

Methane and Markets: Firm Incentives to Emit *

Coly Elhai and Toren Fronsdal
Harvard University

April 17, 2024

Abstract

As the primary component of natural gas, methane is both a powerful greenhouse gas and a valuable commodity. We explore the economic factors that influence firms' decisions to emit. Using novel data on methane emissions from the Permian Basin, we provide empirical evidence that emissions respond to high-frequency price variation. In particular, emissions are positively correlated with natural gas transport costs, as captured by the Henry-Waha Hub price spread, but have an ambiguous relationship with natural gas prices. To rationalize these patterns, we present a dynamic model in which firms make production and emissions decisions in response to oil and gas prices. We find that, while emissions from natural gas flaring and venting decrease with natural gas prices, overall emissions may increase with gas prices due to the extensive margin production response. With the model, we plan to estimate the emissions impact of methane taxes and policies to address pipeline capacity.

*Many thanks to Daniel Varon and Lucas Estrada for providing data and scientific expertise to guide this project. We also thank Jim Stock, Rob Stavins, Nathan Hendren, Ed Glaeser, and Jesse Shapiro for their feedback. We are grateful to participants of the Harvard/MIT Environmental Workshop for their comments. This project is part of the Salata Institute research cluster on reducing global methane emissions. Elhai gratefully acknowledges support from the Chae Family Economics Research Fund and the National Science Foundation Graduate Research Fellowship Program.

1 Introduction

Methane is a powerful greenhouse gas. It is both far more potent and less long-lived than CO_2 , making it a prime target for global emissions reductions efforts. About a quarter of U.S. methane emissions are from the oil and natural gas sector. If a greater share of this methane were captured and sold rather than emitted, the U.S. would be well on its way toward achieving its commitments under the Global Methane Pledge. Unlike most pollutants, methane emissions from the oil and gas sector exert not only a social cost, but a private one as well. Because methane is the primary component of natural gas, methane emissions from this industry represent billions of dollars of lost product. As a result, methane abatement measures can be net cost saving: the engineering and labor costs of such measures can be outweighed by the commodity value of the captured gas (IEA, 2023).

However, the value of natural gas is highly variable. Over the past few years, natural gas spot market prices at Henry Hub, the main North American trading hub, have ranged from nearly \$9 per million Btu to just over \$2 (Figure 2). On top of the fluctuations driven by market-wide supply and demand, producers also face price variation coming from changes in the cost of transporting natural gas. Currently, the only cost-effective way for producers to transport their gas to consumers is through pipelines.¹ When pipelines near full capacity, transport costs increase, pushing down the price that producers receive. In the Permian Basin, for instance, transport costs are captured by the gap between the benchmark Henry Hub price and the local Waha Hub price (a gap referred to as “Waha basis”). Several times, high transport costs have caused Waha prices to drop into negative territory, even while Henry Hub trades well above zero (Figure 2).

As oil and natural gas prices fluctuate, producer incentives to abate methane emissions change too. In this project, we explore how these changes in abatement incentives affect actual emissions from upstream oil and gas. We model forward-looking oil and gas producers who decide in each period (1) how many wells to drill and (2) what share of their gas production to sell. The well drilling problem is one of dynamic investment: given producer expectations over future oil and gas prices and the future stream of production from a new well, producers choose how many wells to drill today. Each period’s production is a function only of past investment decisions, and so the firm decision of what share of gas produced to sell in each period is purely static.² Firms optimize current period profits by selling or disposing of gas depending on the firm’s abatement cost curve, the current commodity value of natural gas, and the current cost of transporting natural gas to market. We assume that each period, transport costs are subject to a random shock, while commodity values follow unit root processes.

In this model, emissions arise from two sources. First, for every period of its life-cycle, a well releases a baseline level of methane emissions. These emissions result from well completion and equipment leakage, and are assumed to depend only on well age, not well productivity. We further assume that producers have no control over these emissions. Second, emissions result from gas disposal through flaring and venting.³ We

¹Liquefaction is an alternative to pipelines for long-distance transport in some cases, but is still very expensive and only economical at scale. With current technology, it is not generally an option for intranational transport.

²As we discuss later, producer decisions tend not to have any influence on flows from existing wells. Producers could choose to shut-in wells to defer their production to later periods, but in practice this option is only exercised in extreme circumstances.

³Flaring is the controlled burning of natural gas to convert the methane to CO_2 , while venting is the release of unburned gas

assume that a fixed share of disposed gas is released as methane emissions. So, greater flaring and venting activity leads to more emissions.

There are several important implications of our model. The model suggests that, given transitory shocks to gas transport costs, emissions will increase as producers vent and flare a higher share of their product. Furthermore, we find that the effect of a (non-transitory) gas price shock is ambiguous. For instance, consider the case of an exogenous price increase. Because firms rationally expect that a price increase today implies higher prices going forward, well drilling activity today will increase, thus increasing emissions. However, a higher price today also increases the share of produced gas that is sold rather than disposed of, thus reducing emissions. The net effect of the price change on emissions will depend on the shape of firm abatement cost curves and how responsive drilling activity is to the price change.

To test these model implications, we conduct an empirical analysis of the interaction between emissions, venting/flaring, and oil and gas prices. For this part of the paper, we focus on the Permian Basin, an area of rich natural resource deposits located in West Texas and the southeastern corner of New Mexico. The Permian is a natural setting for our investigation because it is an area of intense oil and natural gas production. It is the largest oil-producing region in the nation, and the second largest gas-producing region, accounting for 40% and 25% respectively of national totals. It is also a region where rapid production growth over the past decade has frequently strained pipeline capacity, increasing gas transport costs.

Until recently, it has been impossible to accurately track methane emissions at any time scale, let alone at high frequency. New methods (Varon et al., 2022) use satellite measurements and atmospheric inversion techniques to produce weekly measurements of methane emissions over the Permian Basin. Our empirical analysis uses this novel dataset, as well as administrative data on natural gas flaring and venting to analyze how emissions respond to short- and long-run variation in natural gas prices.

Using the differential between the Waha Hub price and Henry Hub price as our measure of gas transport costs, we find that Permian methane emissions and gas disposal are both significantly and positively correlated with transport costs. This is in line with our model, which predicts that producers will dispose of more gas in response to temporary declines in the price they receive for their gas. Gas disposal is also negatively correlated with Waha Hub prices, which we interpret as an approximation of the net-of-transport price that producers receive. However, emissions have a statistically insignificant relationship with Waha prices. This supports our prediction that price increases have an ambiguous effect on emissions, since they increase emissions from new wells while decreasing emissions from gas disposal.

Reducing methane emissions from oil and gas is a topic of great interest to policymakers today. Our findings suggest that a government intervention to reduce the variance of gas transport costs may be able to reduce methane emissions from venting and flaring. In the future, we plan to estimate the dynamic component of our model as well. With these results, we will be able to estimate the emissions impact of a methane tax, as has been proposed by the U.S. EPA. We will also explore complementarities between a methane tax and policies targeting gas transport costs.

into the atmosphere. Although flaring is preferable to venting in terms of methane emissions, even flaring can result in significant methane emissions due to inefficient or unlit flares.

We contribute to an emerging literature on the marginal abatement costs of methane, much of which is summarized in [Agerton, Gilbert and Upton \(2023\)](#). [Lade and Rudik \(2020\)](#) calculates firm-specific abatement cost curves for oil and gas producers in North Dakota using flaring data and the estimated costs of connecting wells to pipeline infrastructure. We expand on this work by linking flaring behavior with methane emissions, which they are unable to measure directly. We also provide a framework to explain how firm incentives to abate could vary not just with the presence of infrastructure but also with the costs associated with its use. In complementary work, [Hausman and Muehlenbachs \(2019\)](#) estimate abatement in the context of natural gas pipelines, finding that firms underspend on leak prevention because they can exercise their monopoly power to pass on the cost of leaked gas to consumers. This research highlights the importance of market incentives in firm emission decisions, a theme that our project explores on the production side of the industry.

Closest to our work is [Marks \(2022\)](#), which estimates a marginal abatement cost curve for methane among oil and gas producers using annual, firm-reported statistics on emissions. There are known issues with these self-reported statistics, since firms may not be forthcoming about (or even aware of) their true emissions. The annual nature of the firm-reported data also makes it impossible for this work to follow high-frequency variation in both emissions and prices. We build on this work by applying estimates from [Varon et al. \(2022\)](#) to the problem. The availability of more accurate, higher-frequency data gives us a better vantage point from which to examine the decisions that operators make. Furthermore, while Marks uses the spot price of natural gas to infer abatement costs alone, our model allows firms to choose production and emissions intensity separately in response to current and expected prices of both oil and gas. We believe that this is a better fit for an industry characterized by long-term investments and joint production.

There is a substantial literature on optimal emissions regulation. For instance, [Fowle, Reguant and Ryan \(2016\)](#) examines greenhouse gas regulation in the cement industry, [Werner and Qiu \(2020\)](#) simulates audit-based methane regulation policies, and [Cicala, Hémous and Olsen \(2022\)](#) model adverse selection in emissions reporting. Our work contributes to this literature by studying the way in which firms’ emissions decisions vary with market forces. Rather than taking as given the cost of abatement, we work to better understand the factors entering into firm decisions and how regulation could interact with these factors.

Finally, our work builds on research into optimal production decisions in the oil and gas industry. In particular, [Anderson, Kellogg and Salant \(2018\)](#) shows that production from existing oil wells does not respond to oil prices. Instead, producers respond on the extensive margin, drilling more wells in response to higher oil prices. We encompass these patterns in our own model of production. We assume that production from wells drilled in previous periods is exogenous and declining over time, while new well drilling does respond to prices. We further incorporate the co-production of oil and gas, the emissions impact of drilling new wells, and an emissions intensity decision for current gas production.

2 Background

2.1 Oil and Gas Extraction in the Permian Basin

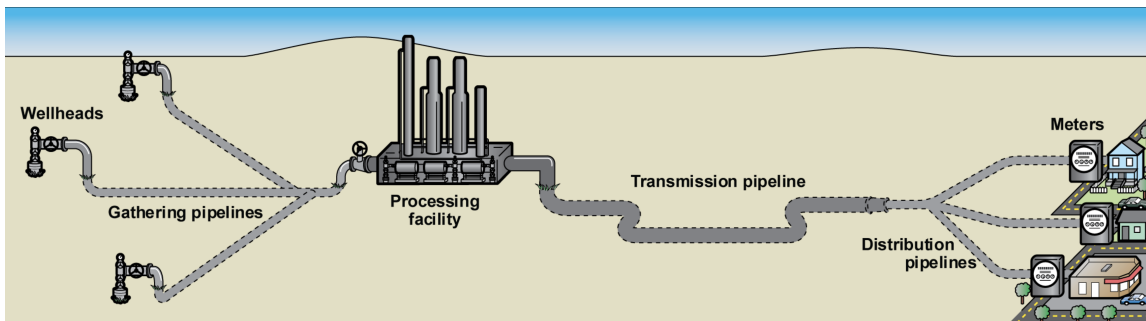
The Permian Basin’s geological formations contain a substantial amount of both oil and natural gas. In this region, drilling for oil produces gas as a byproduct because Permian oil can contain significant quantities of dissolved natural gas. Oil is the more lucrative business in the Permian: even the basin’s top gas producers earn between 70% and 90% of their revenues from oil sales (Table 1). Thus, producers may be willing to sustain very low profits (or even losses) from the gas side of their operation if it allows them to continue producing oil.

Oil is the dominant driver of production across the Permian, but gas-to-oil ratios vary significantly throughout the region. The Delaware and Midland Basins are the most productive sub-basins of the Permian. The Midland Basin occupies the eastern portion of the Permian, while the Delaware Basin is on the western side of the Permian. The Delaware Basin tends to be gassier than the Midland, i.e., it has higher gas-to-oil ratios (Figure A.1). As a result, a large share of the oil produced in the Delaware Basin is produced by wells whose gas-to-oil ratios qualify them as gas wells (Figure A.2).

Fueled by the fracking revolution, natural gas and oil production in the Permian has more than quadrupled in the past decade. Pipeline infrastructure has not always kept pace with this rapid expansion in supply. Frequent shortfalls in pipeline capacity have often driven natural gas spot prices at Waha Hub (the main hub serving the Permian Basin) into negative territory.

This points towards an important feature of natural gas: it is difficult to transport, far more so than oil. Whereas oil can be stored in tanks and carried on trains, natural gas cannot be cost-effectively moved long distances in its gaseous state except via pipeline. Aboveground storage of natural gas is also cost-prohibitive, and belowground storage is constrained by the availability of suitable caverns or depleted reservoirs. Despite recurring capacity issues in the Permian, producers have been unable to find a scalable alternative to long-distance transmission pipelines for bringing their gas to market. Capacity is a challenge further upstream as well: producers need to use gathering pipelines and processing plants to bring their gas to transmission pipelines in the first place (Figure 1). Construction of this upstream infrastructure in the Permian has also failed to keep pace with gas production.

Figure 1: The Natural Gas Supply Chain



Notes: Figure produced by the GAO.

2.2 Methane Emissions from the Oil and Gas Industry

Methane emissions from oil and gas production derive from a variety of sources, both intentional and unintentional. On the intentional side, producers often vent natural gas directly into the atmosphere for safety reasons or to maintain proper equipment pressure. Certain steps in the production process require venting, including well completions and workovers. Some equipment (e.g., pneumatic devices) vent natural gas as part of normal operations ([Agerton, Gilbert and Upton, 2023](#)).

It is also common for producers to flare natural gas. Flaring is the controlled combustion of natural gas, so that methane is transformed into CO₂ and water before entering the atmosphere. As with venting, flaring can be motivated by operational and safety requirements. For instance, flaring is common during drilling, well testing, and well completion. Flaring can also result from economic decisions. Sometimes, wells enter operation before gathering pipelines to connect wellpads to the transmission network have been completed. Other times, there is insufficient gathering, processing, or compression capacity to process all of the gas produced in an area. In either case, producers can choose to flare their gas to avoid the costs of higher marketing fees, well shut-ins, or lost oil sales.

Qualitative work suggests a link between frequent capacity issues and flaring activity. A 2019 Dallas Federal Reserve survey asked 146 oil and gas executives why flaring increased in the Permian Basin that year. Nearly three-quarters of respondents attributed flaring increases to insufficient pipeline takeaway capacity, while nearly half cited a lack of gathering and processing capacity (Figure [A.3](#)).

Flaring imposes a significantly lower environmental cost than venting because most of the methane in flared gas is burned off. However, flaring does not entirely prevent methane emissions: [Lyon et al. \(2021\)](#) find combustion efficiency in the Permian to be around 93% due to unlit and malfunctioning flares. The remaining gas, which was about 80% methane, was vented to the atmosphere.

Flaring and venting are regulated in all oil- and gas-producing states, including New Mexico and Texas. In Texas, flaring is permitted in the first 10 days after a well is completed. Outside of this window, producers must file an exemption request with the Texas Railroad Commission (RRC) and pay a \$375 fee. In theory, producers must provide justifications for an exemption, such as lack of takeaway capacity or a maintenance event. In practice, the RRC approves essentially all flaring requests, as evidenced by permit request data (see section [3](#)). Venting is generally prohibited in Texas, but exceptions are made during and immediately after well completions or for short intervals ([Texas Administrative Code, n.d.](#)).⁴

Unintentional methane emissions come from leaks, which can happen at countless points along the path that natural gas takes from wellhead to consumer. Although producers are often unaware of leaks on their sites, there is some evidence that emissions from leaks respond to producer oversight effort, which in turn depends on beliefs about leak magnitudes ([Lewis, Wang and Ravikumar, 2023](#)).

Because of the vast amounts of natural gas produced and transported in the Permian Basin, the region’s methane emissions are substantial. Permian methane emissions were estimated to be 2.5 Tg in 2019, about

⁴In particular, Texas regulators permit venting up to 10 days after well completion and for up to 24 hours at a time (or up to 72 hours in a month).

15% of the U.S.’ total oil/gas methane emissions, or equivalent to the carbon emissions from the electricity used to power 12 million U.S. homes over the course of one year (Lu et al., 2023). The Permian is not only the largest oil and gas basin by total methane emissions, but also one of the top oil and gas basins by methane intensity of production. Lu et al. (2023) estimate that Permian production had a methane intensity of around 3% in 2019, a significant decline since 2014 but still well above most other major oil/gas producing basins.

Recent estimates by Cusworth et al. (2021) indicate that about half of Permian methane emissions are from production, which is the segment of the industry that we focus on in this paper.⁵ Other work has shown that there is significant heterogeneity across oil and gas production sites in terms of methane intensity. Omara et al. (2018) finds that low-producing well sites emit a much larger proportion of their production than newer, high-producing well sites. Even controlling for production levels and basin, however, emissions remain highly stochastic across sites. The distribution of emissions has a fat right tail, such that the top 5% of high-emitting sites account for 50% of cumulative emissions.

2.3 Satellite Measurement of Methane Emissions

Previous research on the climate costs of oil and gas production has been hampered by the quality of data available on methane emissions. Until recently, large-scale methane measurement has only been possible using firm surveys, bottom-up inventories, and aircraft campaigns. The EPA’s Greenhouse Gas Reporting Program is an example of the first: this annual survey is mandatory for large emitters, but relies on firms being honest and accurate regarding their own emissions. The second method, bottom-up inventories, involves measuring the carbon intensity of different activities (e.g., drilling for oil) and multiplying by how many units of activity (e.g., wells) there are. This method is not suited to tracking how carbon intensity varies across units or over time. The final method, flying aircraft armed with methane sensors over areas of interest, is accurate but resource intensive. It has not been feasible to use this technique to create panel datasets on an entire region’s emissions.

Recent advances in satellite instruments and atmospheric modeling have revolutionized methane measurement. Varon et al. (2022) is an example of this progress. The authors’ work is based on satellite observations from the TROPOspheric Monitoring Instrument (TROPOMI). The TROPOMI instrument can sense methane concentrations at a high spatial resolution, but is unable to determine where the methane originated from. To that end, the authors apply a cutting-edge model of atmospheric transport (GEOS-Chem) combined with prior estimates of emissions from the EDF’s 2018 bottom-up inventory. The result is a set of weekly emissions estimates at a 25×25 km² resolution, covering the entire Permian Basin over the period from May 2018 to October 2020.

3 Data and Descriptive Facts

⁵The authors estimate that the other half of methane emissions come from gathering and boosting (38%) and processing (12%). It is worth noting that this study limits its analysis to persistent point sources, i.e., those detected in at least three over-flights. This rules out intermittent sources of methane, such as flares that are only sometimes operating properly.

3.1 Prices

We use daily natural gas spot price data for Henry Hub and Waha Hub from S&P Capital IQ (Figure 2). In general, prices at both hubs range from \$2 to \$4. Waha Hub prices tend to lie 10¢ to 60¢ below Henry Hub prices, though there are periods (such as between 2018 and 2021) during which this gap is much larger.

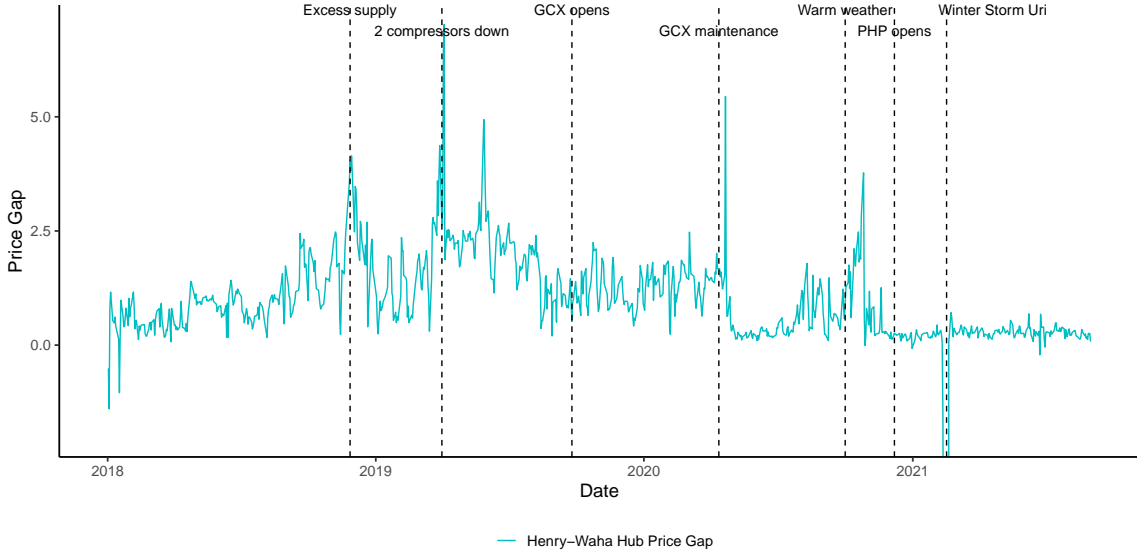
Figure 2: Local and Benchmark Natural Gas Spot Prices



Notes: Daily spot price data from S&P Capital IQ Pro.

The gap between Henry and Waha hub spot prices captures the cost of moving natural gas to market from the Permian Basin. This transport cost is highly variable, much more so than the commodity value of gas. Commodity values are driven by national and international market dynamics, which are unlikely to be dramatically affected by any single event. Accordingly, Henry Hub spot prices display significant variation, but move relatively slowly (Figure 2). In contrast, transport costs are quite sensitive to any imbalance of supply and demand, either in gas or in pipeline space (Figure 3). Particularly when pipeline capacity is tight, as it was from 2018 to 2021, maintenance issues or gas oversupply can cause the Waha basis to rise dramatically. Even outside of these major disruptions, day-to-day swings in basis are large.

Figure 3: Waha Basis, Annotated



Notes: Data from S&P Capital IQ Pro. Annotations added by the authors based on industry reporting. “GCX” is the Gulf Coast Express, a major natural gas pipeline. “PHP” is the Permian Highway Pipeline, another large natural gas pipeline.

We also use oil price data from EIA. In particular, we use data on Cushing WTI spot prices and forward prices. Prices per barrel ranged from about \$40 to \$100 between 2015 and 2023, dipping briefly below zero during the early months of the COVID-19 pandemic in the U.S.

3.2 Production

Oil and gas production data are from Enverus DrillingInfo at the well-month level. This dataset includes information on when each well was drilled and how much it produces each month, as well as features such as well operator and well type. We use this dataset to demonstrate certain facts about oil and gas production.

First, we show that production from gas and oil wells decline over time (Figures A.5 and A.6). This pattern is driven by reservoir pressure, which drops as more product is extracted, thus slowing the pace at which extraction can occur. It is common to model production using decline curves that feature exponential decay, or initial hyperbolic decline followed by slower exponential decay. As described and modeled in [Anderson, Kellogg and Salant \(2018\)](#), this production constraint generally binds: oil producers do not adjust production from existing wells in response to price shocks. We confirm that this same trend exists for both gas and oil production for the period of our study, with no apparent correlation with oil or gas prices. The few periods when production and prices appear to co-move correspond to extreme weather that both increased energy demand and interfered with oil and gas production.

In contrast, well drilling does move with prices. We verify this finding from [Anderson, Kellogg and Salant \(2018\)](#) for our context using data on drilling activity. We find that drilling in the Permian Basin tracks oil prices rather than gas prices (Figure A.7, Table 4), an unsurprising pattern given the dominance of oil in Permian producers’ revenues (Table 1). Furthermore, producers are forward-looking: higher prices for three-month

futures contracts reduce new drilling activity today. These same trends hold for well completions.

3.3 Revenues

Enverus provides a dataset on lease-month level producer revenues for Texan producers, including volumes of product sold (both oil and gas), total sales value, and buyer. This information is originally collected by the Texas Comptroller for tax purposes. In Table 1, we aggregate sales by seller to calculate the share of total revenues coming from oil. We show that, even among the top gas producers by volume, oil accounts for the vast majority (70-95%) of total revenues.

Table 1: Oil Revenue Shares for Top Gas Producers, 2018

Producer	Gas Volume (BCF)	Oil Volume (MMBbl)	Oil Revenue Share
PIONEER NATURAL RESOURCES USA, INC.	270.41	74.45	0.8612
APACHE CORPORATION	226.77	30.34	0.7048
CHEVRON U.S.A. INC.	141.39	29.08	0.7083
XTO ENERGY INC.	124.38	52.29	0.8738
ANADARKO E&P ONSHORE LLC	107.23	25.68	0.8083
COG OPERATING LLC	106.42	26.26	0.7743
PARSLEY ENERGY OPERATIONS, LLC	71.43	22.77	0.8365
ENERGEN RESOURCES CORPORATION	71.05	27.73	0.8715
OCCIDENTAL PERMIAN LTD.	64.04	33.82	0.9434
LAREDO PETROLEUM, INC.	59.35	12.35	0.7793

Notes: Lease-level sales data from Enverus. We aggregate sales volumes and values by reported seller name for all observations in 2018. We present here the data for the top 10 gas producers by volume in 2018. We calculate the oil value share to be the ratio of oil sales value to the sum of oil and gas value for each producer.

3.4 Emissions

We use the weekly estimates of Permian emissions from Varon et al. (2022), as described in Section 2.3. These estimates cover the period May 2018 to October 2020 and are generated at the level of 25×25 km² cells. We primarily use basin-level and subbasin-level aggregates of these estimates.

We supplement emissions data with Texas Railroad Commission (RRC) data on natural gas production, flaring, and venting. These data are collected at the lease-month level when firms fill out their monthly production report (Form PR). Firms must report the volume of gas that they flare or vent, but are not required to include fugitive emissions or gas released during well completion. We then merge RRC data with data from Enverus on well drill dates, first production dates, and the number of wells per lease. To do this, we use an Enverus crosswalk linking RRC well IDs with Enverus lease IDs.

Although the RRC dataset does not separate gas that was flared versus vented, we can validate general trends in gas disposal using flaring data from Lyon et al. (2021). This work uses the methodology from Elvidge et al. (2016) to convert observations from the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite instrument into estimates of the number of flares and volume of gas flared each month. Because this methodology is based on VIIRS-derived radiant light and heat, it may not capture malfunctioning or unlit flares.

4 Model

We present a dynamic model of an oil and gas producer's investment and emissions decisions. The model has an infinite horizon with discrete decision periods of one month. In each period, firm i 's production level is predetermined by actions in previous periods. The firm's state space in period t is given by $(\Omega_{it}, \varepsilon_{it})$, where Ω_{it} contains the observed state variables and ε_{it} is a disturbance term that is known by the firm but unobservable by the econometrician. The observed vector Ω_{it} is given by $(q_{it}, w_{it}, p_t, d_t, r_t)$, where q_{it} is the level of oil production from *existing* wells, w_{it} is the total number of wells the producer operates, $p_t = (p_t^o, p_t^g)$ are the oil and gas prices, d_t is the rig dayrate for drilling a new well, and r_t is the cost of gas pipeline transmission.⁶ Gas production, $g_{it}(q_{it}) = \alpha_i q_{it}$, follows deterministically from oil production based on the gas-to-oil ratio, α_i . We assume that each producer is small and takes p_t , d_t , and r_t as given.

Each period, the producer decides how much of the gas it produces to send to market (i.e., sell), $m_{it} \leq g_{it}$. We assume that the remaining gas is flared. Firms incur marketing costs $c^g(\cdot)$ when they send gas to market. Notably, the choice of m_{it} does not affect the future payoffs for the firm.

Additionally, firms can decide to engage in a costly investment to develop new wells, which begin producing in the subsequent period. Since the marginal cost of production from existing wells is low, our model does not consider exit decisions. While the choice to emit or market gas is a static problem for the producer, the investment in new wells is a dynamic problem.

4.1 Static Emissions

In each period, the firm chooses the amount of gas to market to maximize the per-period payoffs from existing wells:

$$\bar{\pi}(\Omega_{it}) = \max_{m_{it} \leq g_{it}} \underbrace{p_t^o q_{it} - c_i^o(q_{it})}_{\text{oil profit}} + \underbrace{p_t^g m_{it}}_{\text{gas revenue}} - \underbrace{c_i^g(m_{it}; r_t)}_{\text{gas marketing costs}} - \underbrace{\tau ((g_{it} - m_{it})e + w_{it}\ell)}_{\text{emissions tax}}, \quad (1)$$

where ℓ is the per-well baseline methane emissions⁷, e is the emissions factor of flared natural gas, and so $(g_{it} - m_{it})e + w_{it}\ell$ is the total emissions from existing wells. We assume that producers cannot adjust ℓ and e . Firms face a competitive global market for oil and gas and are assumed to be price takers.

Oil profits are the difference between oil revenues, $p_t^o q_{it}$, and the cost of oil extraction, $c_i^o(q_{it})$. Gas revenues are the product of the gas price p_t^g and the amount of gas sold, $m_{it} \leq g_{it} = \alpha_i q_{it}$. Producers are potentially subject to tax $\tau \geq 0$ on each unit of emissions.

The cost of marketing gas, c_i^g , takes into account any costs of processing and transmitting the gas and is given by the following function:

$$c_i^g(m_{it}; r_t) = \gamma_{0i} m_{it}^{\gamma_{1i}} r_t^{\gamma_{2i}} \exp \eta_{it} \quad (2)$$

⁶We assume that the cost of transmission from the Waha Hub in the Permian basin to the Henry Hub is a sufficient statistic for transmission costs.

⁷Independent of producer decisions, some small unavoidable quantity of gas produced will be released into the atmosphere during normal operations of a well, e.g., from pneumatic devices, separators, dehydrators, and compressors. Omara et al. (2022) find that these baseline emissions tend to be fairly independent of production levels.

for $m_{it} \leq g_{it}$ and infinity otherwise, where $\gamma_{0i} > 0$, and $\gamma_{1i} > 1$. The unobserved error term η_{it} is assumed to be normally distributed with variance σ_η^2 . The observed transmission costs r are one component of the total marketing costs for the producer. Fluctuations in transmission costs are driven by bottlenecks in transmission and, since these bottlenecks affect the entire system, they are highly correlated with processing costs. This functional form captures that processing and transmission rates are convex in the quantity of gas marketed and that pipeline congestion increases the costs as well as the convexity of the relationship between quantity and costs.⁸ The latter effect stems from the observation that firms may hold some “firm” capacity contracts with pipelines for a portion of gas they produce—for which transmission rates are fairly invariant to pipeline congestion—but the marginal gas they produce is more likely to face a spot market for transmission that is highly responsive to pipeline bottlenecks.

The (log) marginal cost can be written as:

$$\log c_i^{g'} = \log \gamma_{0i} \gamma_{1i} + (\gamma_{1i} - 1) \log m_{it} + \gamma_{2i} \log r_t + \eta_{it}. \quad (3)$$

4.2 Dynamic Drilling

Firms choose the number of wells to drill in each period, $a_{it} \in A = \{0, 1, \dots, J\}$, to maximize the stream of future-discounted expected profits. Wells drilled in period t begin producing in period $t + 1$. Drilling costs c_t are a function of number of wells drilled and are allowed to vary by period. The firm’s dynamic optimization problem is given by

$$\begin{aligned} V(\Omega_{it}, \varepsilon_{it}) &= \max_a \bar{\pi}_i(\Omega_{it}) - c(\Omega_{it}, a) - \tau f a + \varepsilon_{it}(a) + \beta \mathbb{E}[V(\Omega_{it+1}, \varepsilon_{it+1}) | \Omega_{it}, \varepsilon_{it}, a] \\ &= \max_a \bar{\pi}_i(\Omega_{it}) - c(\Omega_{it}, a) - \tau f a + \varepsilon_{it}(a) + \beta \int V(\Omega_{it+1}, \varepsilon_{it+1}) dF(\Omega_{it+1}, \varepsilon_{it} | \Omega_{it}, \varepsilon_{it}, a) \\ &= \max_a \bar{\pi}_i(\Omega_{it}) - c(\Omega_{it}, a) - \tau f a + \varepsilon_{it}(a) + \beta \int V(\Omega_{it+1}, \varepsilon_{it+1}) dF(\Omega_{it+1} | \Omega_t, a) dG_\varepsilon(\varepsilon_{it+1}) \end{aligned} \quad (4)$$

where β is the discount rate, f is the emissions associated with each drilling event, and $\varepsilon_{it}(a)$ is a profit shock which is assumed to be i.i.d. Type 1 Extreme Value with mean zero and scale parameter σ_ε . The profit shocks are independently distributed over time and across firms.⁹ The third line in equation (4) follows from the conditional independence assumption $F(\Omega_{it+1}, \varepsilon_{it+1} | \Omega_{it}, \varepsilon_{it}, a) = F(\Omega_{it+1} | \Omega_{it}, a) G_\varepsilon(\varepsilon_{it+1})$. The drilling cost is parameterized as $c(\Omega_{it}, a) = a \cdot (\delta_0 + \delta_1 d_t)$.

We define the conditional value function as

$$v_i(\Omega_{it}, a) \equiv \bar{\pi}_i(\Omega_{it}) - c(\Omega_{it}, a) - \tau f a + \beta \mathbb{E}[V(\Omega_{it+1}, \varepsilon_{it+1}) | \Omega_{it}, \varepsilon_{it}, a] \quad (5)$$

⁸We are also considering alternative functional forms, including:

$$c^g(m_{it}; u_t) = \gamma_{0i} m_{it} + \gamma_{1i} u_t m_{it}^2 + \eta_{it} m_{it},$$

which produces the marginal cost curve:

$$c_i^{g'} = \gamma_{0i} + \tilde{\gamma}_{1i} u_t m_{it} + \eta_{it}.$$

⁹We may be able to relax the assumption that $\varepsilon_{it}(a)$ is independent over time and instead assume it is serially correlated, following an AR(1) process, if this is not prohibitively costly to the computational burden.

and conditional choice probability is given by

$$\mathbb{P}(a|\Omega_{it}) = \frac{\exp(v_i(\Omega_{it}, a))}{\sum_{a' \in A} \exp(v_i(\Omega_{it}, a'))}. \quad (6)$$

4.3 Transitions

The transition probabilities are assumed to be Markovian and we assume the firms have rational expectations. The number of wells transitions deterministically as $w_{it+1} = w_{it} + a$. Production is the only other state variable that evolves as a function of the firm's decision. As is common in the engineering literature, the firm's (unbiased) expected oil production from existing wells evolves according to an exponential decline curve. The expected production from a new well is μ . The total production in period $t + 1$ is given by

$$q_{it+1} = \lambda q_{it} + \mu a + \nu_{it+1}^q + 1(a > 0)\nu_{it+1}^a, \quad (7)$$

where $\nu^q \sim \mathbb{N}(0, \sigma_q^2)$ is the production shock for existing wells and $\nu^a \sim \mathbb{N}(0, \sigma_a^2)$ is the production shock for new wells (which may be more volatile than that of existing wells).¹⁰

Prices follow a first-order Markov process with exogenous transitions. Following Kellogg (2014) and Herrnstadt, Kellogg, and Lewis (2024), we model prices, rig dayrates, and transmission costs as the Markov processes

$$\log x_{t+1} = \log x_t + \kappa_0^x + \kappa_1^x x_t + \sigma_x \nu_{t+1}^x, \quad (8)$$

where $x \in \{p^o, p^g, d, r\}$, price volatility σ_x is assumed to be constant, and the shocks ν^{p^g} , ν^{p^o} , ν^d , and ν^r are drawn from an i.i.d. multivariate standard normal distribution.¹¹ We denote Σ_ν as the covariance matrix of the innovations in equation (8).

5 Estimation

For each producer, we estimate α_i , the gas-to-oil ratio, as the cumulative gas production divided by the cumulative oil production over our sample period. We take $e = 0.09$, $\ell = 0.005$, and $f = \dots$ from the engineering literature (Plant et al., 2022; Omara et al., 2022).¹² We further assume a discount rate of $\beta = 0.99$.

Let θ_1 denote $(\gamma_{0i}, \gamma_{1i}, \gamma_{2i}, \sigma_\eta)$, the structural parameters for the per-period profit function. Let θ_2 denote $(\lambda, \mu, \sigma_q, \sigma_a, \kappa, \Sigma_\nu)$, the parameters of the transition functions, where $\kappa = \{\kappa_0^x, \kappa_1^x | x \in \{p^o, p^g, d, r\}\}$. Finally,

¹⁰An alternative transition function is

$$q_{it+1} = e^\lambda q_{it} e^{\nu_{it+1}^q} + \mu a + 1(a > 0)\nu_{it+1}^a,$$

where $\nu^q \sim \mathbb{N}(0, \sigma_q^2)$ is the i.i.d. production shock from existing wells and $\nu^a \sim \mathbb{N}(0, \sigma_a^2)$ is the i.i.d. shock to the initial production of new wells. The motivation for this functional form is that the volatility of the production shock from existing wells is declining in the expected production. Furthermore, the uncertainty of production from new wells may be larger than that of existing wells.

¹¹The distribution of transmission costs is fat-tailed and this should likely be reflected in the model. Further, the distribution of shocks is heavily right-skewed. We should perhaps assume that transmission costs evolve independently of the other processes (which in theory seems tenuous, but in practice, there is little to no correlation between gas prices and transmission costs).

¹²These are currently filler numbers.

let θ_3 denote $(\delta_0, \delta_1, \sigma_\varepsilon)$, the parameters of the dynamic drilling decision. The estimation procedure proceeds in three stages, as we outline below.

5.1 Per Period Profits

The first order condition of per-period profit from existing wells with respect to m_t is given by $p_t^g = c_i^{g'}(m_{it}; r_t)$ for $m_{it} < g_{it}$. We thus seek to estimate the parameters in equation (3) as

$$\log m_{it} = \tilde{\gamma}_{0i} + \tilde{\gamma}_{1i} \log p_t^g + \tilde{\gamma}_{2i} \log r_t + \tilde{\eta}_{it}, \quad (9)$$

where $\tilde{\gamma}_{0i} = \log(\gamma_{0i}\gamma_{1i})/(\gamma_{1i} - 1)$, $\tilde{\gamma}_{1i} = 1/(\gamma_{1i} - 1)$, and $\tilde{\gamma}_{2i} = \gamma_{2i}/(\gamma_{1i} - 1)$. We address the endogeneity of transmission costs and natural gas prices by instrumenting for transmission costs with unplanned pipeline maintenance events and for prices with demand shifters. Following Baumeister and Kilian (2012) and Newell, Prest, and Vissing (2019), we instrument for prices using heating degree days (HDD), cooling degree days (CDD), lagged US working gas inventories, and the Commodity Research Bureau (CRB) Raw Industrial Commodity Index.

Following Anderson, Kellogg, and Salant (2018), we assume $c_i^o(q_{it}) = 0$.

5.2 Transitions

For the evolution of production, we estimate the regression

$$q_{it+1} = \lambda q_{it} + \mu a + \nu_{it+1}, \quad (10)$$

where $\nu = \nu^g + 1(a > 0)\nu^a$. Since production from existing wells evolves independently of a , we can estimate the volatility of shocks from existing wells as

$$\hat{\sigma}_q^2 = \frac{\sum 1(a=0)\hat{\nu}^2}{\sum 1(a=0) - 3}. \quad (11)$$

That is, we obtain an estimate σ_q by considering only periods in which no new wells were drilled. We then obtain σ_a by restricting the data to $a > 0$, obtaining the variance of the residuals, and taking the difference with our estimate for σ_q .¹³

For the evolution of the price and cost state variables p^o , p^g , d , and r , we estimate the set of coefficients in

¹³If we use the alternative specification $q_{it+1} = e^{\lambda} q_{it} e^{\nu_{it+1}^g} + \mu a + 1(a > 0)\nu_{it+1}^a$, then the parameters to estimate for the evolution of production are λ , the log production decline rate; μ , the expected production from new wells; and σ_q and σ_a , the volatility of production shocks from existing and new wells, respectively. Since production from existing wells evolves independently of a , we can estimate λ and σ_q using only periods when $a = 0$. Specifically, we estimate the regression

$$\log q_{it+1} - \log q_{it} = \lambda + \nu_{it+1}^g$$

to recover the estimates $\hat{\lambda}$ and $\hat{\sigma}_q$. Then we can recover the remaining parameters by constructing a data set of periods when $a > 0$ and by estimating the regression

$$q_{it+1} - \exp(\hat{\lambda})q_{it} = \mu a + \nu_{it+1}^a.$$

(My initial intuition is this will lead to a biased estimate of σ_a .)

equation (8) via OLS and use the resulting four sets of residuals to estimate the covariance matrix Σ_ν .

5.3 Dynamics

Although a producer could drill any number of wells in a given period in theory, empirically we observe that producers rarely drill more than a couple of wells each month (only 0.08% of lease-months have $a \geq 4$). As a result, we simplify the choice set to $a \in \{1, 2, 3+\}$ to reduce the computational burden.

The state variables q_{it} , p_t , d_t , and r_t are continuous so the dynamic programming problem must be approximated rather than solved exactly. We estimate the dynamic parameters $\theta_3 = (\delta_0, \delta_1, \sigma_\varepsilon)$ using the simulation-based Hotz-Miller CCP estimator of Hotz et al. (1994).

6 Counterfactuals

After we estimate the model, we would like to examine a range of policy counterfactuals, including the following:

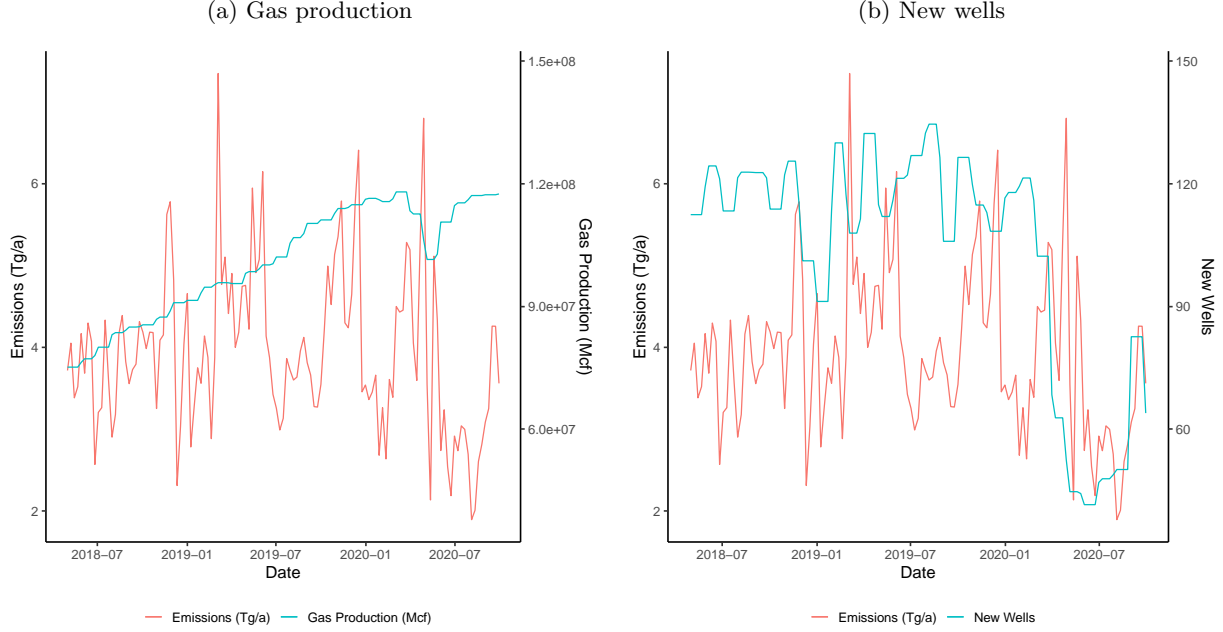
- Taxes: on total emissions, on flaring, on each operational well, on new wells
- Decreased variability of pipeline capacity: Anecdotally, some pipelines are better maintained than others. Changes to pipeline monitoring might reduce the number of unplanned outages, decreasing the variability of pipeline capacity.
- Switch to lower emission drilling techniques: Increased drilling costs, lower emissions from drilling

7 Empirics

7.1 Emissions

We begin by examining the raw data on emissions and oil and gas production. Figure 4 shows that methane emissions are highly volatile throughout the study period. There is no apparent trend either upwards or downwards in emissions even as gas production increased (panel a). In panel b, we see that spikes in new wells (i.e., wells that begin producing in a given month) appear to immediately precede jumps in methane emissions. This is likely due to the emissions intensity of the well completion process, as well as the fact that there is often a delay in connecting new wells to gathering pipelines.

Figure 4: Production and emissions



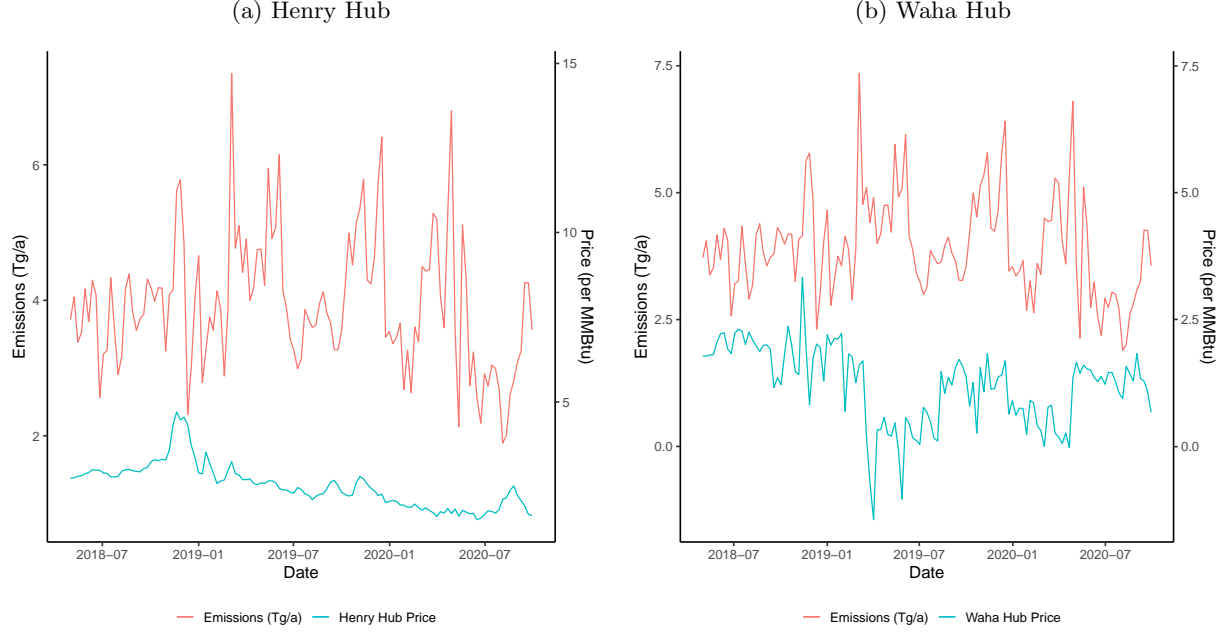
Notes: In a), we plot weekly methane emissions and monthly gas production over time. In b), we plot methane emissions and new wells, which we measure as the number of wells that begin producing in the given month. Weekly methane emissions data are estimated by [Varon et al. \(2022\)](#). Production and new wells data are reported monthly by Enverus.

In Figure 5, we plot emissions against the Henry and Waha Hub natural gas spot prices. Henry Hub is located in coastal Louisiana, and serves as the industry benchmark price because it is connected to many of the country’s most important natural gas markets. Waha Hub is the main hub serving the Permian Basin. Upon visual inspection, it appears that there might be a slight positive correlation between emissions and Henry Hub prices, and a negative correlation between emissions and Waha Hub prices, but this relationship does not appear consistent throughout the period.

However, when we plot the difference between the Henry and Waha Hub spot prices (termed “Waha basis”), a clearer pattern emerges. Henry Hub spot prices almost always exceed Waha Hub spot prices, but a larger Waha basis appears to coincide with or slightly lag emissions spikes. This trend is clearest when we use the maximum price gap for each week (Figure 6), rather than the mean price gap (Figure A.8). Industry sources identify the Waha basis as the most important component of natural gas transport costs, both in terms of magnitude and variance. Thus, the story that emerges from Figure 6 is one of increased emissions when transport costs are higher. Producers choose between selling their natural gas and disposing of it, but are more likely to dispose of their gas when transport costs are high. Since both flaring and venting result in methane emissions, this increase in gas disposal increases total emissions. The fact that the maximum price gap for each week better matches the emissions series than the mean price gap could imply that the marginal abatement cost curve is convex.

To test the relationships we observe in the raw data, we run regressions of emissions on prices and production variables (Table 2). We estimate these regressions for the entire Permian, and then separately by sub-basin.

Figure 5: Emissions and the Hub Prices



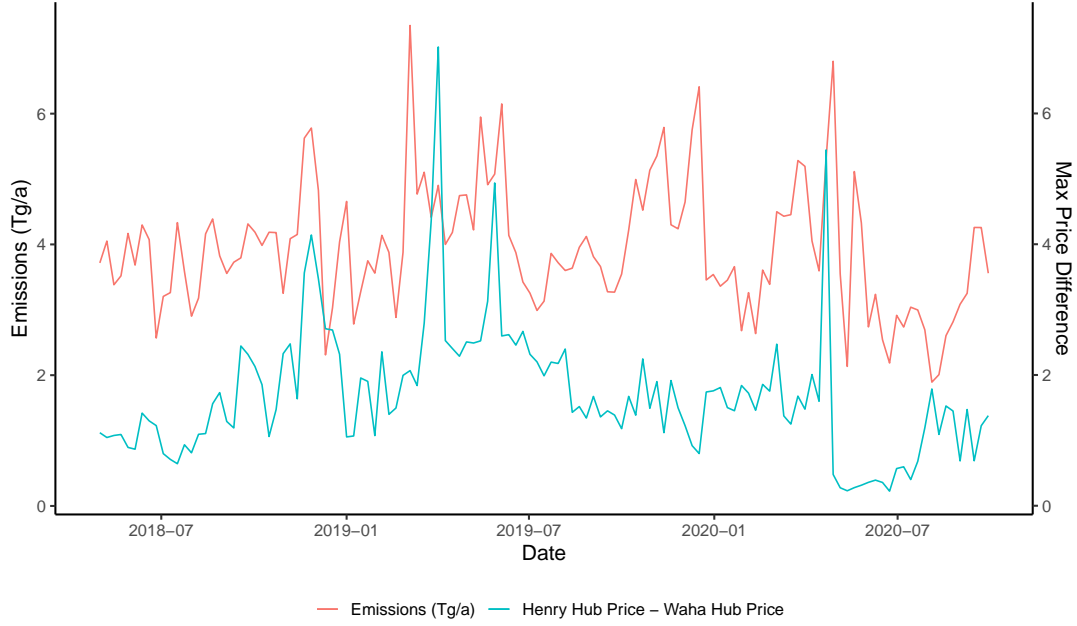
Notes: In a), we plot weekly methane emissions and the Henry Hub spot price, which is observed daily and averaged to the week level. In b), we do the same for the Waha Hub spot price. Weekly methane emissions data are estimated by [Varon et al. \(2022\)](#). Price data are from S&P Capital IQ Pro.

Our regression results are in accordance with our observations from Figure 6, and with our proposed story of increased gas disposal when transport costs increase. For all geographies, the Waha basis is positively correlated with emissions. The relationship is significant for the entire Permian, and for the Midland and Central basins. The coefficient is largest for the Midland, which is the most oil-concentrated sub-basin, but insignificant for the Delaware Basin, which has the highest gas-to-oil ratio of all three sub-basins (Figure A.2). This pattern suggests that producers that rely more on gas sales may be less sensitive to transport costs. These producers may restrict new well drilling when gas is less lucrative, rather than continuing to expand production and disposing of unsellable gas.

In contrast, the coefficient on Waha prices is generally positive but insignificant for all geographies. Our model suggests an explanation for this: high Waha prices could reflect either high commodity values or low transport costs, which have opposite influences on emissions. High commodity values drive drilling and increase emissions, while low transport costs discourage gas disposal, decreasing emissions.

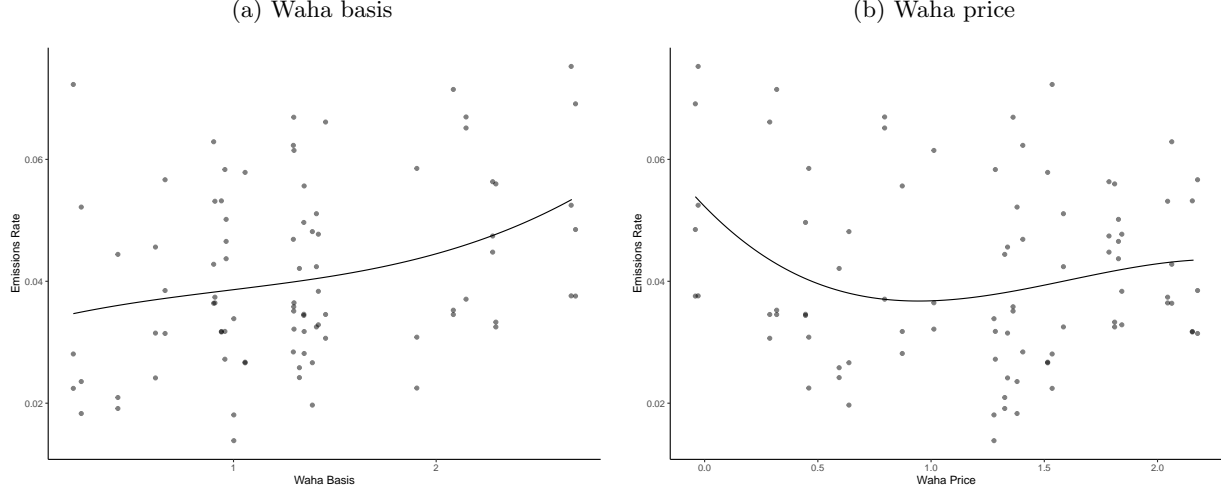
When we plot our observations in price-emissions space, we again find that the Waha basis captures more of the variance in emissions rates than does the Waha price (Figure 7). Emissions are increasing in transport costs, but have a more ambiguous, nonlinear relationship with Waha prices.

Figure 6: Emissions and the Max Weekly Henry-Waha Price Gap



Notes: We plot weekly methane emissions data and the maximum daily Henry-Waha price gap within each week. Weekly methane emissions data are estimated by [Varon et al. \(2022\)](#). Price data are from S&P Capital IQ Pro.

Figure 7: Emissions vs. Waha Basis, Waha Price



Notes: We plot subbasin-month-level emissions rates against the mean Waha basis (panel a) or Waha price (panel b) for each week. Emissions rates are calculated by dividing emissions by total gas production for a given subbasin-month. Over the raw data, we plot a line representing the third degree polynomial of best fit.

Several of the other variables in Table 2 have significant coefficients, though none are robust across geographies. This could be due to confounding relationships between control variables (see Table B.2 for a correlation matrix). For instance, we know that production (in particular, new well drilling) increases with oil prices and leads to more emissions. To disentangle these relationships, we plan to instrument for drilling activity and capacity constraints. For the former, we can gather data on global oil price shocks. For the latter, we plan to

acquire data on unforeseen pipeline disruptions that caused reductions in capacity. Without these instruments, we caution that our regression results are suggestive rather than causal.

Table 2: Methane Emissions, Prices, and Production

	<i>Dependent variable:</i>			
	log(Emissions)			
	All	Midland	Central	Delaware
	(1)	(2)	(3)	(4)
Henry Hub Price	0.008 (0.048)	0.002 (0.060)	0.005 (0.035)	0.052 (0.058)
Henry - Waha Hub Price	0.038 (0.032)	0.143*** (0.035)	0.107*** (0.027)	-0.042 (0.042)
Cushing Spot Oil Price	-0.006** (0.002)	-0.003 (0.002)	0.001 (0.002)	-0.009*** (0.003)
log(Oil Production)	1.187 (0.903)	-1.381** (0.653)	-0.481 (0.600)	2.904** (1.184)
log(Gas Production)	-1.075 (0.755)	0.935 (0.578)	0.279 (0.712)	-2.665** (1.058)
log(New Wells)	-0.344 (0.248)	0.060 (0.261)	0.035 (0.074)	-0.165 (0.231)
log(Lagged New Wells)	0.621** (0.244)	0.372 (0.262)	0.013 (0.075)	0.514** (0.226)
Constant	-0.289 (4.549)	4.691 (5.426)	1.061 (7.426)	-0.650 (4.536)
Observations	127	126	126	126
R ²	0.298	0.276	0.221	0.328
Adjusted R ²	0.256	0.233	0.175	0.289
Residual Std. Error	0.214 (df = 119)	0.243 (df = 118)	0.185 (df = 118)	0.268 (df = 118)
F Statistic	7.205*** (df = 7; 119)	6.413*** (df = 7; 118)	4.784*** (df = 7; 118)	8.241*** (df = 7; 118)

Notes: An observation is a week. Sample covers May 2018 through October 2020. Emissions are in log teragrams per year (Tg/a). Prices reflect the average of prices over the week. Oil and gas production and new wells are measured monthly and interpolated to the week level. Oil and gas production are in barrels and thousands of cubic feet (Mcf), respectively.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7.2 Flaring and Venting

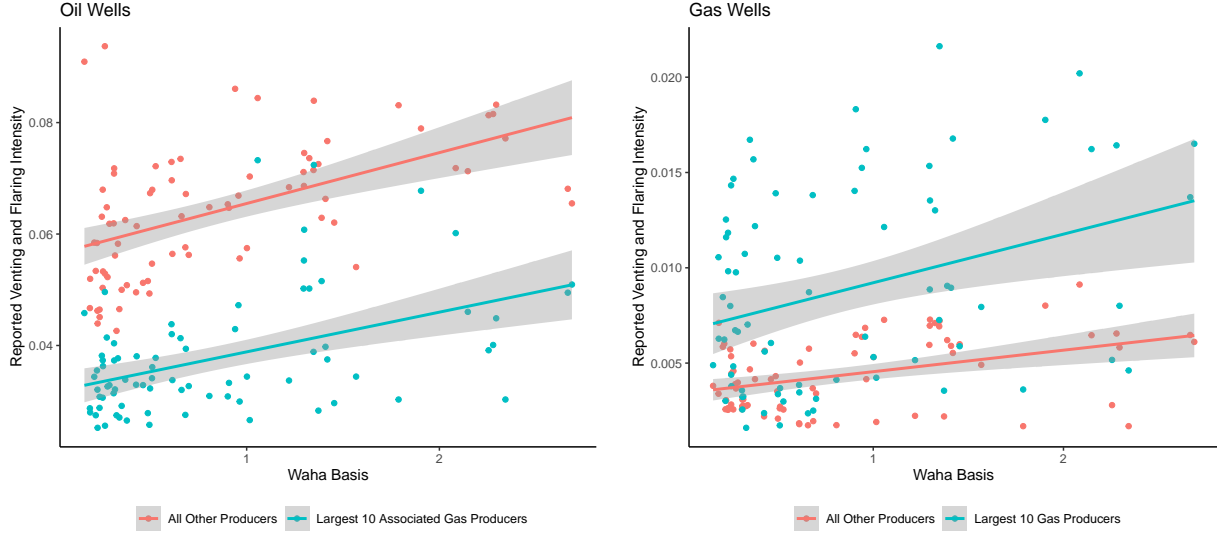
To validate the relationship we propose between gas disposal and transport costs, we look directly at flaring and venting behavior. First, we use monthly producer reports to the Texas Railroad Commission of produced and flared and vented gas volumes. We divide flared and vented volumes by total gas produced to calculate a lease-month level measure of disposal intensity. In Figure 8, we show that disposal rates are generally increasing in the Waha basis, which captures transport costs.

Because this dataset is at the lease level, we are able to separate observations by well type and producer size to determine how these factors affect disposal rates. We identify leases that are owned by the largest 10 gas producers based on observed gas production. The largest producers have lower disposal rates than other producers at all levels of the Waha basis. We also find that disposal rates are far higher for oil wells than for gas wells, again supporting the notion that gas-focused operators are more incentivized to sell their gas even when transport costs are high.

In contrast to our emissions analysis, gas disposal has a clear relationship with Waha price levels as well as Waha basis (Figure 9). As our model suggests, the disposal decision is a static one. Increases in effective price,

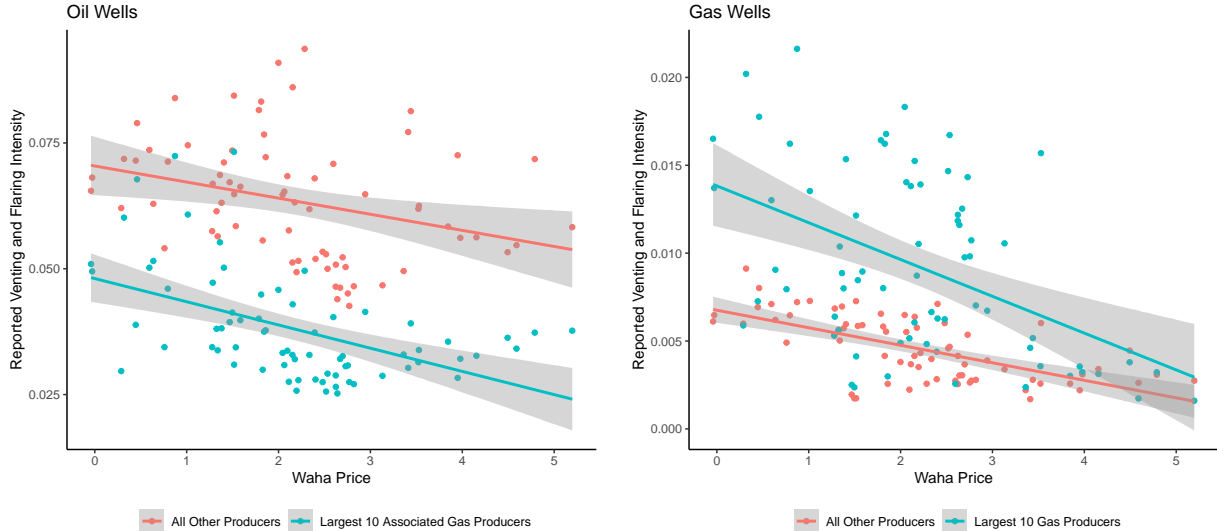
whether due to transport costs or commodity value, always decrease gas disposal rates.

Figure 8: Producer-reported venting and flaring vs. Waha basis



Notes: Each observation is a lease-month. Data span 2017 through 2024. The sample includes all leases in the districts that the Texas Railroad Commission designates as belonging to the Permian Basin (7C, 8, and 8A). “Waha Basis” is the difference between Henry and Waha spot prices, averaged within month. We calculate reported venting and flaring intensity to be the ratio of vented/flared gas to total gas produced. For gas wells, the largest 10 producers are defined as the operators that accounted for the most gas produced during this period. For oil wells, the largest 10 producers are defined as the operators that accounted for the most casinghead gas (i.e., gas coming from oil wells) produced during this period.

Figure 9: Producer-reported venting and flaring vs. Waha prices



Notes: Each observation is a lease-month. Data span 2017 through 2024. The sample includes all leases in the districts that the Texas Railroad Commission designates as belonging to the Permian Basin (7C, 8, and 8A). “Waha Basis” is the difference between Henry and Waha spot prices, averaged within month. We calculate reported venting and flaring intensity to be the ratio of vented/flared gas to total gas produced. For gas wells, the largest 10 producers are defined as the operators that accounted for the most gas produced during this period. For oil wells, the largest 10 producers are defined as the operators that accounted for the most casinghead gas (i.e., gas coming from oil wells) produced during this period.

There is some concern that producers do not accurately report flaring behavior (see for instance [McDonald and Wilson \(2021\)](#)). Therefore, we supplement our analysis using remote-sensed measures of flaring activity. In Table 3, we present estimates of the relationship between the prices and the volume of flared gas, as estimated by [Lyon et al. \(2021\)](#) using VIIRS data. We find a significant, positive coefficient on the Waha basis: a dollar increase in transport costs corresponds to a 16 percent increase in flared gas volumes in Permian as a whole, and a 30 percent increase the Midland Basin. Table B.1 presents the same regressions, but using number of flares (again, remote-sensed) as the outcome rather than flared volume.

Table 3: Flared Gas, Prices, and Production

	<i>Dependent variable:</i>		
	All	log(Flared Volume (Tg/a)) Midland	Delaware
	(1)	(2)	(3)
Henry Hub Price	-0.025 (0.030)	0.085** (0.042)	-0.113*** (0.031)
Henry - Waha Hub Price	-0.007 (0.004)	-0.002 (0.006)	-0.012*** (0.004)
Cushing Spot Oil Price	-0.003 (0.002)	-0.004 (0.003)	-0.005** (0.002)
log(Oil Production)	7.257*** (0.728)	8.882*** (0.621)	4.726*** (0.826)
log(Gas Production)	-5.616*** (0.529)	-5.424*** (0.408)	-4.780*** (0.693)
log(New Wells)	0.230 (0.254)	-0.631** (0.272)	0.521*** (0.186)
log(Lagged New Wells)	-0.212 (0.246)	0.053 (0.262)	-0.074 (0.183)
Constant	-19.846*** (3.290)	-48.102*** (4.072)	7.184*** (2.044)
Observations	199	198	198
R ²	0.580	0.559	0.601
Adjusted R ²	0.565	0.542	0.587
Residual Std. Error	0.269 (df = 191)	0.376 (df = 190)	0.275 (df = 190)
F Statistic	37.745*** (df = 7; 191)	34.354*** (df = 7; 190)	40.928*** (df = 7; 190)

Notes: An observation is a week. Outcome variable is the volume of flared gas, based on VIIRS observations and calibrated to match administrative data. Prices reflect the average of prices over the week. Oil and gas production and new wells are measured monthly and interpolated to the week level. Oil and gas production are in barrels and thousands of cubic feet (Mcf), respectively.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7.3 Drilling

In our model, producers respond to price changes through drilling decisions, as well as through gas disposal decisions. To confirm our theory that drilling decisions are affected by both oil prices and natural gas prices, we regress new wells on prices. Similar to [Anderson, Kellogg and Salant \(2018\)](#), we construct regressions in first differences:

$$\Delta \log(\text{New wells}_t) = \alpha + \beta_0 \Delta \log(\text{Oil Price}_t) + \beta_1 \Delta \log(\text{Oil Futures}_t) + \beta_2 \Delta \log(\text{Gas Price}_t) + \text{error}_t$$

We use two different measures of new wells, each of which we observe at the subbasin-month level using

data from Enverus. First, we use the number of spuds, which is defined as the number of wells for which drilling began in the given month. Second, we use the number of wells that began producing in each month. It can take as little as a month for a well to start producing after drilling begins, but producers can also choose to drill a well and then wait before completing it.

Results are presented in Table 4. We see that both drilling and well completions are significantly and positively associated with front-month oil prices, but significantly negatively associated with three-month oil futures. Gas prices are positively correlated with drilling, but negatively correlated with newly producing wells, perhaps because having more new wells come online pushes gas prices down. Coefficients on gas prices are much smaller in magnitude than those on oil prices, which supports the idea that oil prices are a more important driver of production activity (see also Figure A.7). Results are similar when we add lagged versions of the price variables.

Ideally, we would also be able to test how transport costs affect drilling behavior. However, transport costs are likely sensitive to production from new wells, so regression coefficients would not necessarily be informative about producer decision-making. To circumvent this issue, we hope to construct an instrument for transport costs using data on unexpected pipeline maintenance events.

Table 4: Oil prices, drilling, and production

	<i>Dependent variable:</i>	
	$\Delta \text{Log}(\text{Spuds})$	$\Delta \text{Log}(\text{First Prod})$
	(1)	(2)
$\Delta \text{Log Cushing, Front-month}$	1.567 (1.345)	3.311** (1.417)
$\Delta \text{Log Cushing, 3-month}$	-1.140 (1.892)	-2.481 (1.995)
$\Delta \text{Log Henry Spot}$	0.171 (0.461)	-0.112 (0.487)
Basin = Delaware	0.585*** (0.097)	0.414*** (0.104)
Basin = Midland	2.760*** (0.098)	2.700*** (0.104)
Time trend	-0.001 (0.010)	-0.003 (0.011)
Constant	0.497 (20.403)	5.746 (22.271)
Observations	489	479
R ²	0.647	0.626
Adjusted R ²	0.643	0.621
Residual Std. Error	0.881 (df = 482)	0.928 (df = 472)
F Statistic	147.543*** (df = 6; 482)	131.762*** (df = 6; 472)

Notes: An observation is a month-subbasin. Prices are averaged within month and then differenced. “Spuds” represents the number of wells that begin the drilling process each month. “First Prod” captures the number of wells that begin to produce each month. Drilling data from Enverus. Oil price data from EIA. Gas spot prices from S&P Capital IQ.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

8 Conclusion

Reducing methane emissions quickly will be essential as the world attempts to rein in climate change. Although prior work has explored different methods to regulate methane emissions coming from the oil and gas sector, emissions regulation may not be stringent enough, nor politically palatable enough, to make the necessary impact. In this project, we seek to understand the market forces driving methane emissions due to oil and gas production. A greater understanding of producer incentives will make possible more effective emissions-abatement policy.

We find that emissions are increasing in natural gas transport costs, but not necessarily in local natural gas prices. We explain this pattern using a dynamic model of producer behaviors, in which producers decide how much new drilling to engage in and what share of gas produced to dispose of. Both decisions impact aggregate emissions. In our model and in the evidence we have so far collected, emissions from flaring and venting are increasing in transport costs and decreasing in natural gas prices, while emissions from well drilling have a positive relationship with natural gas prices.

Our next steps involve estimating our model of producer drilling and emissions decisions. With the parameters we estimate, we hope to simulate the emissions impact of a range of policies. Of course, the most salient policy is putting a price on methane emissions. We will calculate the impact of methane taxes and fees on drilling, gas disposal rates, and overall emissions. Our framework will also allow us to assess the effectiveness of more creative policy solutions. For instance, our results so far suggest that transport costs drive methane emissions from venting and flaring. Better regulations regarding pipeline maintenance could reduce the variance of pipeline capacity, thus smoothing the transport costs that producers face and reducing the need for venting and flaring.

References

- Agerton, Mark, Ben Gilbert, and Gregory B. Upton.** 2023. “The Economics of Natural Gas Flaring and Methane Emissions in US Shale: An Agenda for Research and Policy.” *Review of Environmental Economics and Policy*, 17(2): 251–273. Publisher: The University of Chicago Press.
- Anderson, Soren T., Ryan Kellogg, and Stephen W. Salant.** 2018. “Hotelling under Pressure.” *Journal of Political Economy*, 126(3): 984–1026. Publisher: The University of Chicago Press.
- Cicala, Steve, David Hémous, and Morten G Olsen.** 2022. “Adverse Selection as a Policy Instrument: Unraveling Climate Change.” National Bureau of Economic Research w30283, Cambridge, MA.
- Cusworth, Daniel H., Riley M. Duren, Andrew K. Thorpe, Winston Olson-Duvall, Joseph Heckler, John W. Chapman, Michael L. Eastwood, Mark C. Helmlinger, Robert O. Green, Gregory P. Asner, Philip E. Dennison, and Charles E. Miller.** 2021. “Intermittency of Large Methane Emitters in the Permian Basin.” *Environmental Science & Technology Letters*, 8(7): 567–573.
- Elvidge, Christopher D., Mikhail Zhizhin, Kimberly Baugh, Feng-Chi Hsu, and Tilottama Ghosh.** 2016. “Methods for Global Survey of Natural Gas Flaring from Visible Infrared Imaging Radiometer Suite Data.” *Energies*, 9(1): 14. Number: 1 Publisher: Multidisciplinary Digital Publishing Institute.
- Fowlie, Meredith, Mar Reguant, and Stephen P. Ryan.** 2016. “Market-Based Emissions Regulation and Industry Dynamics.” *Journal of Political Economy*, 124(1): 249–302. Publisher: The University of Chicago Press.
- Hausman, Catherine, and Lucija Muehlenbachs.** 2019. “Price Regulation and Environmental Externalities: Evidence from Methane Leaks.” *Journal of the Association of Environmental and Resource Economists*, 6(1): 73–109.
- IEA.** 2023. “Marginal abatement cost curve for oil and gas methane emissions by mitigation measure, 2022 – Charts – Data & Statistics.”
- Lade, Gabriel E., and Ivan Rudik.** 2020. “Costs of inefficient regulation: Evidence from the Bakken.” *Journal of Environmental Economics and Management*, 102: 102336.
- Lewis, Eric, Jiayang (Lyra) Wang, and Arvind Ravikumar.** 2023. “Incentives and Information in Methane Leak Detection and Repair.”
- Lu, Xiao, Daniel J. Jacob, Yuzhong Zhang, Lu Shen, Melissa P. Sulprizio, Joannes D. Maasakkers, Daniel J. Varon, Zhen Qu, Zichong Chen, Benjamin Hmiel, Robert J. Parker, Hartmut Boesch, Haolin Wang, Cheng He, and Shaojia Fan.** 2023. “Observation-derived 2010-2019 trends in methane emissions and intensities from US oil and gas fields tied to activity metrics.” *Proceedings of the National Academy of Sciences*, 120(17): e2217900120.
- Lyon, David R., Benjamin Hmiel, Ritesh Gautam, Mark Omara, Katherine A. Roberts, Zachary R. Barkley, Kenneth J. Davis, Natasha L. Miles, Vanessa C. Monteiro, Scott J. Richardson, Stephen Conley, Mackenzie L. Smith, Daniel J. Jacob, Lu Shen, Daniel J. Varon, Aijun Deng, Xander Rudelis, Nikhil Sharma, Kyle T. Story, Adam R. Brandt, Mary Kang, Eric A. Kort, Anthony J. Marchese, and Steven P. Hamburg.** 2021. “Concurrent variation in oil and gas methane emissions and oil price during the COVID-19 pandemic.” *Atmospheric Chemistry and Physics*, 21(9): 6605–6626. Publisher: Copernicus GmbH.
- Marks, Levi.** 2022. “The Abatement Cost of Methane Emissions from Natural Gas Production.” *Journal of the Association of Environmental and Resource Economists*, 9(2): 165–198.
- McDonald, Jack, and Sharon Wilson.** 2021. “Flaring in Texas: A Comprehensive Government Failure.” Earthworks.
- Omara, Mark, Naomi Zimmerman, Melissa R. Sullivan, Xiang Li, Aja Ellis, Rebecca Cesa, R. Subramanian, Albert A. Presto, and Allen L. Robinson.** 2018. “Methane Emissions from Natural Gas Production Sites in the United States: Data Synthesis and National Estimate.” *Environmental Science & Technology*, 52(21): 12915–12925. Publisher: American Chemical Society.

Texas Administrative Code. n.d.. “Gas Well Gas and Casinghead Gas Shall Be Utilized for Legal Purposes.”

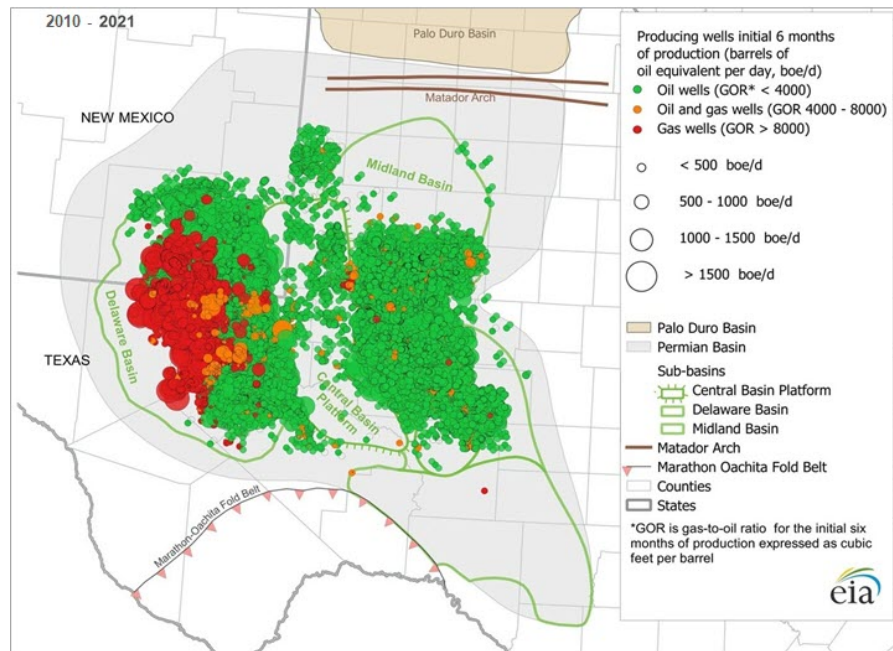
Varon, Daniel J., Daniel J. Jacob, Benjamin Hmiel, Ritesh Gautam, David R. Lyon, Mark Omara, Melissa Sulprizio, Lu Shen, Drew Pendergrass, Hannah Nesser, Zhen Qu, Zachary R. Barkley, Natasha L. Miles, Scott J. Richardson, Kenneth J. Davis, Sudhanshu Pandey, Xiao Lu, Alba Lorente, Tobias Borsdorff, Joannes D. Maasakkers, and Ilse Aben. 2022. “Continuous weekly monitoring of methane emissions from the Permian Basin by inversion of TROPOMI satellite observations.” Atmospheric Chemistry and Physics preprint, European Geosciences Union.

Werner, Karl Dunkle, and Wenfeng Qiu. 2020. “Hard to Measure Well: Can Feasible Policies Reduce Methane Emissions?” Energy Institute at Haas WP 310.

9 Appendix

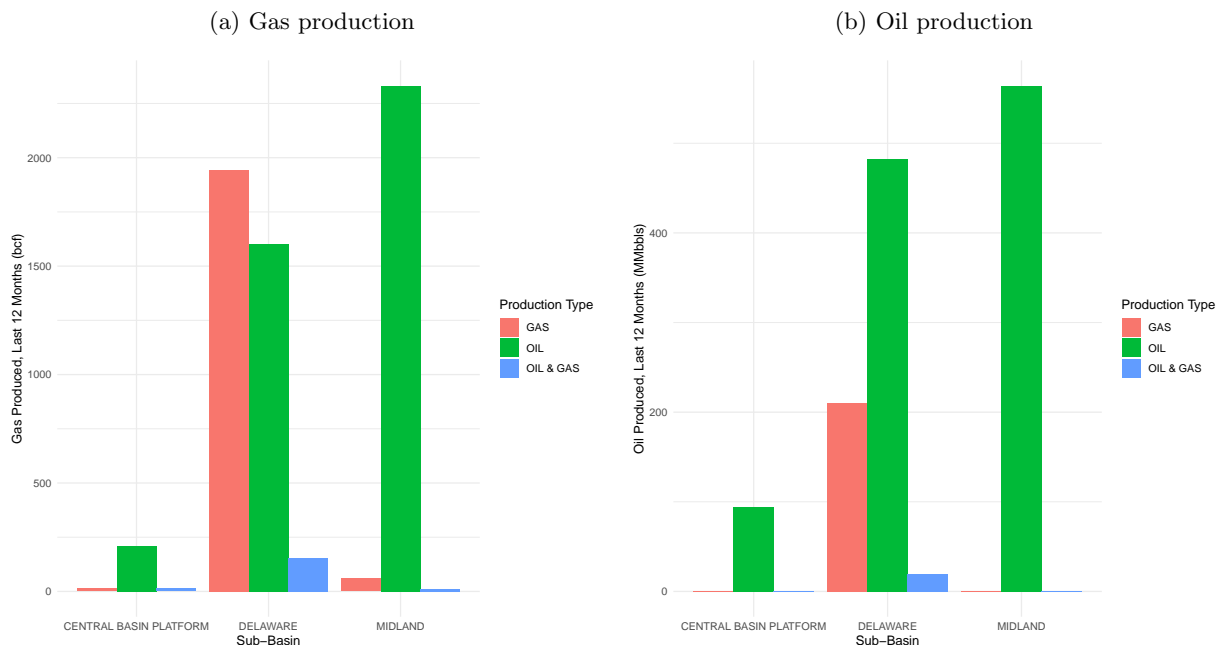
A Figures

Figure A.1: Oil and Gas production



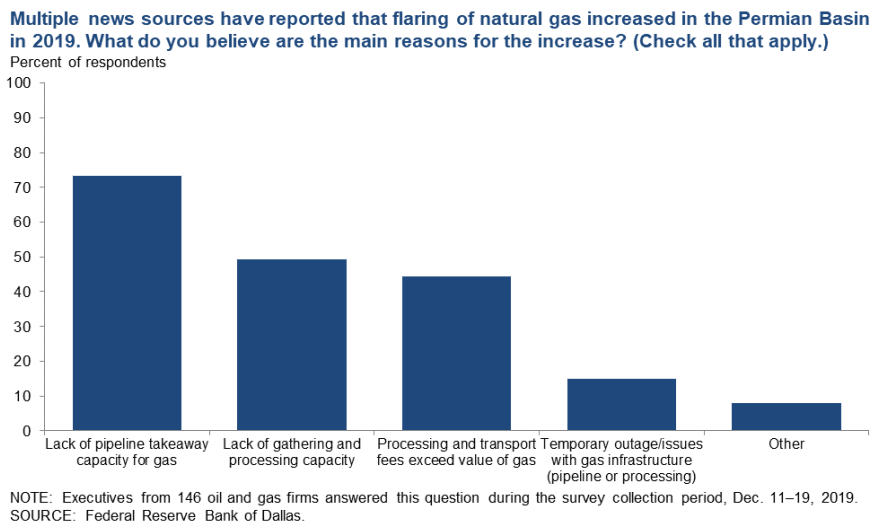
Notes: This figure was produced by the [Energy Information Administration \(EIA\)](#) and summarizes first 6 months production from wells drilled in the Permian between 2010 and 2021.

Figure A.2: Production by basin



Notes: Production data from Enverus. We aggregate the last 12 months of production of gas (panel a) and oil (panel b) produced by different categories of wells in each of the major Permian subbasins. Wells are categorized based on gas-to-oil ratios. We filter to wells that were producing as of December 1, 2022.

Figure A.3: Self-reported reasons to flare



Notes: This chart was produced by the Dallas Federal Reserve as part of their report on their 2019 [survey](#).

Figure A.4: Mitigation decisions and firm size

Response	Percent of respondents (among each group)		
	Small firms	Large firms	All firms
Plan to reduce CO ₂ emissions	22	65	34
Plan to reduce methane emissions	38	65	46
Plan to reduce flaring	43	61	48
Plan to recycle/reuse water	25	48	31
Plan to invest in renewables	2	17	6
None of the above	35	17	30

NOTES: Executives from 83 exploration and production firms answered this question during the survey collection period, Dec. 7–15, 2022. Small firms produced less than 10,000 barrels per day (b/d) in fourth quarter 2022, while large firms produced 10,000 b/d or more. Responses came from 60 small firms and 23 large firms.

SOURCE: Federal Reserve Bank of Dallas.

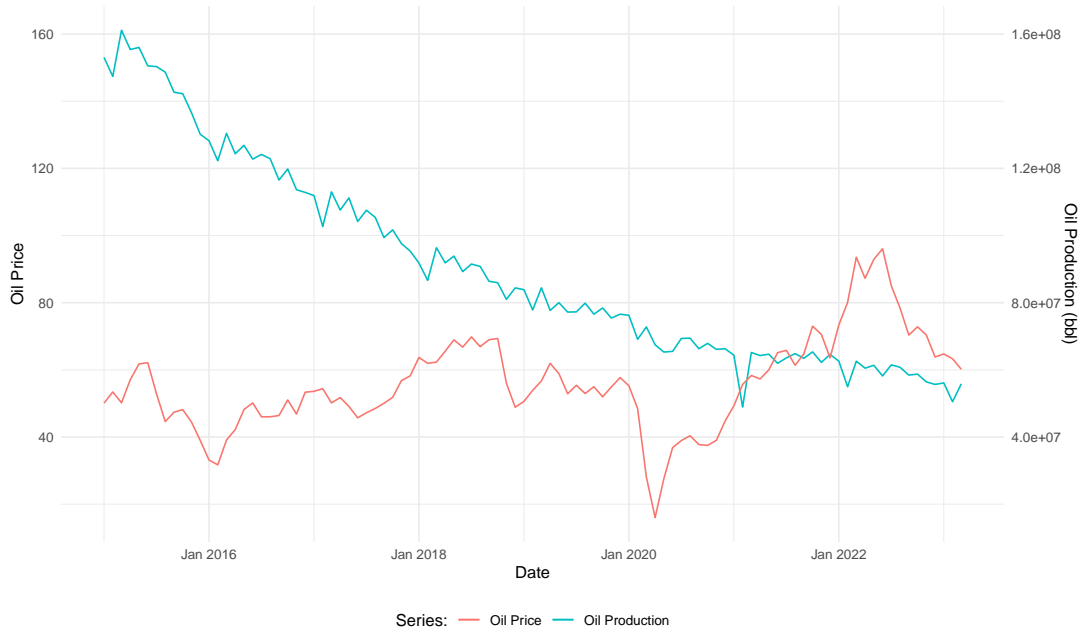
Notes: This chart was produced by the Dallas Federal Reserve as part of their report on their 2022 [survey](#).

Figure A.5: Gas production at existing wells



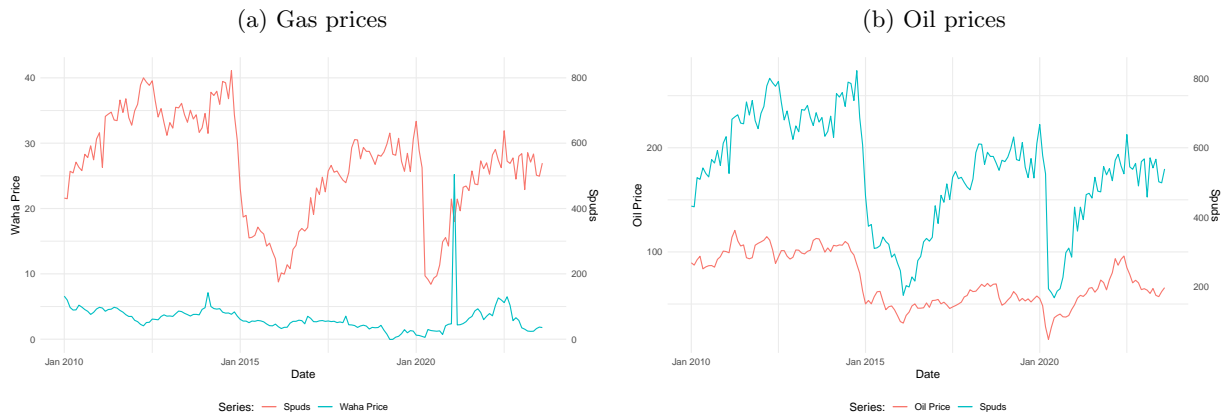
Notes: We depict production data covering January 2015 through March 2023 for Permian Basin wells that were completed in or before January 2015. We plot this against Waha spot prices to show that production from existing wells does not respond to price variation. We derive production data from Enverus. Spot prices are from S&P Capital IQ Pro.

Figure A.6: Oil production at existing wells



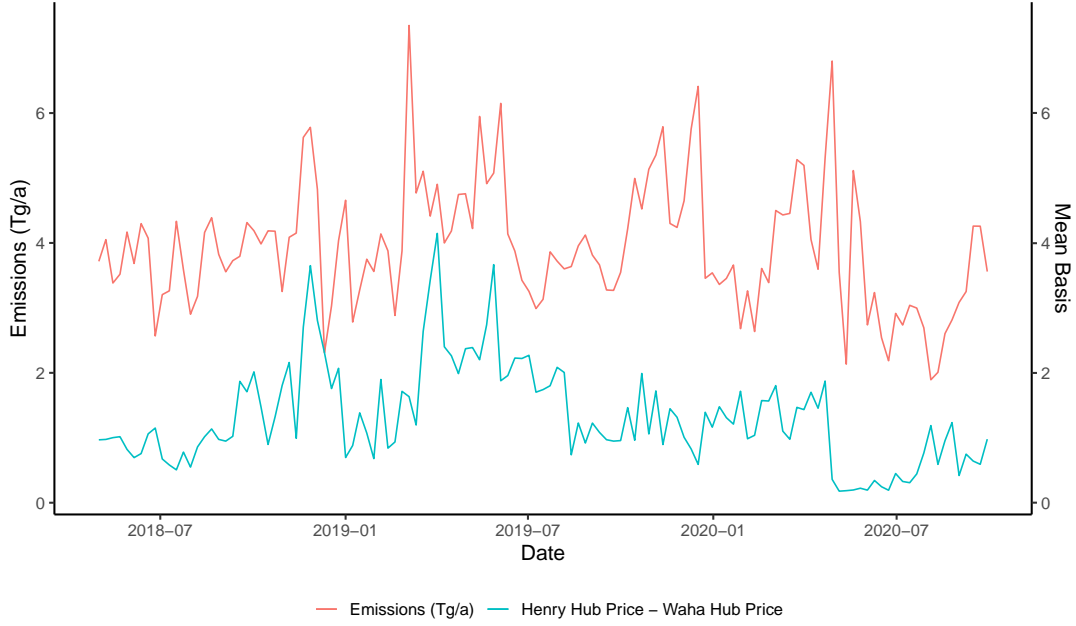
Notes: We depict production data covering January 2015 through March 2023 for Permian Basin wells that were completed before January 2015. We plot this against Cushing spot oil prices to show that production from existing wells does not respond to price variation. We derive production data from Enverus. Spot prices are from S&P Capital IQ Pro.

Figure A.7: Well drilling and prices



Notes: In both panels, we depict number of spuds (the beginning of drilling operations) by sub-basin of the Permian Basin between 2010 and 2023. We plot this against Cushing spot oil prices and Waha spot prices. Production data are from Enverus. Spot prices are from S&P Capital IQ Pro.

Figure A.8: Emissions and the Mean Weekly Henry-Waha Price Gap



Notes: We plot the raw, weekly data for Permian methane emissions (as estimated by Varon et al. (2022)) and the mean Henry-Waha price gap within each week.

B Tables

Table B.1: Methane Flares, Prices, and Production

	<i>Dependent variable:</i>		
	All	log(Num. Flares) Midland	Delaware
	(1)	(2)	(3)
Henry Hub Price	-0.020 (0.012)	0.052*** (0.016)	-0.055*** (0.013)
Henry - Waha Hub Price	-0.006*** (0.002)	-0.002 (0.002)	-0.008*** (0.002)
Cushing Spot Oil Price	-0.001 (0.001)	-0.001 (0.001)	-0.002** (0.001)
log(Oil Production)	2.548*** (0.302)	2.942*** (0.241)	1.990*** (0.354)
log(Gas Production)	-1.893*** (0.220)	-1.597*** (0.159)	-1.847*** (0.297)
log(New Wells)	0.003 (0.105)	-0.266** (0.106)	0.138* (0.080)
log(Lagged New Wells)	-0.027 (0.102)	0.054 (0.102)	-0.008 (0.079)
Constant	-3.367** (1.365)	-15.468*** (1.582)	4.879*** (0.876)
Observations	199	198	198
R ²	0.457	0.501	0.490
Adjusted R ²	0.437	0.483	0.472
Residual Std. Error	0.112 (df = 191)	0.146 (df = 190)	0.118 (df = 190)
F Statistic	22.995*** (df = 7; 191)	27.296*** (df = 7; 190)	26.130*** (df = 7; 190)

Notes: An observation is a week. Outcome variable is the number of clustered VIIRS flaring object detections. Prices reflect the average of prices over the week. Oil and gas production and new wells are measured monthly. Oil and gas production are in sbarrels and thousands of cubic feet (Mcf), respectively.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Correlation matrix

	Waha price	Henry - Waha price	Gas prod.	New wells	Lag new wells	Flared volume	# Flares
Waha price	1	-0.992	-0.003	-0.107	-0.110	-0.124	-0.025
Henry - Waha price	-0.992	1	0.002	0.148	0.150	0.116	0.005
Gas prod.	-0.003	0.002	1	-0.284	-0.291	-0.264	-0.189
New wells	-0.107	0.148	-0.284	1	0.959	0.521	0.375
Lag new wells	-0.110	0.150	-0.291	0.959	1	0.525	0.389
Flared volume	-0.124	0.116	-0.264	0.521	0.525	1	0.930
# Flares	-0.025	0.005	-0.189	0.375	0.389	0.930	1