The Abatement Cost of Methane Emissions from Natural Gas Production

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Abstract

Natural gas produces roughly half as much carbon dioxide as coal when used to generate electricity. However, natural gas is composed of about 90 percent methane, which is itself a greenhouse gas far more potent than carbon dioxide. At present, methane emissions from the natural gas supply chain (in the form of equipment leaks and intentional venting) largely offset its potential climate benefits. This paper uses revealed firm behavior to estimate the cost of reducing these emissions from the extraction segment of the gas industry by examining how production facilities' emission rates respond to changes in natural gas prices. Because firms mitigate emissions up to the point at which their marginal cost of abatement equals their marginal private benefit of being able to sell captured gas, the relationship between emission rates and prices can be mapped to an abatement cost curve. Results indicate that methane emissions from natural gas production can be abated at very low cost relative to other sources of greenhouse gas emissions. In particular, my estimates imply a relatively modest tax on methane emissions equivalent to a $5 per ton carbon price would decrease emissions by about 56 percent. A policy designed to fully internalize the social cost of methane would decrease emissions by about 76 percent while increasing the net cost of natural gas extraction by less than one percent. This finding indicates natural gas is likely to remain highly competitive as an energy source under methane regulation.

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Introduction

Consumption of natural gas has increased considerably over the last decade. In the U.S. electricity sector, natural gas is now the predominant generation resource and its share of the generation mix is expected to continue to increase in the future.[1] While this trend has been driven primarily by low extraction costs following the shale revolution, it has also been influenced by the fact that natural gas produces far less carbon dioxide than other fossil fuels. Looking forward, gas-fired generation's ability to quickly and efficiently ramp up and down is likely to become increasingly important as investment in intermittent wind and solar generation increases. These two environmental features may enable natural gas to play a useful role in the transition to low-carbon energy. At present, however, the potential climate benefits of natural gas are being largely undermined by methane emissions from the gas supply chain.

Methane (CH_4), the principal component of uncombusted natural gas, is itself a greenhouse gas that is shorter-lived than carbon dioxide (CO_2) but vastly more potent. A small fraction of gas escaping anywhere along the supply chain, either through equipment leaks or intentional venting, can have severe climate impacts. Currently, between 2-2.7 percent of total gas production is emitted in the United States, resulting in warming effects similar in magnitude to the warming caused by CO_2 emissions from the combustion of natural gas (Alvarez *et al.*, 2018). To what extent natural gas may be useful for addressing climate change in the future will depend on the cost of reducing these emissions.

This paper investigates these costs for the extraction segment of the natural gas supply chain, where the majority of methane emissions from the industry are generated. My empirical strategy consists of two parts. In the first part, I spatially link natural gas production facilities to geographically dispersed trading hubs to examine how methane emission rates respond to changes in wholesale gas prices. Because in this setting the pollutant is also a

[1] The Energy Information Administration predicts increasing investment in gas-fired electricity generation both with and without fulfillment of the Clean Power Plan (EIA, 2018).

priced commodity, the estimated relationship between emissions and price can be directly mapped to a relationship between emissions and cost.[2] In the second part, I use this estimated relationship to simulate how production facilities' methane emissions would change following the implementation of methane pricing. I then aggregate these results to construct a sector-wide marginal abatement cost curve (MACC).

My results imply that methane emissions from natural gas production are an area of substantial low-cost opportunities for greenhouse gas abatement relative to other sectors. In particular, I estimate that imposing an emissions tax or permit price on (leaked) methane emissions equivalent to a $5 per ton carbon price would reduce methane emissions by 56 percent.[3] This represents a decrease of about 52 million tons of CO_2-equivalent emissions per year at an annual net cost of $70 million, which is only about 0.1 percent of the wholesale value of all gas produced in the United States.[4] I further estimate that a methane price designed to fully internalize its social cost would reduce emissions by about 76 percent at an annual net cost of only $261 million.[5] Under such a policy, the average cost per ton of CO_2-equivalent emissions abated would be about $3.70, which is substantially lower than empirical estimates of abatement costs for many proposed and existing climate policies.

Previously, abatement costs for methane emissions have been primarily estimated using bottom-up engineering approaches.[6] While these engineering cost studies are useful, they are limited in their ability to account for opportunity costs, learning, heterogeneity in real-world

[2] In other words, if there are no market failures, profit-maximizing firms will choose an emission rate that sets the marginal cost of capturing one unit of gas equal to the marginal private benefit of being able to sell that unit of gas, i.e. the gas price.

[3] Note that accurately monitoring CH_4 emissions from the gas supply chain presents a significant challenge to successfully implementing methane pricing at this time. Unlike smokestack CO_2 emissions, fugitive CH_4 emissions are inherently difficult to measure. However, technological advancements are rapidly lowering monitoring costs and market-based instruments may still be effectively deployed under conditions of imperfect measurement (Stranlund *et al.*, 2009; Cremer & Gahvari, 2002).

[4] This figure represents only physical abatement costs and sets aside questions of how tax or permit revenue might be distributed. It also accounts for firms being able to sell captured gas.

[5] Note that this is an out-of-sample prediction, as average annual gas prices range from about $2-$6 per thousand cubic feet (Mcf) over the study period while the social cost of methane is about $27 per Mcf leaked. This figure is for emissions generated in 2020 assuming a 3 percent discount rate and normalized to 2018 dollars (EPA, 2016).

[6] See, for example, ICF (2016), EPA (2015), or Delhotal *et al.* (2006).

conditions, and various other factors. This is well-documented for GHG abatement through investments in energy efficiency (Fowlie *et al.*, 2018; Gillingham & Palmer, 2014; Allcott & Greenstone, 2012) and carbon sequestration (Lubowski *et al.*, 2006; Stavins, 1999).

Instead of relying on engineering cost estimates, this paper relies on the condition that profit-maximizing firms equate marginal private benefits with marginal costs. This condition enables the use of spatial and temporal variation in natural gas prices to identify how much firms expend to reduce emissions.[7] By implicitly capturing the firm's decision-making process to employ the most efficient abatement measures first, this approach is able to account for all factors that are known to the firm but not directly observed by the econometrician. This makes it particularly useful for predicting the effect of regulating methane using an emissions tax or trading program, which would similarly incentivize firms to exploit the least costly abatement opportunities first.

This work falls under a broad strand of literature in economics that uses empirical methods to estimate abatement costs.[8] Previous studies have estimated abatement costs from various existing or proposed environmental policies (Fowlie *et al.*, 2018; Meng, 2017; Anderson & Sallee, 2011) and from the deployment of specific abatement technologies (Callaway *et al.*, 2018). One particularly related example is Cullen & Mansur (2017), who use variation in natural gas prices following the shale revolution to recover a short-run CO_2 abatement cost curve for the U.S. electricity sector. This paper also contributes to an emerging economics literature on methane leakage. Focusing on the distribution sector, Hausman & Muehlenbachs (2016) quantify regulatory distortions that allow gas utilities to pass the cost of leaked gas through to their ratepayers, resulting in inefficient levels of abatement. In the production sector, Lade & Rudik (2017) study the effects of a 2015 mandate limiting at flaring at oil

[7] I collect data on prices from S&P Global and data on methane emissions from the EPA's Greenhouse Gas Reporting Program (GHGRP). As is discussed in detail in Section 3, while the GHGRP is the most comprehensive dataset on methane emissions currently available, it does not provide a direct measurement of emissions, but rather an estimate based on equipment characteristics, emission factors, records of firm activity, and many other inputs. The empirical strategy used in this paper is designed to address noise and potential biases in this measure in order to make use of the signal that is available.

[8] A separate approach, which is typically employed to estimate abatement costs of global climate policies, is the use of computational general equilibrium modeling (e.g. Morris *et al.* 2012; Klepper & Peterson 2006).

and gas wells in North Dakota and estimate potential efficiency gains under a counterfactual market-based regulation.

This paper is the first to empirically estimate a marginal abatement cost curve for methane emissions from natural gas production, which accounts for about 60 percent of methane emissions from the U.S. gas industry (Alvarez *et al.*, 2018).[9] I introduce a novel identification strategy that exploits the fact that the pollutant is also a priced commodity to make detailed predictions about the potential impacts of methane policy.[10] While I have applied this strategy to production, it may be similarly employed to estimate methane abatement costs for the natural gas processing and storage sectors.[11]

I proceed by providing further background on methane leakage in the next section. Section 2 presents a model of firms' extraction and emission decisions that provides intuition for the empirics. Section 3 describes data sources for emissions, production, prices, and other variables used in the analysis. Section 4 presents the empirical strategy used to recover the relationship between emission rates and prices. Section 5 presents the simulation model of methane pricing and compares the estimates in this paper to other estimates of abatement costs. Section 6 concludes.

1 Background

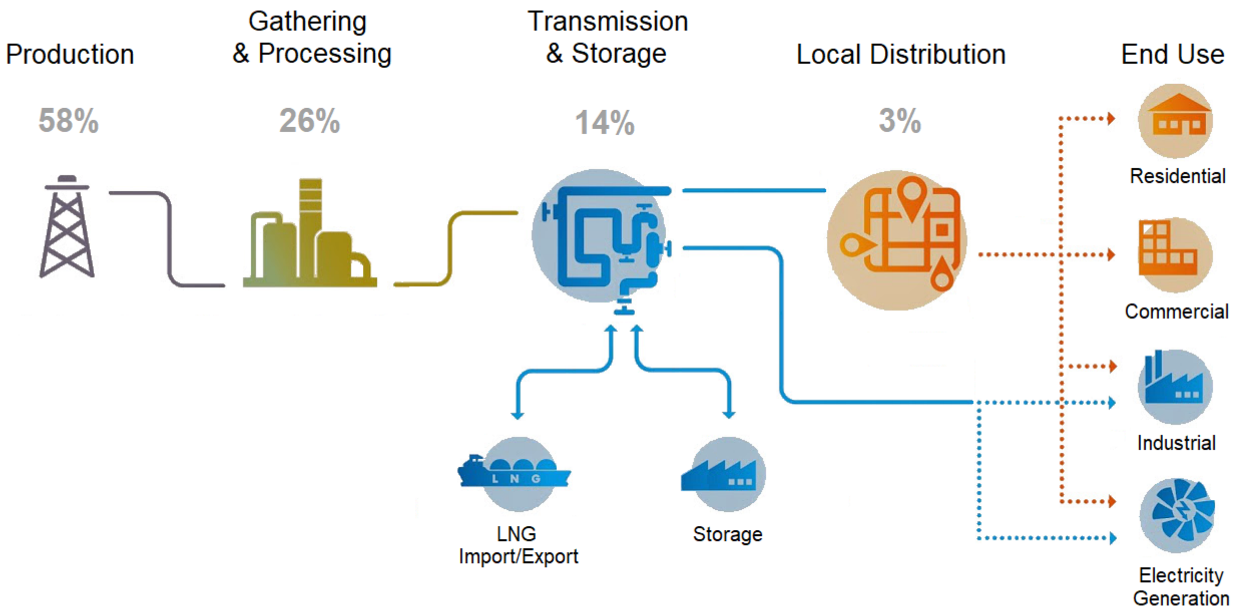
Methane (CH_4) accounts for about 16 percent of greenhouse gas emissions worldwide in terms of warming, making it the second most important greenhouse gas following carbon dioxide (CO_2) (IPCC, 2014). The three primary anthropogenic sources are agriculture, landfills, and the energy sector, where natural gas used for heating and electricity generation is composed of about 90 percent methane. Although there is still considerable uncertainty as to how much

[9] Lade & Rudik (2017) construct MACCs for avoided flaring as part of their analysis. However, their approach relies on engineering cost estimates and considers just one specific abatement technology.

[10] While this is the first paper to directly leverage this feature of methane to construct a MACC, the approach is similar in spirit to a set of recent studies that have used variation in energy prices as a proxy for carbon pricing (Cullen & Mansur, 2017; Ganapati *et al.*, 2016; Aldy & Pizer, 2015).

[11] This method is not applicable to the transmission or distribution sectors, which (at time of publication) are regulated such that pipeline owners are able to pass cost of lost gas through to their customers.

Figure 1: Methane emissions from the various components of the natural gas supply chain.



Estimates from Alvarez *et al.* (2018). Graphic adapted with pemission from AEMO NGFR.

gas is being emitted by each sector, the EPA's Greenhouse Gas Inventory (GHGI) estimates that the energy sector is presently the largest source in the U.S. and that production is the largest source within the sector (see Figure 1).[12] Natural gas production and consumption is projected to increase substantially both within the U.S. and globally for the foreseeable future, making it important to account for methane emissions in any broad-based climate change mitigation strategy (EIA, 2018; IEA, 2017).[13]

Broadly speaking, CH_4 is unintentionally released into the atmosphere at gas production facilities through leaks in extraction, initial processing, and transmission equipment. It is also intentionally vented during certain procedures in well completions, workovers, and maintenance.[14] There is a high degree of heterogeneity in leakage rates across facilities, which

[12] The GHGI is an EPA emissions monitoring project that is related to, yet distinct from, the GHGRP. While the GHGRP is focused on accurately tracking emissions for high-emitting facilities, the GHGI is focused on creating a comprehensive picture of all U.S. emissions at the industry level.

[13] The U.S. Energy Information Administration's Energy Outlook 2018 predicts increasing domestic gas production in all seven considered price and technology scenarios, with a 50 percent increase by 2050 in their reference scenario. The International Energy Information Agency's World Energy Outlook 2017 predicts a 20 percent increase in gas production by 2030 in their Sustainable Development scenario and greater increases in other scenarios.

[14] Well completion consists of all activities between actual drilling and extraction of gas for sale, which

is reflected both in scientific measurement studies (Sanchez & Mays, 2015; Subramanian *et al.*, 2015) and in the GHGRP, where production facilities' emission rates vary from less than .01 percent to over 10 percent. Finally, natural gas is often found alongside petroleum, in which case it may be either vented, flared, or collected and sold (if it is economical to do so) by wells that primarily extract oil.[15]

As of now, regulations on methane emissions from oil and gas production are not well-established in the United States. In late 2016, the EPA introduced performance standards for new wells, processing plants, and compression stations. In 2018, however, the EPA's new administration proposed amendments that would greatly weaken these requirements. Also in 2016, the Bureau of Land Management (BLM) finalized a policy to require wells located on federal and tribal lands to capture high percentages of gas in place of venting and flaring on the basis of conserving federal resources. However, this policy was never implemented and its future remains uncertain. In terms of local regulations, in 2014 Colorado introduced relatively strong performance standards for new and existing wells, including equipment mandates, waste-reducing procedures during well completion, and semi-annual leak detection and repair. In 2015, North Dakota introduced regulations limiting flaring that primarily affected co-produced gas at oil wells.[16]

2 Theoretical Framework

This section develops a theoretical model of the production and emission decisions faced by natural gas production firms in order to motivate the empirical analysis of firms' abatement costs. I begin by deriving firms' first order conditions for leakage and abatement and proceed to demonstrate how a relationship between price and abatement costs can be mapped to a

includes installing equipment and testing, as well as hydraulic fracturing and retrieval of fluids for tight-gas reservoirs. Workovers describe major operations to repair or stimulate gas flow at existing wells.

[15] Because oil and gas are so often co-located, petroleum and natural gas production facilities are not differentiated in the datasets used in this paper.

[16] The EPA regulations came into effect in August 2016. Because this policy affects all production in the United States, its impact should be picked up by time fixed effects. I control for Colorado and North Dakota regulations in the empirical analysis.

relationship between a potential emissions tax and abatement costs.

2.1 The Firm's Problem

Consider the profit function of a gas production firm's operations within a single basin:

$$\pi_t = P_t(Q_t - L_t) - C(Q_t, L_t, X_Q, X_L) \tag{1}$$

P_t is the price of gas in period t, Q_t is the quantity of gas the firm extracts in t, L_t is the quantity of gas it leaks, and $C(\cdot)$ is its total cost. I assume the firm is a price-taker selling into a perfectly competitive wholesale gas market.[17] Because the quantity of gas leaked depends on the amount of gas flowing through the facility's equipment, it is useful to decompose leakage into the product of extraction and a leakage rate $R_t = L_t/Q_t$:

$$\pi_t = P_t(1 - R_t)Q_t - C(Q_t, R_t, X_Q, X_R) \tag{2}$$

In this framework, the firm's problem consists of choosing how much to extract alongside choosing how careful to be to avoid leaks. This characterization makes it possible to separate $C(\cdot)$ into costs of extraction that are unrelated to the facility's leakage rate (i.e., costs of obtaining leases, capital costs for equipment gas does not pass through) and costs that determine the leakage rate (i.e., the additional up-front capital costs for equipment that emits less, labor costs for leak detection and repair). If we assume leakage-related costs are separable for each unit of extraction, we can write the firm's optimization problem as the following:

$$\pi_t = \max_{Q_t, L_t} \; P_t(1 - R_t)Q_t - C_1(Q_t) - Q_t c_2(R_t) \tag{3}$$

Here, $C_1(\cdot)$ is the *total* cost of extraction not related to the leakage rate and $c_2(\cdot)$ is

[17] The U.S. gas production sector has been generally viewed as competitive following deregulation in the 1980s and 1990s (Gabriel *et al.*, 2005).

the *per-unit* cost of having leakage rate R_t. This decomposition allows costs not associated with leakage to be nonlinear in production. For example, one might imagine that the cost of acquiring new leases in a given basin increases as the firm increases production because the total number of leases is finite. On the other hand, costs associated the leakage rate are assumed to be the same regardless of the firm's level of production. For example, paying a worker to inspect one well site for leaks is assumed to cost the same amount whether the firm operates 50 wells or 5,000 wells. However, $c_2(\cdot)$ is nonlinear in R_t—in particular, it is decreasing and convex such that it approaches infinity as the leakage rate approaches zero. The convexity captures the intuition that, due to diminishing returns, bringing the leakage rate down from 5 percent to 4.5 percent will be significantly cheaper than bringing it down from 1 percent to 0.5 percent.

The firm's first-order condition for Q_t sets the marginal revenue generated by extracting one unit of gas equal to the marginal cost of extracting it:

$$P_t(1 - R_t) = \frac{\partial C_1(Q_t)}{\partial Q_t} + c_2(R_t) \tag{4}$$

Note that the firm's marginal revenue for one unit of extraction is lower than just the gas price, as only the portion that is not leaked may be sold. In the firm's first-order condition for R_t, however, the firm's marginal revenue of avoiding one unit of leakage is simply the gas price, since the whole unit may be sold:

$$P_t = -\frac{\partial c_2(R_t)}{\partial R_t} \tag{5}$$

Equation (5) forms the basis for the empirics: When maximizing profits, the firm chooses a leakage rate that sets the price equal to their marginal cost of leakage abatement.[18,19]

[18] Note that $-\frac{\partial c_2(R_t)}{\partial R_t}$ is positive because c_2 is decreasing in R_t.

[19] The one-period framework presented here is useful for setting up a tractable empirical model, but it oversimplifies some important temporal aspects of the firm's true decision making process. In Appendix A.1, I extend this framework to a dynamic model and discuss empirical applications that may become possible with more detailed emissions data, should it become available.

Intuitively, if one unit of gas can be sold for P_t, the firm will be willing to expend up to P_t to prevent it from being lost.

2.2 Addition of an Emissions Tax

The implementation of a tax on methane emissions adds another term to the firm's profit function as follows:[20]

$$\pi_t = \max_{Q_t, L_t} \; P_t(1 - R_t)Q_t - C_1(Q_t) - Q_t c_2(R_t) - Q_t R_t T \tag{6}$$

Here, in addition to costs associated with extraction and costs associated with preventing leakage, the firm must pay $\$T$ for each unit of methane emitted.[21] The first-order conditions for the optimal emissions rate now simplifies to:

$$P_t + T = -\frac{\partial c_2(R_t)}{\partial R_t} \tag{7}$$

Equation (7) illustrates that the firm now chooses a leakage rate that sets its marginal cost of preventing one unit of gas from escaping equal to the commodity value of that unit of gas plus the avoided emissions tax. This implies that an emissions tax on CH_4 would have the same effect on fugitive emissions as a change in the price of gas of the same amount, which makes it possible to use an estimated relationship between leakage and prices to predict how leakage would respond to the implementation of an emissions tax.[22]

[20] In this section as well as in the empirical analysis I consider a hypothetical emissions tax; however, results are also applicable to permit prices under an emissions trading approach. Discussion of whether one instrument may be more appropriate than the other for regulating methane is beyond the scope of this paper.

[21] For simplicity, the theoretical model assumes extracted gas is 100 percent methane. I account for the methane content of extracted gas when simulating the effect of a methane tax in Section 5.

[22] The emissions tax will have some impact on the firm's production decision as well, but to a much lesser degree. The firm's first order condition for Q_t with an emissions tax is $P_t(1-R_t)+R_tT = \frac{\partial C_1(Q_t)}{\partial Q_t} + c_2(R_t)$. R_t is generally very low (the average emission rate for the quality-trimmed sample is just 1.1 percent) and in fact will decrease further as the firm decreases leakage in response to the emissions tax, so the impact of an emissions tax on production will be far smaller than the impact of a price increase of the same amount.

3 Data

The EPA's Greenhouse Gas Reporting Program provides an annual measure of fugitive methane emissions for nearly 700 onshore gas production facilities during the period from 2011 through 2016. Facilities are delineated at the firm-basin level, meanings most facilities include hundreds or thousands of wells. Emissions from all equipment at all wells operated by a firm within a single basin along with all of the firm's completion and well maintenance activity of the firm within that basin are aggregated into a facility-level estimate. Most of the variables used to construct the facility-level emissions estimate are also reported (at the facility level), including specific emissions from various types of equipment and procedures, equipment counts, and levels of extraction.[23] These data are collected through a comprehensive survey that is mandatory for all U.S. facilities producing at least 25,000 tons of CO_2-equivalent GHG emissions (tCO_2e) annually.[24]

In contrast to emissions from fuel combustion, which firms are generally required to report to the GHGRP using continuous emissions monitoring sensors placed in smokestacks, fugitive methane is not measured directly. Instead, the GHGRP provides firms with a framework for calculating these emissions using equipment characteristics and emissions factors (either type-specific or estimated averages) in combination with records of throughput, maintenance, installation, etc. For some devices, firms are also instructed to test for leaks around individual pieces of equipment. The firm is also required to report venting and flaring activity associated with well completions and workovers.[25]

I use the GHGRP because it is the most comprehensive and consistent source of panel data on methane emissions from natural gas currently available for this analysis. However, it should be noted that a number of scientific studies have shown it to be relatively noisy and

[23] Unfortunately, many useful supplementary variables (e.g. gas production, oil production, well IDs) are only available for 2015 and 2016.

[24] This includes a large number of gas processing plants, compression stations, and storage sites, as well as power plants, factories, refineries, landfills, and other types of facilities that are not part of this analysis.

[25] See Table A8 in the Appendix for a partial list of factors that enter GHGRP CH_4 emission calculations that are directly dependent on firm abatement decisions.

subject to some biases.[26] The source of bias that has the biggest implications for this analysis is that GHGRP methodology fails to effectively capture all sources of methane emissions, meaning that both total emissions and total abatement will be understated in this paper. One approach would be to scale emissions up using the best available scientific estimates for actual emissions. However, rather than introducing the additional assumptions necessary to do so, I elect to exclude underrepresented emission sources and present results in terms of emissions as reported to the GHGRP.[27]

Although this overall downward bias in facility-level emissions estimates is carried through to the empirical analysis, particular biases relevant to the responsiveness of firms' emitting behaviors to prices are not problematic as long as they are not systematically correlated with unobserved determinants of natural gas prices. Examples of these biases include differences across firms in levels of effort put toward accurate reporting, changes to the GHGRP methodology over time, and differences in firms' beliefs about the effectiveness of various abatement activities.[28] Such potential biases are netted out by facility and fixed effects, making it possible to accurately recover the abatement behaviors that are effectively captured by the GHGRP.

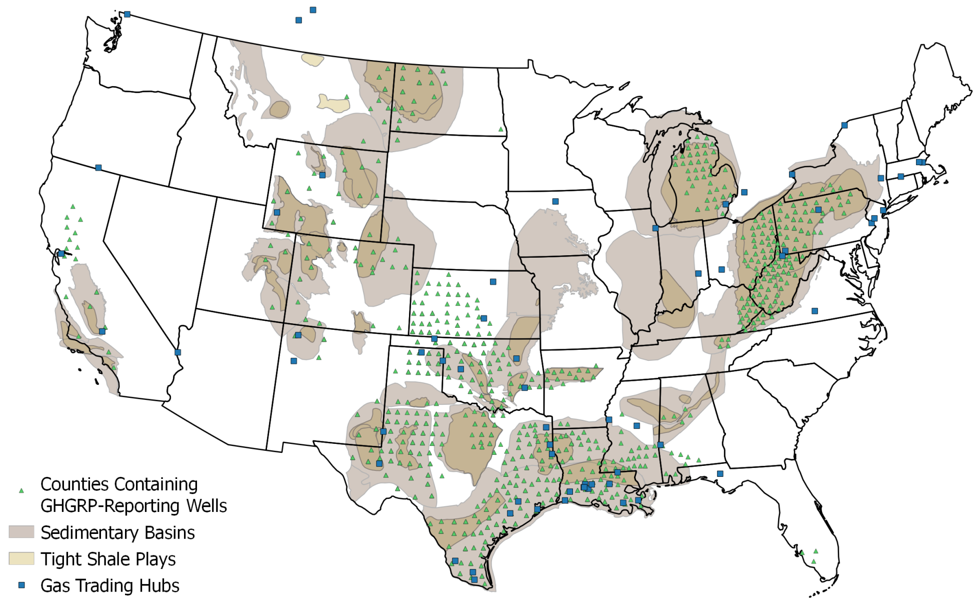
I collect data on facility-level gas and oil production through DrillingInfo (DI), an industry

[26] For example, aerial surveys of the Denver-Julesburg basin and Barnett shale regions have detected CH_4 emissions from production sites about three times greater than those reported to the GHGRP (Lyon *et al.*, 2015; Petron *et al.*, 2014). Subramanian *et al.* (2015) perform a bottom-up study of compression stations that estimates similar levels of underreporting due to "super emitting" facilities with severe leaks, the usage of incorrect emissions factors, and the failure to account for some sporadic emissions sources. Lastly, a recent meta-analysis of many bottom-up and top-down studies concluded that actual CH_4 emissions from the U.S. gas industry are about 60 percent greater than those estimated by the EPA's Greenhouse Gas Inventory (Alvarez *et al.*, 2018).

[27] The scientific literature shows that emissions related to firm decisions about maintenance (i.e. equipment leaks) are particularly poorly captured by the GHGRP. In order to linearly scale estimated abatement up to incorporate these emissions as well, it would be necessary to assume that emissions related to maintenance respond in the same way to prices as emissions related to the other two categories.

[28] To elaborate, when a firm purchases higher quality equipment in response to a price signal, its decision is based on its belief about how much additional gas the new unit will recover. This may differ from the equipment's actual abatement potential or from GHGRP emission factors. If, for example, the firm believes a purchased device's actual emission factor is lower than the factor used in the GHGRP, and the firm's beliefs are closer to reality, the sensitivity of that firm's emission rates to prices will be understated. However, if these beliefs are consistent within firms over time or are updated for all firms in a region in ways that are not correlated with prices, they will be picked up by fixed effects.

Figure 2: GHGRP onshore gas production facilities and natural gas trading hubs.



Production facilities are delineated at the firm-basin level in the GHGRP. Each green triangles marks a county containing at least one well that is part of a GHGRP facility, which in most cases means many wells associated with many different facilities. Basin boundaries are sourced from the Energy Information Administration (these boundaries are for illustrative purposes only and are not used in the analysis).

data provider that collects and digitizes government records of well and permit filings in near real-time. Through DrillingInfo, I am able to observe extraction activity at a daily level for the vast majority of wells in the United States. Because production facilities in the GHGRP are delineated at the firm-basin level (i.e. all of the drilling, extracting, and initial processing equipment used by one firm within one basin is considered to be a single facility), I link the two datasets by aggregating wells in DrillingInfo to the firm-basin level (see Figure 2). Firm names are not always consistent across the two datasets and asset sales are common in the oil and gas industry, both of which present potential sources of error in manually matching the two datasets. I ensure the quality of matches by removing facilities that differ in production in excess of 25 percent between the GHGRP and DrillingInfo, using the variable for production that is reported to the GHGRP in 2015 and 2016 but not in earlier years.[29]

[29] This implies that facilities that stopped reporting before 2015 are excluded from the analysis. Figure A3

Table 1: Summary statistics for the full GHGRP sample and the quality-trimmed sample.

		Full Sample		Trimmed Sample	
	Source	**Mean**	**SD**	**Mean**	**SD**
CH_4 Emissions Rate	GHGRP & DI	0.3894	4.0953	0.0108	0.0152
CH_4 Emitted (MMcf)	GHGRP	217	518	266	389
From Completions	GHGRP	29	169	34	134
From Equipment	GHGRP	117	276	143	222
From Maintenance	GHGRP	49	110	58	116
Gas Production (MMcf)	DrillingInfo	57,729	164,731	63,436	98,459
Oil Production (Mbbl)	DrillingInfo	4,199	10,854	4,523	10,992
Wells Per Facility	DrillingInfo	797	1,409	879	1,489
Completions	DrillingInfo	35	73	47	90
Wholesale Gas Price ($/Mcf)	S&P	3.23	0.83	3.20	0.85
Number of Facilities		683		222	
Total Observations		2,980		1,150	

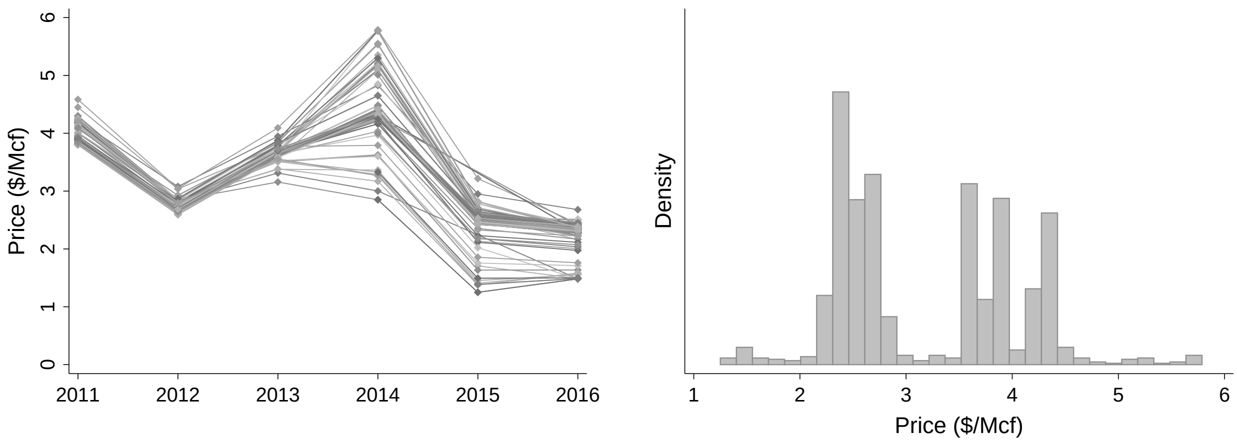
Mcf ≡ Thousand cubic feet; MMcf ≡ Million cubic feet; Mbbl ≡ Thousand barrels

Facility i's methane emission rate R_{it} is constructed by dividing i's total methane emissions in year t by its total gas production in t. To reduce the potential influence of inaccurate reporting, I further trim the 5 percent of outliers in leakage rates on either end (10 percent total). The 223 facilities that remain in the trimmed sample tend to be slightly larger and perform slightly more completions on average, but are otherwise representative of the full sample (see Table 1). On average, each facility has about 900 wells, though there is a substantial degree of variation in facility size, ranging from only a handful of wells to over 10,000. Gas production, oil production, and CH_4 emissions are similarly highly heterogeneous across facilities. The average emission rate for the trimmed sample is 1.08 percent.

I collect spot natural gas prices from S&P Global Market Intelligence. Natural gas is traded at "hubs" that are geographically dispersed across the United States, which sometimes correspond to specific points where many interstate pipelines intersect, but more often actually represent an aggregation of all transactions along certain sections of one or more

shows the distribution of how well facilities match on production and the 25 percent cutoff—which is admittedly somewhat arbitrary, though results are robust to using other thresholds.

Figure 3: Variation in natural gas spot prices (each line represents one facility).



pipelines. For simplicity, I use the centerpoint of hubs that consist of stretches of pipelines, which are geocoded from S&P's energy mapping interface. Spot prices are available at 96 hubs for the six-year period for which GHGRP data are available. I link GHGRP facilities with hubs by taking a weighted average of the prices at hubs closest to the centroids of the counties that the facility operates in (see Figure 2). For example, if a facility operates in 3 counties closest to hub A and 2 counties closest to hub B, the price for that facility would be $\frac{3}{5}P_A + \frac{2}{5}P_B$.

Gas prices are spatially correlated, as gas moves continuously through a nationwide network of pipelines, but this correlation diminishes with distance due to transportation costs and transmission constraints. Accordingly, prices at two hubs close to one another will usually be highly correlated, while prices at hubs located across the country from one another will be much more divergent. As shown in Figure 3, there is considerably more variation in prices in the last three years of the study period than there is in the first three years, which may be in part due to binding transmission constraints during the particularly cold winter of 2014-15.

4 Empirical Framework and Results

In this section, I estimate the relationship between price and emission rates at gas production facilities. I exploit temporal and spatial variation in gas prices, control for a wide array of potential sources of endogeneity with facility and region-by-year fixed effects, and employ a second-order fractional polynomial (FP) model to capture nonlinearities. However, I also demonstrate that my results are robust to a variety of more restrictive and more flexible models. I additionally explore the mechanisms by which firms reduce emissions in response to higher gas prices, including equipment upgrades, avoiding waste during completions, and leak detection and repair.

4.1 Fractional Polynomial Regression

To account for potential nonlinearity, I estimate the relationship between firms' emission rates and gas prices as a second-order fractional polynomial model:[30]

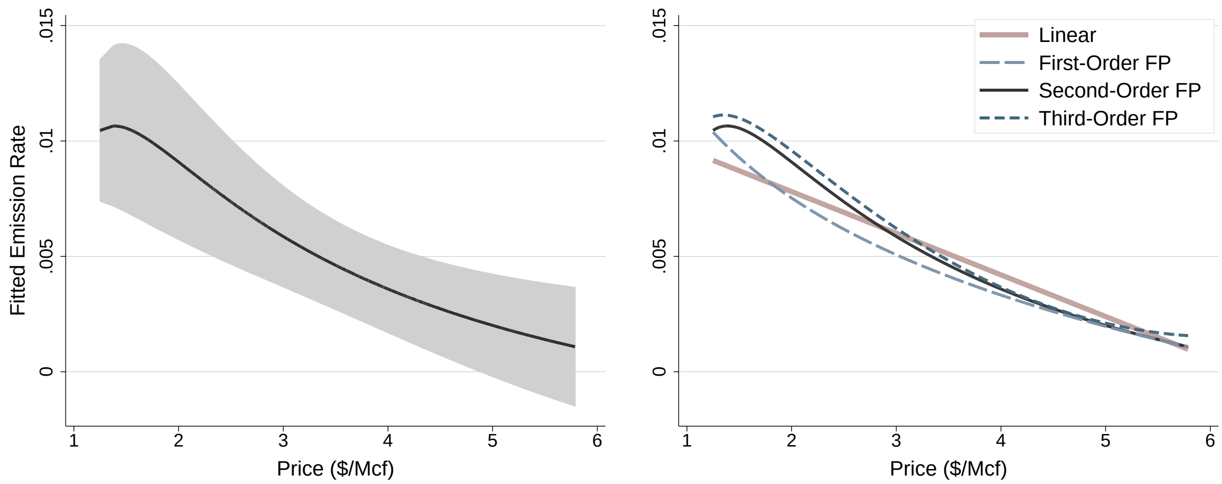
$$R_{it} = \beta_0 + \beta_1 P_{it}^A + \beta_2 P_{it}^B + \mathbf{X}_{it}\psi + \gamma_i + \lambda_{rt} + \varepsilon_{it} \tag{8}$$

R_{it} is the facility i's emission rate in year t and P_{it} is the price of gas it faces. The powers A and B are determined by the data from a set of predefined possibilities as the parameters that provide the best fit under maximum likelihood estimation.[31] Time-varying controls $\mathbf{X}_{it}$ include oil extraction, completions, number of wells, and indicators for whether the majority of the facility's wells were located in Colorado after 2014 or North Dakota

[30] Fractional polynomial models are an extension of traditional polynomial models that allow a more diverse set of transformations of the independent variable of interest. They overcome a number of limitations, such as oversensitivity to tails of the data, while still maintaining the desirable characteristics of linear regression, such as ease of incorporating fixed effects (Royston & Altman, 1994).

[31] The fractional polynomial methodology requires separately estimating specifications for all possible combinations of A and B to determine the best fit. Following standard practice in the literature, I use -2, -1, -.5, .5, 1, 2, and 3 as the possible values of A and B, as well as the natural log (i.e. $\log(P_{it})$ in place of P_{it}^A) (Sauerbrei *et al.*, 2006). In the second-order model—meaning two transformations of P—this implies 44 potential models. Each of these 44 models is separately estimated using maximum likelihood estimation, and only results from the model that provides the best fit in terms of having the highest likelihood are reported.

Figure 4: Relationship between emission rates and prices estimated using a second-order fractional polynomial (left) and comparison with alternative specifications (right).



after 2015.[32] Facility fixed effects γ_i net out facility-specific determinants of emissions and potential biases in GHGRP reporting that are persistent within a facility over time. Region-by-year fixed effects λ_{rt} net out potential biases that are consistent across facilities within a particular region and year, such as regional economic shocks that could affect both prices and behaviors associated with emissions.[33] Region-by-year effects also control for changes to the GHGRP methodology over time that affect all facilities. I weight observations by facilities' average gas production over the study period.[34]

The predicted relationship between price and emission rates from the second-order fractional polynomial model is presented in the left panel of Figure 4. It is evident that at nearly all gas prices there exists a downward-sloping relationship between price and emission rates. Conditional on the included fixed effects, production at low gas prices is predicted to leak at about 1 percent and production at the highest average annual gas prices observed during the

[32] These two fixed effects control for the impact of methane regulations introduced in those states. A robustness check excluding the Mountain region altogether produces results that are highly similar in character but less precisely estimated (see Appendix A.4).

[33] Regions follow the U.S. Energy Information Agency's five natural gas storage regions (Pacific, Mountain, Midwest, South Central, and East).

[34] This makes the estimated curve representative of the effect of price on the emission rate of an average unit of gas production, rather than on the emission rate of an average facility, which is preferable for constructing results for the sector in aggregate.

Table 2: Relationship between natural gas spot price and CH_4 emission rate estimated using linear and fractional polynomial models.

	(1)	(2)	**(3)**	(4)
Model	Linear	1st-Order FP	**2nd-Order FP**	3rd-Order FP
P_{it}	-0.0018***			
	(0.0006)			
$\log(P_{it})$		-0.0061***		
		(0.0017)		
$P_{it}^{-0.5}$				0.0493***
				(0.0168)
P_{it}^{-1}			0.0460***	
			(0.0154)	
P_{it}^{-2}			-0.0319***	-0.0202**
			(0.0123)	(0.0085)
P_{it}^{3}				0.00001
				(0.00001)
Facility FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes
N	1,150	1,150	1,150	1,150
adj. R^2	0.632	0.633	0.633	0.632

Standard errors in parentheses (clustered at the parent firm level with 146 firms)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

study period is predicted leak at about .15 percent. The apparent convexity of this relationship is consistent with diminishing returns to abatement activities—i.e., that those facilities facing generally higher prices have already exploited the cheapest abatement opportunities.[35]

Results are similar across a range of more restrictive and more flexible models. A comparison with first- and third-order fractional polynomials is presented in the left panel of Figure 4. All three demonstrate a downward-sloping, convex relationship between price and emissions. The third-order FP, which tests 164 possible functional forms, is nearly identical to the second except with slightly greater convexity. Coefficient estimates for all three models

[35] Below about \$2/Mcf, the curve becomes concave and even changes sign at the very lowest prices (though this change in slope is not significant). Though it is possible there exists some unknown phenomenon that generates a positive relationship at exceptionally low gas prices, limited support over this range and the fact that this upward-sloping segment disappears in many alternative specifications suggests it is likely to be spurious.

and a linear specification are reported in Table 2. For the fractional polynomial specifications, the transformations of P_{it} that best fit the data are identified by the presence of coefficient estimates—for example, the best fit for the second-order model is $R_{it} = \beta_0 + \beta_1 P^{-1} + \beta_2 P^{-2}$. The best fit for the first-order model is simply a log transformation of price. In this model, a 1 percent increase in price is associated with a 0.006 percentage point decrease in emission rates. Scaling this result up, a 30 percent increase in price—about \$1 for an average facility—would be associated with a 0.18 percentage point decrease in emission rates (i.e. from 1 percent to .82 percent).

As shown in Figure A4 in the Appendix, the existence of a downward-sloping relationship over the range for which there is substantial variation in price (about \$2-\$4.50) persists across many alternative specifications. These include removing weights, trimming emission rates at the 1 percent level instead of at the 5 percent level, and using basin-by-year fixed effects in place of region-by-year fixed effects. As shown in Table A3, wide confidence intervals for the specification with basin-by-year fixed effects are driven by the constant term rather than the coefficients on price, which are precisely estimated. However, a model using only year fixed effects in place of region-by-year effects does not generate meaningful results, indicating the existence of important regional trends that obscure the effect of price on emissions. I additionally find that the existence of a negative relationship between emissions and price is robust to the application of a negative binomial model, which specifically addresses the potential failure of the assumption of normally-distributed errors that may arise when OLS is used in a setting where the dependent variables is a rate. The methodology and results for this model are presented in Appendix A.2.

I investigate two other potential threats to identification using an instrumental variables (IV) approach. Although the included fixed effects control for possible omitted variables that are constant within facilities over time or across facilities within a particular region and year, a valid instrument for price would eliminate the impact of possible omitted variables that vary at the facility-year level. Furthermore, isolating variation from demand-side price shocks would ensure there is no chance of reverse causality.[36] I therefore explore using various weather variables to instrument for price. Results, presented in Appendix A.3, are broadly similar to the results from non-instrumented specifications, but not statistically significant.[37]

4.2 Abatement Mechanisms

To assess whether the aggregate results presented in the previous section are indeed driven by firms adjusting their abatement behaviors in response to changes in prices, I examine a subset of variables that compose the GHGRP's facility-level emissions estimate. In particular, I test whether price changes predict the installation or removal of four types of equipment that are straightforward to measure and known to have high abatement potential, as well as two measures of gas conservation during hydraulic fracturing completions.[38]

The first type of equipment considered is pneumatic pumps, which are used at some wells for injecting chemicals that encourage the flow of natural gas or oil. "Pneumatic" in this context means the pumps rely solely on pressure from gas exiting the well for power, and they are designed continuously emit or "bleed" some fraction of this power gas. Pneumatic pumps can be replaced by electric units that have a higher up-front capital cost but near-zero emissions, so ex-ante one would expect higher prices to predict fewer pneumatic-type pumps. Next are pneumatic controllers, which regulate the flow of gas through equipment or connections. The GHGRP classifies high-bleed and low-bleed controllers based on whether they emit more or less than 6 Scf per day. While some purposes require high-bleed devices, the majority of high-bleed devices can potentially be replaced with more costly low-bleed

[36] In other words, lower emission rates caused by some other exogenous force could decrease prices by increasing the amount of natural gas available for sales. This effect would attenuate my results, as it would imply a positive correlation between emission rates and prices.

[37] Inconclusive results from the IV model are at least partly due to limited statistical power. The limiting dataset is the GHGRP, which reports emissions at a facility-year level (production and price variables vary at a daily level). This approach may become viable in the future if satellite methane emissions data with sufficient temporal and spatial resolution becomes available.

[38] Although data on about a dozen equipment types are available in the GHGRP, pneumatic controllers and pumps are well-suited for regression analysis because their contributions to aggregate emissions (as reported in the GHGRP) are based solely on equipment counts and operating times, with a uniform emissions factor.

Table 3: The relationship between price and equipment counts for four types of emitting devices (Columns 1-4) and two measures of firms' activities to avoid leakage during well completions and workovers (Columns 5 and 6).

	(1) **Pneumatic Pumps**	(2) **Intermittent Pneumatic Controllers**	(3) **High-Bleed Pneumatic Controllers**	(4) **Low-Bleed Pneumatic Controllers**	(5) **Venting Days**	(6) **Mcf of Gas Recovered For Sales**
P_{it}	-212.5**	-692.9***	-9.8	3.9	-6.7	67,064,000
	(93.9)	(260.3)	(284.8)	(20.5)	(5.9)	(71,686,000)
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	737	1,055	1,055	1,055	716	716

Standard errors in parentheses (clustered at the parent firm level with 146 firms)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

devices or zero-bleed devices that are powered by electricity rather than gas (McCabe *et al.*, 2015).[39] Additionally, another class of controllers only releases emissions intermittently. Intermittent-bleed controllers are much more heterogeneous in emission rates, but they can also often be replaced by low-bleed or zero-bleed devices.

Another substantial source of methane emissions is flaring and venting gas into the atmosphere during well completions and workovers. Up to 2014, the GHGRP required firms to report the number of days gas was vented into the atmosphere for each completion or workover, as well as the quantity of gas (if any) that was captured for sales.[40] Although changes in gas prices should not affect firms' decision between venting or flaring gas, higher gas prices will incentivize firms to capture gas for sales rather than either flare or vent it.

I separately estimate linear regressions of each of these variables using the same set of independent variables as before.[41] Results, presented in table Table 3, are consistent with firms

[39] There is no clear ex-ante prediction for low-bleed devices, as higher prices may cause firms to switch from high-bleed to low-bleed devices and/or cause firms to switch from low-bleed to zero-bleed devices.

[40] In 2015, the GHGRP changed its methodology to allow two potential equations for firms to calculate emissions from completions and workovers. The new methodologies likely improved the quality of measurement, but are considerably less straightforward to analyze.

[41] For consistency, these regressions use the same trimmed sample as above. However, because these variables are in levels rather than rates and are thus not reliant on matching with DrillingInfo data, it is possible to estimate them using entire GHGRP sample. The results of this robustness check are presented in Table A4

adjusting their emitting behaviors in response to price in most cases. In particular, I find that higher prices predict fewer intermittent-bleed controllers, fewer gas-driven pneumatic pumps, fewer days on which gas from completions or workovers was vented, and more gas from these operations being recovered for sales (though only the former two are statistically significant).[42] There is no evidence that counts of high-bleed devices or low-bleed devices are affected by price.[43] Although results for these GHGRP microdata variables are mixed, they are consistent with identifying a stronger result for specifications using the facility-level emissions estimate. The aggregation of many inputs captures more signal than can be recovered from any individual component while weakening the influence random noise caused by reporting errors.

4.3 Emissions by Source

Moving up one level in the GHGRP microdata to CH_4 emissions from various source categories enables further exploration of which behaviors drive the curve estimated above. Rather than estimate 15 separate regressions for each of the 15 separately-reported sources, I group sources into three broad categories: Emissions resulting from equipment purchase decisions, emissions from completions and workovers, and emissions associated with leak detection and repair. For example, in addition to pneumatic controllers and pumps, the equipment category includes emissions from dehydrators (which vary in components, dimensions, and input chemicals), and storage tanks (which may or may not use vapor recovery apparatus).[44] Emissions from sources that do not directly involve any firm decisions about emitting behavior, such as combustion CH_4 emissions, are excluded from this portion of the analysis.

I separately estimate the relationship between price and emission rates for each of the

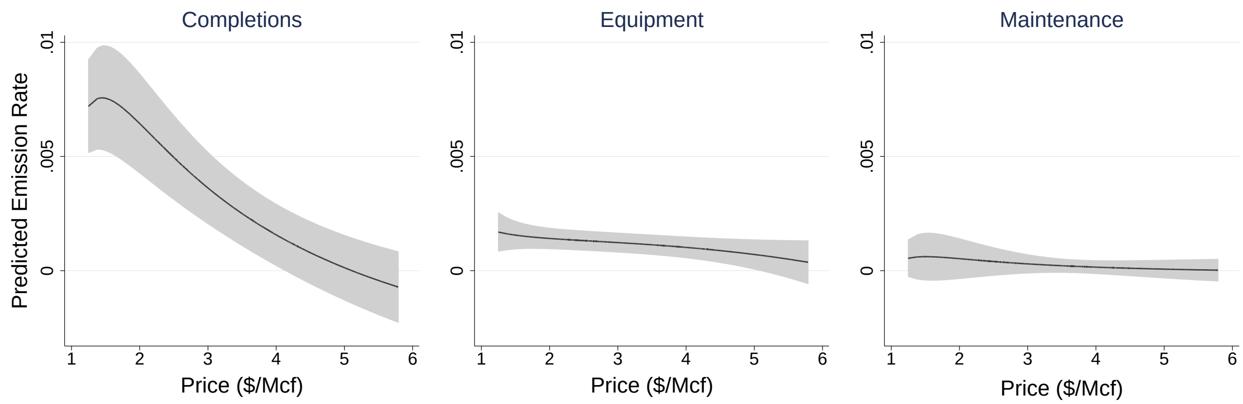
in the Appendix.

[42] Smaller sample sizes for pneumatic devices and pumps are due to missing data and smaller sample sizes for completion variables are due to missing data and the fact that the GHGRP stopped recording these variables in 2016.

[43] The expected impact of a higher opportunity cost for lost gas on low-bleed pneumatic devices is ambiguous ex-ante, as they may either be used to replace high-bleed or intermittent-bleed devices or themselves replaced with zero-bleed devices.

[44] A full account of which variables compose each category is provided in Table A8 in the Appendix.

Figure 5: Relationship between emission rates and price by emission source.



three source categories using the same second-order fractional polynomial model as before. Results, presented in Figure 5, show that the responsiveness of emissions rates to price detected above is driven primarily by emissions from well completion and to a lesser extent by emissions associated with equipment purchase decisions. Although there may be many reasons for this result, it is likely that timing plays a large role. In a given year, a facility's emissions from completions derive from decisions about how careful to be to avoid wasting gas when completing wells that year. In contrast, emissions related to the type of equipment installed at a facility derive from decisions made in previous years as well as decisions made the same year. Furthermore, past and present equipment choice decisions are made considering expectations of future prices as well as the current spot price.[45] Although there is insufficient power to separately identify the effect of lagged and forward prices on a facility's equipment emissions, it is plausible they are decreasing in these prices as well, making the estimate for the sensitivity of overall emissions to price a conservative one.[46]

[45] I formalize these conditions in Appendix A.1, which extends the theory section of this paper to a dynamic framework.

[46] By excluding lagged prices and forward prices, the reduced-form framework used in this paper is an oversimplification of the firm's true decision-making process. As the only measure of price included on the right-hand side, the spot price serves as a proxy for past prices, expectations of future prices, and past expectations of future prices (as well as current prices). A dynamic model would be necessary to separately identify the effects of these different price measures. Unfortunately, the facility-year delineation of the GHGRP affords limited statistical power for including additional measures of price as explanatory variables.

Emissions from leak detection and maintenance do not appear to be responsive to changes in the natural gas price.[47] However, it is important to note that leaks from equipment failure are most difficult to measure, making it likely this result is driven by the GHGRP methodology being less effective in detecting emissions reductions through improved maintenance. If this is the case, it would be another avenue by which my estimates of the sensitivity of overall leakage rates to price are conservative.

5 Predicting the Effect of an Emissions Tax

This section builds upon the results of Section 4 by using a straightforward simulation model to predict the effect of a tax on methane. Starting facilities at their average emission rates and prices faced over the study period, I incrementally increase prices and adjust facilities' emission rates following the slope of the estimated curve. I calculate emissions reductions and costs as prices increase, then aggregate these values to construct a marginal abatement cost curve for the sector. I examine abatement costs and benefits at a subset of policy-relevant methane prices and demonstrate that these results are robust to a variety of alternative model selection choices. Finally, I conclude the section by comparing these predictions to engineering estimates of abatement costs for methane emissions and to estimates of abatement costs in GHG-emitting sectors.

5.1 Simulation Model

The core of the simulation model consists of increasing the effective prices faced by facilities and decreasing their emission rates based on the slope of the curve estimated in the previous section.[48] Section 2 illustrates that the effect of higher prices on facilities' emission rates

[47] I also investigate 1-year lagged maintenance emissions under the hypothesis that leaks may not be detected and reported until the following year, which also produces a null result.

[48] I choose the second-order FP as my preferred specification primarily because it produces the most reasonable curve for out-of-sample predictions. Although the second- and third-order fractional polynomials produce highly similar curves over the data's support for gas prices, in the third-order model the cubic term dominates at higher prices, leading to an upward-sloping segment that is implausible in reality. As a

directly maps to the effect of a tax, as both increase the opportunity cost of lost gas in the same way. For simplicity, the theoretical framework presents this mapping as 1-to-1. In practice, however, a properly-implemented tax would only affect the methane content of the emitted gas. In this simulation, I assume all facilities extracted gas is 83 percent methane (the average for facilities in the GHGRP sample), such that a \$1 tax will decrease facilities emission rates by the same amount as would a \$0.83 price increase.[49]

As a reasonable baseline, the simulation starts facilities at their average values for emission rates and prices over the study period. A tax is then applied and increased incrementally in discrete steps of Δ_{T} up to \$32/Mcf, which roughly corresponds to a \$50/ton tax on CO_2.[50] Each step k increases facilities' opportunity cost of lost gas (denoted ρ below) by Δ_{T} times the methane content of the extracted gas (denoted μ). With $\bar{P}_i$ as facility i's baseline price, the opportunity cost of lost gas facility i faces in step k is then $\rho_{ik} = \bar{P}_i + \mu\Delta_{\mathrm{T}}k$. Facility i's emission rate in step k evolves according to the first derivative of the estimated second-order fractional polynomial fit:

$$R_{ik} \;=\; R_{ik-1} + \mu\Delta_{\mathrm{T}}R'(\rho_{ik}) \;=\; R_{ik-1} + \mu\Delta_{\mathrm{T}}(-\beta_1\rho_{ik}^{-2} - \beta_2\rho_{ik}^{-3}) \tag{9}$$

β_1 and β_2 are the estimated regression coefficients from Column 3 of Table 2. Rather than assume facilities can achieve zero emissions, I lower-bound emission rates at the lowest observed average emission rate among facilities in the trimmed sample (0.0223 percent).[51] Figure 6 illustrates this process.

Emissions reductions are recovered for each facility at each step as change in the facility's emission rate times the its initial level of gas production. Because the quality-trimmed sample

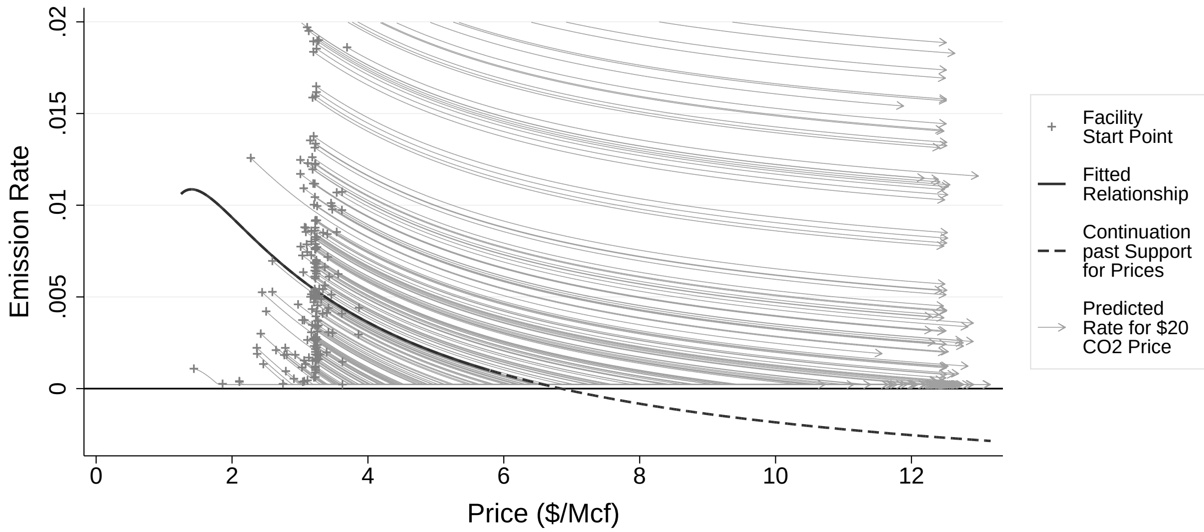
robustness check, I run the model using the first-order fractional polynomial curve, which predicts slightly greater abatement but at a slightly higher cost than the second-order model.

[49] In the context of describing methane emissions across the gas supply chain, Section 1 states that natural gas is composed of about 90 percent methane. That figure refers to "pipeline quality" gas, which has been processed to remove impurities and heavier gaseous hydrocarbons.

[50] For computational tractability, I use $\Delta_{\mathrm{T}} = \$0.05$. Results are not sensitive to choice of step size below \$1.

[51] Results are robust to lower-bounding facilities' emission rates at 0.1 percent. About one-tenth of facilities in the trimmed sample have average emission rates below 0.1 percent.

Figure 6: Predicted change in facilities' emission rates as an emissions tax is implemented.



Each facility is assumed to start at its average emission rate and average price faced over the study period, indicated by a +. As a tax on CH_4 is applied and increased, facilities decrease emission rates following the slope of the estimated relationship between emission rates and prices. The dotted line shows the continuation of the curve past the support of variation in prices (i.e. the range past which estimates become out-of-sample predictions). A tax on methane corresponding to a $20/ton tax on CO_2 is illustrated here. Note that emission rates are censored above 2 percent for readability.

of GHGRP facilities accounts for only about 40 percent of total gas production in the United States, I scale production up in order to make the estimated abatement cost curve reflective of a sector-wide emissions tax. To appropriately capture heterogeneity across facilities in leakage rates and prices (which are correlated with facility size), I proportionally increase facilities' production before running the simulation.[52] With $\bar{Q}_i$ denoting facility i's scaled baseline production, total abatement A at step K is calculated as:

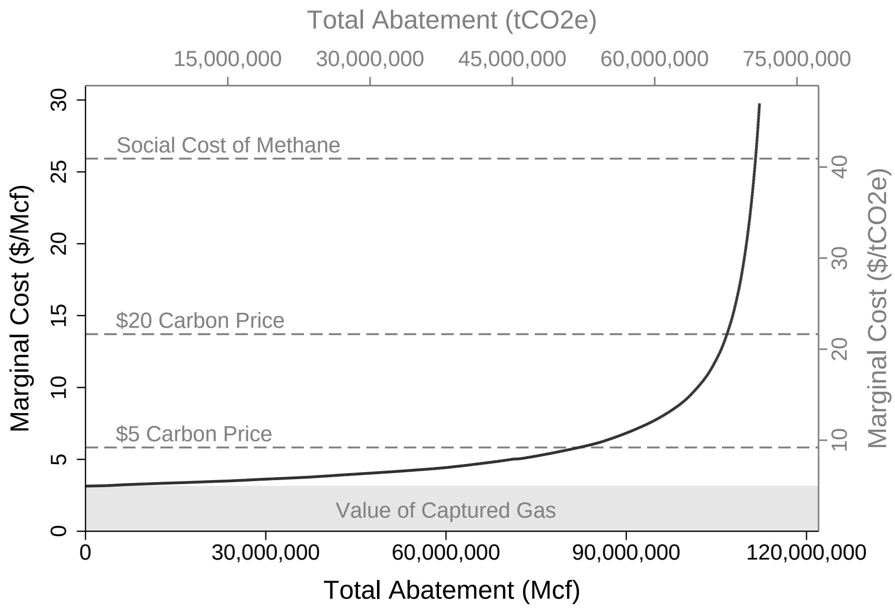
$$A_K = \sum_{k=1}^{K} \sum_{i} \bar{Q}_i (R_{ik} - R_{ik-1}) \tag{10}$$

Here, A_K is equivalent to predicted abatement under a methane tax of $\Delta_{\mathrm{T}} k$/Mcf. Marginal abatement cost at each step is the abatement-weighted average of ρ_{ik}.[53] Plotting total abate-

[52] Specifically, I multiply each facility's production by the ratio of the EIA estimate for gross gas production in the United States in 2016 (32,635 Bcf) to total gas production from the trimmed sample (13,012 Bcf).

[53] It is also possible to recover marginal cost at each step as the change in total cost divided by the change

Figure 7: Marginal abatement cost curve for methane emissions from natural gas production.



Note that carbon price policies do not directly correspond to marginal abatement costs because a.) firms expend about \$5/tCO_2e (just over \$3/Mcf) to capture gas in the absence of policy and b.) carbon price policies only affect the methane content of extracted gas.

ment against marginal abatement costs produces the marginal abatement cost curve shown in Figure 7. To facilitate comparison with other polluting sectors, I convert these variables to tons of CO_2-equivalent emissions on the alternate axes.[54] In general, the curve demonstrates that methane emissions from natural gas production are an area with substantial low-cost opportunities for greenhouse gas mitigation. Total CH_4 emissions from the natural gas production (as estimated by the GHGRP methodology and scaled up to include all U.S. production) are about 147,000,000 Mcf, meaning the majority of emissions from the sector can be abated. While the cost of realizing these reductions depends on the target level of abatement, it evident that a large portion of these reductions can be achieved at very low cost.

Point estimates and bootstrapped standard errors for three selected policy-relevant tax

in total abatement.

[54] I use the 100-year warming potential of 34 from the IPCC's Fifth Assessment Report (i.e. one ton of emitted methane results in warming equivalent to 34 tons of CO_2). One ton of methane at standard pressure contains 53.68 Mcf of gas, so 1 Mcf of methane = 34/53.68 tons of CO_2-equivalent emissions.

Table 4: Simulation results for a subset of potential methane prices.

Methane Tax	**Equiv. Carbon Price**	**Total Abatement**	**Total Abatement**	**Total Cost**	**Value of Captured Gas**	**Net Cost**
($/Mcf)	($/tCO$_2$e)	(tCO$_2$e)	(Percent)	($)	($)	($/Mcf)
3.17	5.00	51,974,000	56.1	333,574,000	264,142,000	0.0024
		(20,432,000)	(22.1)	(130,763,000)	(103,386,000)	(0.0010)
12.67	20.00	67,480,000	72.9	534,022,000	342,871,000	0.0067
		(28,060,000)	(30.3)	(237,556,000)	(141,536,000)	(0.0035)
27.37	43.21	70,632,000	75.9	624,502,000	359,045,000	0.0093
		(30,378,000)	(32.8)	(309,830,000)	(153,109,000)	(0.0057)

$27.37/Mcf is the social cost of methane under a 3% discount rate following (EPA, 2016)
Variables in Mcf and dollars rounded to nearest 1,000
Bootstrapped standard errors in parentheses

levels are presented in Table 4.[55] I estimate that a $5 carbon price (corresponding to a $3.17/Mcf tax on methane) would decrease emissions from the sector by 56 percent. This corresponds to a decrease of about 82 billion cubic feet of fugitive methane emissions annually, which is about 52 million tons of CO_2-equivalent emissions. At this tax level, the marginal unit of abatement would cost firms about $5.83/Mcf ($9.20/tCO$_2$e) and the total cost to the sector would be $334 million. However, the total wholesale value of the captured gas (calculated at the facility level using average gas prices faced over the study period) would be $264 million, implying an overall net cost increase of $70 million, which is only about 0.24 cents per Mcf of gas sold.[56]

The convexity of the MACC demonstrates diminishing returns to increasing taxes as the cheapest abatement opportunities are exploited. I estimate that a $20 carbon price (corresponding to an $12.67/Mcf tax on methane) would decrease emissions by 73 percent

[55] For the bootstrap, I impose the functional form $R_{it} = \beta_0 + \beta_1 P^{-1} + \beta_2 P^{-2}$, which is the best second-order FP fit for the full sample, rather than allowing the bootstrapped sample to fit the fractional polynomial in each iteration. This prevents cases where bootstrap samples may generate a functional form that becomes upward sloping at higher prices. Observations are clustered at the facility level for resampling. For each of 100 iterations, a random sample of 222 facilities is drawn with replacement, then used to estimate the β_1 and β_2 used in that iteration. However, the original sample is used for the baseline prices and emission rates of facilities.

[56] This calculation uses the EIA's 2016 estimate for marketed U.S. gas production (28,479 Bcf).

(about 106 Bcf or 67 million tCO_2e).[57] The total cost would be $534 million and the value of conserved gas would total $343 million, implying a (still relatively modest) net cost increase of 0.67 cents per Mcf of gas sold. A tax designed to fully internalize the social cost of methane would reduce emissions by 76 percent at a net cost of 0.93 cents per Mcf sold.[58] As this is less than 1 percent of the wellhead price of gas anywhere in the country, this result indicates that natural gas is likely to remain competitive in a world where fugitive methane emissions are incorporated in climate legislation.

As with any simulation model, these results are dependent to some extent on model selection choices. I find that they are robust to three intuitive modifications: Increasing the lower-bound for facilities' emission rates, starting facilities at 2016 prices and emission rates, and using the estimated relationship between emissions and price from the first-order fractional polynomial model. Results, presented in Tables A5-A7 in the Appendix, generally indicate that choices that decrease total abatement correspondingly decrease costs, and vice-versa. The modification that raises costs the most is using the first-order FP curve, which is steeper at higher gas prices than the second-order fit. However, even in this specification, fully internalizing the social cost of methane reduces the net cost of gas extraction by only about half a percent.

[57] Note that this level of tax is an out-of-sample sample prediction, as support in gas prices only ranges from about $1.50-$6. Bias could go in either direction. For example, many low-cost abatement opportunities possible at lower gas prices (i.e. those detected by this analysis) may not applicable at higher prices, creating an upward bias. However, it is also likely that many powerful abatement technologies only become cost effective at prices greater that $6, and thus are not at all reflected in this MAC, meaning actual reductions at higher taxes would be greater than those predicted here.

[58] I use $27.37/Mcf for the social cost of methane, which reflects emissions generated in 2020 assuming a 3 percent discount rate and normalized to 2018 dollars. This figure is drawn from 2016 EPA recommendations based on research by Marten *et al.* (2015). Marten et al.'s estimate has the advantage of directly estimating damages from methane instead of converting them from CO_2. However, it is important to note that their estimate is based on a warming potential for methane from the IPCC's Fourth Assessment Report, and has not been updated to account for the higher warming potential recommended by the IPCC's Fifth Assessment Report. I use the Fifth Assessment Report's recommended warming factor of 34 elsewhere in this paper.

5.2 Comparison with Other Abatement Cost Estimates

The MACC estimated above suggests substantially lower abatement costs than most engineering studies of methane leakage. For example, a 2015 EPA cost-benefit analysis of a proposed set of regulations that would affect the entire gas supply chain estimated that they would reduce emissions by only 3.8-4.2 million tCO_2e annually at a net cost of $150-210 million (EPA, 2015).[59] In contrast, this paper estimates these initial reductions to be near costless under the implementation of methane pricing. Although substantial methodological differences undoubtedly contribute to this disparity, the regulatory instrument considered also has an impact. The proposed EPA regulations mandate certain types of equipment and practices for new wells, which will be more or less cost-effective at different well sites, and which are also unlikely to be the most cost-effective measures on average due to the regulator having imperfect information. However, a methane tax or permit trading system characteristically results in the most cost-effectiveness abatement measures being undertaken first.[60]

Another reference for methane abatement costs is a 2016 technical report by ICF, which constructs a MACC for the entire natural gas industry using engineering cost estimates (ICF, 2016).[61] That study aligns somewhat more closely with the findings in this paper, identifying abatement opportunities covering 88 Bcf per year that could be achieved at a net cost of $296 million. The abatement cost curve estimated in this study predicts that a reduction of 88 Bcf per year would cost roughly $87 million. One other notable difference is that the ICF MACC predicts negative abatement costs for about 17 Bcf of this abatement. As with the McKinsey curve (Enkvist *et al.*, 2007), the existence of GHG abatement opportunities that have positive private benefits indicates either a failure of their methodology to fully capture

[59] These figures are for emissions generated in 2020 with a social cost of methane based on a 3 percent discount rate.

[60] For example, the $5 carbon tax scenario considered in this paper, which roughly doubles the opportunity cost for firms to emit gas, would make a large number of equipment upgrades that were not quite cost effective before worthwhile. However, the very same equipment upgrades might be much less cost-effective at other wells due to heterogeneous real-world conditions, and these upgrades would be passed over.

[61] The 2016 ICF study is an update to a highly similar analysis conducted in 2014 (ICF, 2014).

some nuanced costs or the presence of a market failure that prevents firms from realizing these potential savings.

One study with predictions that align quite closely with those made in this paper is Mayfield *et al.* (2017), who estimate that the the optimal level of abatement would reduce emissions from the transmission segment of the gas industry by 80 percent.[62] Mayfield et al. use engineering cost estimates as an input for a Monte Carlo simulation model in which a social planner employs lowest-cost abatement technologies first, which is broadly analogous to the implementation of methane pricing. The fact that the MACC for the production sector estimated here—which uses an entirely separate methodology and does not use any data on costs—predicts abatement costs generally in line with or below previous engineering estimates greatly strengthens the conclusion that methane emissions emissions from the natural gas industry can be reduced at relatively low cost.

This implication is especially clear when comparing the estimates in this paper to abatement costs for greenhouse gas emissions from other sectors. At time of publication, the EU ETS permit price was roughly \$25 and the California permit price was \$15, implying that any additional abatement in sectors covered by their respective permit trading programs would cost at least as much. In contrast, my results imply that cutting methane emissions from natural gas production in half could be achieved at a carbon price below \$5.

Considering average abatement costs, the methane policy equivalent to a \$5 carbon tax, which would reduce sector emissions by 56 percent, is predicted to cost only \$1.34 on average per ton of CO_2-equivalent emissions captured. The policy equivalent to fully internalizing the social cost of methane is predicted to have an average cost of only \$3.76/tCO_2e. Meng (2017) estimates that industry believed an emissions trading scheme proposed in the U.S. in 2009 would have cost \$5-19/tCO_2. Callaway *et al.* (2018) estimates that the abatement cost of installing new renewable energy generation to be at least \$25/tCO_2e for wind and \$43/tCO_2e for solar. Finally, Fowlie *et al.* (2018) estimates CO_2 abatement costs from

[62] This estimate is based on a slightly lower social cost of methane equivalent to \$24.77/Mcf.

household weatherization to be \$201/tCO_2. This disparity in abatement costs indicates that methane emissions from natural gas production are an efficient area to prioritize to mitigate greenhouse gas emissions in the short run.

6 Conclusion

This paper estimates the marginal abatement cost curve for methane emissions from the natural gas production industry. Because identification is derived from actual firm behavior, results implicitly capture firms' decision-making process to engage in cost-effective abatement. This methodology is therefore well-suited for predicting the effects of regulating methane using market-based instruments, which generate the same incentives.

I find evidence that market-based regulation of methane emissions would achieve substantial greenhouse gas abatement at very low cost. The equivalent of a \$5 carbon tax applied to methane could reduce emissions from the sector by 56 percent. This corresponds to roughly 46 million tons of CO_2-equivalent emissions per year, which is close to 1 percent of total U.S. greenhouse gas emissions. Such a policy would imply a net cost of \$73 million annually (not including administrative costs) while reducing future climate damages on the order of \$1.7 billion. Fully internalizing the social cost of methane would reduce emissions from the sector by roughly 75 percent while increasing the net cost of gas production by less than \$0.01/Mcf, indicating that methane regulation could be established with minimal competitiveness impacts.

A number of important caveats to these results have been raised throughout the paper, and two in particular merit further discussion here. First, estimated CH_4 emission reductions are only representative of emissions as they are reported to the GHGRP. While the GHGRP is the most comprehensive record of methane emissions from the natural gas industry currently available, it does not effectively capture many ways in which facility operators mitigate leakage, and these are therefore not picked up in this analysis. For example, the role of leak detection and repair in reducing emissions is only minimally captured by the GHGRP. Fortunately, recent advancements in satellite CH_4 monitoring may soon enable more accurate estimation of abatement costs and open the door to many other avenues for empirically investigating methane emissions from all parts of the gas supply chain (Jacob *et al.*, 2016).

Second, realizing abatement at the costs estimated in this paper requires the successful implementation of a methane tax or trading program.[63] Designing such a program in a setting where an accurate, low-cost monitoring technology is not readily available presents a formidable challenge. One approach would be to use an inventory calculation such as the GHGRP. Indeed, since the results of this paper are based upon emissions as estimated by the GHGRP, it is reasonable to believe enforcing a market-based instrument based on a reporting survey would be effective in reducing emissions at low cost. Although not all emissions would be captured, this approach is advantageous in being readily practicable. However, the introduction of real penalties would incentivize firms to abate based on emissions as detected by the GHGRP, rather than based on their own knowledge about which abatement technologies are most efficient for their specific facilities, which would further increase the divergence from the theoretical optimum level of abatement. Another approach would be to use direct measurements. Although continuous monitoring of all production sites promises to be cost-prohibitive for many years, intermittent sampling by sensors mounted on aircraft or ground vehicles may be practically feasible in the very near future or even today (Emran *et al.*, 2017; Fredenslund *et al.*, 2017; van den Bossche *et al.*, 2017). Such a program might be particularly cost-effective if sampling were randomly structured to develop firm-level estimates rather than to estimate emissions for individual wells. Beyond applied questions regarding which technologies to use and how frequently to sample emissions, this approach necessitates deeper consideration into how to handle measurement error in a way that is fair

[63] Abatement costs under the implementation of conventional regulation (such as equipment mandates) would be higher than those predicted here, as regulators have imperfect information as to the lowest cost abatement technologies. However, given the current challenges in monitoring CH_4, the advantage of many types of conventional regulation that they are straightforward to enforce merits considerable weight in the short run.

to firms and preserves incentives.

As natural gas continues to expand its role in the transition to sustainable energy, it is critical that its particular externalities be effectively managed to optimally balance its utilization with other energy sources. So long as methane emissions are minimally regulated, CO_2-focused regulations that shift usage of other fossil fuels to gas will be severely attenuated in their intended climate impacts. Moreover, comparatively low abatement costs establish a case for prioritizing methane regulations from the gas supply chain. Although our knowledge of the causes and scale of methane pollution from the natural gas sector has expanded enormously over the last decade, there are still many unanswered questions surrounding the design of policy to reduce it to efficient levels. Estimating the costs and benefits of various regulatory approaches, exploring of the equilibrium effects of climate policy that does not address methane emissions, and developing the theory of regulation under conditions of imperfect measurement are key areas where further research might inform such policy.

References

Aldy, Joseph E, & Pizer, William A. 2015. The competitiveness impacts of climate change mitigation policies. *Journal of the Association of Environmental and Resource Economists*, **2**(4), 565–595.

Allcott, Hunt, & Greenstone, Michael. 2012. Is there an energy efficiency gap? *The Journal of Economic Perspectives*, **26**(1), 3–28.

Alvarez, Ramón A, Zavala-Araiza, Daniel, Lyon, David R, Allen, David T, Barkley, Zachary R, Brandt, Adam R, Davis, Kenneth J, Herndon, Scott C, Jacob, Daniel J, Karion, Anna, *et al.* 2018. Assessment of methane emissions from the US oil and gas supply chain. *Science*, eaar7204.

Anderson, Soren T, & Sallee, James M. 2011. Using Loopholes to Reveal the Marginal Cost of Regulation: The Case of Fuel-Economy Standards. *American Economic Review*, **101**(4), 1375–1409.

Callaway, Duncan S, Fowlie, Meredith, & McCormick, Gavin. 2018. Location, location, location: The variable value of renewable energy and demand-side efficiency resources. *Journal of the Association of Environmental and Resource Economists*, **5**(1), 39–75.

Cremer, Helmuth, & Gahvari, Firouz. 2002. Imperfect observability of emissions and second-best emission and output taxes. *Journal of Public Economics*, **85**(3), 385–407.

Cullen, Joseph A, & Mansur, Erin T. 2017. Inferring carbon abatement costs in electricity markets: A revealed preference approach using the shale revolution. *American Economic Journal: Economic Policy*, **9**(3), 106–33.

Davis, Lucas W, & Muehlegger, Erich. 2010. Do Americans consume too little natural gas? An empirical test of marginal cost pricing. *The RAND Journal of Economics*, **41**(4), 791–810.

Delhotal, K Casey, De la Chesnaye, Francisco C, Gardiner, Ann, Bates, Judith, & Sankovski, Alexei. 2006. Mitigation of methane and nitrous oxide emissions from waste, energy and industry. *The Energy Journal*, 45–62.

EIA. 2018. *Annual Energy Outlook 2018 with Projections to 2050*. US Energy Information Administration.

Emran, Bara J, Tannant, Dwayne D, & Najjaran, Homayoun. 2017. Low-altitude aerial methane concentration mapping. *Remote Sensing*, **9**(8), 823.

Enkvist, P, Nauclér, Tomas, & Rosander, Jerker. 2007. A cost curve for greenhouse gas reduction. *McKinsey Quarterly*, **1**, 34.

EPA. 2015 (August). *Regulatory Impact Analysis of the Proposed Emission Standards for New and Modified Sources in the Oil and Natural Gas Sector*. Office of Air and Radiation, U.S. Environmental Protection Agency.

EPA. 2016 (August). *Addendum to Technical Support Document on Social Cost of Carbon for Regulatory Impact Analysis under Executive Order 12866: Application of the Methodology to Estimate the Social Cost of Methane and the Social Cost of Nitrous Oxide*. Interagency Working Group on Social Cost of Greenhouse Gases, United States Government.

Fowlie, Meredith, Greenstone, Michael, & Wolfram, Catherine. 2018. Do energy efficiency investments deliver? Evidence from the weatherization assistance program. *The Quarterly Journal of Economics*, **133**(3), 1597–1644.

Fredenslund, Anders Michael, Mønster, J, Kjeldsen, Peter, & Scheutz, Charlotte. 2017. Screening method to assess the greenhouse gas mitigation potential of old landfills, based on downwind methane concentration measurements. *In: Sardinia 2017, 16th International Waste Management and Landfill Symposium*. CISA Publisher.

Gabriel, Steven A, Zhuang, Jifang, & Kiet, Supat. 2005. A large-scale linear complementarity model of the North American natural gas market. *Energy economics*, **27**(4), 639–665.

Ganapati, Sharat, Shapiro, Joseph S, & Walker, Reed. 2016. *The Incidence of Carbon Taxes in US Manufacturing: Lessons from Energy Cost Pass-Through*. Tech. rept. National Bureau of Economic Research.

Gillingham, Kenneth, & Palmer, Karen. 2014. Bridging the energy efficiency gap: Policy insights from economic theory and empirical evidence. *Review of Environmental Economics and Policy*, **8**(1), 18–38.

Greene, William. 2008. Functional forms for the negative binomial model for count data. *Economics Letters*, **99**(3), 585–590.

Hausman, Catherine, & Kellogg, Ryan. 2015. *Welfare and distributional implications of shale gas*. Tech. rept. National Bureau of Economic Research.

Hausman, Catherine, & Muehlenbachs, Lucija. 2016. Price Regulation and Environmental Externalities: Evidence from Methane Leaks.

ICF. 2014 (March). *Economic Analysis of Methane Emission Reduction Opportunities in the U.S. Onshore Oil and Natural Gas Industries*. Tech. rept. ICF International. Prepared for Environmental Defense Fund.

ICF. 2016 (May). *Economic Analysis of Methane Emission Reduction Potential from Natural Gas Systems*. Tech. rept. ICF International. Prepared for ONE Future Inc.

IEA. 2017. *World Energy Outlook 2017*. International Energy Agency.

IPCC. 2014. *Climate Change 2014: Mitigation of Climate Change*. Working Group III Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change.

Jacob, Daniel J, Turner, Alexander J, Maasakkers, Joannes D, Sheng, Jianxiong, Sun, Kang, Liu, Xiong, Chance, Kelly, Aben, Ilse, McKeever, Jason, & Frankenberg, Christian. 2016. Satellite observations of atmospheric methane and their value for quantifying methane emissions. *Atmospheric Chemistry and Physics*, **16**(22), 14371–14396.

Klepper, Gernot, & Peterson, Sonja. 2006. Marginal abatement cost curves in general equilibrium: The influence of world energy prices. *Resource and Energy Economics*, **28**(1), 1–23.

Lade, Gabriel E, & Rudik, Ivan. 2017. *Costs of inefficient regulation: Evidence from the Bakken*. Tech. rept. National Bureau of Economic Research.

Lubowski, Ruben N, Plantinga, Andrew J, & Stavins, Robert N. 2006. Land-use change and carbon sinks: econometric estimation of the carbon sequestration supply function. *Journal of Environmental Economics and Management*, **51**(2), 135–152.

Lyon, David R, Zavala-Araiza, Daniel, Alvarez, Ramon, Harriss, Robert, Palacios, Virginia, Lan, Xin, Talbot, Robert, Lavoie, Tegan, Shepson, Paul, Yacovitch, Tara I, *et al.* 2015. Constructing a spatially resolved methane emission inventory for the Barnett Shale region. *Environmental science & technology*, **49**(13), 8147–8157.

Marten, Alex L, Kopits, Elizabeth A, Griffiths, Charles W, Newbold, Stephen C, & Wolverton, Ann. 2015. Incremental CH4 and N2O mitigation benefits consistent with the US Government's SC-CO2 estimates. *Climate Policy*, **15**(2), 272–298.

Mayfield, Erin N, Robinson, Allen L, & Cohon, Jared L. 2017. System-wide and superemitter policy options for the abatement of methane emissions from the US natural gas system. *Environmental science & technology*, **51**(9), 4772–4780.

McCabe, David, Greertsma, Meleah, Matthews, Nathan, Fleischman, Lesley, & Schroeder, Darin. 2015 (January). *Waste Not: Common Sense Ways to Reduce Methane Pollution* *from the Oil and Natural Gas Industry*. Tech. rept. Clean Air Task Force, Natural Resources Defense Council, and Sierra Club. Technical Report.

Meng, Kyle C. 2017. Using a Free Permit Rule to Forecast the Marginal Abatement Cost of Proposed Climate Policy. *American Economic Review*, **107**(3), 748–84.

Morris, Jennifer, Paltsev, Sergey, & Reilly, John. 2012. Marginal abatement costs and marginal welfare costs for greenhouse gas emissions reductions: results from the EPPA model. *Environmental Modeling & Assessment*, **17**(4), 325–336.

Petron, Gabrielle, Karion, Anna, Sweeney, Colm, Miller, Benjamin R, Montzka, Stephen A, Frost, Gregory J, Trainer, Michael, Tans, Pieter, Andrews, Arlyn, Kofler, Jonathan, *et al.* 2014. A new look at methane and nonmethane hydrocarbon emissions from oil and natural gas operations in the Colorado Denver-Julesburg Basin. *Journal of Geophysical Research: Atmospheres*, **119**(11), 6836–6852.

Royston, Patrick, & Altman, Douglas G. 1994. Regression using fractional polynomials of continuous covariates: parsimonious parametric modelling. *Applied statistics*, 429–467.

Sanchez, Nicolas, & Mays, David C. 2015. Effect of methane leakage on the greenhouse gas footprint of electricity generation. *Climatic change*, **133**(2), 169–178.

Sauerbrei, Willi, Meier-Hirmer, Carolina, Benner, A, & Royston, Patrick. 2006. Multivariable regression model building by using fractional polynomials: description of SAS, STATA and R programs. *Computational Statistics & Data Analysis*, **50**(12), 3464–3485.

Stavins, Robert N. 1999. The costs of carbon sequestration: a revealed-preference approach. *The American Economic Review*, **89**(4), 994–1009.

Stranlund, John K, Chavez, Carlos A, & Villena, Mauricio G. 2009. The optimal pricing of pollution when enforcement is costly. *Journal of Environmental Economics and Management*, **58**(2), 183–191.

Subramanian, R, Williams, Laurie L, Vaughn, Timothy L, Zimmerle, Daniel, Roscioli, Joseph R, Herndon, Scott C, Yacovitch, Tara I, Floerchinger, Cody, Tkacik, Daniel S, Mitchell, Austin L, *et al.* 2015. Methane emissions from natural gas compressor stations in the transmission and storage sector: Measurements and comparisons with the EPA greenhouse gas reporting program protocol. *Environmental science & technology*, **49**(5), 3252–3261.

van den Bossche, Michael, Rose, Nathan Tyler, & De Wekker, Stephan Franz Joseph. 2017. Potential of a low-cost gas sensor for atmospheric methane monitoring. *Sensors and Actuators B: Chemical*, **238**, 501–509.

Appendix

A.1 Theory Extensions

This section extends the one-period theoretical framework in the main text to a dynamic model, then further extends that dynamic model to separately consider emissions associated with completions, equipment, and maintenance. Although the results presented here are not practical for extending to empirical analysis given current data limitations, they provide intuition for many of the intertemporal aspects of firms' production and emission decisions.

A.1.1 Dynamic Model

I begin by supposing that instead of choosing a level of production and an emission rate within a single period, the firm owns a stock of wells at the start of each period, chooses how many new wells to drill, and chooses the emission rate of these new wells. For simplicity, I assume wells are homogeneous and that each well generates one unit of production per period. I further suppose the number of wells owned by the firm in a given period W_t can be broken down into new wells drilled that period W'_t and wells leftover from the previous period. Building from Equation 3, the firm's instantaneous profit function is reformulated as:

$$\pi_t = P_t W_t (1 - R_t) - C_1(W'_t) - W'_t c_2(R'_t) \tag{11}$$

I disregard maintenance costs (for now), so the only costs incurred by the firm are those for new wells. Facility emission rates evolve as the weighted average of the emission rate of existing wells plus the emission rate of new wells, and wells depreciate at a rate of $1 - \delta$.

Accordingly, the equations of motion for these two variables are as follows:

$$W_t = \delta W_{t-1} + W'_t \tag{12}$$

$$R_t = \frac{\delta W_{t-1}}{W_t} R_{t-1} + \frac{W'_t}{W_t} R'_t \tag{13}$$

Applying a discount factor of β, the firm's intertemporal optimization problem is:

$$\pi = \max_{\{W'_t, R'_t\}_t} \sum_{t=0}^{T} \beta^t \big(\mathbb{E}[P_t] W_t (1 - R_t) - C_1(W'_t) - W'_t c_2(R'_t)\big) \tag{14}$$

$$S.T. \quad W_t = \delta W_{t-1} + W'_t \tag{15}$$

$$R_t = \tfrac{\delta W_{t-1}}{W_t} R_{t-1} + \tfrac{W'_t}{W_t} R'_t \tag{16}$$

$$W'_t \geq 0, \ R'_t \in (0,1) \tag{17}$$

Starting from any given period τ, the firm's profit stream is only dependent on their choice of R' and W' in τ and in future periods. Substituting in the equation of motion for R_t facilitates taking the first-order condition for emissions from new wells:

$$\begin{aligned}
\mathbb{E}[\sum_{t=\tau}^{T} \pi_t] = {} & P_\tau W_\tau \big(1 - \tfrac{\delta W_{\tau-1}}{W_\tau} R_{\tau-1} - \tfrac{W'_\tau}{W_\tau} R'_\tau\big) - C_1(W'_\tau) - W'_\tau c_2(R'_\tau) && (18) \\
& + \beta \mathbb{E}[P_{\tau+1}] W_{\tau+1} \big(1 - \tfrac{\delta W_\tau}{W_{\tau+1}} (\tfrac{\delta W_{\tau-1}}{W_\tau} R_{\tau-1} + \tfrac{W'_\tau}{W_\tau} R'_\tau) - \tfrac{W'_{\tau+1}}{W_{\tau+1}} R'_{\tau+1}\big) - C_1(W'_{\tau+1}) - W'_{\tau+1} c_2(R'_{\tau+1}) \\
& + \beta^2 \mathbb{E}[P_{\tau+2}] W_{\tau+2} \big(1 - \tfrac{\delta W_{\tau+1}}{W_{\tau+2}} (\tfrac{\delta W_\tau}{W_{\tau+1}} (\tfrac{\delta W_{t-1}}{W_t} R_{t-1} + \tfrac{W'_t}{W_t} R'_t) + \tfrac{W'_{\tau+1}}{W_{\tau+1}} R'_{\tau+1}) - \tfrac{W'_{\tau+2}}{W_{\tau+2}} R'_{\tau+2}\big) - \ \ldots \\
& + \ \ldots && (19)
\end{aligned}$$

$$\frac{\partial \pi}{\partial R'_t} = - W'_\tau \tfrac{\partial c_2}{\partial R'_\tau} - W'_\tau P_\tau - \beta \delta W'_\tau \mathbb{E}[P_{\tau+1}] - \beta^2 \delta^2 W'_\tau \mathbb{E}[P_{\tau+2}] + \ \ldots \ = 0 \tag{20}$$

$$-\frac{\partial c_2}{\partial R'_\tau} = \sum_{\iota=0}^{T} \beta^\iota \delta^\iota \mathbb{E}[P_{\tau+\iota}] \tag{21}$$

Equation 21 shows that the firm chooses an emissions rate for new wells that sets the marginal cost of having emission rate R'_τ for new wells equal to the present discounted value of expected future prices. Unfortunately, it is not possible within the GHGRP data to separate out emissions from new wells from those of existing wells, as a single emission rate is reported for each facility. With the addition of DrillingInfo variables for the firms' number of existing wells and new wells,[64] it is hypothetically possible to back out the emission rate for new wells. However, this process breaks down in practice, possibly because it introduces additional noise by amplifying any imperfect matching between the two datasets. The advent of satellite methane emission monitoring at the level of spatial resolution requisite for estimating emissions from individual well sites (or well-level reporting within the GHGRP or another survey) would generate a direct measurement of R'_τ that could be used to estimate Equation 21.

A.1.2 Incorporating Emission Sources

Finally, I extend the model to separately consider emissions that are associated with capital purchase decisions, emissions associated with maintenance (i.e. leak detection and repair), and emissions associated with completions. This breakdown is relevant specifically within the dynamic model because emissions from each of these sources follow from decisions the firm makes based on very different time frames.[65] For example, when a firm purchases equipment for a new well, their decision on how much to expend to acquire less-emitting equipment is based primarily on expectations of future gas prices over the expected lifetime of the equipment.

[64] Annual production from new wells and existing wells is also necessary here, as the assumption that each well extracts gas at the same rate does not hold in actuality.

[65] This is also true of equipment upgrades for existing wells, where there is an additional cost associated with forgoing the remaining potential lifetime of existing equipment and labor costs for installing the upgrade that would not be incurred in its absence. For simplicity, I omit equipment upgrades from the model.

With these modifications, the firm's optimization problem is now:

$$\pi = \max_{\{W_t', M_t, R_t'^k, R_t'^c\}_t} \sum_{t=0}^{T} \beta^t \big[\mathbb{E}[P_t]\big(W_t^e(1 - R_t^e f(M_t)) + W_t'(1 - R_t'^k - R_t'^c)\big) \tag{22}$$

$$- C_1(W_t') - W_t^e c_m(M_t) - W_t' c_k(R_t'^k) - W_t' c_c(R_t'^c)\big]$$

$$S.T. \quad W_t^e = \delta(W_{t-1}^e + W_{t-1}') \tag{23}$$

$$R_t^e = \tfrac{\delta W_{t-1}^e}{W_t^e} R_{t-1}^e + \tfrac{\delta W_{t-1}'}{W_t^e} R_{t-1}'^k \tag{24}$$

$$W_t' \geq 0,\ M_t' \geq 0,\ R_t'^k \in (0,1),\ R_t'^c \in (0,1) \tag{25}$$

W_t does not appear in this formulation, as it has been broken down into wells that existed upon entering the period W_t^e and new wells built that period W_t', which is a choice variable as before. Furthermore, now instead of simply choosing how leaky those new wells will be, the firm chooses the emission rate of the equipment at those new wells $R_t'^k$, the leakage rate for completions $R_t'^c$ (i.e. what percent of the wells' first year of production will be allowed to escape during the completion process), and how much effort to devote toward maintenance to repair leaks M_t. Revenues are separated into those generated from existing wells and those generated by new wells. Revenues from existing wells depend on the baseline emissions rate from those wells and a factor $f(M_t)$, which is decreasing and convex in maintenance.[66] Revenues from new wells depend on $R_t'^k$ and $R_t'^c$. Costs resulting from decisions that affect emissions rates are again broken down into equipment, completion, and maintenance categories. The equations of motion for W_t^e and R_t^e are adjusted slightly to reflect the separation of existing wells from new wells.

First order conditions for the decision variables, starting from any time period τ, now

[66] $f(\cdot)$ starts at some factor greater than one for zero maintenance effort, as emissions will be greater than the previous years rate due to equipment degradation if no maintenance is performed. $f(\cdot)$ then approaches 1 asymptotically as maintenance effort increases toward infinity. This formulation assumes that firms engage in leak detection and repair on at least an annual basis, such that leaks do not persist across years.

simplify to the following:

$$-\frac{\partial c_c}{\partial R'^c_\tau} = P_\tau \tag{26}$$

$$-\frac{\partial c_m}{\partial M_\tau} = P_\tau R^e_\tau \frac{\partial f}{\partial M_\tau} \tag{27}$$

$$-\frac{\partial c_2}{\partial R'^k_\tau} = \sum_{\iota=0}^{T} \beta^\iota \delta^\iota \mathbb{E}[P_{\tau+\iota}] \prod_{j=0}^{\iota} f(M_{\tau+j}) \tag{28}$$

The first notable observation is that the firm's decision rule for emissions from completion in any given period depends only on the price in the current period. This is likely to be a contributing factor to the empirical result in Section 4.2 that emissions from completion are most responsive to current prices. Intuitively, the firm's decision rule for maintenance effort is a function of the price in the current period, the baseline emission rate of wells that exist going into the current period, and the sensitivity of those emission rates to maintenance effort. The first order condition for emissions related to equipment purchase decisions includes the present discounted value of gas as in the previous section, but now also depends on future maintenance decisions. Because the firm's decisions on maintenance effort and emissions for new wells are intertwined in this framework, they are not directly estimable using a reduced-form approach.

A.2 Negative Binomial Model

To address the possibility that results could be driven by improper specification in using OLS to estimate the effect of price on CH_4 emission rates, I additionally estimate this relationship using a negative binomial framework. In general, the assumptions of OLS are not precisely satisfied in models that have a rate or proportion as the dependent variable.[67] In this case, models that explicitly treat the dependent variable as a count are likely to provide a better fit. Two of the most frequently used count data models are Poisson regression and negative binomial regression, which is a generalization of Poisson that allows the dependent variable's variance parameter to differ from the mean.[68]

Rather than using emission rates as the dependent variable, this specification uses emissions in levels as the dependent variable and treats the quantity of gas extracted as an exposure variable.[69] This empirical framework operates under the analogy that each unit of extraction may either be leaked or contained, and the coefficient of interest recovers the effect of price on the probability that each unit will be leaked. The probability that in total e units of gas are leaked is then given by:

$$\Pr(E_{it} = e|\mu) = \frac{e^{-\mu}\mu^e}{e!}$$

Where E_{it} is the level of emissions at facility i in year t and e is drawn from a negative binomial distribution with parameter μ that takes the form:

$$\mu = exp(\beta_0 + \beta_1 P_{it}^A + \beta_2 P_{it}^B + \mathbf{X}_{it}\psi + \gamma_i + \lambda_{rt} + \varepsilon_{it}) \tag{29}$$

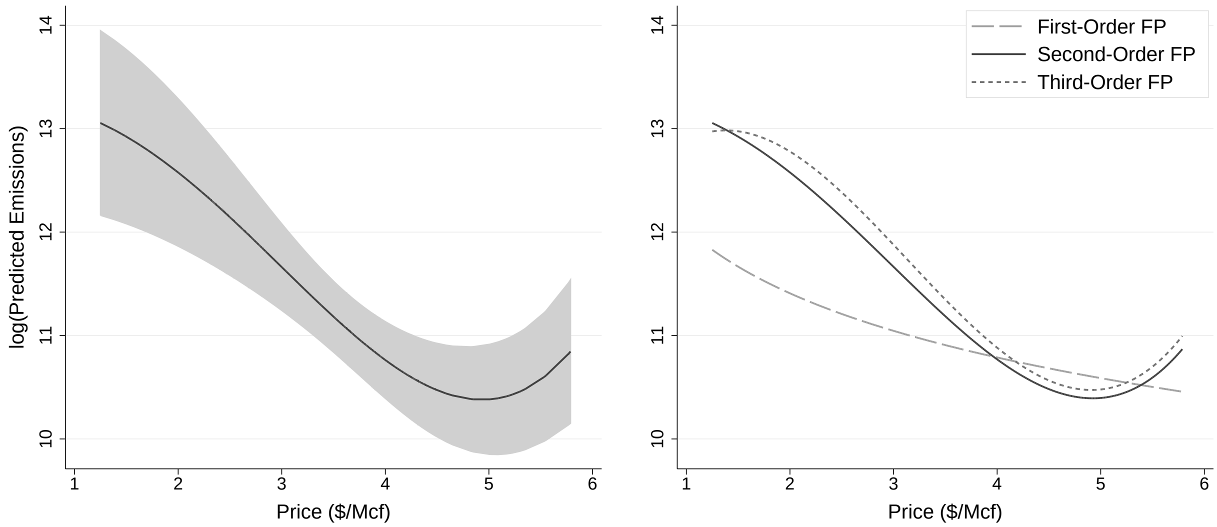
The fractional polynomial methodology is carried through to Equation 29, although it

[67] For example, it is impossible for errors to be normally distributed if the outcome variable is lower-bounded at zero, and rate variables with a large proportion of data clustered near 0 or 1 are less likely to have approximately normally-distributed errors.

[68] Negative binomial models provide a better fit than Poisson when the conditional variance of the dependent variable exceeds it's conditional mean (Greene, 2008). That is the case here, as the conditional mean of CH_4 emissions is about 253 MMcf and the conditional variance is about 89,000 MMcf.

[69] *i.e.* Rate = Count/Exposure

Figure A1: Robustness check employing a negative binomial model instead of OLS. The left panel shows a second-order fractional polynomial fit, and the right panel shows a comparison with higher- and lower-order specifications. For reference, exp(13) = 442,413 Mcf and exp(10.5) = 36,315 Mcf, indicating that emissions are predicted to decrease by about one order of magnitude as prices increase from the lowest to the highest observed in the sample.



is not possible to include regression weights in the negative binomial models. Controls and fixed effects are also consistent with the specification in the main text, with the exception that extraction Q_{it} is used to determine exposure. Coefficients and model parameters are estimated using maximum likelihood. The best model fit for the second-order fractional polynomial is shown in the left panel of Figure A1. This curve is broadly similar to the result from the OLS second-order fractional polynomial specification and especially similar to the robustness check that omits regression weights (see Figure A4). Coefficient estimates for this specification and for first- and third-order fractional polynomials are reported in Table A1. Although the negative binomial framework may be a more appropriate specification along some dimensions, the OLS framework used in the main text is more directly useful for constructing a sector-wide marginal abatement cost curve.

Table A1: Results from a robustness check using a negative binomial model in place of OLS, including a linear specification (1), and first-, second-, and third-order fractional polynomial fits (2-3).

	(1)	(2)	**(3)**	(4)
Model	Linear	1st-Order FP	**2nd-Order FP**	3rd-Order FP
P_{it}	-0.1905			
	(0.1799)			
$\log(P_{it})$		-0.8953		
		(0.5620)		
P_{it}^3			-0.1407***	
			(0.0308)	
$\log(P_{it}) \times P_{it}^3$			0.0730***	
			(0.0160)	
P_{it}^2				0.9126***
				(0.3272)
$\log(P_{it}) \times P_{it}^2$				-1.3507***
				(0.3920)
$\log(P_{it})^2 \times P_{it}^2$				0.4637***
				(0.1239)
Facility FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes
N	1,114	1,114	1,114	1,114

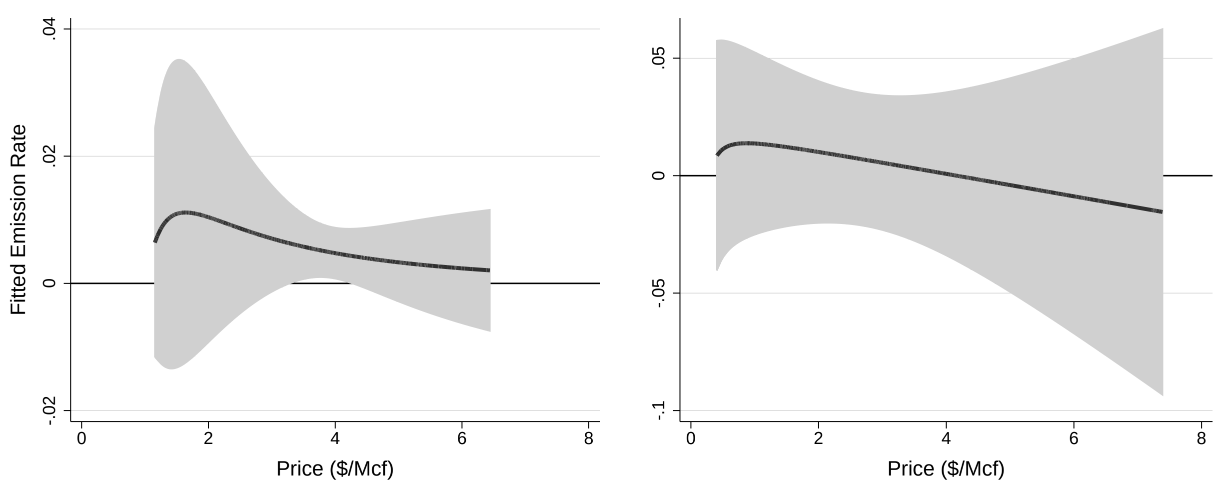
Standard errors in parentheses (clustered at the parent firm level with 146 firms)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A.3 Instrumental Variables Regression

To address potential endogeneity from reverse causality or omitted variables that vary over time within regions, I explore instrumenting for price using exogenous weather shocks. In particular, I use average annual heating degree days (HDD), a temperature measure corresponding to degrees below 65 Fahrenheit.[70] To satisfy the exclusion restriction, temperature must not be correlated with emission rates except through its impact on gas prices. Because it is difficult to ensure this holds for a facility's own temperature, I additionally employ a strategy using weather in areas surrounding a facility conditional on weather at that facility, which directly satisfies exclusion restriction (Davis & Muehlegger, 2010; Hausman & Kellogg, 2015).[71] The intuition underlying the second approach is that temperature in surrounding areas will affect demand, but it will be entirely exogenous to production activities in that area conditional on temperature in that area. In both approaches, I also include one-year lagged temperature, as storage volumes from the previous year may also impact demand.

Figure A2: Estimated relationship between emission rates and prices using weather at a facility as an instrument for price at that facility (left) and using weather in regions neighboring a given facility as an instrument for price at that facility (right).



[70] HDD is recognized throughout the natural gas industry to be a very strong predictor of demand.
[71] I assign facility i's own temperature ($\text{HDD}_{i,t}$) by taking an average of temperature at the hubs used to construct the price for i and create a variable for temperature in areas around facility i ($\text{HDD}_{-i,t}$) by taking an average of temperature at hubs immediately adjacent to i's hubs.

Table A2: Results from robustness checks using weather variables as instruments for price.

	1st Stage with Weights		2SLS Own Weather		2SLS Nearby Weather	
	(1)	(2)	(3)	(4)	(5)	(6)
	P_{it}	$P_{i,t}$	P_{it}	R_{it}	P_{it}	R_{it}
HDD$_{i,t}$	0.0232*	0.00379	0.0772***		-0.0153	-0.000349
	(0.0135)	(0.0283)	(0.0138)		(0.0138)	(0.000929)
HDD$_{i,t-1}$	0.0284		0.0429***			
	(0.0191)		(0.00997)			
HDD$_{-i,t}$		0.0351			0.160***	
		(0.0688)			(0.0240)	
HDD$_{-i,t-1}$		0.0261			0.0959***	
		(0.0367)			(0.0115)	
$\widehat{P}_{it}^{-2}$				-0.00107		-0.00396
				(0.0103)		(0.00665)
$log(\widehat{P}_{it}^{-2}) \times \widehat{P}_{it}^{-2}$				0.0653		0.0204
				(0.102)		(0.0240)
Weights	Yes	Yes				
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1150	1150	1150	1150	1150	1150

Standard errors in parentheses (clustered at the parent firm level with 146 firms)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the first stage, I regress price on a measure of temperature (either own temperature or temperature in nearby areas) and one lag, including the same fixed effects and controls as before. Results are presented in Table A2. Weighting observations based on facilities' mean gas production (as in the main text), the instrument relevance condition fails in the first stage (Columns 1 and 2). Omitting regression weights, a strong relationship of the expected sign is detected in the first stage (Columns 3 and 5). The second stage is estimated as a second-order fractional polynomial, as in the main text. As shown in Figure A2, the relationship between emission rates and prices appears similar to the non-instrumented relationship. However, the second stage results are not statistically significant (Columns 4 and 6).[72]

[72] The two transformations of price that provide the best fit in the second-order fractional polynomial model are the same in both models: $\widehat{P}_{it}^{-2}$ and $log(\widehat{P}_{it}^{-2}) \times \widehat{P}_{it}^{-2}$.

A.4 Additional Robustness Checks

Table A3: Results from robustness checks excluding weights (1), using a 1% threshold for Winsorizing facility emission rates (2), using basin-by-year fixed effects in place of region-by-year fixed effects (3), using year fixed effects (4), excluding the Mountain region (5), and excluding 2016 (6). All specifications are second-order fractional polynomials.

	(1)	(2)	(3)	(4)	(5)	(6)
Model	Unweighted Regression	Trimming Leaks at 1%	Basin-Year FE	Year FE	Excluding Mountain	Excluding 2016
P_{it}^2	-0.00291**	-0.0023*				-0.0021
	(0.00118)	(0.0014)				(0.0013)
P_{it}^3	0.0004**	0.0003		0.00006		0.0003
	(0.0002)	(0.0002)		(0.00011)		(0.0002)
$P_{it}^3 \times \log(P_{it})$				-0.00003		
				(0.00005)		
P_{it}^{-1}			0.0536***			
			(0.0169)			
P_{it}^{-2}			-0.0386***		0.0104*	
			(0.0133)		(0.0058)	
$P_{it}^{-2} \times \log(P_{it})$					0.1047	
					(0.0642)	
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes			Yes	Yes
N	1,150	1,246	1,126	1,156	872	1,036
adj. R^2	0.662	0.340	0.629	0.635	0.278	

Standard errors in parentheses (clustered at the parent firm level with 146 firms)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Robustness check for mechanisms by which firms' emitting behavior responds to price using the full GHGRP sample. Note that using the unrestricted GHGRP sample requires omitting the production control variables retrieved from DrillingInfo.

	(1)	(2)	(3)	(4)	(5)	(6)
	Low-Bleed Pneumatic Devices	**High-Bleed Pneumatic Devices**	**Intermittent Pneumatic Devices**	**Pneumatic Pumps**	**Venting Days**	**Gas Recovered For Sales**
P_{it}	-32.38	-9.24	-134.4	-91.94**	-7.816	31,202,000
	(119.6)	(15.99)	(213.5)	(43.82)	(6.083)	(34,662,000)
Colorado_{2014+}	658.3	-205.3	128.2	-142.9	-3.513	9,239,000
	(1183.3)	(136.2)	(563.8)	(96.46)	(3.306)	(10,344,000)
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	2,593	2,593	2,593	1,855	2,017	2,017

Standard errors in parentheses (clustered at the parent firm level with 146 firms)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Robustness check lower-bounding facilities potential emission rates at 0.1 percent instead of at .0223 percent.

Methane Tax	**Equiv. Carbon Price**	**Total Abatement**	**Total Abatement**	**Total Cost**	**Value of Captured Gas**	**Net Cost**
(\$/Mcf)	(\$/tCO$_2$e)	(Mcf)	(Percent)	(\$)	(\$)	(\$/Mcf)
2.79	5.00	65,876,000	45.1	271,485,000	212,562,000	0.0021
		(28,279,000)	(19.3)	(117,476,000)	(91,049,000)	(0.0009)
11.18	20.00	85,582,000	58.5	438,883,000	275,874,000	0.0057
		(40,085,000)	(27.4)	(226,449,000)	(128,785,000)	(0.0035)
27.37	48.97	42,263,000	61.6	530,323,000	290,292,000	0.0084
		(15,388,000)	(30.4)	(321,038,000)	(142,621,000)	(0.0064)
N		1,150	1,150	1,150	1,150	1,150

Variables in Mcf and \$ rounded to nearest 1,000
Bootstrapped standard errors in parentheses

Table A6: Robustness check starting facilities at 2016 values for prices and emission rates rather than average values over the study period.

Methane Tax	**Equiv. Carbon Price**	**Total Abatement**	**Total Abatement**	**Total Cost**	**Value of Captured Gas**	**Net Cost**
(\$/Mcf)	(\$/tCO_2e)	(Mcf)	(Percent)	(\$)	(\$)	(\$/Mcf)
2.79	5.00	61,255,000	53.7	189,883,000	141,938,000	0.0017
		(25,852,000)	(22.7)	(82,525,000)	(59,761,000)	(0.0008)
11.18	20.00	74,707,000	65.4	293,188,000	172,902,000	0.0042
		(35,877,000)	(31.4)	(166,497,000)	(82,712,000)	(0.0030)
27.37	48.97	77,262,000	67.7	341,345,000	178,772,000	0.0057
		(43,179,000)	(34.5)	(239,652,000)	(90,665,000)	(0.0054)
N		1,150	1,150	1,150	1,150	1,150

Variables in Mcf and $ rounded to nearest 1,000
Bootstrapped standard errors in parentheses

Table A7: Robustness check using the estimated curve from the first-order fractional polynomial ($R_{it} = \beta_0 + \beta_1 log(P_{it})$) in the simulation model.

Methane Tax	**Equiv. Carbon Price**	**Total Abatement**	**Total Abatement**	**Total Cost**	**Value of Captured Gas**	**Net Cost**
(\$/Mcf)	(\$/tCO_2e)	(Mcf)	(Percent)	(\$)	(\$)	(\$/Mcf)
2.79	5.00	75,622,000	51.7	317,725,000	243,513,000	0.0026
		(27,534,000)	(18.8)	(114,115,000)	(88,463,000)	(0.0009)
11.18	20.00	109,060,000	74.6	609,751,000	351,036,000	0.0091
		(40,943,000)	(28.0)	(245,542,000)	(157,731,000)	(0.0042)
27.37	48.97	119,595,000	81.8	827,475,000	384,703,000	0.0155
		(49,452,000)	(33.8)	(455,370,000)	(157,731,000)	(0.0108)
N		1,150	1,150	1,150	1,150	1,150

Variables in Mcf and $ rounded to nearest 1,000
Bootstrapped standard errors in parentheses

Table A8: GHGRP variables used to construct emission rates from equipment, completions, and maintenance. Each emissions source is a publically-available variable reported by the GHGRP. The third column consists of components of the equations used to calculate the estimated emissions from various sources (these are not publicly available) that are specifically related to firm decisions about emissions from the various category types. Equation components that are unrelated to firm decisions (such as population emissions factors) are not shown.

Category	Emissions Source	Relevant Decision Component(s)
Equipment	Pneumatic Controllers	Type (High-, Low-, or Intermittent- Bleed)
	Pneumatic Pumps	Number of Devices
	Storage Tanks	Whether has Vapor Recovery
	Associated Gas Venting/Flaring	Whether to Vent, Flare, or Sell
	Centrifugal Compressors	Emissions from Wet Seal Degassing Vents
	Dehydrator Vents	Absorbent Type
		Pump Type
		Use of Stripping Gas
		Use of Flash Tank Separator
		Dimensions of Dehydrator Vessel
		Whether has Vapor Recovery
Completions	Well Testing	Whether Gas is Vented or Flared
	Completion/Workover Venting	Time Gas is Vented
		Whether used Separator
	Liquid Unloading	Time Venting Each Well
		Flow Rate
Maintenance	Centrifugal Compressors	Emissions from Wet Seal Degassing Vents
	Storage Tanks	Direct Emissions Measurement
		Time Dump Valve is Not Closing Properly
	Equipment Leak Surveys	Number & Type of Leaking Devices
		Time Assumed to be Leaking

Figure A3: Distribution of the ratio of the production variable from the DrillingInfo dataset to the same variable from the GHGRP for the years 2015 and 2016. Deviations in excess of 25 percent are trimmed from the sample.

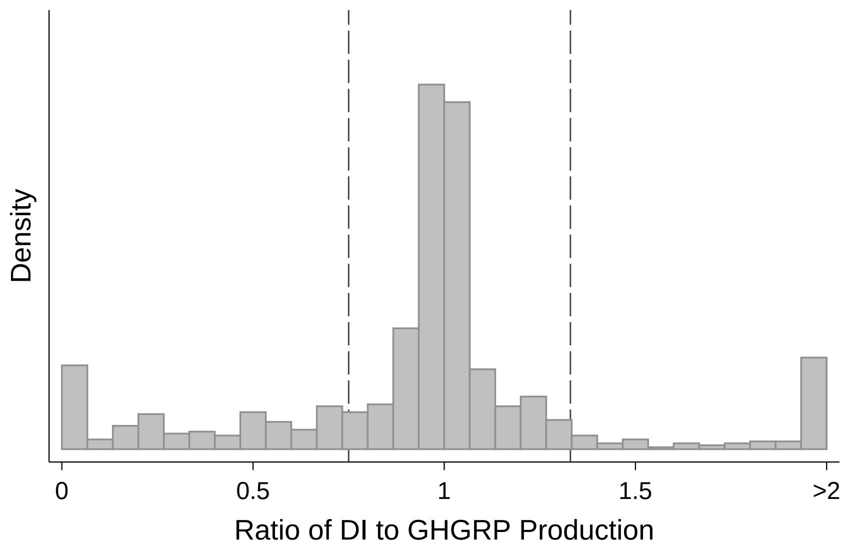


Figure A4: Robustness checks for the second-order fractional polynomial regression of emission rates on price.