences of economic sanctions using field-level data from Venezuela's oil sector. Exploiting the 2017 U.S. financial sanctions as a quasi-natural experiment, we estimate difference-in-differences and triple-differences models comparing Venezuelan fields to those in Argentina, Brazil, Colombia, and Ecuador. Sanctions increased flaring intensity by roughly 58% while sharply reducing production and investment. The effects were smaller for majority state-owned assets, consistent with PdVSA reallocating scarce resources toward fully controlled operations. These findings demonstrate that sanctions can reduce output yet raise emissions intensity, revealing a

previously overlooked externality of economic statecraft. Methodologically, the paper links satellite-based flaring measures with operational data to provide asset-level causal evidence. Substantively, it shows that ownership structure mediates the environmental cost of sanctions, underscoring the need to integrate governance and political economy considerations into both climate and foreign policy design.

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7 Appendices

7.1 Appendix A: Flaring Allocation Parameter Sensitivity Tests

Figure A1 shows the percent of total flaring volume allocated by radius size for the flaring allocation strategy. After reaching a radius of 13km, the allocated share begins to flatten out with no significant increases in share allocated after 15km. As such, 15km was selected as the final radius for the allocation strategy.

Figures A2 and A3 are sensitivity tests evaluating changes in the parameters p and α. Changes in these parameters did not affect the allocated volumes, so the final parameters were set as $p = \alpha = 1$

7.2 Appendix B: Robustness Checks

Winzorization Robustness

Table B1: Robustness: DiD under Alternative Top-Tail Winsorization of Flaring Intensity

Dependent Variable:	log(Flaring Intensity)			
	99.5th pct	98.5th pct	98th pct	97.5th pct
Model:	(1)	(2)	(3)	(4)
Variables				
Treated × Post	0.4659***	0.4482***	0.4288***	0.4169***
	(0.1612)	(0.1596)	(0.1557)	(0.1530)
Fixed-effects				
RE.ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	7,176	7,176	7,176	7,176
R^2	0.77776	0.76998	0.76861	0.76755

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

Note: Results for alternative top-end winsorization values. Each column is identified by the percentage in the distribution to which the top end values were winsorized

Table B1 shows the results for the baseline DiD for flaring intensity as the outcome using different levels of upper-tail winsorization. Each column checks a different values of winsorization of the right tail of the distribution of flaring intensity. All of the results remain significant, indicating that the results are not driven purely by outliers.

Figure A1: Allocation Coverage by Search Radius

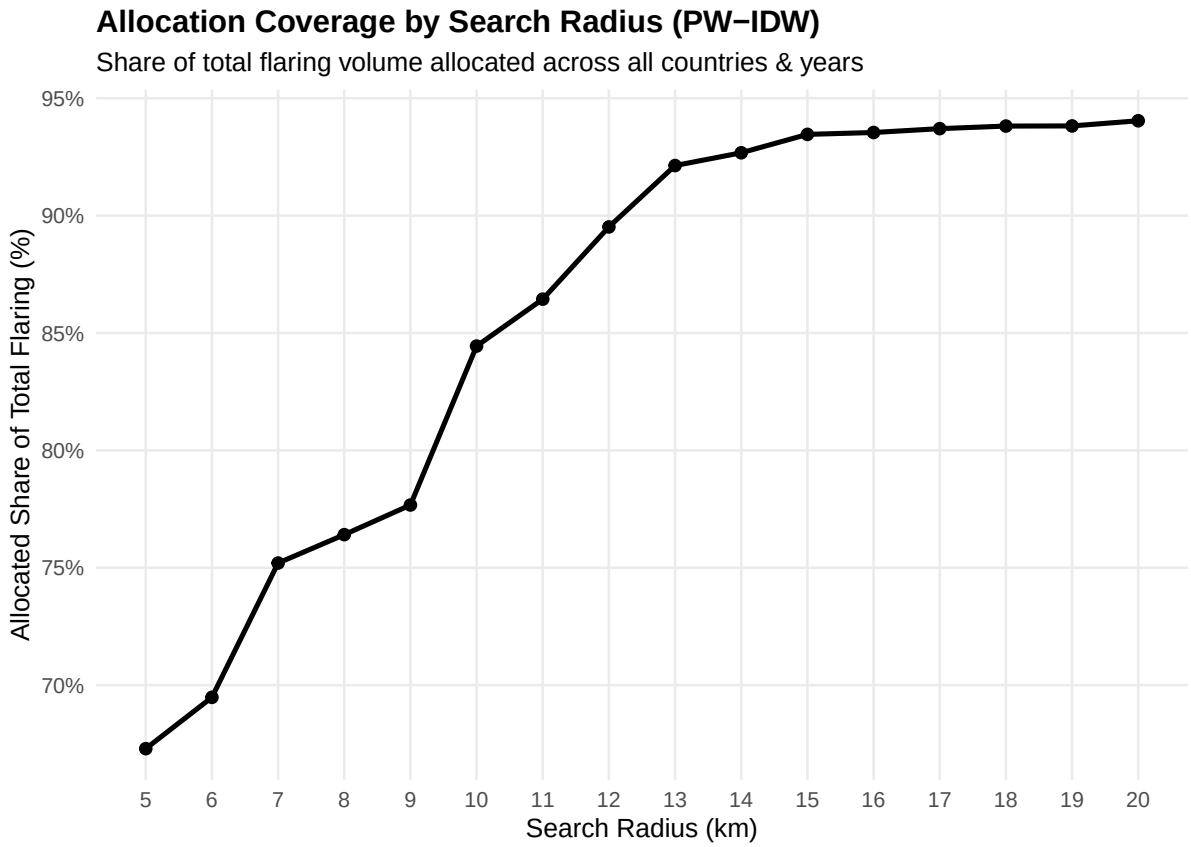
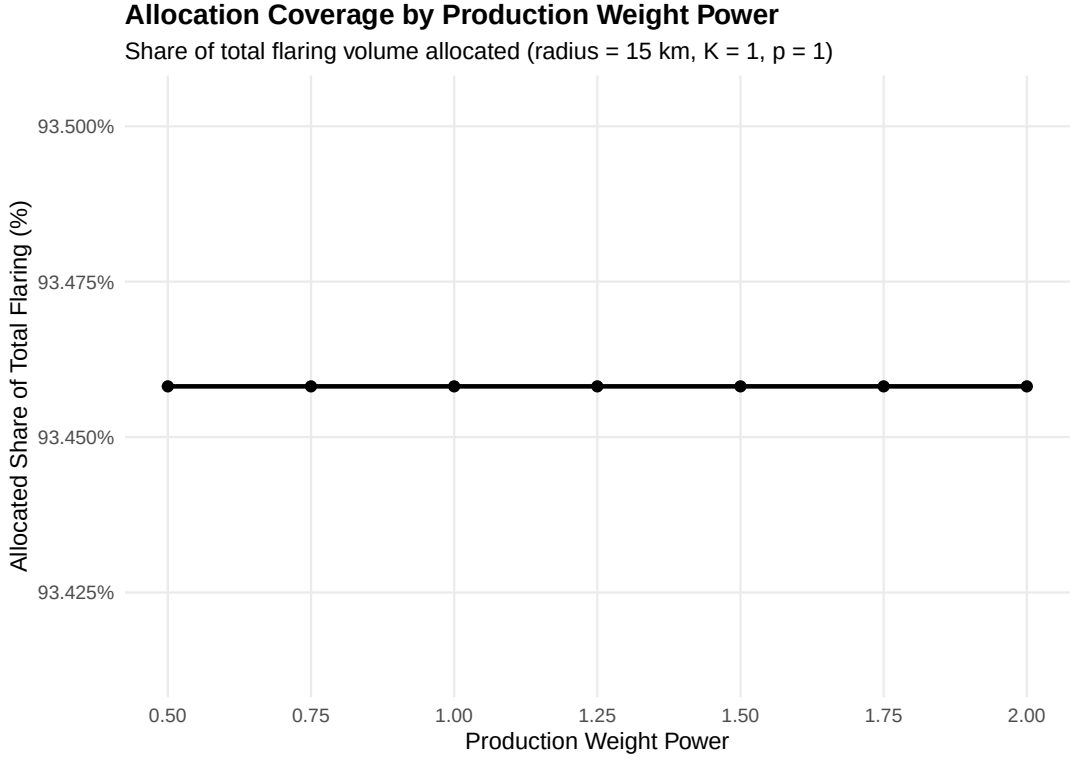


Figure A2: Allocation Coverage by Production Weight Power



Transformation Robustness

Table B2: DiD: Baseline — Untransformed Outcomes

Dependent Variables:	Flaring Intensity	Production (bbl)	Cum. CAPEX (USD)	OPEX OPEX (USD)
Model:	(1)	(2)	(3)	(4)
Variables				
Venezuela	144.2***	-4,369,017.4***	74,656,603.1	-33,693,359.3**
× Post	(48.62)	(1,554,849.2)	(55,344,162.3)	(14,006,416.3)
Fixed-effects				
RE.ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	7,176	7,176	7,172	7,172
R^2	0.70760	0.80617	0.98674	0.81051
Within R^2	0.01327	0.03196	0.00371	0.00740

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

Table B3: DiD: Baseline — Inverse Hyperbolic Sine-Transformed Outcomes

Dependent Vars.:	Flaring Intensity (asinh)	Production (asinh)	Cum. CAPEX (asinh USD)	OPEX (asinh USD)
Model:	(1)	(2)	(3)	(4)
Variables				
Venezuela	0.4470***	-0.6878***	-0.1135***	-0.7504***
× Post	(0.1725)	(0.1755)	(0.0226)	(0.1705)
Fixed-effects				
RE.ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	7,176	7,176	7,172	7,172
R^2	0.76570	0.85113	0.99606	0.83420
Within R^2	0.00539	0.00953	0.00631	0.00959

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

Dependent Vars.:	Flaring	Production	Cum. CAPEX	OPEX
Vars.:	Intensity m^3/bbl	(bbl)	(USD)	(USD)
Model:	(1)	(2)	(3)	(4)
Variables				
Treated × Post	221.4**	-4,566,996.2***	129,471,882.0	-63,059,176.2**
	(95.66)	(1,763,163.0)	(85,674,871.8)	(24,477,702.7)
Post × High NOC	-18.98	-138,558.0	45,152,616.4	249,266.8
	(12.83)	(116,880.3)	(32,766,719.3)	(1,474,344.8)
Treated × Post	-115.2	-401,769.3	-101,569,917.1	26,031,322.2
× High NOC	(108.5)	(2,811,849.8)	(112,948,645.8)	(28,646,903.3)
Fixed-effects				
RE.ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	6,433	5,370	6,430	5,369
R^2	0.70336	0.78447	0.98677	0.86131

*Signif. Codes: ***: p < 0.01, **: p < 0.05, *: p < 0.1*

[htbp]

Table B4: DDD: Indicator Specification — Inverse Hyperbolic Sine-Transformed Outcomes

Dependent Vars.:	Flaring	Production	Cum. CAPEX	OPEX
Vars.:	Intensity (asinh)	(asinh)	(asinh)	(asinh)
Model:	(1)	(2)	(3)	(4)
Variables				
Treated × Post	0.6008**	-1.273***	-0.1090***	-1.287***
	(0.2829)	(0.3362)	(0.0362)	(0.2788)
Post	-0.0397	-0.2323**	-0.0988***	-0.1136
× High NOC	(0.0898)	(0.0977)	(0.0288)	(0.0939)
Treated × Post	-0.2242	0.8199**	0.0265	0.7107**
× High NOC	(0.3551)	(0.3864)	(0.0438)	(0.3475)
Fixed-effects				
RE.ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	6,433	5,370	6,430	5,369
R^2	0.76517	0.87379	0.99622	0.86203

*Signif. Codes: ***: p < 0.01, **: p < 0.05, *: p < 0.1*

Dependent Vars.:	Flaring	Production	Cum. CAPEX	OPEX
Vars.:	Intensity m^3/bbl	(bbl)	(USD)	(USD)
Model:	(1)	(2)	(3)	(4)
Variables				
Treated × Post	485.4*	-3,361,204.2	213,547,078.5	-103,964,343.5
	(261.0)	(5,565,440.0)	(217,173,848.0)	(60,801,317.1
Post × Avg NOC Part.	-0.2282*	-167.7	732,713.5**	12,775.7
	(0.1375)	(1,171.9)	(324,875.5)	(14,627.0)
Treated × Post	-3.938	-17,662.4	-1,927,577.8	672,524.2
× Avg NOC Part.	(2.850)	(72,780.6)	(2,542,351.5)	(669,306.7)
Fixed-effects				
RE.ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	6,433	5,370	6,430	5,369
R^2	0.70384	0.78449	0.98680	0.86135

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

[htbp]

Table B5: DDD: Continuous Specification — Inverse Hyperbolic Sine-Transformed Outcomes

Dependent Vars.:	Flaring Intensity (asinh)	Production (asinh)	Cum. CAPEX (asinh)	OPEX (asinh)
Model:	(1)	(2)	(3)	(4)
Variables				
Treated × Post	1.206	-2.675***	-0.0097	-2.677***
	(0.7757)	(0.8435)	(0.0741)	(0.7149)
Post	-0.0005	-0.0020*	-0.0009***	-0.0010
× Avg NOC Part.	(0.0010)	(0.0011)	(0.0003)	(0.0010)
Treated × Post	-0.0087	0.0228**	-0.0009	0.0218***
× Avg NOC Part.	(0.0089)	(0.0089)	(0.0008)	(0.0078)
Fixed-effects				
RE.ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	6,433	5,370	6,430	5,369
R^2	0.76530	0.87409	0.99621	0.86240

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

Figure A3: Allocation Coverage by p

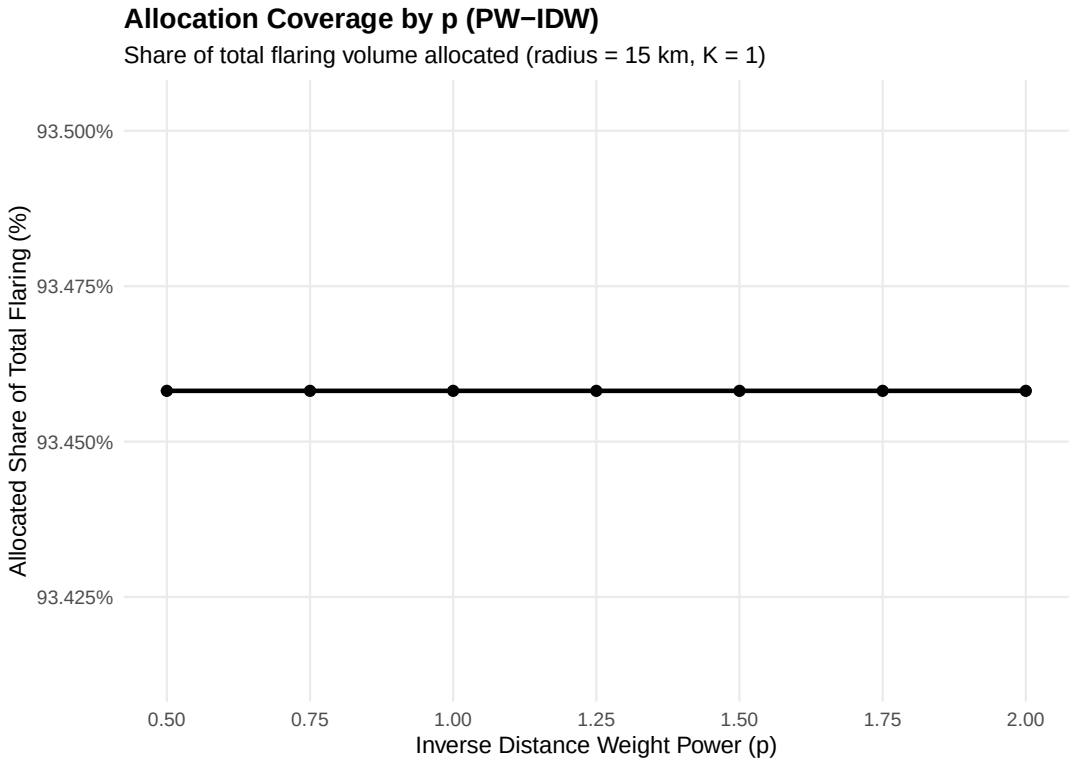


Table B6: DiD by NOC Participation Group—Untransformed

Dependent Variable:	Flaring Intensity (m^3/bbl)		
	$\leq 60\%$	>60–<100%	100%
Model:	(1)	(2)	(3)
Variables			
Treated × Post	234.4**	92.73	119.9**
	(111.8)	(118.7)	(55.38)
Fixed-effects			
RE.ID	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	3,320	1,123	1,990
R^2	0.60885	0.47263	0.78146

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

Table B7: DiD by NOC Participation Group—Inverse Hyperbolic Since Transformation

Dependent Variable:	asinh(Flaring Intensity)		
	$\leq$ 60%	>60–<100%	100%
Model:	(1)	(2)	(3)
Variables			
Treated × Post	0.6169*	0.4544	0.4542**
	(0.3363)	(0.4163)	(0.2278)
Fixed-effects			
RE.ID	Yes	Yes	Yes
Year	Yes	Yes	Yes
Observations	3,320	1,123	1,990
R^2	0.75268	0.70248	0.80653

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

Placebo Tests

Table B8: Anticipation Placebo DiD Checks

Dependent Variable:	log(Flaring Intensity)	
	Cutoff: 2015	Cutoff: 2014
Model:	(1)	(2)
Variables		
Treated × Post(2015)	-0.0549	
	(0.1449)	
Treated × Post(2014)		-0.0549
		(0.1330)
Fixed-effects		
RE.ID	Yes	Yes
Year	Yes	Yes
Observations	7,176	7,176
R^2	0.76978	0.76977

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

Alternative Control Groups

The robustness of the baseline DiD results is supported by the findings in Tables B8 and the alternative control group analysis in Table B9. Table B8 reports placebo tests using cutoff dates of 2014 and 2015 rather than the true sanctions onset in 2017. In both cases, the estimated coefficients are small in magnitude and statistically insignificant, providing no evidence of pre-trends or anticipatory effects. This supports the parallel

Table B9: DiD using Altenative Control Groups—Excluding Each Control Country

Dependent Var.:	log(Flaring Intensity)			
	Excl. Argentina	Excl. Brazil	Excl. Colombia	Excl. Ecuador
Model:	(1)	(2)	(3)	(4)
Variables				
Venezuela × Post	0.5507***	0.4311***	0.3853**	0.4817***
	(0.1616)	(0.1624)	(0.1624)	(0.1627)
Fixed-effects				
RE.ID	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	4,782	5,945	5,745	6,101
R^2	0.80265	0.76011	0.76902	0.77411

*Signif. Codes: ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$*

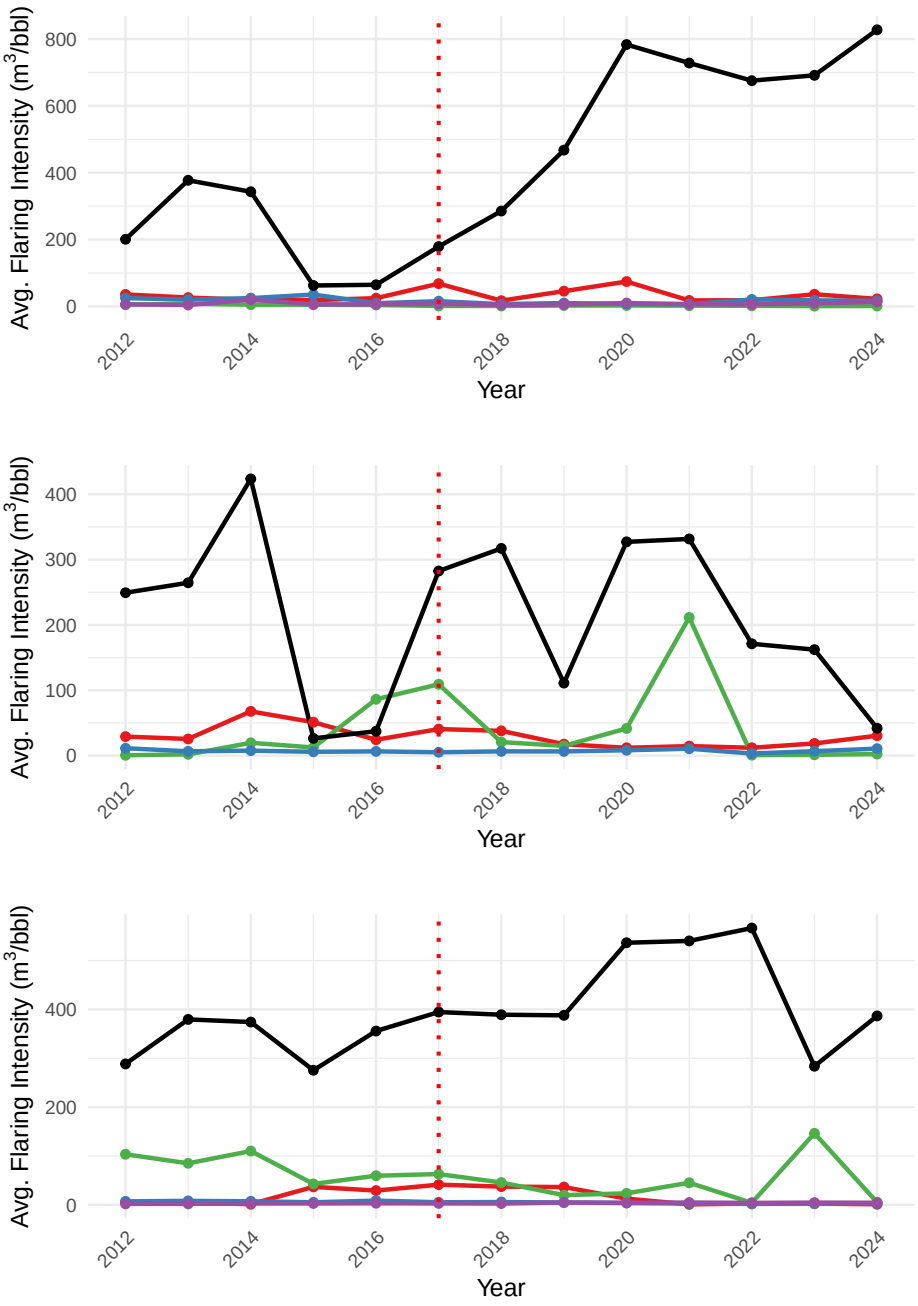
trends assumption underlying the DiD design and suggests that the post-2017 treatment effects are not driven by trends that predate the sanctions.

The next robustness exercise, whose results can be found in Table B9, excludes one control country at a time from the estimation sample to ensure that results are not disproportionately driven by a single control group. The results remain positive and statistically significant across all specifications, with point estimates remaining in the same range as the baseline. This suggests that the estimated effect of sanctions on flaring intensity in Venezuela is not sensitive to the inclusion or exclusion of any one control country, further reinforcing the credibility of the main findings.

7.3 Appendix C: NOC Group DiD Identification Plots

7.4 Appendix D: Within Venezuela DiD Identification Plots

Figure C1: Average Flaring Intensity by NOC Ownership Group



(0, 0) node[inner sep=0] ;
(-3.9, 8.7) node $\leq$ 60% NOC Ownership; (-3.2, 3) node $>$ 60$-$ $<$ 100% NOC Ownership;
(-4, -3) node 100% NOC Ownership;

Note: This figure depicts average flaring intensity per asset by country. Countries are colored as follows: Argentina, red; Brazil, green; Colombia, blue; Ecuador, purple; Venezuela, black.

Figure D1: Within-Venezuela Event-Study Results for Flaring Intensity, Production, OPEX. and CAPEX

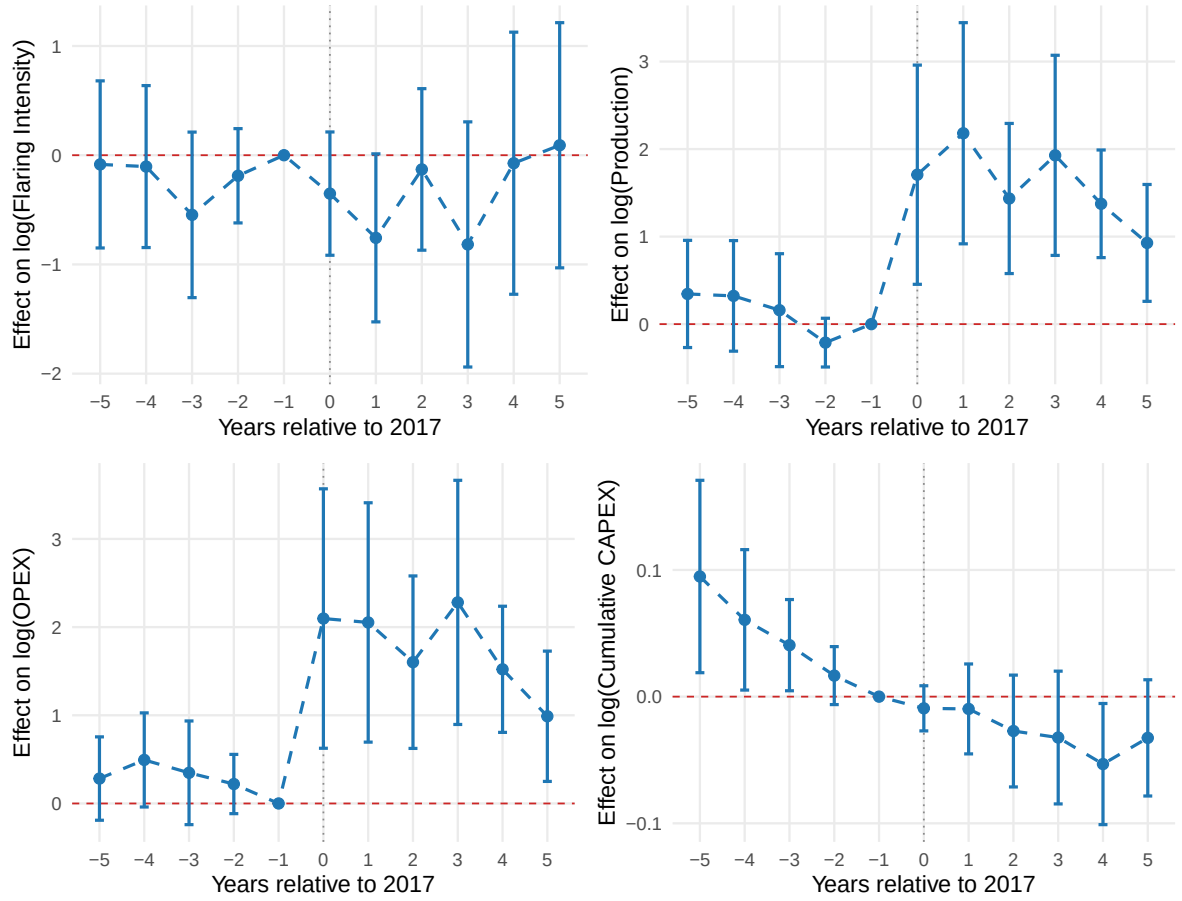


Figure D2: Within Venezuela Average Flaring Intensity by NOC Ownership Group

