Why Methane Matters: A Dual Approach to Policy Impact and Abatement Cost Modeling in the U.S. Oil and Gas Sector

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Abstract

This paper examines the impact of regulatory announcements on methane emissions and evaluates the economic potential for methane abatement in US oil and gas basins. We first conduct an event study analysis of an adopted but not yet implemented US regulation that would impose substantial fees on methane super-emitters. The results suggest that the implicit tax signal embedded in the regulation announcement far exceeds the marginal abatement cost for a substantial share of installations, although this estimate reflects only a single average point on the cost curve. To capture the full distribution of costs, we then construct marginal abatement cost curves for the Permian, Appalachian and Anadarko U.S basins. This expanded analysis reveals sizeable "missed-money" opportunities: approximately 8% of methane emissions could be abated at zero net cost and nearly 50% could be avoided for less than 1.5 USD/t CO_2e. These cost estimates are significantly lower than recent estimates, revealing considerable untapped potential for cost-effective methane mitigation.

Keywords: regulation, missing money, abatement cost

JEL Classification: L51; Q4; Q5

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1 Introduction

Methane (CH_4) is widely recognized as the second most important greenhouse gas (GHG) after carbon dioxide (CO_2), owing to its much higher radiative efficiency: over a 20-year time horizon its global warming potential is roughly 82 times that of CO_2. Although its atmospheric mixing ratio is far lower than that of CO_2, its combination of high short-term potency and relatively short atmospheric lifetime makes methane mitigation an especially powerful lever for near-term climate forcing ((Shindell et al., 2024)). Atmospheric methane has increased at an average rate of about 0.9% per year since the 19^{th} century, and the latest Intergovernmental Panel on Climate Change (IPCC) Assessment reports that anthropogenic methane emissions are "very likely" to have already contributed between 0.37 °C and 0.87 °C of observed global warming, with a central estimate of 0.57 °C (Szopa et al., 2021). The IPCC further concludes, with "high confidence", that pathways consistent with limiting global warming to 1.5 °C require substantial reductions in anthropogenic methane alongside deep cuts in CO_2.

Like CO_2, methane emissions originate from both natural and anthropogenic sources. Natural emissions come from wetlands, biomass decomposition, and other biological processes, accounting for over 360 million metric tons (Mt) released into the atmosphere each year. However, anthropogenic emissions now represent more than half of total methane emissions, reaching approximately 380 Mt annually. These human-induced emissions can be divided into three main sectors: energy, waste, and agriculture. According to recent studies (Jackson et al., 2020), roughly 40% of global anthropogenic methane emissions originate in the energy sector, i.e oil, natural gas, and coal, where large shares of emissions are thought to be technically controllable and, in some cases, economically avoidable. In the energy sector, these methane emissions primarily originate from three sources: leaks (during production, extraction and transportation), flaring, and direct venting. All three represent particularly significant sources of methane and CO_2 emissions. Flaring involves intentionally burning methane gas during oil extraction, converting it to CO_2 while still generating substantial emissions. According to the International Energy Agency, approximately 140 billion cubic meters of gas are flared worldwide each year, emitting roughly 350 Mt of CO_2 equivalent (International Energy Agency, 2022). A recent World Bank report reveals an increasing trend, with flaring responsible for approximately 381

million tonnes of carbon dioxide equivalents (CO2e) in 2023[1]. Venting and fugitive emissions (i.e., intentional and unintentional leaks), on the other hand, correspond to direct methane releases into the atmosphere without combustion. Fugitive emissions are unintentional methane emissions, while venting emissions are intentional and occur during maintenance operations, pipeline purging, or equipment malfunctions. The shale gas industry contributes significantly to venting emissions, with recent studies estimating that hydraulic fracturing operations generate between 2% and 4% of total methane emissions from the US energy sector (Rutherford et al., 2021). Furthermore, upstream oil and gas operations account for nearly 23% of global methane emissions from fossil fuel activities, with incomplete combustion during flaring contributing an additional 10-20% of methane that should be converted to CO_2 (Zhang et al., 2020).

This matter has begun to draw attention increase from economists. Yet, compared with the vast literature on carbon pricing and CO_2 mitigation (Fischer and Morgenstern, 2006; Du et al., 2015; Misconel et al., 2022), formal economic analysis of methane abatement costs, incentives, and firm behavioral responses remains relatively sparse.[2] Developing an empirical economic evidence base around methane is therefore central both to climate policy design and to improving social cost assessments of non-CO_2 greenhouse gases. Importantly, methane mitigation can generate dual gains: environmental benefits from avoided warming and substantial economic value from captured gas.

Policy momentum has accelerated in recent years. Internationally, more than 150 countries have endorsed the *Global Methane Pledge*, committing to reduce human-caused methane emissions by 30% by 2030 relative to 2020 levels (Global Methane Pledge, 2025). Although non-binding, the pledge has spurred domestic initiatives and regulatory proposals, particularly

[1]While flaring remains a carbon-intensive practice generating substantial CO_2 emissions, it represents the economically rational second-best solution when direct gas capture and commercialization are not cost-effective. The economic rationale for flaring over venting stems from the differential climate impact costs: given that methane exhibits a global warming potential 28 times higher than CO_2 over a 100-year horizon, converting methane to CO_2 through flaring reduces the social cost of carbon emissions by approximately 96% compared to direct venting. However, this cost-benefit analysis shifts when considering the economic value of captured gas. Studies indicate that routine flaring represents an annual economic loss of approximately $20 billion globally, as these associated gases could theoretically be monetized through pipeline infrastructure or compressed natural gas facilities (World Bank, 2020).

[2]There is a growing engineering and atmospheric-science literature quantifying emissions and technical abatement options, but systematic integration into economic models, marginal abatement cost, and policy evaluation remain underdeveloped.

in major emitting jurisdictions such as the United States and the European Union. In the United States, federal policy under the Biden administration moved beyond the prior patchwork of state-level approaches. The Inflation Reduction Act of 2022 established the *Methane Emissions Reduction Program*, including the *Waste Emissions Charge* (WEC) i.e. the first nationwide fee structure targeting excess methane emissions from the oil and gas sector (U.S. Environmental Protection Agency, 2024).

Regulatory uncertainty, however, remains a defining feature of the policy environment. On 14 March 2025, a joint resolution under the Congressional Review Act rescinded the EPA's final rule implementing the WEC, effectively nullifying the mechanism and re-introducing ambiguity into federal methane pricing and compliance expectations (U.S. Congress, 2025). This policy whiplash underscores the need for empirical evidence on how market actors respond not only to implemented regulations but also to regulatory announcements, proposed rules, and signals that shift expectations about future compliance costs. Addressing this need, our empirical strategy exploits a granular dataset of nearly 5,000 inventory observations covering the 2015-2023 period.

At the same time, rapid advances in measurement technologies are transforming the information landscape around methane ((Jacob et al., 2022)). High-resolution satellite platforms (e.g., GHGSat), aircraft-based detection campaigns, and increasingly widespread continuous monitoring systems have revealed large and spatially heterogeneous emission events. Multiple empirical studies find substantial gaps between reported inventories and actual observed emissions, with underreporting often exceeding 50% and, in extreme cases, differing by an order of magnitude (Zhang et al., 2020; Riddick and Mauzerall, 2023). However, few studies have leveraged these new emissions data for economic analysis. Yet these measurement advances create opportunities to empirically estimate abatement costs at fine spatial and temporal scales, moving beyond aggregate sectoral averages to capture the heterogeneity that drives cost-effective mitigation strategies. This motivates our second research question: How do improved emissions data inform our understanding of the distribution of methane abatement costs, and how does this distribution vary across sources and sectors ? To address this question, we leverage high-resolution satellite data disaggregated by U.S. basin and emission source to estimate the distribution of abatement costs and evaluate sector-specific mitigation potential in 2024.

More specifically, we focus on three highly emissive U.S basins: the Permian, Appalachian, and Anadarko.

This paper contributes to the emerging economic literature on methane mitigation in two ways. First, we assemble an original panel of observational methane data aligned to regulatory and policy announcement timelines to test whether US firms reduced their methane emissions in anticipation of, or in response to, the announcement of the WEC regulation. By combining bottom-up data with policy event windows, we can directly assess the extent to which regulatory signals are internalized by firms before formal implementation, thereby offering new insights into the credibility and effectiveness of climate-related policy commitments. We employ multiple econometric specifications, including difference-in-differences and event study designs, to identify causal effects and trace the dynamic response of emissions to regulatory announcements. Our results reveal that operators respond strongly to anticipatory regulatory signals, adjusting emissions ahead of formal implementation. Second, using remote sensing data combined with production and operational scaling factors, we estimate the marginal and average costs of methane abatement in the energy sector for three US basins[3], and assess the extent to which abatement is economically attractive when accounting for recovered gas value and avoided compliance costs. Precisely, we rely on emissions distribution shares from the IEA to disaggregate remotely-sensed emissions[4] into specific production sources. To the best of our knowledge, this is the first study to estimate methane abatement costs using satellite data while examining heterogeneity both across different U.S basins and across emission source types. This sheds light on whether current patterns of methane emissions reflect a form of "missing money" problem, in which low-cost or even cost-negative abatement opportunities remain unrealized due to imperfect information, misaligned incentives, or regulatory uncertainty. Identifying the extent of this gap is critical to designing efficient policies that can unlock cost-effective mitigation and accelerate reductions in methane emissions by the energy sector.

The paper is organized as follows. Section 2 reviews recent trends in methane emissions, outlines the main detection techniques, and surveys the related literature on impact assessment

[3]The Permian, Appalachian and Anadarko

[4]The French company Kayrros, specialized in remote sensing detection, provided us satellite emissions from venting, flaring and fugitive sources.

and marginal abatement cost curves. Section 3 describes the dataset and presents the summary statistics. Section 4 sets out the empirical strategy. Section 5 presents the results on the effects of the regulation on firms' emissions and constructs basin-specific marginal abatement cost curves. **??** discusses policy implications, and Section 6 concludes.

2 Background

Two Main Types of Data for Methane Emissions Detection

Bottom-up methodologies for quantifying methane emissions constitute the foundational approach used by national and international agencies for emissions inventory development and remain the current standard for the IPCC. These methods multiply activity data (such as the number of facilities, production volumes, or operational hours) by standardized emission factors derived from equipment-specific measurements and engineering calculations (International Energy Agency, 2023). The Environmental Protection Agency (EPA) utilizes bottom-up approaches in its Greenhouse Gas Inventory, applying detailed emission factors for different equipment types across the oil and gas supply chain, including wellheads, compressor stations, and processing facilities (U.S. Environmental Protection Agency, 2023). Similarly, the Energy Information Administration (EIA) incorporates bottom-up methodologies in its energy-related emissions assessments, particularly for upstream oil and gas operations (U.S. Energy Information Administration, 2023). The International Energy Agency (IEA) employs these approaches in its Global Methane Tracker, combining facility-level activity data with region-specific emission factors to estimate sectoral emissions at national and global scales (International Energy Agency, 2024). However, bottom-up methods face significant limitations due to the heterogeneity of emission factors across different operational conditions, equipment vintages, and maintenance practices. Moreover, bottom-up methods inherently rely on producer-reported data, which is often underestimated. Recent studies indicate that bottom-up estimates may underestimate actual emissions by 25-50% compared to top-down satellite-based measurements, primarily due to the difficulty in capturing intermittent large emission events and the reliance on average emission factors that may not reflect real-world operational variability (**?**).

On the other hand, to face bottom-up methods' limitations, satellite-based methods, i.e.

top-down methods, have been developed using remote sensing to better quantify in real time methane emissions in the energy sector. This field of research has experienced unprecedented growth in the past decade, with significant technological advances in both passive and active sensor technologies, and the number of satellites launched follows an upward trend in recent years (Jacob et al., 2022). Satellite-based methane detection generally relies on identifying absorption in the short-wave infrared (SWIR) spectral range, where methane exhibits strong absorption features. Methane absorption occurs specifically in the near-infrared (NIR) and short-wave near-infrared (SWIR) wavelengths, particularly in the spectral bands around 1560-1660 nm (band 11) and 2090-2290 nm (band 12).

Current satellite missions adopt diverse spectral strategies, each involving trade-offs among spatial coverage, spectral resolution, and temporal revisit frequency[5]. Multispectral satellites like Sentinel-2 (S2) use the MultiSpectral Instrument (MSI) with 20 m spatial resolution for SWIR bands B11 and B12, achieving a global 2-5 day revisit time , providing frequent monitoring but with limited spectral bands. In contrast, Sentinel-5P (S5P) is a flux mapper which provides offline imagery of methane concentrations through its TROPOMI instrument with daily global coverage but at coarser spatial resolution (7×3.5 km). Hyperspectral satellites such as PRISMA, enMAP and EMIT provide high SWIR spectral resolution that enables precise methane detection. EnMAP and PRISMA are in tasking mode, meaning that each imagery collection is subject to fees. EnMAP offers 30m spatial resolution with spectral sampling distances of 6.5 nm and 10 nm in the VNIR and SWIR regions respectively, but with a revisit frequency of only 27 days for the exact location. NASA's EMIT imaging spectrometer, initially designed for dust composition mapping, has demonstrated crucial capabilities in detecting methane and carbon dioxide super-emitters , measuring 285 spectral bands with a 75 km viewing swath at high spatial resolution, though with irregular revisit patterns due to its International Space Station orbit. One must point out that if some sensors were specifically designed to detect atmospheric gases like methane (Sentinel-5P) some others were not (Sentinel-2, EnMAP, PRISMA, EMIT) and were used afterwards, when the satellite was already in orbit.

[5]A higher revisit frequency generally increases confidence in satellite observations; however, satellites with shorter revisit times often offer either reduced spatial coverage or lower spectral resolution.

Assessment of Regulatory Impact

A central challenge in regulatory impact assessment is to estimate causal effects in a non-experimental setting, where randomized control trials are not feasible and policy evaluation must therefore rely on observational data. Among the most widely used methods in this context are Difference-in-Differences (DiD) and event study designs. Both approaches exploit variation across time and groups to isolate the effect of a treatment, under the key assumption that, absent the treatment, treated and untreated groups would have followed parallel trends. Angrist and Pischke (2009) provide a comprehensive introduction to the DiD framework, highlighting that identification does not require treated and control groups to start at the same level of the outcome variable, but rather that their counterfactual trends would have evolved similarly in the absence of treatment. This so-called "parallel trends" assumption is the cornerstone of DiD. Recent contributions have focused on testing the robustness of this assumption and extending DiD methods to more realistic contexts. Rambachan and Roth (2023) study the sensitivity of DiD estimators when pre-treatment trends are not perfectly parallel. They develop a framework to formally assess deviations from parallel trends and propose robustness checks and estimation strategies that account for heterogeneous pre-trends. This is particularly relevant in empirical settings where initial outcome levels differ significantly across groups, potentially violating the standard DiD identifying assumption. Another active line of research has examined the implications of staggered adoption, where treatment is implemented at different points in time across units. In such cases, conventional two-way fixed effects estimators may yield biased estimates of the average treatment effect (Chaisemartin and D'Haultfœuille (2023)). Sun and Abraham (2021) develop alternative estimation strategies that remain valid under heterogeneous treatment timing. Their method corrects for biases due to differential timing and heterogeneous treatment effects and has rapidly become a benchmark in applied work using staggered DiD designs. Event study designs are closely related to DiD, as they estimate dynamic treatment effects by modeling leads and lags of treatment relative to the treatment period. These designs are widely used in economics and finance to study the temporal dynamics of policy changes or shocks. However, the validity of event studies depends on the same parallel trends assumption, and the recent methodological advances by Rambachan and Roth (2023) and Sun and Abraham (2021) also inform the interpretation of event study estimates. Overall, the evolution of the

DiD and event study literature has shifted from simple static comparisons to more sophisticated approaches that relax or test key identifying assumptions. This provides applied researchers with more credible tools to estimate causal effects in settings where treatment assignment is not randomized.

Marginal Abatement Cost Curve

The Marginal Abatement Cost Curve (MACC) has been widely used in the economic literature to represent the relationship between the level of emissions reduction and the associated marginal costs, in contexts ranging from climate policy design to energy transition planning and local air pollution control. It illustrates the cost of reducing each additional unit of pollution. Typically, the theoretical MACC is upward-sloping and convex, reflecting the fact that as abatement increases, eliminating an additional unit of pollution becomes progressively more expensive (Baumol and Oates, 1988; Tietenberg and Lewis, 2023).

Methane, however, represents a notable exception to this general pattern. At least in the short term, a large share of abatement opportunities can be achieved at relatively low or even negative costs, before more costly measures are required for deeper reductions. Recent studies consistently suggest that marginal abatement costs for methane are substantially lower than for other greenhouse gases, although results differ across estimators, regions, and time horizons (Aldy et al., 2025; Marks, 2022). For instance, the International Energy Agency estimates that around 40% of methane emissions from fossil fuels could be avoided at no net cost, based on average energy prices in 2023 (International Energy Agency, 2024). This figure rises to 50% in other assessments, such as those by McKinsey (2021). Furthermore, abatement costs are characterized by pronounced heterogeneity across methane emission sources and mitigation technologies, thereby underscoring the need for in-depth, source-specific and technology-level analysis.

The available econometric studies, though mostly focused on a few North American basins and specific sectors, provide useful insights on policy effectiveness and abatement costs. In the Bakken shale, for example, Lade and Rudik (2020) show that a binding flaring standard led to rapid reductions, with new wells decreasing flaring by 14–20 percentage points in the

first year, accounting for most of the regional decline. At the same time, the study highlights strong heterogeneity in connection costs: applying a uniform standard generates inefficiencies, whereas a tax equivalent to the federal royalty schedule would reduce total costs by nearly half while achieving comparable environmental benefits. This contrast between standards and price instruments is particularly relevant for methane policy design. Structural simulations by Beatty (2022) show that a moderate tax (5 USD/Mcf) could reduce flaring by about 39% in the Permian, but that the response varies greatly depending on infrastructure density. Combined with the results of Lade and Rudik (2020), this work suggests that price flexibility is particularly useful in environments where marginal abatement costs vary by operator and location. Exploiting gas price signals, Marks (2022) finds a decreasing and convex relationship between price and emissions, with an implicit price of about 5 USD is sufficient to abate 60% of emissions. This is well below many engineering estimates and raises the possibility of a "missing money" problem. However, recent studies tend to suffer from two main limitations: they either rely on underestimated bottom-up data, or they focus on highly specific emission types within narrowly defined geographic regions, or both. As a result, they fail to provide a comprehensive yet granular understanding of methane emissions across broader spatial and operational contexts. In the absence of transparent data, detailed scientific assessments, and targeted policy incentives, avoidable methane releases are often allowed to persist. This paper addresses this gap by conducting an integrated analysis that simultaneously considers venting, flaring, and fugitive emissions across multiple major oil and gas basins in the United States. While (Stavins et al., 2025) highlights the potential of remote-sensing data to enable the future construction of robust methane abatement cost curves, this paper operationalizes that insight by employing such data to estimate marginal abatement cost curves in practice.

3 Data

3.1 Bottom-up data

For this analysis, we used the The U.S. Environmental Protection Agency's (EPA's) Greenhouse Gas Reporting Program (GHGRP) public data, which reports annual methane emissions by emission type from 2011 to 2023. Data reports Methane emissions (CH4) emissions, Carbon

Dioxide (CO2) emissions and Nitrous Oxide (N2O) emissions. We only focused on methane emissions for this analysis. These data are collected annually and are mandatory for facilities that emit more than 25,000 metric tons of CO2e per year. However, many facilities below this threshold also report their methane emissions annually. In this analysis, we considered only data reported on "Oil & Gas" production under "subpart W" as it is the only sector affected by the regulation. Therefore, this analysis does not include emissions from sources in the "Gathering & Boosting" segment, as Production and Gathering & Boosting infrastructure may be collocated, and different companies may classify equipment differently in their Subpart W reporting. Each operator is identified by an individual "Facility id" which allows observation of emissions at the operator level. Data are collected and reported by each operator individually. Even if the GHGRP is the most comprehensive and consistent source of panel data on methane emissions currently available, it should be noted that several scientific studies have shown it to be relatively noisy and biased (Daniel et al. (2015)).

The facilities in our dataset belong exclusively to sectors directly linked to fossil fuel extraction and processing. According to their NAICS classification, they fall within crude petroleum extraction (211120), natural gas extraction (211130), oil and gas extraction (211111), and the extraction of natural gas liquids such as propane and butane (211112). In addition, the dataset includes facilities engaged in drilling oil and gas wells (213111) and providing support activities for oil and gas operations (213112), as well as a smaller number of installations in fossil fuel-based electric power generation (221112). This industry composition ensures that the analysis is focused on the core segments most affected by methane emissions regulation.

In addition to methane emissions, we collected a wide set of related data. First, weather is known to be a potential factor of variation in operational efficiency in the oil and gas industry. Extreme weather conditions (such as extremely low temperatures or storms) can slow drilling, transportation or production operations. Similarly, rain or snow can affect logistics, access to production sites, and associated costs. Cold temperatures can affect equipment and energy consumption to heat facilities, increasing operating costs. For all these reasons, we decided to account for weather variations. To do so, we use the meteostat API to extract temperature and precipitation values for each operator's location and the nearest meteorological station.

Secondly, as we focused exclusively on methane emissions from the Oil & Gas sector, we need to account for production and activity differences that could affect emission levels independently of the regulation. To this end, we include controls for the number of wells, production, and prices of oil and gas by U.S. State. All hydrocarbon production data come from the Drilling Productivity Report, which provides detailed and up-to-date measures. To control for gas prices in the analysis, we collected gas prices at each US State using the Energy Infromation Administration (EIA) API. Specifically, we chose the City Gate price. The citygate price of natural gas refers to the price at which natural gas is sold at a specific delivery point in a pipeline network, usually where it transitions from long-distance transportation pipelines to local distribution systems. It is a crucial indicator for local gas distributors, as it determines the cost at which they purchase gas to supply residential, commercial, and industrial consumers. Similarly, we collected annual crude oil prices and production from the EIA. This latter also provides the number of oil and gas wells by state. We consider both oil and gas wells in the "Number of wells" control variable, naturally following the assumption that they would have a positive impact on methane emissions. Finally, we must point out that on the 50 US states, the GHGRP reporting data only contains data for the following 20 states: *Alaska, Alabama, Arkansas, California, Colorado, Kansas, Kentucky, Louisiana, Michigan, Mississippi, Montana, North Dakota, New Mexico, Ohio, Oklahoma, Pennsylvania, Texas, Utah, West Virginia, Wyoming.*

Table 1: Descriptive Statistics for Methane Emissions Analysis

	N	Mean	Std	Min	25%	50%	75%	Max
Methane emissions	4,872	83,794.48	167,774.99	0.25	10,023.25	30,899.75	86,460.56	2,959,739.50
Log(emissions)	4,872	10.1439	1.8226	-1.3863	9.2127	10.3385	11.3674	14.9006
Above 25000	4,872	0.555	0.497	0	0	1	1	1
Gas price	4,872	5.10	2.46	2.52	3.72	4.29	5.77	19.27
Oil well	4,872	98,027.25	76,851.29	547	12,863	162,446	174,714	182,427
Gas well	4,872	82,496.81	47,357.99	311	41,950	120,831	126,380	133,422
Oil production	4,872	872,039.21	750,783.68	2,265	153,423	1,159,332	1,739,660	2,011,515
Oil price	4,872	59.79	18.87	29.82	44.95	55.04	75.62	96.51

Table 1 presents descriptive statistics for the main variables used in the analysis. The dataset includes 4,872 observations, meaning 4,872 facilities over the 9 years (2015–2023). On average, facilities reported approximately 83,794 metric tons of methane emissions, with a significant standard deviation, indicating considerable variability across facilities. Over the 4,872 facilities distributed on the 9 years, 50% emitted less than 30,899 metric tons of methane while 50% of facilities emitted more than this threshold. The log-transformed emissions have a mean

of 10.14 and range from -1.39 to 14.90, indicating that the log transformation has reduced skewness while preserving the distribution's spread.

Furthermore, the distribution of facilities around the regulatory threshold of 25,000 metric tons shows a relatively balanced spread, with a sufficient number of observations just below and just above this cutoff. This suggests that the dataset captures a wide range of facility sizes and emissions levels, providing a solid basis for descriptive and comparative analysis.

In addition to the main emission variables, the dataset encompasses several control variables capturing facility characteristics and operational context. These latter include the number of gas and oil wells, annual oil production, oil and gas prices, and other facility-level attributes. Overall, the controls illustrate heterogeneity across facilities in terms of scale, production, and market exposure, enabling a detailed characterization of the sample.

One interesting measure for an accurate overview of methane emissions across several regions is methane intensity. The following map (Figure 1) shows methane intensity heterogeneity from gas production in different US States[6]. Specifically, Texas and Michigan have particularly high methane intensity scores, with respectively 0.346% and 0.281%, amounts larger than the recommended 0.2% by the Oil and Gas Climate Initiative (OGCI).

3.2 Top-down data

Contrary to the approach adopted by International Energy Agency (2023) for estimating the marginal abatement cost curve, our analysis relies on top-down emissions estimates rather than traditional bottom-up inventories. As previously noted, bottom-up approaches tend to underestimate total methane emissions. For instance, Shen et al. (2021) found that oil and gas methane emissions in Mexico are more than twice the official estimates. Similarly, Shen et al. (2022) reported that satellite-based estimates of methane emissions are approximately 80% higher in Canada and 40% higher in the U.S. than bottom-up inventories. Riddick and Mauzerall (2023) also demonstrated that methane emissions from oil and gas activities in the

[6]We referred to the American Gas Association Natural Gas Sustainability Initiative (NGSI) protocol for calculating methane emissions intensity (see **??**).

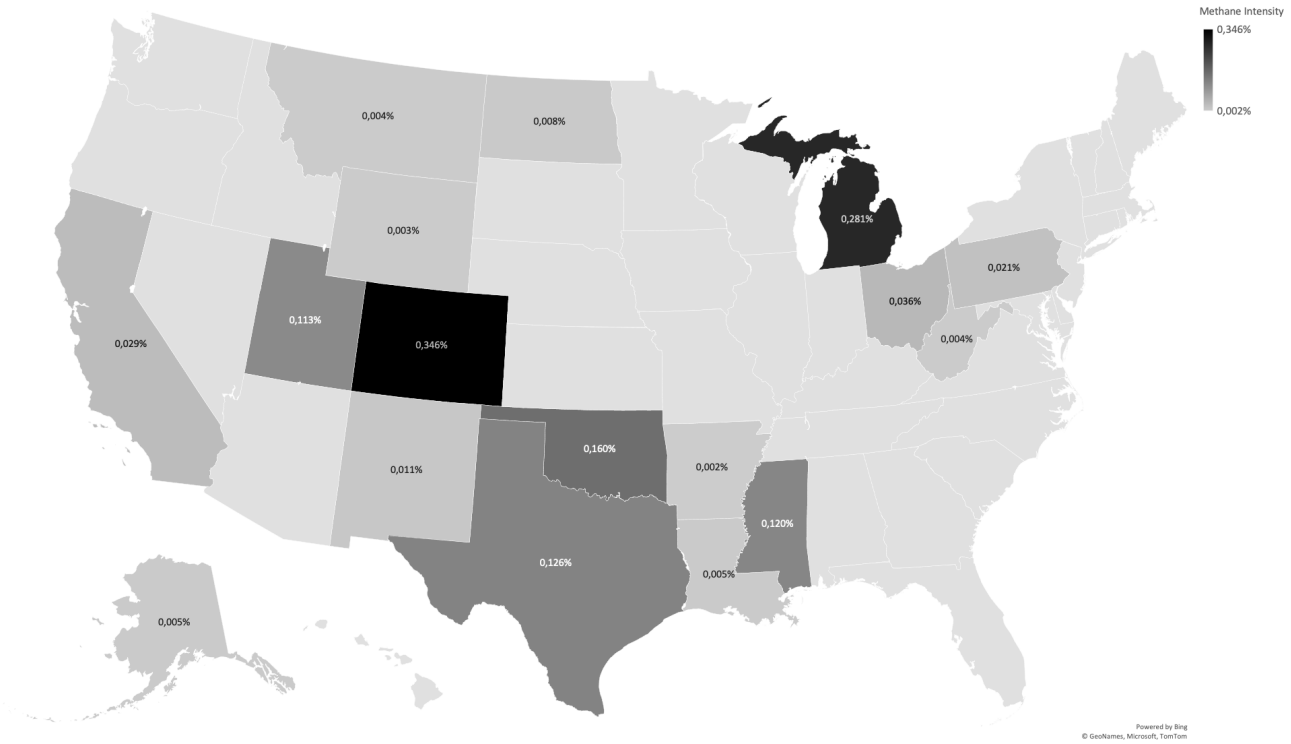


Figure 1: Methane intensity by US-State

UK are five times higher than the official figures. In general, investigators note that conventional bottom-up methods include only known processes and fixed emission factors, so they are "inherently biased low" and "likely [to be] substantially underestimated".

To address this limitation, we use satellite-based detection data provided by the French company Kayrros. These data integrate multiple satellite platforms with varying spectral capabilities, including Sentinel-5P, TROPOMI, Sentinel-3, Sentinel-2, Landsat, EMIT, PRISMA, VIIRS and enMAP to provide comprehensive methane emission measurements. For the abatement cost analysis, we combine three types of data. First, we use aggregated basin-level fugitive emissions, corresponding to non-permanent leaks. These represent the primary data collected by Kayrros, which employs inversion models to quantify methane released into the atmosphere by detecting methane plumes. Emissions are then aggregated at the U.S. basin scale. Second, we incorporate venting emissions, which correspond to methane deliberately released into the atmosphere[7]. These are derived from Kayrros' dataset on so-called super-emitters, which capture particularly intense emissions over short time periods. Basin-scale venting emissions are extrapolated using Monte Carlo simulations to provide a comprehensive estimate across the U.S. basins. Finally, to account for flaring emissions, i.e. methane intentionally burned

[7]Venting can occur for various operational or safety reasons.

before being released into the atmosphere (thus producing CO_2 instead of CH_4[8]), we apply a novel method based on radiant heat (RH) and spatial clustering. The radiant heat, defined as the thermal power released during this combustion reaction, reveals to be proportional to the amount of methane burned[9]. This proportionality allows for a linear approximation between RH and flaring volumes. Spatially, flaring emissions are estimated through a clustering-based approach applied to VIIRS NightFire hot-spot detections[10]. From these clusters, a linear regression is performed, using World Bank data as ground truth, to obtain asset-scale flaring volumes. Annual flaring emissions are then aggregated at the basin level. For all three sources of emissions (fugitive, venting, and flaring), data were collected for the year 2024. The value we obtained corresponds to the observed flaring. However, some studies have shown that only 91% of the methane burnt is actually transformed in $Co2$ (Plant et al., 2022). Therefore, to account for the unobserved fraction, referred to here as the "Incomplete-flare", i.e., the portion that was not fully combusted, we estimated the total amount of methane emitted and retained the corresponding portion to adjust our calculations accordingly.

4 Method

4.1 Regulation Announcement Effect : Difference in Difference Estimate

To evaluate the annoucement effect of the WEC, we consider a differences-in-differences (DiD) model with two time periods: $t = 1$ (2015–2022) and $t = 2$ (2023). Period 1 refers to the period before the announcement of the law on the methane emission fee, while period 2 refers to the year just after the announcement. The tax (900 USD per Metric ton of CH_4) was meant to be applied only to producers emitting more than 25,000 tons of CO_2e annually[11]. We define two groups : the control and the treated group. Units indexed by i belong to one of two populations. Units from the treated population ($D_i = 1$) are emitters with total emissions

[8]In a flare, methane undergoes complete combustion according to $CH_4 + 2O_2 \rightarrow CO_2 + 2H_2O$.

[9]This follows from molar stoichiometry, where the energy released is linearly proportional to the volume of fuel oxidized.

[10]Clusters are constructed with a DBSCAN algorithm accounting for the 750 m spatial resolution of VIIRS, then used as spatial aggregates.

[11]More specifically, the WEC imposes two conditions for tax liability: (i) exceeding 25,000 tCO_2e annually, and (ii) exhibiting an emission rate above 0.2% for onshore production. Due to the unavailability of facility-level emission rate data, we focus exclusively on the emissions threshold criterion.

greater than 25,000 tonnes and receive the treatment of interest between period $t = 1$ and $t = 2$, whereas units from the control population ($D_i = 0$) are emitters with total emissions less than 25,000 tons and remain untreated in both periods. The DiD estimator captures the average treatment effect on the treated (ATT) by comparing the changes in emissions over time between the treated and control groups. The causal estimand of interest is the average treatment effect on the treated (ATT) in period $t = 2$:

$$\hat{\tau}_2^{DiD} = \underbrace{\mathbb{E}\big[Y_{i,2} - Y_{i,1} \,\big|\, D_i = 1\big]}_{\text{treated group variation}} - \underbrace{\mathbb{E}\big[Y_{i,2} - Y_{i,1} \,\big|\, D_i = 0\big]}_{\text{control group variation}} \tag{1}$$

This estimate measures the average causal effect of the WEC regulation announcement on super emitters ($>$ 25000 tons) after the announcement of the regulation on methane emissions.

In order to compute $\hat{\tau}_2^{DID}$, and as recommended by Roth et al. (2023); Chaisemartin and D'Haultfœuille (2023); Wooldridge (2021), we use the two-way fixed effects (TWFE) regression specification

$$Y_{i,t} = \alpha_i + \phi_t + (\mathbf{1}[t = 2] \cdot D_i)\beta + \epsilon_{i,t}, \tag{2}$$

which regresses methane emissions (in logs) $Y_{i,t}$ on the individual fixed effect α_i, a time fixed effect ϕ_t, and an interaction of a post-treatment indicator with treatment status β (i.e the effect of the regulation on super emitters).

Our first model (equation 3) applies the (naive) canonical DID :

$$Y_{i,t} = +\beta(\text{treated}_i \times \text{post}_t) + \alpha_i + \phi_t + \varepsilon_{it}, \tag{3}$$

The key identifying assumption underlying equation 3 is that, in the absence of treatment, the average outcomes of the treated and comparison groups would have evolved along parallel trends. Yet, this assumption is not always straightforward to validate and can be difficult to fully trust. Even if visual inspection suggests that both groups exhibit similar pre-treatment dynamics (see Figure **??** in **??**), some concerns may remain regarding the credibility of this assumption. Therefore, one way to increase the credibility of the parallel trends assumption in our study is to require that it holds only conditional on observable covariates. Indeed, if we condition on a sufficiently rich set of covariates, such as the number of wells, gas and oil prices, gas production, or weather conditions, we may reasonably assume that treatment as-

signment (emissions above 25,000 metric tons) is approximately random once these covariates are accounted for. This approach is supported by the literature on conditional DID and program evaluation with observable covariates (Heckman et al., 1997; Lechner, 1999; Callaway and Sant'Anna, 2021). Imposing only conditional parallel trends offers an additional degree of robustness, since conditional random assignment may fail as long as the remaining unobservables have additive and time-invariant effects on emissions. Equation 4 includes the conditionality on covariates:

$$\mathbb{E}\big[Y_{i,2}(0) - Y_{i,1}(0) \mid D_i = 1, X_i\big] = \mathbb{E}\big[Y_{i,2}(0) - Y_{i,1}(0) \mid D_i = 0, X_i\big] \tag{4}$$

Moreover, to guarantee that for each treated unit with covariates X_i, there are at least some untreated units in the population with the same value of X_i, we need to impose an overlap condition (the positivity condition[12]). We show how this condition is verified with our data in **??**. Given the conditional parallel trends assumption, and the overlap condition, the Average Treatment on Treated (ATT) conditional on Xi=x becomes

$$\tau_2(x) = \mathbb{E}\big[Y_{i,2}(1) - Y_{i,2}(0) \mid D_i = 1, X_i = x\big] \tag{5}$$

Our second model (Equation 6) implements a first specification of conditional DID including five hydrocarbon-related co-variates. We include oil price and production, gas price and production as well as the number of oil and gas wells by U.S basins. Installation and Year fixed effects are included.

$$Y_{i,t} = \beta_1(\text{Regulation}i_t) + \alpha_i + \phi_i + \sum_{k=1}^{K} \gamma_k X_{kit} + \varepsilon_{it} \tag{6}$$

Our third model Equation 7 adds three other covariables. Beyond hydrocarbon prices and production levels, we add meteorological variables (precipitation and temperature). In addition, we introduced an interaction term between treated facilities (super-emitters) and the indicator

[12]For the ATT to be unbiased, we need the conditional probability of belonging to the treatment group, given observed characteristics, to be uniformly bounded away from one, and the proportion of treated units to be bounded away from zero. That is, for some $\epsilon > 0$,

$$P(D_i = 1 \mid X_i) < 1 - \epsilon \quad \text{almost surely, and} \quad \mathbb{E}[D] > 0.$$

of whether the facility is located in a state that was already subject to regulation ("already regulated"). However, in this third model (equation 7), we relaxed the time fixed effects to better capture cross-sectional heterogeneity.

$$Y_{i,t} = \beta_1(\text{Regulation}i_t) + \beta_2(\text{Past Regulation}_i) + \alpha_i + \sum_{k=1}^{K} \gamma_k X_{kit} + \varepsilon_{it} \tag{7}$$

In a fourth model (equationEquation 8), we finally add the year effects to the installation fixed effects. This fourth model still relies on the conditional parallel trend assumption.

$$Y_{i,t} = \beta_1(\text{Regulation}_{i_t}) + \beta_2(\text{Past Regulation}_i) + \alpha_i + \phi_t + \sum_{k=1}^{K} \gamma_k X_{kit} + \varepsilon_{it} \tag{8}$$

To complement the baseline difference-in-differences (DiD) specification, we estimate an event study model. While the canonical DiD design provides an average treatment effect before and after the introduction of the regulation, the event study framework allows us to trace the dynamic evolution of treatment effects over time. In theory, this approach has two main advantages. First, it enables a direct test of the parallel trends assumption, as the estimated pre-treatment coefficients (i.e. before 2023) should not display systematic differences between treated and control facilities (Angrist and Pischke, 2009). Second, it provides insights into the timing and persistence of the treatment effect, by showing whether impacts emerge immediately after the policy change or only with a delay (Bertrand et al., 2004). However, in our case, we only have one year post-treatment which prevents us from observing this characteristic. Following the standard two-way fixed effects (TWFE) framework, we interact treatment status with relative time-to-treatment indicators, allowing us to estimate dynamic treatment effects relative to the last pre-treatment period. Given that treatment in our setting occurs at the same date for all treated units (a sharp adoption design), this strategy does not suffer from the negative weighting issues highlighted by recent contributions in staggered adoption contexts (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). We define our Event Study model as

$$Y_{i,t} = \alpha + \sum_{\ell \neq -1} \beta_\ell \, \mathbf{1}\{t - T_{0,i} = \ell\} \cdot \text{treated}_i + \phi_t + \alpha_i + \sum_{k=1}^{K} \gamma_k X_{kit} + \varepsilon_{it}, \tag{9}$$

where the dynamic treatment effect is captured by β_ℓ associated with the event-time indica-

tors $\mathbf{1}\{t - T_{0,i} = \ell\}$. These indicators take the value 1 if unit i is observed ℓ periods before ($\ell < 0$ [13]) its treatment date $T_{0,i}$. The coefficients β_ℓ therefore measure the effect of the treatment ℓ periods relative to the event, compared to the reference period ($\ell = -1$). Time fixed effects are represented by ϕ_t, while α_i captures unit-specific fixed effects. Finally, X_{kit} denotes the vector of control covariates included in the model.

As a second robustness check and to account for potential differences in observed characteristics between the Super-Emitters (treated group) and the small emitters (control group), we use the inverse probability weighting (IPW) approach, following the framework proposed by Abadie (2005). We specify our model as

$$Y_{it} = \alpha + \beta(Regulation) + \beta_1 Treated_i + \beta_2 Post_t + \sum_{k=1}^{K} \gamma_k X_{kit} + \varepsilon_{it} \tag{10}$$

where the estimates uses the weighted least square with the weights[14]:

$$w_i = \begin{cases} \dfrac{1}{e_i(X_i)}, & \text{if Treated}_i = 1, \\ \dfrac{1}{1 - e_i(X_i)}, & \text{if Treated}_i = 0. \end{cases}$$

Regarding the study design, two elements have to be specified. First, the threshold of 25 000 tons emitted per year correspond to two criteria. On the one hand the WEC regulation is defined to be applied only on hydrocarbons producers emitting more than 25 000 t/CO_2. On the other hand, but in line with the first, the literature already defined this category of emitters as "Super Emitters" which allows us to separate clearly both group. Second, we define the "treated" status in a statically way. A facility is considered treated if it exceeds the regulatory threshold of $25,000$ metric tons of CO_2 equivalent in at least one year. Once a facility meets this criterion, it is classified as treated for all years, regardless of whether its emissions subsequently fall below the threshold. This approach is a methodological decision designed to maintain a consistent definition of treatment over time, rather than an assumption about the behavior of individual facilities. It ensures that each facility belongs to a single group "treated" or "control"

[13] In our setting we only have lags as we only have the 1 period $T_{0,i}$ which is affected by the regulation (2023). Therefore we cannot observe leads with $\ell > 0$.

[14] See **??** for more details

throughout the study period, even if its true value of emissions differs. However, we must point out that the number of facilities for which they have values of methane emissions differing from their assigned group is relatively small, which should not biased the resulting coefficient.

5 Results

5.1 Empirical analysis : The announcement effect of the U.S regulation

5.1.1 Difference in Difference analysis

We now present the results of our empirical analysis, examining the effect of the US methane regulation (the WEC[15]) on facility-level emissions.

Table 2 shows the difference in difference estimates with and without fixed effects, controlling for various variables. The dependent variable in all three models is the logarithm of CH4 (methane) emissions. The key variable of interest, the "Regulation" term which represents the announcement of the US methane regulation, captures the difference-in-differences estimate, i.e. the treatment effect for the treated facilities after 2022. Across all specifications, the *Regulation* coefficient is negative and statistically significant at the 1% level, indicating that treated facilities experienced a reduction in methane emissions after the introduction of the policy. The Model (1) is simple a canonical DID, while Model (2) adds control variables such as the number of wells, oil and gas prices, production levels, and meteorological factors. Model (3) includes additional interaction terms, but relaxes the Year fixed effects and Model (4) combines both fixed effects with all controls.

Since the dependent variable is in natural logarithms, the coefficients can be easily interpreted[16]. Model (1) estimates a 30.1% reduction in methane emissions from treated facilities following the announcement of the regulation. Model (2), which introduces controls for oil and gas market conditions, production, and meteorological variation, yields a slightly smaller effect

[15]Waste Emissions Charge

[16]For a coefficient β from a regression of $\ln(Y)$ on a binary variable, the approximate percentage change in Y associated with a one-unit increase in the binary variable is given by $100 \times (e^{\beta} - 1)$.

Table 2: DID estimates

	Dependent variable: CH_4 emissions (Natural log)			
	Model 1	Model 2	Model 3	model4
	(1)	(2)	(3)	(4)
Regulation	-0.358***	-0.339***	-0.260***	-0.340***
	(0.130)	(0.130)	(0.062)	(0.130)
Number of wells		0.000	0.000***	0.000
		(0.000)	(0.000)	(0.000)
Oil price		0.025*	-0.000	0.021
		(0.013)	(0.001)	(0.013)
gas price		-0.002	-0.019***	-0.004
		(0.009)	(0.006)	(0.009)
Oil production		0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)
Gas Production		-0.000*	-0.000**	-0.000*
		(0.000)	(0.000)	(0.000)
Past Regulation			-0.303	-0.531
			(0.322)	(0.361)
Precipitation			0.000	0.000
			(0.000)	(0.000)
Temperature			-0.025	-0.013
			(0.019)	(0.021)
Installation FE	Y	Y	Y	Y
Year FE	Y	Y	N	Y
Observations	4872	4872	4872	4872
N. of groups	864	864	864	864
R^2	0.003	0.008	0.044	0.009
Residual Std. Error	0.045	0.069	0.171	0.076
F Statistic	13.020***	5.094***	20.343***	4.089***

Notes: OLS regressions of the natural log of installation-level methane emissions on a policy dummy (*Regulation*) equal to one for treated installations after 2022. Specifications (1) to (4) include installation fixed effects; specification (2), (3) and (4) include global controls such as hydrocarbons prices and production as well as meteorological variations. Specification (1) estimates a simple canonical DID while specification (2), (3) and (4) estimate a conditional DID. Specification (3) relaxes the year fixed effects. Robust standard errors clustered at the installation level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

of 28.8%, suggesting that the main result is not driven by these confounding factors. In Model (3), the inclusion of the interaction term *Past Regulation*, capturing facilities located in states with pre-existing methane regulations, indicates that these facilities experience an additional decrease of about 26.5%. This suggests that prior regulatory exposure in Colorado, California and Wyoming may have reinforced the policy's effectiveness, although the estimate is not statistically significant. Finally, Model (4), our preferred specification which combines installation and year fixed effects with all the control variables, confirms the robustness of the main

effect, with an estimated 28.8% reduction in methane emissions. Taken together, the results consistently indicate that the WEC induced a substantial decline in methane emissions, with the estimated reduction ranging between 23% and 30% across specifications. Additionally, we verified the absence of endogeneity between methane emission and oil and gas production levels **??**.To test the sensitivity to the 25,000 tCO_2e threshold and address potential manipulation concerns—whereby emitters close to the threshold might strategically adjust their production to avoid the tax—we implemented a "donut-hole" specification, excluding observations within the top and bottom 10% of each group nearest to the cut-off[17]. The results confirm the regulatory effect (26% reduction), though the estimate is only marginally significant **??**.

As a primary robustness check, placebo tests were conducted by estimating the treatment effect (captured by the "Regulation" term) for years prior to the actual policy announcement. The idea is to test whether or not the result of the DID changes when one changes the year of the regulation and is necessary to verify the DID is not biased (Card and Krueger, 1993; Angrist and Pischke, 2009; Bertrand et al., 2004). **??** reports the results of difference-in-differences estimations where the treatment is artificially assigned in 2022 and 2021. In both placebo regressions, the interaction term is small in magnitude and statistically insignificant, indicating that no spurious treatment effect is detected before 2023. By contrast, the coefficient on the interaction term in 2023 is negative and statistically significant at the highest level, consistent with a reduction in emissions following the actual treatment. These findings strengthen the credibility of the conditional parallel trends assumption, as they suggest that the observed effect in 2023 is unlikely to be driven by pre-existing trends or anticipatory behavior.

5.1.2 Event study analysis

In addition to the difference-in-differences (DID) framework, we estimated a set of alternative specifications to assess the robustness of the results. Specifically, we considered an event-study specification to assess the validity of the parallel trends assumption and to examine the dynamic effects of the regulation before and after its introduction. In addition, we implemented an inverse probability weighting (IPW) estimator to address potential imbalances between covariates. Table 3 summarizes the results across all approaches.

[17]We removed the top 10% of the control group and the bottom 10% of the treated group

Table 3: Summary of results

	Dependent variable: CH_4 emissions (Natural log)			
	Canonical DID	Conditional DID	Event Study	IPW
	(1)	(2)	(3)	(4)
Regulation	-0.358***	-0.340***	-0.337**	-0.336**
	(0.130)	(0.130)	(0.171)	(0.137)
Global controls	N	Y	Y	Y
Installation FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	4872	4872	4872	4872
N. of groups	864	864		
R^2	0.003	0.009	0.436	0.469
Adjusted R^2			0.433	0.469
Residual Std. Error	0.045	0.076	1.372	1.375
F Statistic	13.020***	4.089***	42.347***	537.824***

Notes: OLS regressions of the natural log of installation-level methane emissions on a policy dummy (*Regulation*) equal to one for treated installations after 2022. Specifications (1) to (4) include installation fixed effects; specification (2), (3) and (4) include global controls such as hydrocarbons prices and production as well as meteorological variations.Specification (1) estimates a simple canonical DID while specification (2) estimates a conditional DID. Specification (3) estimates an event study around the treatment year, while specification (4) uses inverse probability weighting (IPW). Robust standard errors clustered at the installation level are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

The empirical findings presented in Table 3 provide compelling evidence of the regulatory impact of the WEC regulation announcement on methane emissions. Our preferred specification (2) employs a conditional difference-in-differences estimator that incorporates comprehensive global controls. This specification yields a statistically significant reduction of 28% in methane emissions following regulatory implementation (coefficient of $-0.340, p < 0.01$), representing our most reliable estimate given its superior control for time-varying confounders including hydrocarbon price fluctuations, production variations, and meteorological conditions. The robustness of this core finding is substantiated through multiple identification strategies that converge on remarkably consistent point estimates: the event study[18] approach (3) produces a close coefficient of -0.337, while the inverse probability weighting[19] estimator (4) yields -0.336, demonstrating that methodological artifacts or specific modeling assumptions do not drive our results. Even the canonical difference-in-differences specification without global controls (1) produces a similar magnitude effect (-0.358), suggesting that unobserved time-varying het-

[18] see **??** for more details

[19] see **??** for more details

erogeneity is not substantially biasing our estimates. The consistency of these findings across methodologically distinct approaches, each relying on different identifying assumptions and addressing different potential sources of bias, provides strong evidence against alternative explanations such as coincident shocks, selection effects, or specification sensitivity. Furthermore, the inclusion of installation fixed effects across all specifications controls for time-invariant unobserved heterogeneity, while the robust standard errors clustered at the installation level appropriately account for within-unit correlation in the error structure.

5.2 Marginal Abatement Cost Curve

5.2.1 The shape of the curve

Econometric estimates suggest that an implicit tax of about 900USD per tCO_2e exceeds the marginal abatement cost for many methane "Super-Emitters". Yet this estimate remains incomplete, representing only an average point on the marginal abatement cost curve. To analyse the full range and dispersion of costs, we must dive into the abatement cost curves that illustrate the complete distribution of potential abatement costs. Notably, the MACC highlights whether or not some part of methane emissions can be mitigated at negative cost, meaning that reductions can generate net profits due to the sale of recovered gas. Depending on the type of gas sold, between 65% and 85% of methane can be converted into marketable gas. In our model, we assumed an 83% conversion rate, consistent with the values reported in the literature for U.S. basins[20]. Figure 2 presents the abatement cost curve for the Permian Basin[21].

In our model, we adopt a natural gas average selling price of 2.2 USD, 57% higher than the one parametrized in the International Energy Agency (2023) model, as it appeared to be under-evaluated. Our new price level is consistent with the 2024 U.S. industrial price reported by the U.S. Energy Information Administration (2023). The abatement cost curve indicates that a share of methane emissions could, in fact, be mitigated at zero net cost, meaning that oil and gas producers would generate positive revenue by capturing and selling the recovered gas. We estimate this "missing money" represents 15.8 million USD for the Permian basin, i.e

[20] see **??**

[21] The Permian Basin is a major sedimentary basin spanning West Texas and southeastern New Mexico, and is currently the largest oil- and gas-producing region in the United States.

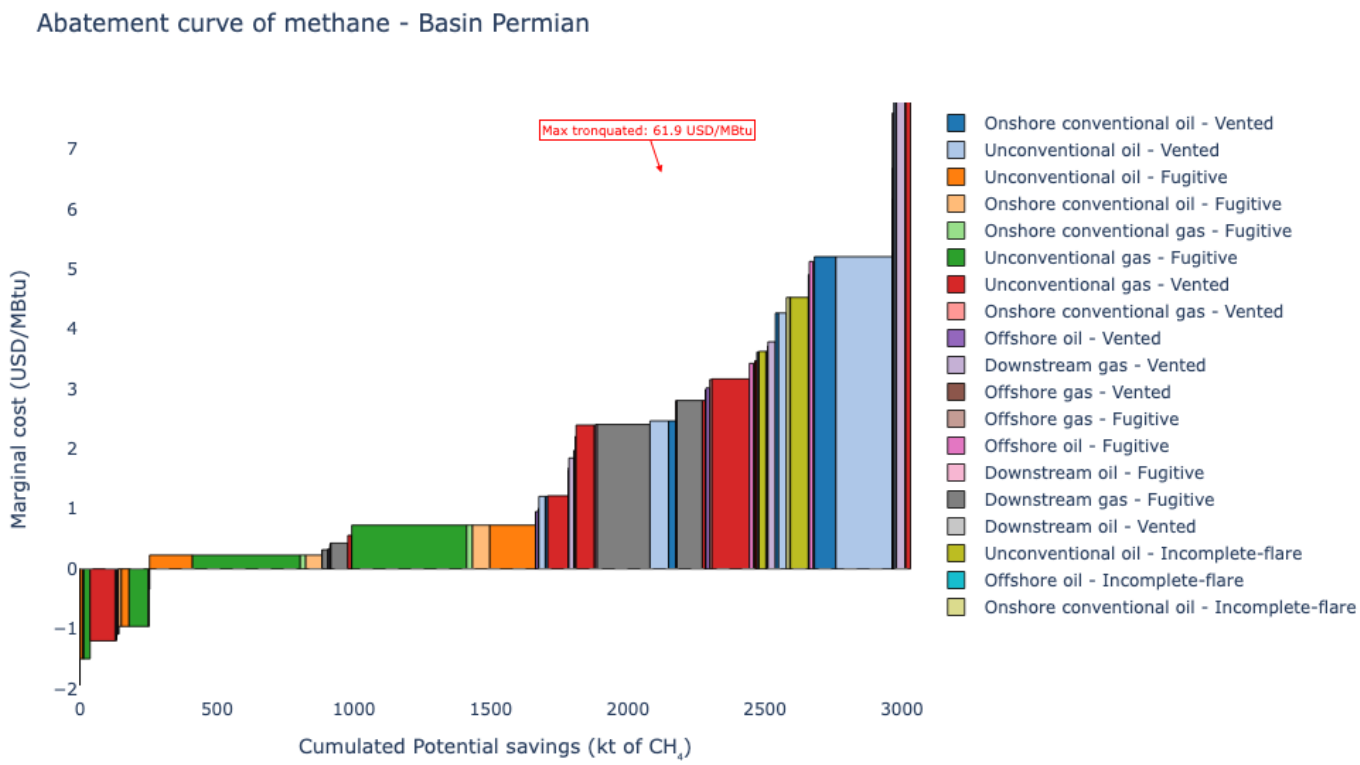


Figure 2: Marginal abatement cost curve : Permian

254 kt of methane. More importantly, our results show that 50% of total methane emissions (1,515 kt Ch_4) can be abated for less than 1.5 USD/t CO_2e (with a mean cost of 0.7 USD/t[22]). We must metion as well that approximately 70% of methane emissions could be abated at a cost of USD 5 per tonne of CO_2e. Achieving full abatement, however, entails a marginal cost of up to 121 USD/t of CO_2e. If similar cost structures are observed in both the Appalachian and Anadarko basins, the shares ny sources type differs substantially (see **??**). The granular analysis (disaggregated by emission source type and basin) reveals a substantially lower share of methane emissions from venting in the Appalachian and Anadarko basins. Moreover, the steep increase in marginal abatement costs observed across the three basins underscores the economic and technical challenges associated with eliminating the remaining, harder-to-abate methane emissions. Additionally, a reasonable estimate of the average selling gas price appears critical to correctly shape the abatement cost curve. We find that the under-estimation of this input by the IEA led to a 30% under-evaluation of the missing money (potential savings) in the Permian Basin[23].

[22]In order to retrieve the value in USD/t we applied the following conversion rate: 1Kt $Ch_4 = 54,000$ MBtu as recommended by the IEA. Then we used the 28 ratio to convert CH4 in CO_2e as suggested by the IPCC

[23]When performing the model with the initial average selling gas price of 1.42, the missing money is estimated

By aggregating abatement cost estimates across the three basins, we identify a "missing money" of approximately 32 million USD, associated with 524 kt of methane emissions, representing 8% of total emissions, that could be mitigated at no net cost. The overall shape of the resulting marginal abatement cost curve, as well as the magnitude of this missing money (based on remote-sensing data), is consistent with the patterns highlighted by (Stavins et al., 2025) (based on bottum-up data), despite his analysis not accounting for the granularity by basin considered here. Our analysis shows that 89,441 kt CO_2e (equivalent to 3,194 kt of CH_4) could be abated under a methane emissions tax of just USD 1.5 per tonne of CO_2e applied to hydrocarbon producers. This mitigation potential is approximately seven times higher than that estimated by (Beatty, 2022), who considered only flaring emissions at a benchmark price of USD 5 per Mcf, and six times higher than the figures reported by Marks (2022), whose analysis focused solely on fugitive emissions. By integrating and comparing three major sources of methane emissions (flaring, venting, and leaks) across three U.S. basins, our approach reveals substantial basin-level heterogeneity in methane abatement opportunities, while also identifying a larger and more cost-efficient abatement potential than that reported in more narrowly scoped studies.

5.2.2 Sensitivity analysis

To comprehensively assess the sensitivity of our cost calculation framework, we employed a Monte Carlo simulation. Our simulation framework randomly sampled 10,000 parameter combinations from calibrated probability distributions[24] across seven input variables: discount rate, CH_4 emission ratio at the well, CH_4 emission ratio in the pipeline, gas price, capital cost, labour, and technology efficiency (see **??** for theoretical background and detailed equations). The Monte Carlo simulation generated a comprehensive dataset of cost outcomes, which served as training data for a machine learning-based sensitivity analysis.

We trained a multilayer perceptron model to oberve the potential non-linear relationships between these input parameters and the resulting cost outcomes. To quantify the relative contribution of each input parameter to cost predictions, we employed SHAP (SHapley Additive

at 10 million USD, 5 million less than with our model priced at 2.2 USD.

[24]The calibrated probability distribution is either uniform or lognormal depending on the variable of interest, see **??** for further details

exPlanations) analysis.

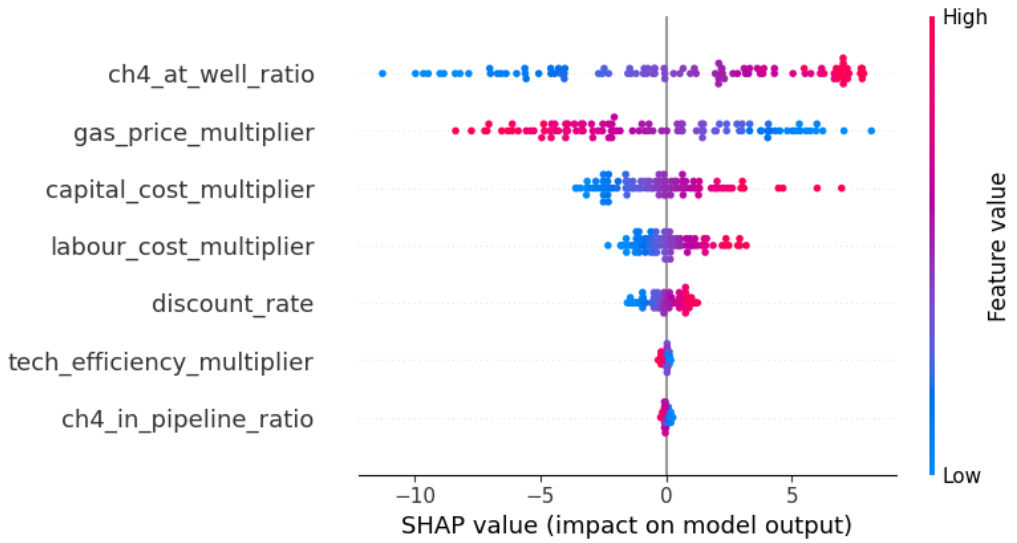


Figure 3: Shapley Analysis with MLP model

The analysis revealed that the CH_4 emission ratio at the well and the gas price exhibit the highest feature importance, followed by capital cost and labour cost multipliers. The sensitivity analysis based on the MLP model highlights the dominant role of the methane content at the wellhead (CH4-to-gas ratio), which alone explains nearly half of the total model variance (48.6%). This parameter determines the volume of methane contained in raw natural gas at the point of production and therefore strongly influences both estimated emission levels and the potential revenues from capture. While the model is highly sensitive to this variable, its value is relatively well established for U.S. basins, leaving little scope for substantial variation in practice. The second most influential factor is the gas price multiplier (35%), underscoring the central role of gas market dynamics in determining the cost-effectiveness of abatement measures. Capital and labour cost multipliers follow at a distance, while the methane content in pipeline-quality gas (ch_4 in pipeline ratio) has relatively limited influence (0.2%). The discount rate variable, though not the most influential (0.7%), still plays a non-negligible role in shaping the net present value of abatement projects. The baseline assumption inInternational Energy Agency (2023) of an 8% discount rate, while commonly used in industry analyses, may overestimate the opportunity cost of capital in the context of long-term climate objectives. This choice reflects a more "Nordhausian" approach, emphasizing market-based efficiency and the cost of capital. However, from a normative perspective, an 8% rate can be seen as excessively high. Reducing the discount rate would increase the present value of future emission reductions,

thereby improving the economic viability of many abatement options, particularly those with more extended payback periods.

To assess the robustness of these findings, we replicated the analysis using a random forest regressor (see **??**). Although the random forest model achieves slightly lower performance than the the MLP model, the ranking and relative magnitude of feature importances were broadly consistent with those obtained from the MLP, reinforcing the conclusion that methane emission intensity at the well and gas price dynamics are the key drivers of abatement costs. These results highlight the need for particular attention when setting gas price assumptions in abatement cost models.

6 Conclusion

This paper provides new empirical and modeling evidence on the cost-effectiveness and regulatory impacts of methane abatement in the U.S. oil and gas sector. Using facility-level data and a difference-in-differences identification strategy, we find that the announcement of the Waste Emissions Charge (WEC) significantly reduced methane emissions by approximately 28–30%, with consistent results across multiple robustness checks. This confirms the presence of a clear and measurable "announcement effect", suggesting that market actors adjust their behavior even before the full implementation of regulations.

In the second part of the analysis, we construct basin-level Marginal Abatement Cost Curves (MACCs) using top-down rather than bottom-up data. Our results show that approximately 8% of methane emissions, equivalent to 524 kt CH_4, can be abated at zero net cost, representing a missed economic opportunity of $32 million in 2024 across the three basins. Furthermore, a carbon-equivalent tax of just $1.5 per tonne of CO_2e would enable the mitigation of nearly 3,200 kt of methane, or 89 MtCO_2e. These figures are substantially higher than those reported in prior studies focusing on specific emission types. By jointly considering flaring, venting, and fugitive emissions across multiple production basins, our work reveals a far greater and more cost-effective abatement potential than previously recognized.

These findings are encouraging for methane mitigation policy, though some elements war-

rant attention. Our empirical analysis captures only short-term announcement effects, as our data end in 2023. Future research should investigate whether the observed reductions persist, intensify, or diminish over time, particularly in response to political or regulatory shifts. Second, our MACC analysis relies on a static framework using annualized, aggregated top-down data. While we conduct extensive sensitivity analyses, a valuable extension would involve constructing dynamic MACCs using monthly or daily data to better capture intra-annual variations in cost-effectiveness. Finally, our analysis focuses primarily on climate-related benefits and does not account for the broader co-benefits of methane abatement, particularly public health improvements from reduced ground-level ozone formation. Incorporating a social cost of methane that reflects both climate and health damages would provide a more comprehensive assessment of the societal value of abatement policies.

Notwithstanding, our findings suggest that methane abatement is not only technically and economically feasible but also urgently underutilized. A combination of regulatory pressure (as evidenced by the WEC effect), methane pricing mechanisms, and better-informed cost modeling can unlock significant climate benefits at low or even negative costs. As regulatory uncertainty persists, these results underscore the importance of sustained policy commitment and improved data infrastructure to realize the substantial, cost-effective abatement potential that remains largely untapped in the U.S. oil and gas sector.

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Declaration of Conflicting Interests

The authors declare no conflicts of interest.

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