

How Do Natural Gas Pipeline Networks Affect Emissions From Drilling and Flaring? *

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November 1, 2022

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Abstract

Most oil wells co-produce natural gas. Producers can choose to burn this valuable co-product on site (known as flaring) if the cost of connecting to the existing natural gas pipeline network is sufficiently high. While flaring is damaging to the climate, there exists surprisingly little research on the economics of flaring. I construct and estimate a dynamic model of producer drilling and flaring decisions which depend on the current state of the pipeline network and expectations over its evolution. My model also allows producers to internalize spillover effects for their neighbors – any pipeline they build will extend the network and weakly decrease their neighbors’ future pipeline connection costs. Using my model estimates, I simulate pipeline development and flaring outcomes under counterfactual policies: a flaring tax, a flaring ban, and a gas subsidy. My counterfactual simulations show that flaring abatement costs are higher than previous studies but suggest that a flaring tax could substantially reduce flaring. A \$5/Mcf tax reduces flaring by 39%.

*I am deeply grateful for my advisor, Josh Linn, and committee members, Louis Preonas, James Archsmith, and Rob Williams for helpful comments, feedback and encouragement. This paper was supported by the Alfred P. Sloan Foundation Pre-doctoral Fellowship on Energy Economics, awarded through the NBER.

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1 Introduction

Networks are frequently studied in economics, but typically in contexts where space is either unimportant or abstracted away from such as communication networks or two-sided markets. When space is abstracted away from networks can be modeled using graph theoretic techniques or even more simple descriptors such as numbers of network participants. For example, [Rochet and Tirole \(2003\)](#), in their classic models of two-sided markets, simply specify buyer and seller gross surplus as a function the of number of participants on each side. Typically network problems are characterized by “network externalities.” Consider the early development of phone or internet networks where users are positively affected by the entrance of a new user.¹

However, there are many examples of network problems where space is crucial and where dynamics are important such as electricity grids, electric vehicle charging networks, and pipeline networks. These structures are still characterized by traditional “network externalities,” but in addition dynamics and space become important. The effect of a new entrant into the network is dependent upon where that entrant is cited, and the state of the network in $t + 1$ depends on its state in t . For example, consider the siting and construction of new renewable energy sources. Many of the best places to site renewable energy projects are located in very rural areas with relatively little transmission infrastructure. When a new generation source, like a wind or solar farm, is proposed the developer is often on the hook for expensive upgrades to transmission infrastructure that later entrants can use without sharing in the costs ([Department of Energy, 2022](#)). Clearly, there are “network externalities” – one producer’s decision to upgrade the grid will affect future potential entrants, but in addition the decision to enter generates spatial and temporal dependencies. Moreover, in all of these examples network externalities interact with more traditional environmental externalities. These types of problems are very hard to model, so thus far they have been largely ignored. This paper will focus on the growth of a natural gas pipeline network, its relationship with producer decisions to connect to it, and its implications for environmental outcomes.

In this paper, I set up and estimate a dynamic model of producer decisions to drill and connect

¹However, network externalities need not be positive or even monotonic.

to natural gas pipelines in the Permian Basin in Texas, accounting for the fact that the pipeline network grows over time and that producers might consider spillover effects for their neighbor – that when a driller connects, the pipeline network expands, weakly reducing costs for nearby potential wellsites. Oil wells often co-produce natural gas, and producers have the option to burn the gas at the wellhead (flare) if the cost of connecting to pipelines is too high. Flaring is socially costly, so this paper will be primarily focused on investigating the relationship between the pipeline network and producer drilling and flaring decisions. I answer three main questions. First, how do producers choose to drill and flare and how is that decision affected by the pipeline network? Second, how might potential policies aimed at reducing flaring affect flaring and production decisions, and the growth of the pipeline network over time? Lastly, do producers internalize spillovers for their neighbors, and if not, how much does this matter for flaring?

Flaring likely has large social costs. Natural gas primarily consists of methane (CH_4) a very potent greenhouse gas, but when it is burned that is mostly converted to CO_2 . Flaring is less socially costly than simply letting the methane escape into the atmosphere.² However, there is likely a wedge between the social cost of flaring gas at the wellhead and the social cost of selling it for end use precisely because flares are oftentimes inefficient or unlit, allowing methane to escape into the atmosphere. A study by the Environmental Defense Fund found that 7% of gas flared is actually released directly as methane. Their estimates imply that flares in the Permian Basin release 300,000 Bcf of uncombusted natural gas per year—resulting in around a half billion dollars in external damages just from methane from flares (EDF, 2022). Flaring is mostly unpriced in the U.S. In fact, most leases do not contain royalty clauses on flared gas, and most states do not tax flared gas. Pipelines are expensive. The Interstate Gas Association of America (INGAA) reported that in 2016 an 8” gathering pipeline costs \$264,856 per mile (ICF, 2018). Thus, it’s easy to see why flaring can be an attractive option for producers – especially when gas prices are low, when

²Assuming a discount rate of 3% the social cost of carbon is around \$50 per ton while the social cost of methane is \$1500 per ton (Interagency Working Group on Social Cost of Greenhouse Gases, 2021). An Mcf of gas weighs around 50lbs. When burned it is converted into about 121 pounds of CO_2 . Therefore if 100% is converted to CO_2 the social cost of burning an Mcf of gas is around \$3. If instead, the same amount of gas is vented, this would result in whopping \$37.5 in damages. Thus, it’s easy to see why the social cost of flaring is heavily dependent upon the efficiency of the flares – which is still hotly debated.

the expected level of gas production from a well is low, or when the well is very far away from existing pipelines.

In my model, drillers hold leases with time-limited options to develop parcels of land by drilling a well. As more pipelines are built over time, connection costs for new wells decline. Producers have expectations over the evolution of prices and connection costs, and choose when to drill and whether to flare or connect to pipelines. The state space of my model is too large to compute a full solution method (through backward induction) so I leverage the insights of [Joseph Hotz and Miller \(1993\)](#) and [Arcidiacono and Miller \(2011\)](#) and using a two-step estimator with conditional choice probabilities (CCPs) to estimate the parameters of the model. Estimation of the model uses variation in expected revenues, which comes through changing prices and differences in lease-level geology, and variation in distance to pipelines to back out the implied fixed costs of drilling, the implied costs of building pipelines, and whether spillovers are internalized.

Previous work on flaring has not considered dynamics, has ignored the drilling margin, has relied heavily upon engineering estimates, and has not considered the potential for spillovers and whether they are internalized. The closest paper is perhaps [Lade and Rudik \(2020\)](#), which is more focused on demonstrating how regulatory mechanisms matter rather than predicting specific firm behavior. They demonstrate that a flaring tax would reduce flaring at lower costs than an equivalent-in-magnitude reduction achieved by firm-level standards due to heterogeneous abatement costs across firms. To do this they construct firm-level marginal abatement curves using estimates of pipeline costs pulled from an industry report. This paper does not consider dynamics or spillovers, and does not take into account whether policy would affect the drilling margin. They argue that all of these factors would bias their own estimates of abatement costs upward. However, my model, which does consider dynamics, spillovers, and the drilling margin, suggests that abatement costs are *higher* than those found by Lade and Rudik (2020). This is driven by my estimated pipeline costs being higher than the industry report and the role of error terms in my model.

This paper also contributes more generally to the economics literature on oil and gas development. It's common in this literature to treat the decision to drill as a dynamic optimization problem (see [Paddock, Siegel, and Smith \(1988\)](#), [Kellogg \(2014\)](#)). However, my paper is the first

that borrows the use of CCPs to estimate the parameters of a drilling function. This paper demonstrates that credible estimates of the parameters of drilling functions can be estimated this way. Next, the context of my paper is quite similar to that of [Covert and Kellogg \(2017\)](#) who study the choice between shipping crude via rail (which is environmentally costly and has high variable costs) and via pipeline (which has high investment costs, negligible variable costs, and significantly lower environmental damages). They find that pricing the externalities of rail shipping leads to a 12-29% increase in pipeline capacity. In my context the “dirty”, low fixed-cost option is flaring, while the clean high fixed-cost option is constructing a pipeline. I find that pricing the externalities of flaring leads to a negligible increase in pipeline investment but a sizable reduction in flaring.

My model estimates indicate that industry reported estimates of pipeline costs underestimate the true costs of pipeline building and that firms do not consider spillovers to their neighbors. I run counterfactual simulations to explore the importance of spillovers and evaluate policy options to reduce flaring. My counterfactual simulations suggest that the benefits of spillover internalization are relatively small — potentially explaining why spillovers are not internalized. My policy counterfactuals suggest that a tax on flaring close to its social cost would substantially reduce flaring. A \$5/Mcf tax reduces flaring by 39% while a 3\$/Mcf tax reduces flaring by 29%.

2 Background

Oil and gas are often co-produced in wells. Oftentimes, the driller is primarily interested in the oil and gas is treated as a by-product. This happens when the oil-to-gas ratio at a potential well site is high, when gas prices are very low, or when the well is far away from existing infrastructure. When the costs of collecting the gas are high, it is a common practice for drillers to flare the gas. Texas allows producers to flare for up to 10 days after a new well completion, then requires a permit to continue flaring. The Texas Railroad Commission (RRC) states that to receive a permit, the operator “must provide documentation that progress has been made toward establishing the necessary infrastructure to produce gas rather than flare it” ([Texas Railroad Commission](#)). However, the number of flaring authorizations has ballooned over the past decade with the increase in fracking. I’ve plotted the number of exceptions over time in [figure 1](#) which I’ve obtained via a Public

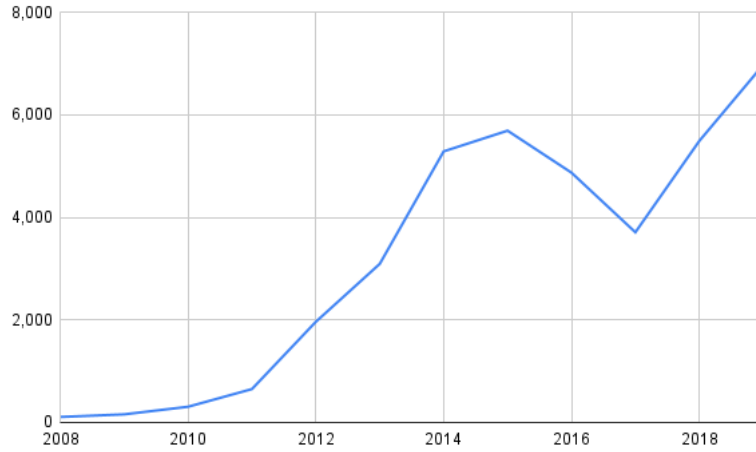


Figure 1: Number of Flaring Exceptions Issued by the Texas RRC by Year

Information Act request. In practice, many permits are issued because the gas is “uneconomical to collect.” Moreover the Texas RRC has a reputation for “rubber stamping thousands of flaring permits without requiring oil companies to come up with a plan to curb the practice” (Chapa, 2021). In fact, between 05/02/2021 and 05/02/2022 401 applications for permanent exemptions have been approved and zero have been denied.³

My paper studies flaring caused by producers choosing to not build pipelines. However, other causes of flaring do exist. Agerton and Upton (2020) show that substantial portions of flaring come from wells that have previously sold gas—implying that the wells are indeed connected but must flare due to pipeline capacity or processing constraints. In this paper, I ignore processing and capacity constraints since I cannot directly observe processing and pipeline capacity utilization rates.⁴

Producers drilling in new fields often drill first, then wait to build infrastructure until they are sure the well will be productive, or until gathering and processing capacity becomes available in the area. This leads to any produced gas being flared during the interim. In figure 2 I show

³Beginning on 05/02/2021, the Texas RRC implemented online applications for flaring permits, and has made this data publicly available at <https://webapps.rrc.state.tx.us/swr32/publicquery.xhtml>.

⁴Moreover, the analysis of Agerton and Upton (2020) seems to complement the main idea of this paper. They show that the proportion of gas from unconnected wells in three out of four basins decreases over the 2008-2020 period, consistent with the idea that the practice of flaring without connecting to a pipeline will be more prevalent earlier in a basin’s productive life and decrease as the network get built out and as infrastructure becomes available.

completed wells and permitted pipelines at four points in time. In the first two panels, there are many wells that are unconnected (and therefore flaring any associated gas), but will eventually go on to be connected by the last panel.

The pipeline networks which collect gas likely exhibit some network properties. Once a line is built, more connections can be added to that line at a later date (subject to capacity constraints). This means that the costs of connection at a given site likely decrease over time as new infrastructure creeps closer to that site. In figure 3 you can see that between 2005 and 2020, the pipeline network in the Permian Basin, especially the westernmost parts, fills out substantially. In theory, contracting would likely be able to internalize this network externality. However, little research has been done on whether this happens and to what degree.

Typically drillers will contract out with mid-stream gas gathering companies to have their wells connected. These gathering companies are one way that network externalities might be internalized. For example, a gathering company might be willing to charge below marginal cost to connect a well that would generate lots of spillovers. However, the industry is mixed between independent well operators and gatherers and larger producers which are vertically integrated and have the ability to both drill and build pipelines. In this paper, like many others in the literature, I abstract away from these firm-type heterogeneities.

3 Data

3.1 Lease Data

I use lease data collected by Enverus (formerly DrillingInfo). This lease data provides the spatial polygon of the lease as well as observables such as the grantor, grantee, effective date, expiration of primary term, and royalty rate. I process the raw lease data through two layers of clustering, described more in the appendix. The first issue in the lease data is that there are often multiple rows identifying what is clearly the same lease. This seems to be primarily a result of undivided mineral interests.⁵ To deal with this, I follow many of the lease processing choices of [Herrnstadt](#),

⁵For example, multiple members of a family might each show up as a distinct grantor with her own row in the data.

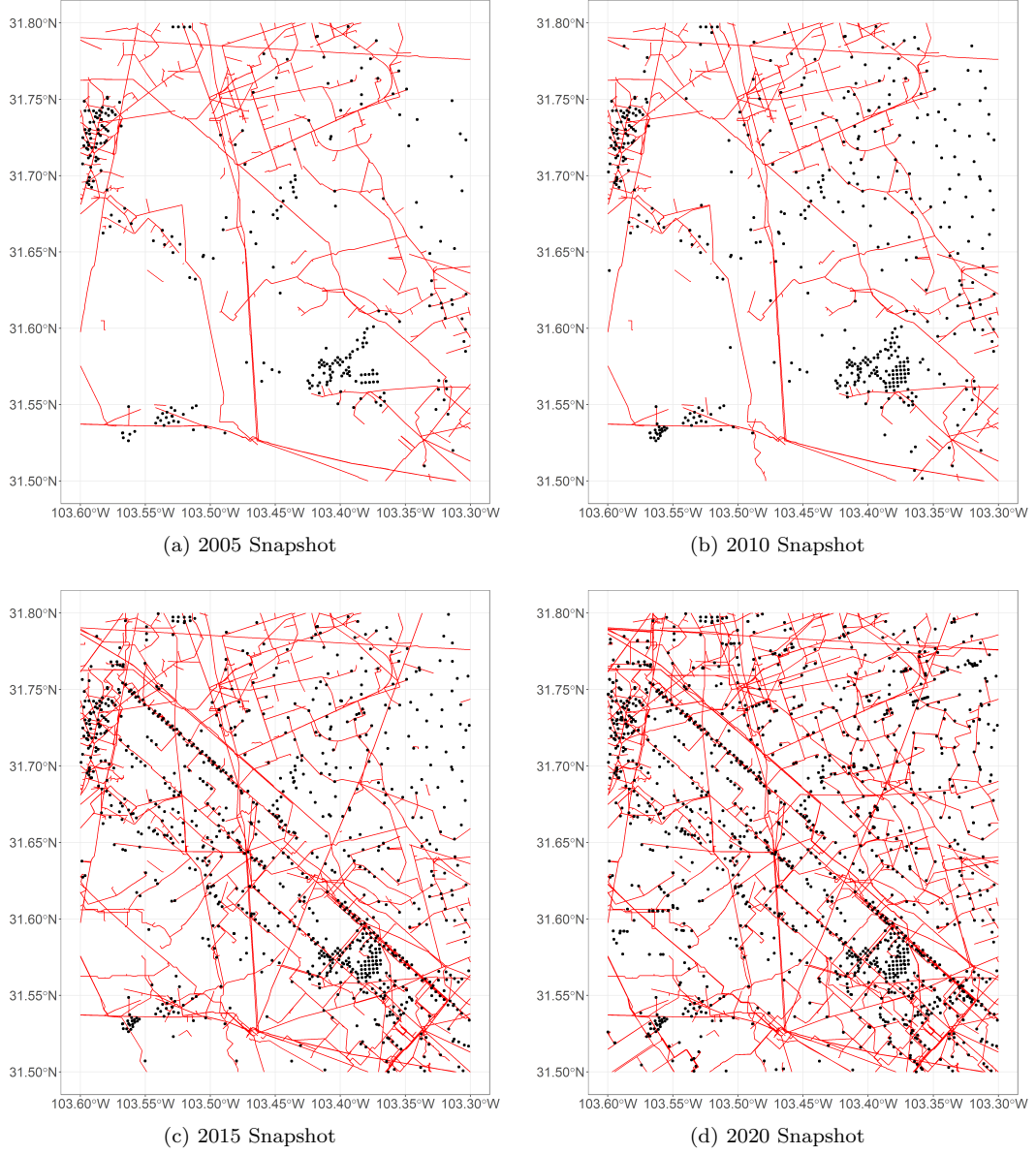


Figure 2: Snapshots of the development of a field from 2005-2020. Black dots are the locations of well surface holes, and red lines are natural gas pipelines permitted by that date.

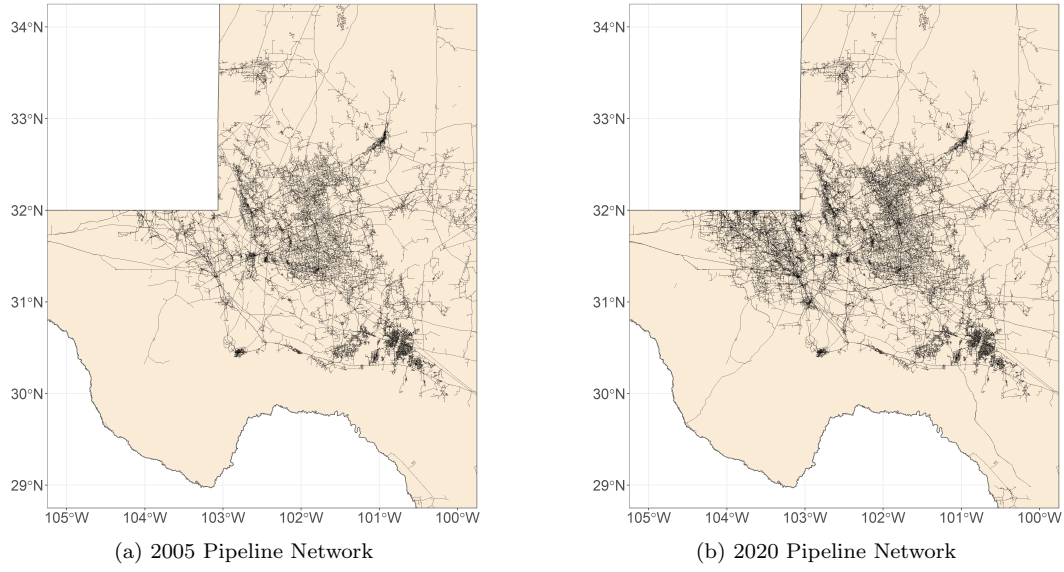


Figure 3: 15 Years of Network Expansion

[Kellogg, and Lewis \(2020\)](#). Namely, I use a hierarchical clustering algorithm on the observables of leases to collapse these into single rows.

Next, I identify lease amendments by also using a hierarchical clustering algorithm, this time, only on the spatial data. For example, there might be two rows of data corresponding with the same polygon. One has a primary term from 12-01-2005 through 12-01-2008, the other has a primary term running from 12-01-2007 through 12-01-2010. I interpret this as a lease amendment whereby the primary term is extended mid-lease. More details on the processing of the lease data can be found in the Appendix.

In my analysis I only use leases from the Permian Basin.⁶ The reason for this is primarily computational. Different basins have vastly different geological characteristics, and time-profiles of drilling. In my computational model, I would be unable to compute basin-time fixed effects, so I simply select the Permian Basin, the most active basin in Texas for my time sample (2010-2019).

Figure 4 plots the leases in my estimation sample.

⁶I use U.S. EIA boundaries to define the Permian basin. These boundaries can be found at the [EIA](#).

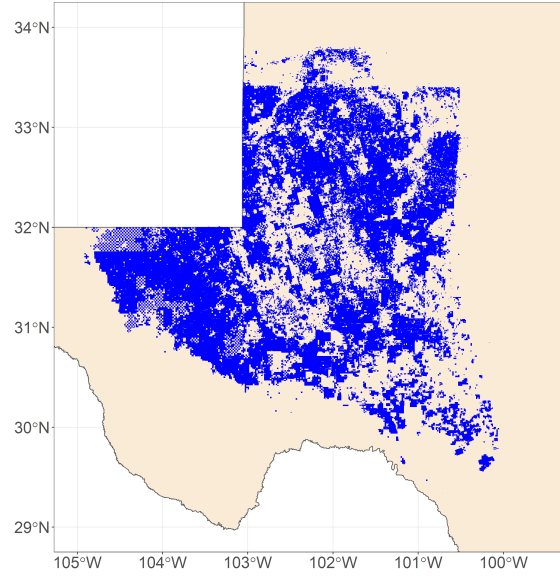


Figure 4: Leases in the Sample

3.2 Expected Production

I use well-level monthly production data obtained from Enverus to predict expected production for leases (both drilled and never drilled). Enverus provides data on well-level monthly production of both oil and gas. It also contains information on the observables of the well such as the spud and completion dates, and the depth, lateral length, and location. To construct expected oil and gas production from lease i at t , which I call ξ_{it}^o and ξ_{it}^g , respectively, I calculate the inverse-distance weighted mean of expected production from all wells completed within the last 18 months of t within 20km of i . Section 6.4 provides more detail on how I construct expected production.

3.3 Texas Railroad Commission Data

I obtain geospatial pipeline data from the Texas Railroad Commission (RRC). I also collect data on when individual pipelines were permitted from 2010 through 2019, which allows me to construct the evolution of the gathering network over those 9 years. Unfortunately, these permitting dates are not necessarily construction dates and construction typically happens after permitting. Moreover, I am unable to observe expansions to a line under the same permit, so these data contain errors where the direction of bias is ambiguous.

I also obtain lease-level monthly production data from the Texas Railroad Commission.⁷ These data report gas volumes broken down into sold, flared, and vented volumes. I infer a connection date for each lease as the earliest date when gas is sold. Then I merge that date into the Enverus production dataset using an RRC lease-Well API crosswalk.

3.4 Data Construction

I begin by turning the lease data into a quarter-lease panel dataset with a start date of 2010-01-01 and an end-date of 2019-12-01. I spatially join the lease data with the Enverus well data. A lease becomes “drilled” if I observe a well spudded between the expiration and effective dates and intersect the lease polygon. I call a lease “unconnected” if either zero gas is sold for the first year of the lease or if there are at least 200 days between the first production dates and first connection date (inferred from Texas RRC data) and over 70% of the RRC lease’s first-year of produced gas is flared.

Before dropping any data, there are 64,948 leases and 617,846 lease-quarter observations. I drop 18,989 lease-quarter observations (3%) due to missing distance or expected productivity. Another 37,319 are dropped because of missing neighbor observables (which are needed to calculate the spillover effects).

In addition I am missing observations on whether a drilled lease becomes connected. There are 24,159 drilled leases and I cannot determine how much 851 of those flared. I drop all lease-quarter observations for those wells. I also randomly drop a proportionate amount of never-drilled leases since my estimation strategy hinges on being able to estimate the probability of drilling and connecting. I am left with 57,776 leases and 528,883 lease-quarter observations. Summary statistics for the leases are presented in Table 1.

Most leases have a primary term length of three years. Both the 25th percentile and 75th percentile lease have primary term lengths of 36 months. About 40% of leases become drilled and of those about 10% of leases that are drilled are unconnected. The average lease is about a kilometer and a half away from the nearest pipeline, though many leases have a pipeline that

⁷“Leases” defined by the RRC are not the same as the defined by Enverus.

Table 1: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Primary Term Length	57776	38.775	15.252	-2	36	36	360
EffectiveYear	57776	2013.026	3.405	1995	2011	2016	2020
ExpirationofPrimaryTerm	57776	2016.288	3.398	2010	2014	2019	2045
Unconnected	23575	0.099	0.299	0	0	0	1
Expected Discounted Oil	57776	0.005	0.005	0	0.001	0.008	0.024
Expected Discounted Gas	57776	0.02	0.033	0	0.002	0.024	0.432
Start Distance	57776	1.478	3.522	0	0	1.345	34.239
End Distance	57776	1.402	3.508	0	0	1.127	34.239
Royalty	33514	0.232	0.032	0.01	0.2	0.25	3.1

intersects with the lease polygon.

4 Descriptive Results

To motivate the setup of my model and confirm that the variation in the observables has the predicted effect on drilling and flaring outcomes I estimate some descriptive regressions. The first set of regressions explores how flaring outcomes conditional on drilling vary across leases. The second set of regressions explores how the lease observables affect the timing of drilling – regardless of flaring outcomes.

First, I divide the spatial extent of the Permian basin into $0.05 \text{ longitude} \times 0.05 \text{ latitude}$ grids.⁸ The idea is that the underlying geology of different leases is similar within a grid. This approach is similar to [Covert and Sweeney \(2019\)](#) who use a 10 mile by 10 mile grid to control for underlying geology to study revenues received by landowners under auctions versus informal negotiations.

Specifically, the equations I estimate are:

$$y_{it} = \beta_1 d_{it} + \beta_2 d_{it}^2 + \beta_3 \xi_{it}^o + \beta_4 \xi_{it}^g + \beta_5 p_t^o + \beta_6 p_t^g + \beta_7 N_{it}^{\text{benefit}} + \gamma_{g(i)} + \epsilon_{it} \quad (1)$$

where y_{it} is the outcome of interest, d_{it} is the distance from lease i at time t to the nearest pipeline, ξ^g , and ξ^o are expected discounted gas and oil production, p_t are oil and gas spot prices during quarter t , N^{benefit} measures how many leases would have their distance reduced by i connecting, and $\gamma_{g(i)}$ is a grid fixed-effect. The outcomes of interest are quantity flared, quantity of

⁸In the Permian, these grids are approximate 10 square miles – smaller than [Covert and Sweeney \(2019\)](#) use in their paper with a similar research design.

gas sold, the percentage of gas flared, and a dummy for whether the lease is unconnected during its first year. I expect distance to be correlated with increased flaring, high natural gas prices to be correlated with decreased flaring, and high oil prices to be correlated with increased flaring. The coefficients on N^{benefit} will be negative if leases which could generate higher spillovers for their neighbors are more likely to connect.

Results from these regressions are presented in table 2. All dependent variables are standardized. The first three columns present OLS results with standardized dependent variables, the last column presents the coefficients of a logistic regression with the binary dependent variable, $1(\text{Unconnected})$. The last column is the primary column of interest since it maps to the outcomes in the full dynamic discrete choice model. Focusing on column (4), the effect of distance is quite large. A one standard deviation increase in distance increases the odds of a well being unconnected by 68% ($\exp(0.576 - 0.057)$). More productive wells tend to be far less likely to remain unconnected. However, looking at columns (1), (2) and (3) suggest that wells with higher expected oil productivity tend to both flare more and sell more gas, while wells with higher expected gas productivity do not flare more gas than their less productive counterparts. The effect of prices is small but significant in a few columns. Higher oil prices are associated with higher percentages of gas flared, while high gas prices are associated with lower percentages of gas flared. None of these regressions present strong evidence that leases are more likely to connect if they have neighbors that might benefit from that choice.

Next I show how the observables are associated with drilling probabilities using a similar grid fixed-effect strategy. I run a logit of:

$$\mathbb{1}(i \text{ drilled during } t) = \beta_1 d_{it} + \beta_2 d_{it}^2 + \beta_3 \xi_{it}^o + \beta_4 \xi_{it}^g + \beta_5 p_t^o + \beta_6 p_t^g + \beta_7 N_{it}^{\text{benefit}} + \gamma_{g(i)} + \epsilon_{it} \quad (2)$$

Results are presented Table 3. Again, distance has a strong negative effect on the likelihood of drilling while expected oil production has a strong positive effect. Here, the characterization of drillers being primarily interested in oil seems true. Higher expected oil productivity and higher oil prices are both strongly associated with increases in the propensity to drill, while neither expected gas productivity or gas prices have significant coefficients. A one standard deviation increase in

Table 2: Effect of Observables on Flaring Outcomes Conditional on Drilling

	Percent Flared (1)	Q Flared (2)	Q Sold (3)	Unconnected (4)
Distance	0.238*** (0.073)	0.006 (0.048)	-0.013 (0.054)	0.576* (0.350)
Distance ²	-0.025* (0.014)	-0.003 (0.008)	0.008* (0.004)	-0.057 (0.050)
Expected Oil Productivity (ξ^o)	0.005 (0.023)	0.141*** (0.021)	0.116*** (0.026)	-1.24*** (0.245)
Expected Gas Productivity (ξ^g)	-0.096*** (0.035)	-0.019 (0.034)	0.234*** (0.043)	-0.452** (0.205)
Oil Price (p_t^o)	0.056*** (0.015)	0.002 (0.015)	-0.051*** (0.012)	0.082 (0.107)
Gas Price (p_t^g)	-0.019* (0.011)	-0.007 (0.014)	0.011 (0.010)	-0.005 (0.083)
N Benefiting Leases	0.008 (0.014)	-0.007 (0.011)	-0.013 (0.019)	0.121 (0.153)
Family	OLS	OLS	OLS	Logit
Observations	18,846	19,737	19,737	5,135
R ²	0.627	0.503	0.698	
Within R ²	0.015	0.012	0.088	
Squared Correlation				0.288
Pseudo R ²				0.268
BIC				8,562.2
Grid fixed effects	✓	✓	✓	✓

Notes: Each column displays estimates of equation 1. Standard-errors are clustered at the grid-level. All independent variables are standardized.

ξ^o is associated with a 127% increase in the likelihood of drilling while a one standard deviation increase in the price of oil is associated with a 38% increase in the likelihood of drilling.

The coefficient on N benefiting leases is negative. If firms internalized benefits for their neighbors, we would expect that coefficient be positive. However, N benefitting leases is likely correlated with a leases number of undrilled adjacent leases and firms might prefer to wait to see if adjacent tracts are productive before drilling or might be interested in the productive inputs used by neighboring firms.⁹ These issues have been previously explored by [Décaire, Gilje, and Taillard \(2019\)](#), [Covert \(2015\)](#), and [Covert and Sweeney \(2022\)](#).

Table 3: Fixed-Effect Logit of Observables on Drilling Outcomes

	Drill	
	(1)	(2)
Distance	-0.617*** (0.187)	-0.763*** (0.134)
Distance ²	-0.001 (0.022)	0.025* (0.014)
Expected Oil Productivity (ξ_o)	0.417 (0.394)	0.819*** (0.104)
Expected Gas Productivity (ξ_g)	-0.216 (0.510)	-0.093 (0.085)
N Benefiting Leases	-0.433*** (0.068)	-0.199*** (0.065)
Gas Price (p^g)		0.039 (0.045)
Oil Price (p^o)		0.325*** (0.059)
Standard-Errors	Grid-date	Grid
Observations	30,087	200,341
Squared Correlation	0.315	0.091
Pseudo R ²	0.338	0.212
BIC	44,158.5	56,027.4
Grid-date fixed effects	✓	
monthstilexp fixed effects	✓	✓
Grantee fixed effects	✓	✓
Grid fixed effects		✓

Note: Each column displays estimates of equation 2. Standard errors are clustered at the grid level. All independent variables are standardized.

⁹When a well is drilled, the depth is usually observable by neighbors. The inputs in the fracking job are also required to be disclosed on fracfocus.org.

5 A Dynamic Model of Drilling and Flaring

In each quarter up until and including the time of the leases expiration, the lessee observes a vector of the state variables, \vec{x}_{it} and makes the decision to either wait, drill and flare, or drill and gather. I denote this set $j \in \{W, F, G\}$. Once the lessee decides to drill, either with $j = G, F$, that period becomes the terminal period. The operator then receives the expected sum of discounted revenue from production and pays the drilling and connecting costs.¹⁰ This means the drillers' problem is a finite-horizon optimal stopping problem with two potential actions for stopping, and can be formulated as a dynamic programming problem with a Bellman equation.

Thus, the firm's problem is

$$V(\vec{x}_{it}, \epsilon_{it}) \equiv \max_j E \left[\sum_{t=1}^T \beta^{t-1} (\pi(j, \vec{x}_{it}) + \epsilon_{itj}) \right] \quad (3)$$

where T is expiration quarter of the lease, $\pi(j, \vec{x}_{it})$ is the per-period profit of taking action j , with observable lease state variables, \vec{x}_{it} . ϵ_{itj} is an unobserved shock assumed to be i.i.d. Type-I Extreme Value with scale parameter σ . Unlike discrete choice estimation of consumer preferences where the outcome is scale-less indirect utility, σ is identified since expected revenues are being measured directly in dollars. The set of state variables, \vec{x}_{it} , include i 's distance to the nearest gathering line at t , d_{it} , the price of oil and gas, p_t^o, p_t^g , the expected sum of discounted production, ξ_{it}^o, ξ_{it}^g , the effect of building a pipeline on i 's neighbors $\Delta \tilde{V}_{it}$, the time t (and hence the time until i 's expiration date), and the royalty rate of the lease, r_i .¹¹

The firm's maximization problem can be expressed in Bellman form as:

$$V(\vec{x}_{it}, \epsilon_{it}) = \max_j \{ \pi(j, \vec{x}_{it}) + \epsilon_{itj} + E[V(\vec{x}_{it+1} | \vec{x}_{it})] \} \quad (4)$$

¹⁰An underlying assumption here is that each lease can only be drilled once. This is clearly not true - many parcels could contain multiple wellsites. However, this is a simplifying assumption also made by [Herrnstadt, Kellogg, and Lewis \(2020\)](#).

¹¹I only consider pipeline construction spillovers. I do not, for example, think about common pool problems that can arise in some natural resource extraction problems (see [Cynthia Lin \(2013\)](#) for an exploration of common pool problems and lease option exercise). The common pool problem is not a major issue in shale formations, since hydrocarbons are only released after fracturing the rocks under high pressures, causing little or no impact on neighboring parcels ([Décaire, Gilje, and Taillard, 2019](#)).

The deterministic part of per period payouts are given by:

$$\pi_i(j, \xi_{it}^o, \xi_{it}^g, p_t, d_{it}, \Delta\tilde{V}) = \begin{cases} R_i^o(p_t, \xi_{it}^o) - C_t^F & j = F \\ R_i^o(p_t, \xi_{it}^o) + R_i^g(p_t, \xi_{it}^g) - C_t^G(d_{it}, \Delta\tilde{V}) & j = G \\ 0 & j = W \end{cases}$$

where R^o and R^g are the expected revenue from oil and gas, respectively, and C^F , C^G are the costs of drilling and flaring and drilling and gathering. Revenues are calculated as expected discounted production (ξ) multiplied by the spot price less royalty and taxes (4.6% for oil and 7.5% for gas).

$$R_i^o(p_t, \xi_{it}^o) = \xi_{it}^o p_t^o (1 - r_i - 0.046)$$

$$R_i^g(p_t, \xi_{it}^g) = \xi_{it}^g p_t^g (1 - r_i - 0.075)$$

I assume costs can be decomposed into:

$$C_t^F = \delta^F + \delta_{y(t)}$$

$$C_t^G = \delta^G + \delta_{y(t)} + \alpha_d d_{it} - \alpha_{\tilde{V}} \sum_k \Delta\tilde{V}_{ik}$$

δ^F and δ^G are the fixed costs associated with flaring and gathering, respectively. $\delta_{y(t)}$ are year fixed effects that allow the price of drilling to move over time. $\delta_{y(t)}$ capture changes in the rental rate of drilling rigs as well as changes over time in average well depth or complexity. $\Delta\tilde{V}_{ik}$ is a measurement (in the same units \bar{V} is denoted in) of how much building a pipeline to i increases the value of a neighboring lease, k , and will be discussed in greater detail in the next section. The logic behind this cost function is that pipeline connection costs will be a function of overall distance, but that there might be a discount to the drilling firm if the pipeline is expected to be valuable for the gathering firm in the future. $\alpha_{\tilde{V}}$ will measure the proportion of spillover benefits internalized by firm i .

Define the ex-ante value function as the expected value of V_{it} before the revelation of ϵ_{it} :

$$\bar{V}_{it}(\vec{x}_{it}) \equiv \int V_{it}(\vec{x}_{it}, \epsilon) f(\epsilon) d\epsilon \quad (5)$$

where $f(\cdot)$ is the distribution of the error term, ϵ .

Finally, let $\Omega(\cdot)$ be the transition probabilities of the state variables and define the conditional value function as the value of making a choice j in period t (less the error term), then behaving optimally from $t + 1$ onward:

$$v_{it}(j, \vec{x}_{it}) \equiv \pi_i(j, \vec{x}_{it}) + \beta \int \bar{V}_{it+1}(\vec{x}_{it+1}) \Omega(\vec{x}_{it+1} | \vec{x}_{it}) d\vec{x}_{it+1} \quad (6)$$

Since the error terms are assumed to be type-I Extreme Value, the choice probabilities are given by the familiar logit form:

$$Pr(i \text{ chooses } j | \vec{x}_{it}) = \frac{\exp(v_{it}(j, \vec{x}_{it})/\sigma)}{\sum_k \exp(v_{it}(k, \vec{x}_{it})/\sigma)} \quad (7)$$

6 Estimation

6.1 Dynamic Discrete Choice Estimation

Because of the assumption on the error term, ϵ , [Joseph Hotz and Miller \(1993\)](#) and [Arcidiacono and Miller \(2011\)](#) show that the ex-ante value function admits the closed form:

$$\bar{V}_{it}(\vec{x}_{it}) = -\sigma \ln(Pr(j = \tilde{j} | \vec{x}_{it})) + v_{it}(\tilde{j}, \vec{x}_{it}) + \sigma\gamma \quad \forall \tilde{j} \quad (8)$$

where γ is Euler's constant. The intuition here is that the ex-ante value function can be found by evaluating the conditional value function, v , at any \tilde{j} , then applying a correction which is larger when the probability of choosing \tilde{j} is smaller. The constant term at the end, $\sigma\gamma$ is simply the expected value of ϵ . I omit this term for the remainder of the paper since choice probabilities are invariant to an additive constant in each v_j .

Since $\bar{V}(\vec{x}_{it})$ can be evaluating using any choice \tilde{j} , I can select a terminating action $\tilde{j} = G$, then

$$\bar{V}_{it}(\vec{x}_{it}) = -\sigma \ln(\Pr(j = G|\vec{x}_{it})) + \pi(G, \vec{x}_{it}) \quad (9)$$

Equation 9 can be substituted into the conditional value function, equation 6 to yield:

$$v_{it}(j, \vec{x}_{it}) = \pi(j, \vec{x}_{it}) + \beta \int [-\sigma \ln(\Pr(j_{t+1} = G|\vec{x}_{it+1})) + \pi(G, \vec{x}_{it+1})] \Omega(\vec{x}_{it+1}|\vec{x}_{it}) d\vec{x}_{it+1} \quad (10)$$

All of the pieces of equation 10 can be constructed from the data. $\pi(\cdot)$ is simply a linear function of the parameters and observables. $\Pr(j_{t+1}=G|\vec{x}_{it+1})$ and $\Omega(\vec{x}_{it+1}|\vec{x}_{it})$ can be directly estimated from the data. Since π is linear in the stochastic state variables, it can be brought outside the integral and evaluated at $E[\vec{x}_{it+1}|\vec{x}_{it}]$. To construct $\int -\sigma \ln(\Pr(j_{t+1} = G|\vec{x}_{it+1})) \Omega(\vec{x}_{it+1}|\vec{x}_{it}) d\vec{x}_{it+1}$, I estimate the transition function for \vec{x}_{it} , $\Omega(\vec{x}_{it}|\vec{x}_{it+1})$, then take simulation draws of \vec{x}_{it+1} , calculate the log probabilities associated with the simulation draws, then average.

For each j , you can express the v as:

$$v(j, \vec{x}_{it}) = \begin{cases} \xi_{it}^o p_t^o - (\delta^F + \delta_t) & j = F \\ \xi_{it}^o p_t^p + \xi_{it}^g p_t^g - (\delta^G + \delta_t + \alpha_d d_{it} - \alpha_v \sum_k \Delta \tilde{V}_{ik}) & j = G \\ \beta [\xi_{it}^o E[p_{t+1}^o] + \xi_{it}^g E[p_{t+1}^g] - (\delta^G + E[\delta_{t+1}] + \alpha_d E[d_{it+1} - \alpha_v \sum_k \Delta \tilde{V}_{ik}]) + & j = W \\ \sigma \int -\ln(\Pr(j_{t+1} = G|\vec{x}_{it+1})) \Omega(\vec{x}_{it+1}|\vec{x}_{it}) d\vec{x}_{it+1} \end{cases} \quad (11)$$

The parameters of to be estimated are $\alpha_d, \alpha_{\tilde{V}}, \delta_C, \delta_G, \delta_t$, and σ . In theory, β is identified also, but its common practice in the dynamic discrete choice literature to simply pick a reasonable value for β . I select 0.98, implying a yearly rate of about 0.92. δ_t and $E[\delta_t]$ are not all identified without some restrictions. The same issue appears in [Gowrisankaran et al. \(2012\)](#) and [Murphy \(2018\)](#). Both papers fit δ_{t+1} and δ_t to an AR(1), though their exact estimation process varies. I choose to estimate

$$\delta_{t+1} = \omega_0 + \omega_1 \delta_t + \eta_t$$

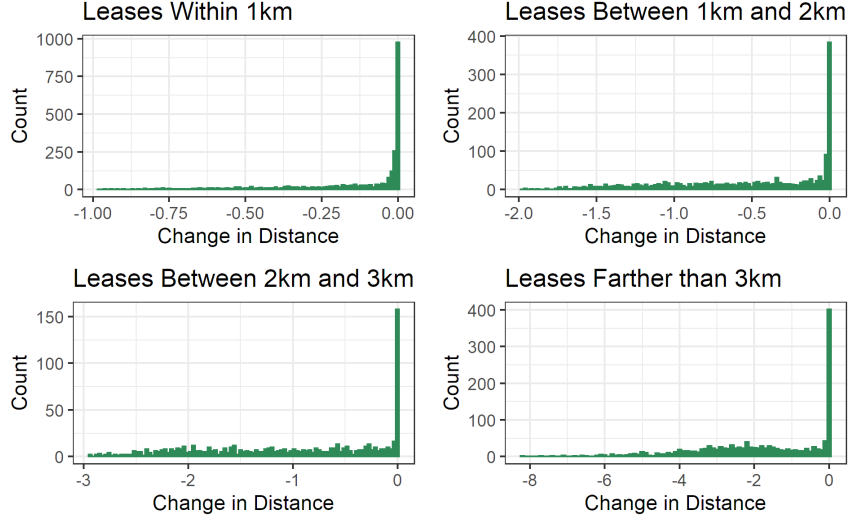


Figure 5: Positive changes in distance (m) for leases at varying distances

within the likelihood function. Then replace $E[\delta_{t+1}]$ with $\hat{\delta}_{t+1}$.

6.2 Transition Probabilities - $\Omega(\vec{x}_{it+1}|\vec{x}_{it})$

Some of the state variables, such as the time fixed effects, transition deterministically. Other state variables, namely $\xi_{it}^o, \xi_{it}^g, \Delta\tilde{V}_{it}$, transition over time. However, I do not want to think of the firm as “waiting for good draws” of these state variables so I assume that their expected value in $t + 1$ is equal to their value in t . Kellogg (2014) essentially makes the same modelling assumption.¹²

That leaves transitions in d_{it} , p_t^o , and p_t^g . To simulate changes in d_{it} I simply take draws from the observed distribution in Δd_{it} for different bins of d . Figure 5 plots these distribution of these distance changes.

To follow estimate the transition of p_t^o and p_t^g I follow Hernnstadt et al (2020) and Kellogg (2014) and estimate the following Markov process for both oil and gas:

$$\ln(p_{t+1}) = \ln(p_t) + \kappa_o + \kappa_1 p_t + \sigma \eta_{t+1} \quad (12)$$

In this price process κ_0 and κ_1 are drift and mean reversion parameters, respectively. Coef-

¹²Kellogg(2014) does not so explicitly try to construct expected production. Instead, he assume production rationalizes costs (whereas I essentially do the opposite). However, in his dynamic model he makes the assumption that producers do not integrate over their expectation of new realizations in expected production to calculate their continuation value of the lease.

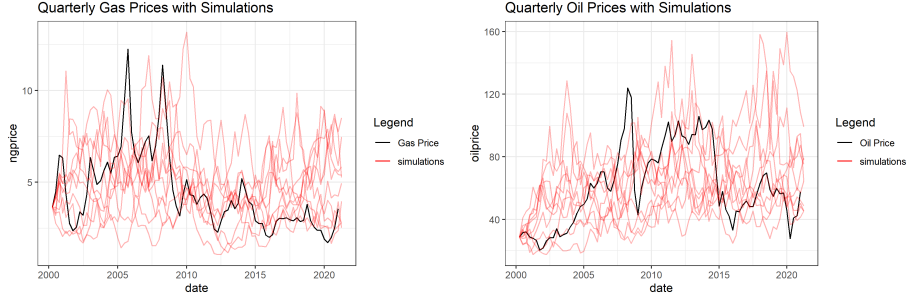


Figure 6: EIA Spot Prices and Examples of Simulated Price Paths

ficients from the estimation of equation 12 are found table 4. I've also plotted the time series of prices along with some simulations based off of these parameters in figure 6. The estimated coefficients indicate that both price series are process with positive expected drift and mean reversion, but that they are predominantly driven by the error term. You can see that for both processes, the residual standard error is much larger than the constant (drift term).

Table 4: Estimated Markov Process Parameters

	<i>Dependent variable:</i>	
	$\Delta \log \text{ oil price}$	$\Delta \log \text{ gas price}$
	(1)	(2)
Price	-0.002** (0.001)	-0.022** (0.010)
Constant	0.107** (0.048)	0.096* (0.049)
Observations	83	83
R ²	0.059	0.055
Adjusted R ²	0.047	0.043
Residual Std. Error (df = 81)	0.168	0.193
F Statistic (df = 1; 81)	5.047**	4.697**

Note: *p<0.1; **p<0.05; ***p<0.01

6.3 Construction of \tilde{V}

Consider the example in figure 7. There are nearby leases, A and B . A is considering building and connecting a well. If A chooses to connect, the future connection costs for B will decrease in the next period by $\alpha_d(|AB| - |B|)$. B should be willing to compensate A up to the difference in B 's

ex-ante value: $\overline{V}_{Bt}(p_t, d_{Bt} = |AB|) - \overline{V}_{Bt}(p_t, d_{Bt} = |B|)$ to connect.¹³

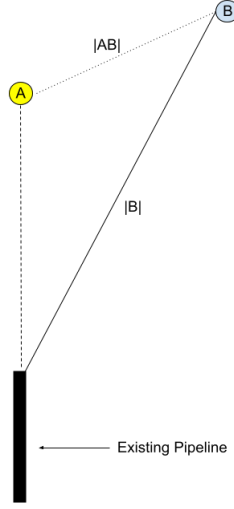


Figure 7: Hypothetical example showing that lease B 's connection distance depends upon the choice of lease A .

I can use the Hotz-Miller identity, equation 9, to simplify this difference to become a the sum of a difference in expected log probabilities and a difference in costs.

$$\overline{V}_{Bt}(p_t, |AB|) - \overline{V}_{Bt}(p_t, |B|) = \ln(\text{pr}(j_t = G ||B|, p_t)) - \ln(\text{pr}(j_t = G ||AB|, p_t)) + \alpha_d(|AB| - |B|) \quad (13)$$

In practice, the construction of pipes and wells are typically completed by separate companies. However, the general principle still applies. A gathering company might be willing to offer a discount to A (to entice it to connect), with the hopes of decreasing its future costs and increasing its expected number of future customers. However, the gathering company is unlikely to be able to capitalize the entire change in \overline{V}_B , and therefore will be unable (and potentially unwilling) to pass that entire change on to A . Moreover, there might be other price distortions such as market power that would lead the gathering companies to not pass along a discount to A . My estimation strategy will estimate the proportion of this change in value captured by driller when the he chooses to

¹³Some readers might notice that if the goal is to connect both A and B at minimum cost, the best way to do it would be to construct $|B|$, then draw a line orthogonal to $|B|$ to A . I believe that this is a *planning* issue as opposed to a spillover issue. For example, you would expect if A and B were owned by the same firm they would be more likely to select this minimum distance solution. I leave this issue of network optimization for future work, and simply focus on these cost spillovers.

connect.

To construct \tilde{V} , for each lease-quarter I draw the shortest line from that lease to already existing pipes. For all leases $k \in K$ within 2km of that hypothetical line, I save their actual and counterfactual distances. Then I construct $\tilde{V}_{it} = \sum_{k \in K} \Delta \bar{V}_{ik}$ using the estimated pipeline cost parameters of the model.

6.4 Construction of Expected Revenue

To measure expected productivity at each lease at time t , I take an inverse-distance weighted mean of expected production, ξ_i , from all wells completed within the past 18 months of t within 20km of the lease. In the dynamic model $\hat{\xi}_{it}$ enters as a state variable. Since the time window used to compute $\hat{\xi}$ moves with t , this means that expected productivity will change over time, despite the fact that the actual geology of the lease is time-invariant. This seems reasonable given that the outcome of neighboring wells likely leads to firms updating their beliefs.

Expected production from each well is an estimated term. To construct estimated production, I make a common assumption in the literature – to follow the Arps Model and assume production decays exponentially from a well.¹⁴ Oil and gas production in each time period, t , is given by:

$$o_{jt} = O_{j0} t^{\beta^o} \exp(\nu_{jt}^o)$$

$$g_{jt} = G_{j0} t^{\beta^g} \exp(\nu_{jt}^g)$$

where O_{j0} , G_{j0} are the initial rates of production, β are the decline rates, and ν are the model errors.

I estimate the decline rates, β^o and β^g , separately for wells drilled by year by estimating the well fixed-effect equations:

¹⁴An assumption used throughout the construction of expected production is that producers take expected production from their leases as a given. This is both technically false and a good simplifying assumption. Producers can affect their production by varying well depth, horizontal length, and amount of fluid used in fracturing. However by constructing expected production using nearby wells, I am essentially assuming that well-design questions are already enveloped-in and allowing expected production to reflect changes in technology over time and differences in optimal well construction across space.

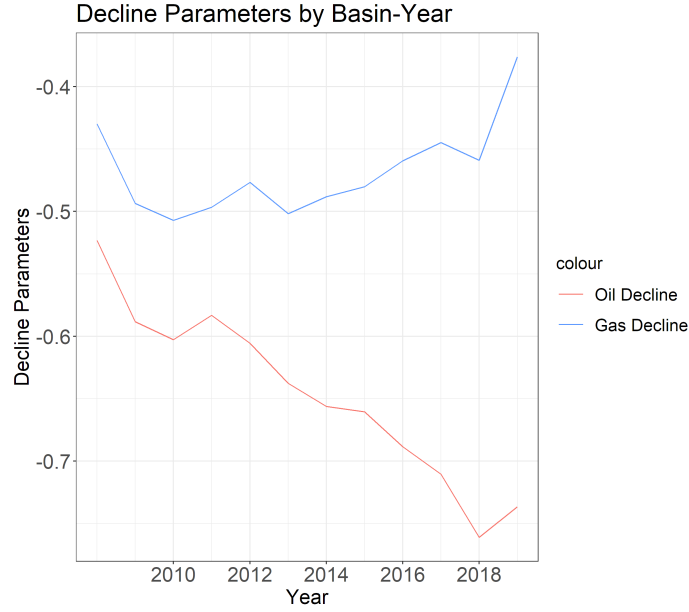


Figure 8: Plot of estimated Permian basin decline parameters by drilling year. Oil decline parameters are plotted in red while gas decline parameters are plotted in blue.

$$\log(g_{jt}) = \beta^g \log(t) + \delta_j + \nu_{jt}^g$$

$$\log(o_{jt}) = \beta^o \log(t) + \delta_j + \nu_{jt}^o$$

I've plotted the estimated $\hat{\beta}^g$ and $\hat{\beta}^o$ in figure 8. For context, a decline parameter of -0.5 implies that 46% of discounted production over the first five years of a well's life will occur during the first year. With the estimated decline parameters in hand I can calculate expected monthly production by observing the well's initial production rate, which I obtain from Enverus. I use second-month production instead of first-month, since the first-month values are often truncated by not having a full month of production. Finally, I obtain expected well-level lifetime production by summing and discounting expected monthly production for each well over a five year period.

6.5 Estimation of Conditional Choice Probabilities

Ideally, I would be able to construct conditional choice probabilities non-parametrically. However, the relatively large state space makes this impossible. Following other papers in the literature such as Murphy (2010), I estimate conditional choice probabilities by estimating a logit with b-spline

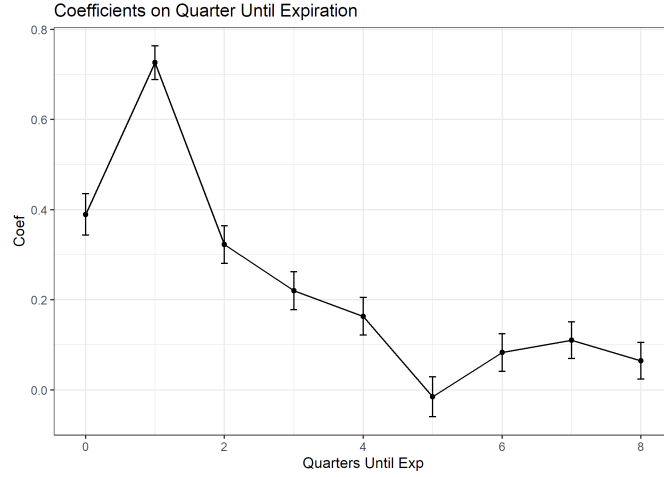


Figure 9: Coefficients on Quarter Until Expiration

expansions. Specifically I estimate:

$$\hat{Prob}(j = G|\vec{x}_{it}) = \Lambda \left(\sum_{s=1}^5 \phi_s^{\xi^o} S_s^{\xi^o}(\xi_{it}^o) + \sum_{s=1}^5 \phi_s^{\xi^g} S_s^{\xi^g}(\xi_{it}^g) + \sum_{s=1}^5 \phi_s^d S_s^d(d_{it}) + \sum_{y=2011}^{2019} \phi_y + \sum_{\tau=0}^8 \psi_\tau \right) \quad (14)$$

where Λ denotes the logistic CDF, $S(\cdot)$ are the spline basis functions of the argument in the superscript, ϕ_y are year fixed-effects, and ψ_τ are quarter-until-expiration fixed-effects.

7 Results

7.1 Conditional Choice Probabilities

The coefficients from the logit match the expected intuition from the underlying dynamic model. I've plotted the quarter until expiration coefficients in figure 9. In the dynamic model the probability of drilling and gathering should increase exponentially until the time of expiration. The shape of the estimated fixed effects is mostly consistent with this, with the main exception being that the coefficient at the quarter of expiration is lower than the coefficient for one quarter away from the time of expiration. These coefficients are an important source of variation in the expected probability of drilling since they do not directly affect the payout associated with drilling.

7.2 Dynamic Discrete Choice Results

Results for the dynamic discrete choice can be found in table 5 and the estimated year fixed effects are plotted in figure 11. Standard errors are calculated with 50 bootstraps where I sample leases with replacement. Expected revenue was entered into the likelihood as \$10,000,000 in revenue, so each parameter can be interpreted as tens of millions of dollars. The scale parameter of the error term is estimated to be \$7 million. This implies a standard deviation of the error term of $\$7 \text{ million} \cdot \pi/\sqrt{6} = \9 million .

The estimated fixed costs are \$38,000,000 and \$21,000,000, which are quite high. However, these are the implied costs for a randomly selected lease – most of which are not observed drilling. The implied cost for drilled wells is the estimated fixed cost plus the error term (which is structurally a cost shock). Conditional on drilling the error term is expected to be positive and relatively large. Thus, the expected cost for wells actual observed drilling is far lower. The same issue appeared in Murphy (2010) in his study of parcel development in San Francisco using very similar methods. His estimated cost of development were very high, but the fixed costs of development for parcels which actually developed were far more believable. I actually find that when the expectation of the error term for drilled wells is included with the fixed costs, most of the implied fixed costs are positive – this suggests that my estimates of revenue are biased downward. I’ve plotted the implied fixed costs in figure 10. You can also see that after including the expectation of the conditional error, the fixed costs for gathered wells are greater for gathered wells than flared wells.

The estimated cost of distance is also quite high. The estimated cost per kilometer of pipeline for less than 1km is almost \$10,000,000. I estimate that the cost per km is decreasing in overall distance. However, these cost estimates are biased upwards since my counterfactual simulations show that predicted pipeline distance is less than actual distance built – eg if a lease is 1km from the nearest pipeline, in expectation more than 1km will be built. Part of this gap is a no-brainer – sometimes pipelines need to go around things. Another part is likely a capacity issue since I observe many pipelines being constructed in parallel. This would bias my cost estimates upward and will be discussed in greater detail in the following section.

In order to assess the empirical magnitudes of the cost parameters and of the spillover inter-

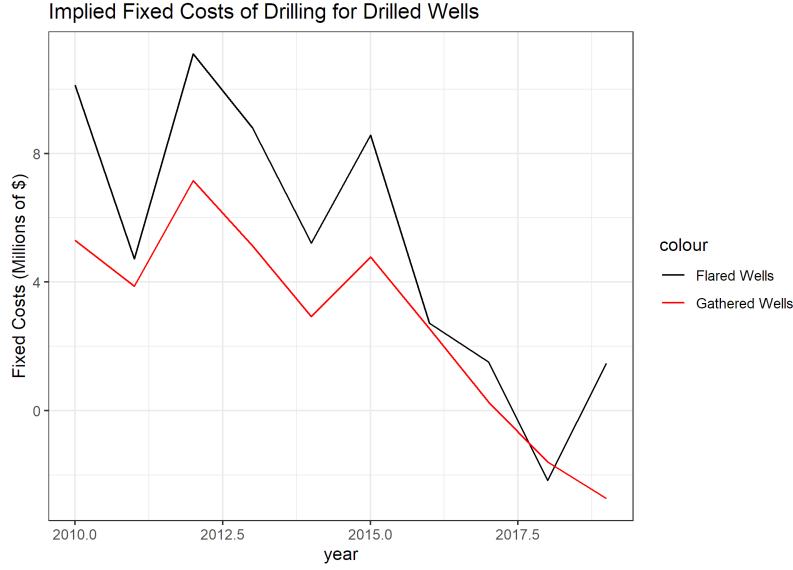


Figure 10: Expected value of fixed costs for drilled wells by year. For flared wells this is calculated as $C_f + \delta_y(t) + E[\epsilon_{iFt} | i \text{ chose } F \text{ during } t]$. It is calculated analogously for gathered wells.

nalization parameter, I use a forward simulation procedure described in the next section.

	Estimate	sd	Interval95
Error Scale Parameter (σ)	0.70	0.13	(0.442, 0.962)
Fixed Costs of Flaring (C_f)	-3.87	0.86	(-5.55, -2.183)
Fixed Costs of Gathering (C_g)	-2.13	0.54	(-3.179, -1.083)
<i>Spillovers</i> $\Delta\tilde{V}$	0.03	0.00	(0.02, 0.035)
Distance (d)	-0.96	0.19	(-1.336, -0.582)
$d \times \mathbb{1}(1 \leq d < 2)$	0.01	0.09	(-0.168, 0.194)
$d \times \mathbb{1}(2 \leq d < 3)$	0.36	0.11	(0.146, 0.579)
$d \times \mathbb{1}(3 \leq d)$	0.81	0.17	(0.49, 1.139)

Table 5: DDC Results

8 Simulations and Policy Counterfactuals

Having estimated my model, I now proceed to using my model estimates for simulations. The first set of simulations I discuss involve constructing a close analogue to the static marginal abatement curves constructed by Lade and Rudik (2020). Then, I proceed to a full dynamic forward simulation which will allow me to assess the performance of my model estimates, examine the estimated magnitudes of the parameters, and make predictions about drilling and flaring outcomes under varying policy counterfactuals.

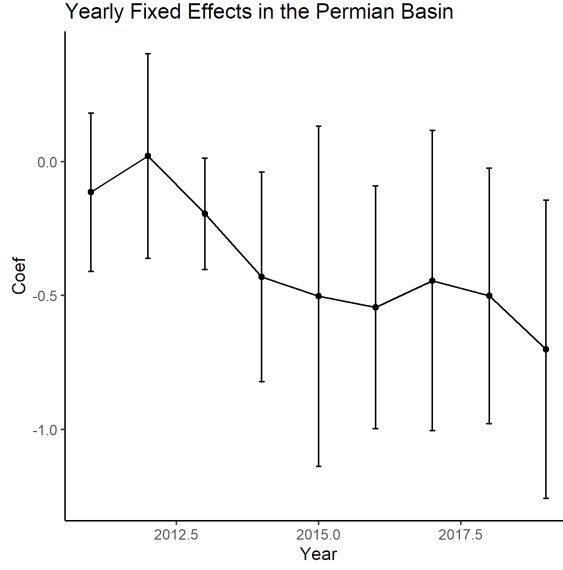


Figure 11: Year Fixed Effects

8.1 Estimated costs perform better than reported costs

To compare my results with previous work I follow the methodology of Lade and Rudik (2020) and construct static marginal abatement curves on my own sample using first, the reported cost estimates used in that paper, then my own cost estimates.

Lade and Rudik (2020) calculate the marginal abatement cost for wellpad i as:

$$MAC_{it} = \frac{FC + \alpha_d d_i}{G_{it}}$$

where G_i is the sum of discounted expected production from well i from t onwards. The industry-wide abatement curve is calculated by calculating MAC_{it} for each well, i , then ordering them by cost. Since my unit of analysis is the lease-level I use leases as opposed to wellpads. Lade and Rudik (2020) use a fixed cost estimate of \$202,000 lifted from a survey result. They predict α_d by using an ordered probit to predict necessary pipeline width, and pipeline cost estimates lifted from the same survey results.

I construct a simplified version of their cost curves. First I use the same costs they did, lifted from the report from INGAA. However, I do not do an ordered probit and instead make the conservative calculation of assuming all pipelines are 8".¹⁵ Next, I use my own distance and cost

¹⁵This is conservative because 8" pipelines are the most expensive in their model, and I find that

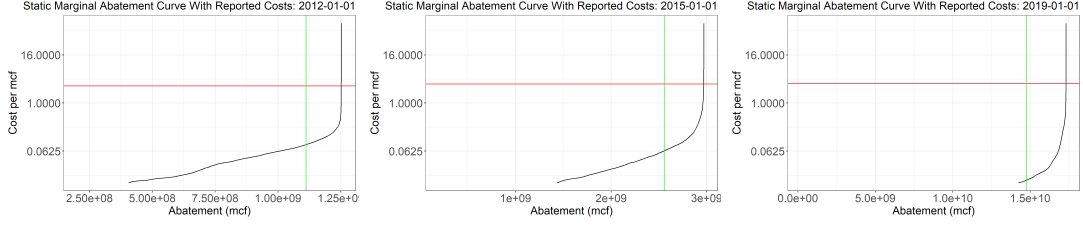


Figure 12: Static Marginal Abatement Curve Calculated with Engineering Estimates of Cost. The red line gives the observed spot price of gas at the time, while the green line gives the observed level of abatement.

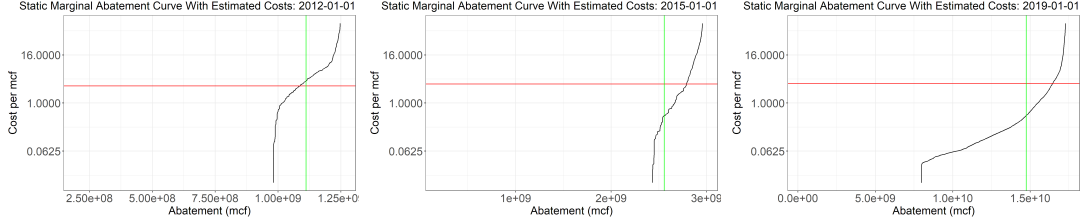


Figure 13: Static Marginal Abatement Curve Calculated with Estimated Costs. The red line gives the observed spot price of gas at the time, while the green line gives the observed level of abatement.

measures lifted from my model. The fixed cost estimates are taken as the difference in fixed costs between flared and gathered wells. I use the estimates from figure 10, since they reflect differences in fixed costs for drilled wells as opposed to values from table 5, which reflect estimated fixed costs for randomly selected leases.

I've plotted the former in figure 12 and the latter in figure 13. I've also plotted the spot price of gas in red, and the observed level of abatement in green. When using engineering estimates, the observed level of abatement is too low – implying that the cost curves are also too low. When using my own cost estimates, the abatement cost curve shifts upwards, decreasing the wedge between expected and observed abatement.

8.2 Full dynamic simulations: computational procedure

To calculate a full dynamic forward simulation, I can no longer rely on having $\log(pr(j = G))$ in hand to calculate $E[V_{t+1}]$. Therefore, I take simulation draws of prices and distance changes, then use backwards induction to calculate the expectation of V . I take draws of ϵ_{it} to determine the action of each lease in each period. For each period, after the gathered leases are determined, generally these engineering estimates over predict abatement.

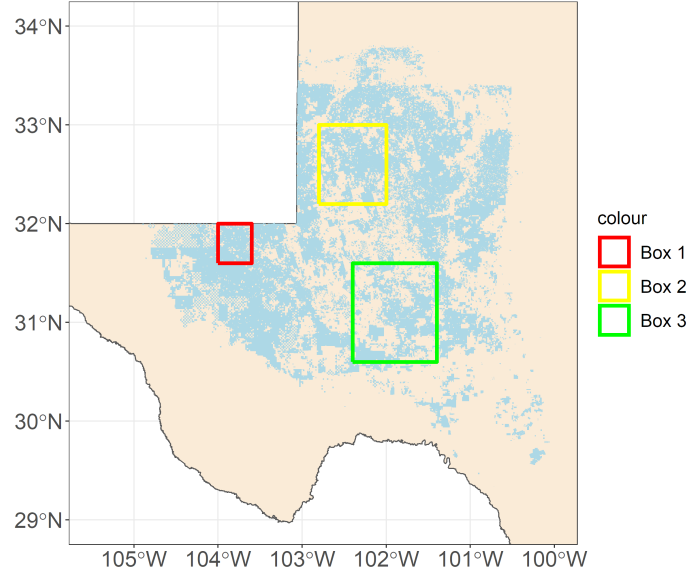


Figure 14: Plot of the counterfactual boxes. Leases are plotted behind in light blue.

I draw a line from the existing network to each lease. Then distances for remaining leases are re-computed for $t + 1$.

Since this process relies on taking draws of distance changes and the distribution of distance changes varies with the policy counterfactual, this routine iterates until the expectation of predicted distance changes is close to the expectation of the distribution of distance changes used to compute the counterfactual. Specifically, I specify that the mean predicted distance change must be within 10m of the mean of the distance changes used to compute the counterfactual. In practice, most counterfactual runs only iterate once. All converge within two iterations. This implies two things – first that the counterfactuals do a very good job of predicting observed distance changes. Second that the network is not particularly sensitive to changes in policy. This will be demonstrated in the following subsections.

Due to computational constraints, I can only compute counterfactuals on samples of the Permian Basin. I’ve plotted the samples I selected below in figure 14. These boxes were selected since they are from disparate regions of the Permian basin.

Box	Actual Distance Constructed	Simulation Distance
Box 1	1129.875	93.63384
Box 2	3133.516	116.0214
Box 3	814.2046	268.3943

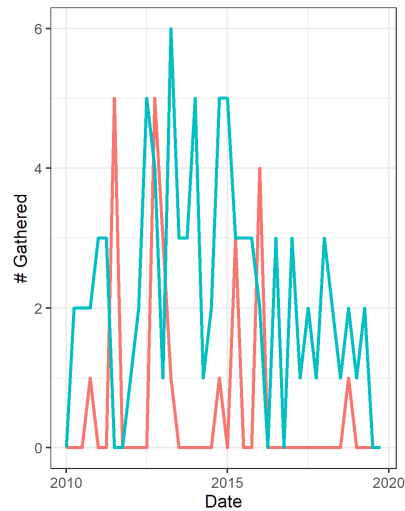
Table 6: Actual and Predicted Pipeline Distances (km)

8.3 Performance of counterfactuals against observed activity

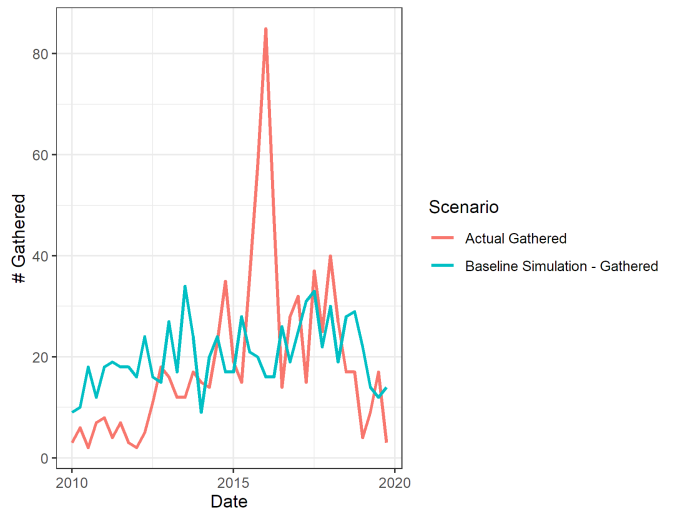
To assess the fit of the simulations I’ve plotted the predicted versus actual lease outcomes below in figure 15 for each box. Expected productivity is spatially correlated, so when counterfactuals are computed on only a small part of the basin it’s unsurprising that predicted flaring or gathering might be systematically above or below the observed level. For example, actual flaring is higher than the baseline counterfactual in Box 2 and lower in Box 1. However, the counterfactual simulation on Box 3 looks quite good. Overall, you would expect that if I could run counterfactuals on the basin as a whole, the errors across smaller areas would average out and the fit for the overall basin would be good.

As noted in the discussion of the computation of my counterfactuals, the counterfactuals match predicted distance changes with observed distance changes quite well. However, the overall prediction of pipelines built tends to be far too low. A comparison of predicted versus observed pipeline construction over my sample period (01/01/2010-12/01/2019) is in table 6. The discrepancies are likely due to the fact that my model ignores capacity and processing constraints. In practice, I observe many parallel pipelines, which could not be rationalized in my model. However, it does resolve why the estimated per-mile costs of pipelines in my model are so high. Recall that my estimate of pipeline costs for pipeline costs per kilometer was \$9.6 million for distances less than 1km, \$6 million for distances between 2km and 3km, and \$1.5 million for distances greater than 3km. In Box 2, predicted pipeline construction was off by a factor of 27 – implying that for every well connected that was 1 km away from pipelines, 27km of pipelines was actually built. Adjusting my pipeline costs by this factor would produce a per kilometer estimate of \$355,555 for distances less than 1km and \$55,555 per km for distances greater than 3km. Predicted construction in box 3 was three times lower than the actual length constructed, implying a per kilometer cost of \$3.2 million for distances less than 1km and \$500,000 for distances greater than 3km.

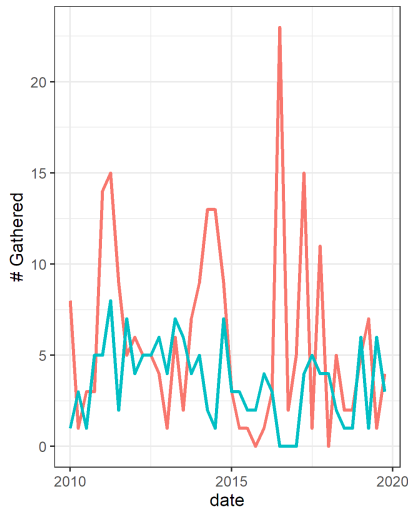
Box1 - Actual Versus Simulated Flared
Actual = 24, Simulated=87



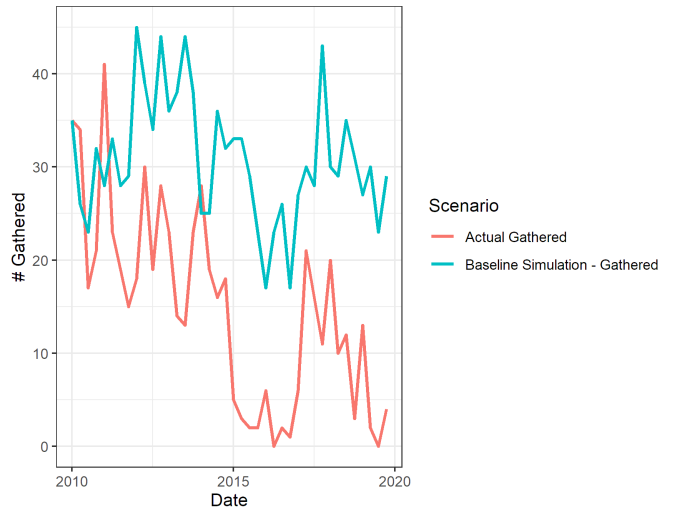
Box1 - Actual Versus Simulated Gathered
Actual = 766, Simulated = 807



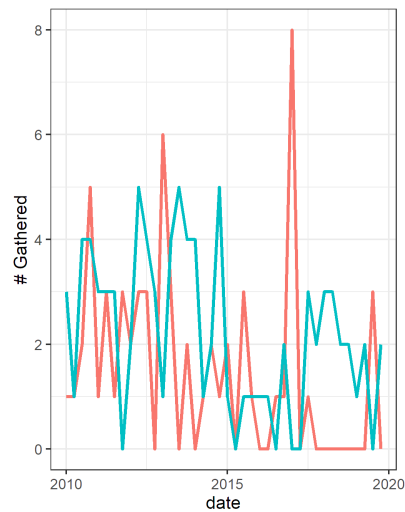
Box2 - Actual Versus Simulated Flared
Actual = 230, Simulated = 142



Box2 - Actual Versus Simulated Gathered
Actual = 593, Simulated = 1233



Box3 - Actual Versus Simulated Flared
Actual = 60, Simulated = 88



Box3 - Actual Versus Simulated Gathered
Actual = 774, Simulated = 796

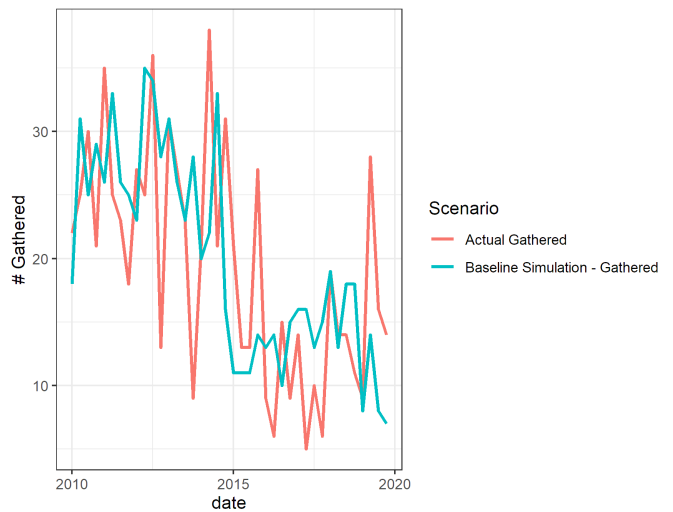


Figure 15: Actual Versus Simulated Outcomes

8.4 Spillover internalization does not appear to be a major driver of flaring

To assess how the importance of the spillover internalization parameter, I run counterfactual simulations in Box 1 where I switch the parameter to 1 – implying perfect internalization. These are plotted in figure 16. This figure plots the number of wells of each type (gathered or flared) drilled in each time period, as well as the percentage of production relative to the baseline simulation. Perfect internalization does seem to induce some wells that had previously been flaring to gather, leading to a small increase in gathered gas volumes and a small decrease in flared gas volumes. I also present total production figures in table 7.

Overall, the effects of spillover internalization seem to be relatively small. One explanation for this is that the costs of gathering appear to be relatively small compared to the very high fixed costs of gathering. I run a comparison of perfect versus zero internalization where I double the costs of pipelines. These results are also plotted in figure 16. This seems to increase the wedge between the two internalization scenarios ($\alpha_{\bar{v}} = 1$ and $\alpha_{\bar{v}} = 1$), but not dramatically.

8.5 The effect of a flaring tax, flaring ban, and gas subsidy on drilling and flaring

To assess the performance of potential policies I run simulations in Box 1 with various levels of flaring taxes, a gas subsidy, and a flaring ban. These results are plotted in figure 17, and aggregate production figures can also be found in table 7. A subsidy poorly targets flaring. A \$1 per Mcf gas subsidy increases total gas production by 4% but only decreases flaring by 2% at a cost (in just this box) of \$600 million. A tax targets flaring quite well. A \$5/Mcf tax reduces flared volumes by 39%, increases gathered volumes by 5%, decreases oil produced by 2%, and raises \$150 million in revenue.

Flaring volumes seem to respond linearly to taxes at low levels of the tax, then less than linearly as the tax gets higher. A \$1 /Mcf tax reduces flared volumes by 9% while a \$2/Mcf tax reduces flared volumes by 20%. More than doubling that tax to \$5/Mcf less than doubles the reduction in flared volumes to 39%. Lastly, a ban eliminates all flaring, leads to a small increase in gas

	Gas Gathered (10 Bcf)	Oil From Gathered Wells (10 million barrels)	Gas Flared (10 Bcf)	Oil From Flared Wells (10 million barrels)	Total Oil Production (10 million barrels)
Baseline Simulation	57.85	7.58	4.91	0.69	8.27
Subsidy of \$1	60.30	7.89	4.82	0.67	8.56
Flaring Ban	59.20	7.78	0.00	0.00	7.78
Tax of \$0.55 per Mcf	58.03	7.61	4.68	0.66	8.27
Tax of \$1 per Mcf	58.07	7.62	4.45	0.63	8.26
Tax of \$2 per Mcf	58.04	7.61	3.90	0.55	8.16
Tax of \$3 per Mcf	58.19	7.63	3.48	0.50	8.13
Tax of \$5 per Mcf	58.22	7.63	3.00	0.43	8.07
Spillovers Internalized	60.73	7.91	4.62	0.65	8.55
Gathering Costs Doubled	49.53	6.49	5.16	0.72	7.21
Spillovers Internalized & Gathering Costs Doubled	54.73	7.16	4.74	0.67	7.82
Network Fixed at $t = 0$	48.32	6.29	5.11	0.72	7.01

Table 7: Total oil and gas production in Box 1 in various simulations

production (and hence only a small increase in pipeline investment), and causes a small decrease in oil production.

8.6 Endogenous network growth has a substantial effect on drilling and flaring

Lastly, I show that allowing the network to grow endogenously is actually quite important for simulation outcomes. I run the simulation but fix lease distances to their values at $t = 2010-01-01$. Flared wells increase modestly, but connected wells decrease drastically. Results from this simulation are plotted in figure 18, and aggregate production in this simulation can be found in table 7. Total gas production is 16% lower if the network cannot grow, demonstrating that growth over time is an important determinant of drilling outcomes.

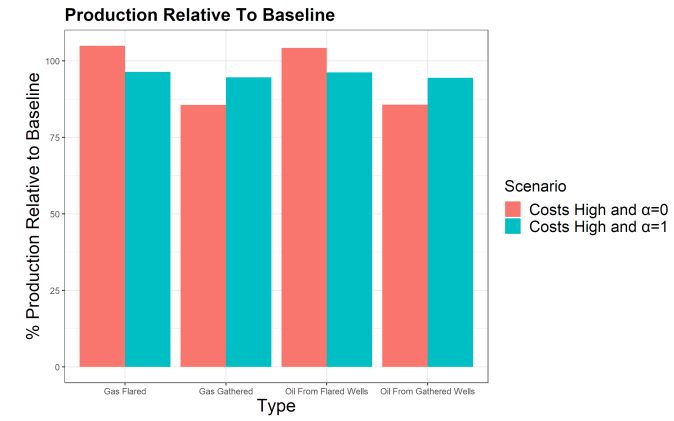
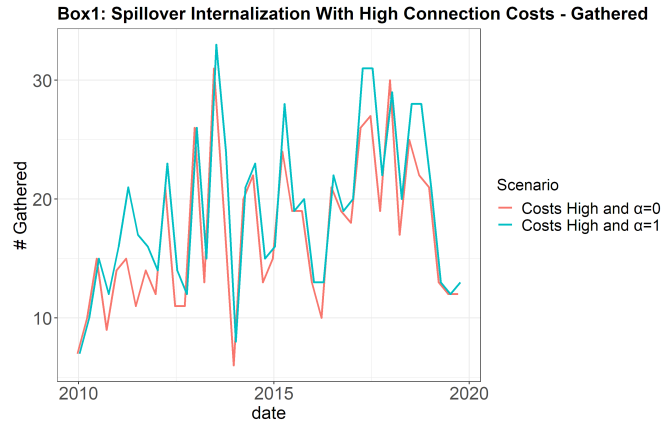
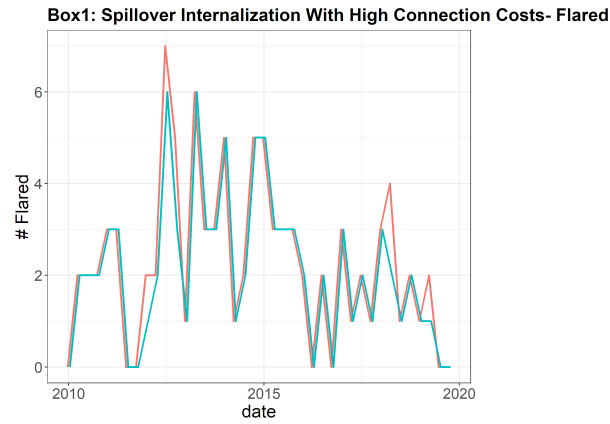
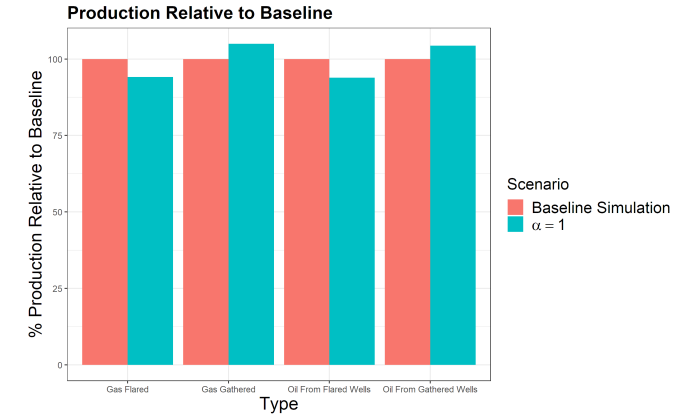
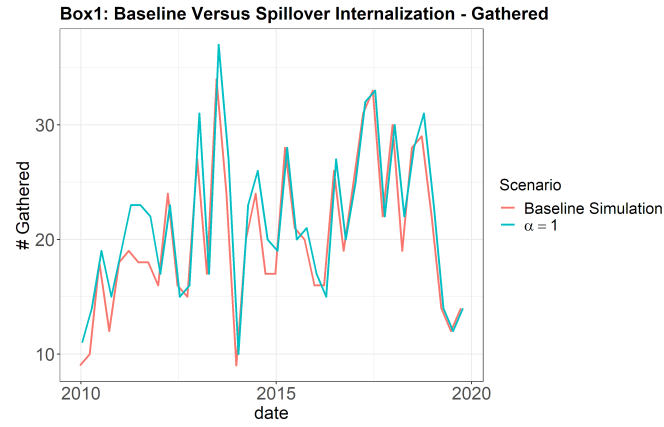
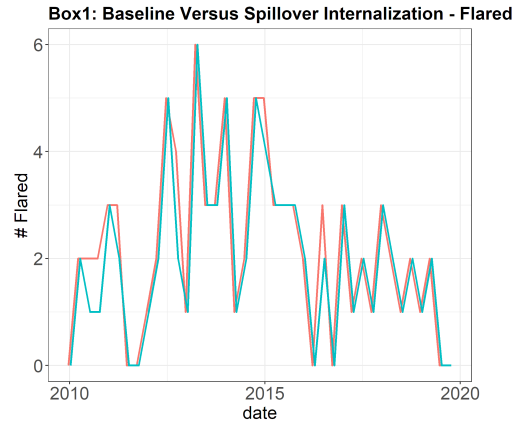


Figure 16: Simulated outcomes with the spillover internalization parameter switched to 1. The line plots present number of wells drilled in each category over time, while the bar charts present total production from each well type relative to the baseline. The graphs in the top panel of this figure only alter the spillover internalization parameter. The graphs in the lower panel multiply the costs of pipelines by 2 to determine whether this would increase the wedge between $\alpha_{\tilde{V}} = 0$ and $\alpha_{\tilde{V}} = 1$.

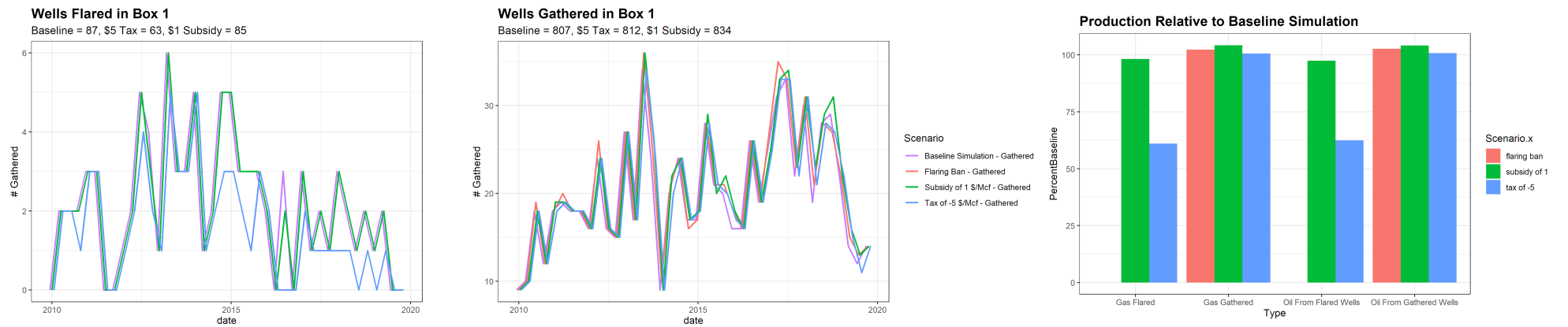


Figure 17: Outcomes of Flaring Ban, Flaring Tax, Gas Subsidy

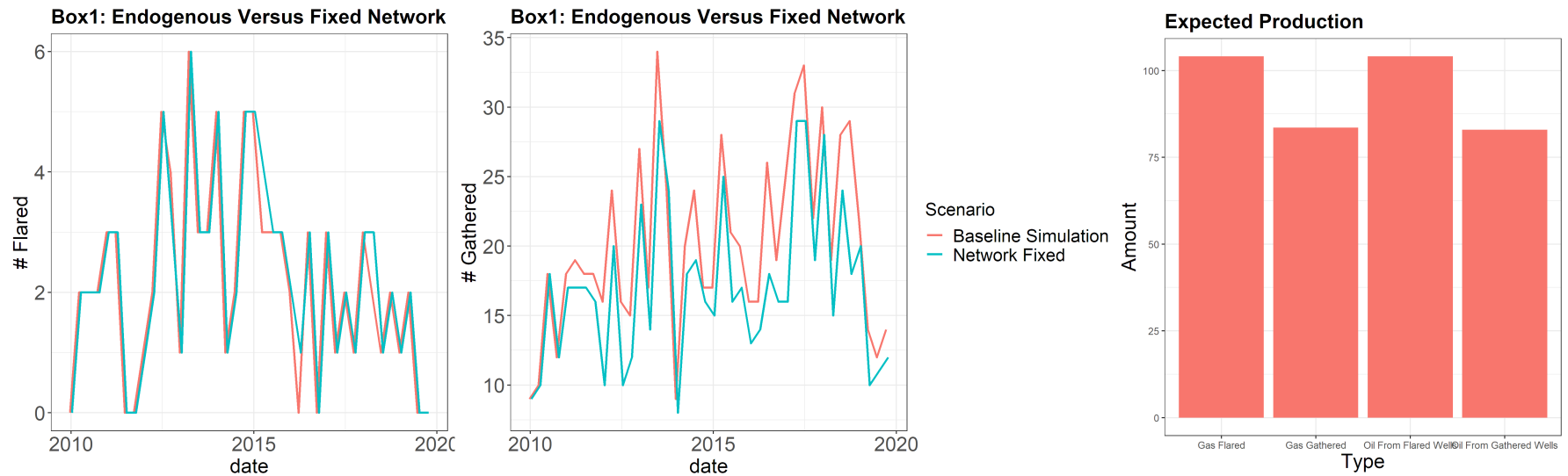


Figure 18: Outcomes with network fixed at $t = 2010-01-01$ versus endogenous

9 Conclusion

I show that distance to pipeline infrastructure matters for flaring outcomes and that as the network grows over time, connections become less costly. My model indicates that flaring abatement is relatively costly, but that a tax near the likely social cost could substantially reduce flaring. A \$5 per Mcf tax would reduce flared volumes due to wells not connecting by 39%. Moreover, my results find that the majority of the decrease in flaring wells comes from flaring wells switching to not drilling rather than switching to connecting. In addition, I also find that subsidies poorly target flaring, and that bans only lead to a small increase in pipeline investment. My model estimates also suggest that spatial spillovers are not internalized. However, my counterfactual simulations suggest that the lack of spillover internalization does not have a substantial effect on flared volumes and that the lack of internalization might simply be due to the benefits of internalization being relatively small.

This paper makes a few important contributions to the literature. First, this paper is the first to explore the endogenous relationship between drilling and gas pipeline construction. Second, this paper is the first paper which explores how policies aimed at reducing flaring might affect the drilling margin. Third, this paper is the first which estimates pipeline costs directly instead of relying on reported costs. Combined, these contributions make this paper the best model of how potential policies to reduce flaring would affect the drilling and connecting decisions of firms.

These decisions have large consequences for U.S. greenhouse gas emissions, making this paper a timely contribution for policymakers interested in addressing climate change. The U.S. EIA estimates that in 2020 about 420 million Mcf of natural gas was vented or flared in the U.S. ([U.S. Energy Information Administration, b](#)). Assuming a social cost of flaring between \$3 and \$6 implies that flaring accounts for billions of dollars in climate damages annually.

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10 Appendix

10.1 Processing the Leases

I run the raw lease data through two rounds of clustering. The first round is intended to identify and remove duplicates. The second round is intended to identify lease amendments and changes to lease ownership.

For the first round of clustering I follow many of the lease processing choices of [Herrnstadt, Kellogg, and Lewis \(2020\)](#). In the Enverus data on leases, there are many likely duplicates that need to be dealt with. There are many cases where the same plot is leased to the same grantee by multiple grantors. These observations are likely a result of undivided mineral interests. For example, multiple members of a family might each show up as a distinct grantor with her own row in the data. I keep all observations labeled as “Leases,” “Lease amendments,” “memos of leases,” and “lease extensions.” I drop observations on mineral rights assignments, lease ratification, royalty deeds, and mineral deeds. Next, I construct a dissimilarity matrix which I pass along to an agglomerative hierarchical clustering method implemented by the `agnes` function in the `cluster` package, version 2.2.1, in R.

The entries of the dissimilarity matrix are calculated as which I calculate as:

$$d_{ij} = \sum_k m_k(x_i^k, x_j^k)$$

where $m_k(\cdot)$ is equal to 0 if the k th attribute of lease i and j are identical, and positive but less than or equal to 1 otherwise. The attributes and calculation of m_k are as follows:

- $m_k(x_i^k, x_j^k) = |x_i^k - x_j^k|$ for various continuous variables. I use this on both the start and end date of the leases, and the Demerau-Levenshtein string distance between the grantors and grantees. Once I calculate all the pairwise combinations, I then rescale all the observations by dividing through by the max (for each characteristic), so all the date differences lie between 0 and 1.
- $m_A(x_i^A, x_j^A) = \frac{|x_i^A \cap x_j^A|}{2(|x_i^A| + |x_j^A|)}$ - where x_i^A is the spatial polygon of i . This measures the average

percentage overlap in area between i and j , and will be bound between 0 (if the polygons do not intersect) and 1 (if the polygons are exactly the same).

Before clustering, there are over 500,000 observations in the data. Constructing a $500,000 \times 500,000$ matrix would be infeasible. Even when accounting for the fact that the matrix would be symmetric it would have over 100 billion elements. To deal with this, I run the clustering algorithm at the year of expiration date level.

After this initial round of clustering, primarily intended to identify rows of duplicates, I run this data through one more layer of clustering. This time, I just consider the average percentage overlap between two leases and group them together if the percentage overlap is over 70%. Once two leases are clustered together, I consider the lease with the greatest Instrument Date active at time t to be the active lease and throw out the older ones. Consider the hypothetical scenario below: In this example, for all dates before 12-01-2009, the expiration date would be treated as

Effective Date	Expiration Date	Instrument Date	Polygon
12-01-2007	12-01-2010	12-01-2007	A
12-01-2009	12-01-2012	12-01-2009	A

12-01-2010. So for example at 12-01-2008, there would be 24 months until the lease expiration. Once the new lease becomes active after 12-01-2009, the time until expiration would reset to 36 months.