Races to Extract in Oil and Natural Gas Production

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Abstract

Subterranean pools of oil and natural gas often span multiple leases so that it is possible for neighboring hydrocarbon producers to interfere with each other's production. This chapter draws upon extensive production and injection data from Slaughter field in West Texas to quantify the spillover between leases. I then compare estimates of the spillover parameter across different ownership structures to evaluate the effect of ownership concentration on production, finding evidence of a race to extract when rights to the resource *in situ* are not secure. Q30, C31

1 Introduction

The goal of this paper is to quantify the spillovers in production and injection in oil and natural gas recovery in Slaughter field of West Texas. Oil and natural gas deposits are concentrated spatially in reservoirs, yet it is often the case in Texas that no single producer has rights to the entire reservoir (Libecap and Wiggins, 1985). Because property rights to the oil and natural gas are administered according to the "rule of capture," ownership is not fully secured until the resource is extracted. While in the ground, it is an example of a common good: rival but nonexclusive.

Under these circumstances the resources can be the subject of fierce competition as neighboring producers race to extract. Economic rents are dissipated in the drilling and operation of more wells than are needed to efficiently drain the reservoir (Weitzman, 1974). Additionally, owing to the dynamics of recovery, overly rapid extraction can result in damage to the reservoir and lowered cumulative recovery (Dake, 2001).

The present age of the majority of Texan fields only compounds the common pool inefficiencies. In order to maintain the productivity of a maturing field, operators shift production wells into injection. These injection wells pump substances (*e.g.*, water, carbon dioxide, natural gas) into the reservoir to drive the resource towards neighboring production wells where it is then extracted. Injection is costly, and it makes little sense to undertake injection when ownership of the reservoir is highly fractured and neighboring wells are likely to be owned by competing operators. The resulting miserly secondary injection can lead to substantial losses in recovery (Libecap and Wiggins, 1985). Injection wells may also be used to offset the production at neighboring wells. A neighbor's production creates a cone of depression in the resource bearing strata; oil and natural gas tend to flow towards this depression. To prevent the resource from escaping the lease, injection wells may be drilled along the border to halt resource emigration. These offset injection wells are unnecessary for production and represent another economic cost of intra-field competition (Libecap, 1989).

The spatial interdependence of oil and natural gas production brings the potential for economic inefficiency because competing producers discount the value of leaving resource *in situ* for future periods resulting in a "race to extract." The goal of this paper is to demonstrate how a race to extract can be prevented through unitary ownership. I use a spatial econometric model to explicitly characterize spillovers in production while controlling for unobserved spatial autocorrelation. This type of spatial model has been used recently to estimate spillovers in production of fossil groundwater aquifers (Savage and Brozovic, 2011) (Brozovic et al., 2006) (Pfeiffer and Lin, 2009). The model is estimated using extensive and novel data provided by HPDI Corporation. The main result is as expected: when neighboring wells are under unitary ownership, extraction proceeds at a comparatively slower pace than when wells have competing operators.

2 Background

Spillovers in the production of oil and natural gas, where one producer's extraction interferes with that of another, have been pervasive since the initial discovery of the resources (Yergin, 2008). Addressing these spillovers in production are economically important because resource rents can be dissipated in excess effort and capital (Gordon, 1954) (Scott, 1955) (Hardin, 1968) (Weitzman, 1974) (Brown, 1974). Whereas it might take only a few wells to efficiently drain a field, competing producers may drill many more in order to extract and secure the resource so that it is not lost to neighboring producers. The capital tied up in excess wells could be more efficiently used elsewhere in the economy. Additionally, the common pool nature of the hydrocarbons undermines the producer's incentive to conserve and so is dynamically inefficient (Eswaran and Lewis, 1984) (Khalatbari, 1977) (Long, 1974) (Long, 1975)

(Dasgupta and Heal, 1979) (Reinganum and Stokey, 1985).

What is peculiar to oil recovery, however, is that the race to extract can cause damage to the reservoir, limiting ultimate recovery (Libecap and Wiggins, 1985) (Chermak and Patrick, 2001). Thus, the consequences of the common pool are not limited to economic inefficiencies of too costly extraction, too soon, but to physical inefficiencies as well. Overly rapid production destroys the resource. Oil and natural gas exist in solution, and it is the expansion of natural gas that drives the oil to the well-face and then up to the surface. Rapid extraction can cause the natural gas to bubble out of the mixture. The natural gas is more mobile than oil, and is quickly drawn off. Meanwhile, the oil becomes increasingly viscous, and so difficult to move as to be permanently unrecoverable. It may well be that it is economically efficient to sacrifice cumulative recovery in favor of present extraction (Clark, 1973), but this aspect of oil and natural gas exploitation has yet to be studied by economists.

The spillovers in production are essentially issues of property rights. When production spillovers are large and involve a small number of agents, it is reasonable to expect private contracting to solve the problem. In a series of papers, Libecap and Wiggins describe the contracting failure in Texas. Libecap and Wiggins (1984) consider three mechanisms through which leaseholder can address production spillovers: lease consolidation, unitization, where competing leaseholders hire a single operator to jointly develop the field, and prorationing agreements on output. The authors examine five oil fields in Texas, and find that firm concentration is an important determinant of private contracting. Bargaining costs increase with the number of firms, inhibit unitization and consolidation, and in some cases, the ownership of the field is so fractured as to even prevent prorationing agreements. Libecap and Wiggins (1985) study the impediments to unitization agreements. Comparing Wyoming, Oklahoma and Texas, the authors find Texas to be particularly poor at unitizing fields because the unananimity required for unitization creates a holdout problem. Wiggins and Libecap (1985) model unitization negotiations, and test the model empirically, finding that imperfect information about reserves when combined with diffuse landholding prevents unitization. When contractual response fails, lease owners will even split individual leases among competing operators to increase inflow onto the property (Yuan, 2002). The work of Libecap and Wiggins nowhere expressly quantifies the size of the spillovers and how these spillovers differ when ownership of the resource is unitary or highly fractured. The present paper contributes to the understanding of the economics of oil and natural gas production by showing that unitary ownership does significantly abate the race to extract as previous theoretical models have predicted.

Regulation is also important to consider when measuring possible interference between leases. Regulation of hydrocarbon production in Texas is overseen by the Texas Railroad Commission and comes in three flavors: command and control, taxes and production quotas. Of the command and control regulations, well-spacing regulations and regulations on the inclination of drilling (slant and horizontal drilling) are the most relevant in addressing issues of common pool production. Slant drilling is prohibited without special permission. Additionally, the statewide spacing rule disallows the drilling of wells within 467' of a property line or within 1200' of an existing well.[1] Although well-spacing guidelines have the virtue of easy verification and enforcement, one-size-fits-all regulations are not flexible enough to account for the heterogeneity in permeabilities and flow dynamics. Owing to local geologic conditions wells 100' apart may communicate less than wells 3000' apart in more permeable rock. Optimal well-spacing guidelines should account for the local geologic parameters, and assign well spacing accordingly. By measuring the effect of neighbor's production on own production, this paper can provide evidence as to the efficacy of spacing regulations.

Well-spacing exceptions may be granted to protect ownership rights, or to prevent resource waste. In the former case, a producer would be allowed to drill closer to a property line if drilling according to regulation would result in substantial portion of the resource underlying the lease to be captured by neighboring producers. In the latter case, exception may be granted if the oil could not otherwise be recovered. Yet these two goals frequently conflict when production tracts are small, as is the case in Slaughter field. Until the decision *Halbouty vs. Texas Railroad Commission* (1962) small lease holders were given a greater production allowable, to cover the costs of drilling plus a reasonable profit, even at the expense of neighbor's production (Lowe, 2003). The alternative to well-spacing exceptions, preferred by most states, is forced pooling.

Monthly quotas on production are assigned in Texas as a percentage of a maximum allowable production for the well. Maximum allowable production is based on the depth of the well, and the lease size. In Texas, natural gas is subject to a

[1] Texas Administrative Code, Title XVI, Part 1, Chapter 3

royalty at of 7.5% of the value of production, while oil is subject to a lower royalty of 4.6% of the value. While these taxes are not consistent with Pigouvian taxation to address the problems of common pool production (Dasgupta and Heal, 1979), economic theory predicts that these royalties slow the rate of extraction (Gamponia and Mendelsohn, 1985).

The interaction between regulation, contracting, geology and firm production decisions determines the nature of the spillover. This paper provides empirical evidence as to how these complex interactions play out on Slaughter field. I find, after controlling for secondary injection, that regulation and contracting have not been fully successful in securing property rights. Indeed the empirical model uncovers evidence consistent with a race to extract.

3 Methods

The goal of the chapter is to estimate the impact of neighbor's production, y_j, on own production, y_i, for a cross-section of leases indexed $i, j = 1, 2, 3......, N$. Doing this via OLS regression would result in biased parameter estimates because of simultaneity. The problem is that production at j is not predetermined: lease i affects the production of lease j, while the production of lease j simultaneously affects production at lease i. Adding further difficulty is that production on a patch is partially determined by unobserved geological characteristics such as porosity and permeability, and these unobserved variables are likely to be correlated through space. This makes it difficult to tease out what part of production is impacted by neighbors production, and what part of production is the result of correlated but unobserved geological characteristics. Disentangling genuine spatial dependence from autocorrelation is necessary for achieving the goals of this chapter. Fortunately, Kelejian and Prucha (1998) and Kelejian and Prucha (1999) develop a computationally feasible generalized method of moments procedure for controlling for spatial dependence and spatial autocorrelation. The canonical model I estimate is

$$\begin{aligned} y &= X\beta + \lambda W y + u \\ u &= \rho M u + \epsilon \end{aligned} \tag{1}$$

where y is an $N \times 1$ vector of the dependent variable, X is an $N \times k$ matrix of the k independent variables, W and M are $N \times N$ spatial weighting matrix, β is a $k \times 1$ vector of regression parameters, λ and ρ are scalar spatial parameters, u is an $n \times 1$ vector of regression disturbances, and finally, ϵ are i.i.d. innovations. Full technical assumptions necessary for estimation of the model, as well as the moment condition exploited for estimation, can be found in Kelejian and Prucha (1998) Kelejian and Prucha (1999); however, two assumptions are important to understand the intuition of the model. First, the contribution of nearby producing leases (a, b, c) on the production at lease i are assumed to be a linear function of production, some weighting function (in our case a function of distance) and vector of spillover parameters, $(\lambda_a, \lambda_b, \lambda_c)$, such that $y_i = \lambda_a w(i,a) y_a + \lambda_b w(i,b) y_b + \lambda_c w(i,c) y_c$. In order to estimate the model, we assume that $\lambda_a = \lambda_b = \lambda_c = \lambda$ (otherwise there would be N parameters and N observations. The second assumption is that $|\lambda| < 1$, which insures that spatial spillovers are non-explosive. Similar assumptions hold for the structure of the errors.

Execution of this Generalized Spatial Two-Stage Least Squares (GS2SLS) model requires three stages. In the first stage, to control for simultaneity in production decision, Wy is instrumented for by $H = (X, WX, W^2X, \ldots)$. The implicit exclusion restriction is that a neighbor's X affects your production only through how the neighbor's X affects her own production. Identification comes through the spatial structure—the interaction between X variables and the weighting matrix—and so there is no excluded instrument. This first stage generates consistent results for β and λ, but these estimates are inefficient because the information available in the structure of the autocorrelated errors has yet to be exploited. In the second stage, residuals, $\tilde{u}$, from the first stage are plugged into a moment condition to estimate spatial autocorrelation parameter, ρ, and the innovation variance, σ_ϵ^2. In the last stage, the structure of the autocorrelation is exploited to arrive at more efficient estimates of β and λ.

Interpretation of the spatial parameters depends on the choice of weighting matrix, W. The choice of weight matrix, in turn, is defined by the conceptual framework one uses to interpret the spatial data. There are two possibilities: viewing the data as a lattice of discrete spatial connections, or viewing the data as sample points from a continuous surface (Anselin, 2002). In the former case, w_{ij}, representing whether i is connected with j takes on discrete values, 0 or 1. The drawback is that defining the connections can be arbitrary. When the observations are viewed as a sample from a continuous surface, w_{ij} often takes the value of the (inverse) distance between observation i and j. When distance weighting is used, the spatial autoregressive parameter has the potential to be interpreted as a reservoir specific transfer coefficient, which reveals geologic information on reservoir permeability, porosity, and viscosity[2]. Of course strategic interaction between agents will result in biased estimates of the transfer coefficient. To see this consider the primary model of the paper,

$$\begin{aligned} y &= X\beta + \lambda_F F y + \lambda_U U y + u \\ u &= \rho M u + \epsilon. \end{aligned} \tag{2}$$

Here M represents an inverse distance weight matrix controlling for autocorrelation in unobservables. The goal is to see if there is a difference in estimated spillover coefficients between leases that have the same owners and leases with different owners. Weight matrix W from the previous specification is broken up into two separate weight matrices, F and U ("F" for "friendly", "U" for "unfriendly"). Weights in F take on inverse distance weights only when leases i and j have the same operator; conversely, weights in U take on values when leases i and j have different operators. Estimates of friendly (λ_F) and unfriendly spillovers (λ_U) can then be estimated and compared. Without strategic interaction, spillover parameters should be identical and negative, the result of the cone of depression caused by production. With strategic interaction, the estimates of spillovers should be biased upwards and should diverge with $\lambda_F < \lambda_U$. The divergence occurs because the rights to the resource *in situ* are less secure when competing operators own nearby leases. In fact, we may even see a race to extract, which would manifest itself as apparently positive spillovers

[2]Well reaction functions specified by Theis and Darcy flow equations have been used in physical-economic models of water recovery. See Savage and Brozovic (2011) Brozovic et al. (2006) Pfeiffer and Lin (2009).

in production, $\lambda_U > 0$. The positive spillovers come from lease-owners shifting their production profile towards the present. Discussion and results from this model can be found in Section 5.5.

To identify the shift in the production profile due to security of ownership, a variety of cross-sections per field must be analyzed. Field age and ownership structure of the fields affects the degree and nature of spillovers. Early in the life of a highly decentralized field, the measured autoregressive parameter should be positive, reflecting a race to extract. Later in the life of the decentralized field, the spillover may decline toward zero as damage to the reservoir halts flow between wells. Conversely, in a highly concentrated area, the autoregressive parameter might be zero over the entire life of the reservoir as a result of effective management.

4 Data

Data for analysis is provided by HPDI Corporation, which collects, compiles and publishes oil and natural gas production data for 31 US States, 4 Canadian provinces and the Federal offshore areas in the Gulf of Mexico and the Pacific. Previous research has indicated that Texas is a state where common pool problems can be substantial (Libecap and Wiggins, 1984) (Libecap and Wiggins, 1985) (Wiggins and Libecap, 1985). Not coincidently, Texas also has the most extensive data available, with time series for production, injection and well tests going back even before 1960. Data on leases size come from W-1 drilling permits, public information made available by the Texas Railroad Commission.

The focus of the analysis is Slaughter field in West Texas, located near the Texas-New Mexico border. Wells are mapped in Figure 1. This field has a variety of characteristics making it a worthy focus or research. First, it ranks in the top 20 fields in the US country in terms of 2009 proved reserves for oil (EIA 2009), and is therefore of economic interest. Second, in order to quantify the importance of unitization and ownership concentration, it is necessary to have within field variation of ownership concentration.[3] A local Herfindahl concentration index mapped for Slaughter field in Figure 2 shows the field has variation in ownership concentration.

Slaughter Field was discovered in 1937. My earliest data only goes back to 1955. Figure 3 shows the evolution of the number of productive wells on the field over time. Figure 4 shows the field aggregated history of production. Peak oil production occurred in the middle 1970s. Also evident is a sharp drop in natural gas production between December 2004 and January 2005. This is apparently due to the weighty tails of the distribution. When looking at a figure of logged average well production, no such drop off in production is evident(Figure 5). A large part of the decline in gas production at the end of 2004 can be attributed to a significant decline in gas production on the Slaughter Estate Unit and Central Mallet Unit. These units, under the operation of Occidental Permian Ltd., were the subject of legal controversy. Carbon dioxide and hydrogen sulfide injections on the Slaughter Estate Unit–which have aided in the recovery of oil– contaminated gas in the reservoir making it difficult to process. Occidental Permian, however, owns the gas processing plant, and the

[3] Because the underlying permeabilities and porosities will differ across fields, the estimated spillover parameter will not be comparable across fields, and so cross-field variation in ownership can not be exploited to demonstrate the impact of ownership concentration on the spillover.

Texas Supreme Court held in *Helen Jones Foundation vs. Occidental Permian, 2011* that Occidental used the increased costs of processing as cover to avoid paying royalty owners.

Summary statistics for Slaughter field can be found in Table 1, the bottom panel displays summary statistics for the subset of the data used for regression analysis. Production data is at the lease-level, while injection data is at the well level. Data for production spans January 1955 to May 2009, injection data becomes extensive beginning in the late 1980s. The regression sample represents a subsample of production data for the month of January in 1990, 1995, 2000, and 2005.

5 Results

This section presents results from cross sectional and panel models of Slaughter field, with and without injection. Cross sectional models are valuable in measuring how the spillover parameter evolves with time, but are limited in the sense that they cannot account for unobserved fixed effects specific to location. Panel models allow for unbiased estimates when spatial fixed effects are present. Both cross-sectional and panel models are run with and without injection. The goal of the various models is to demonstrate a race to extract when ownership is comparatively less secure–that is, well operators should increase their rate of extraction leaving less in the ground for the future. As a descriptive exercise I first run specifications of my statistical model with a local concentration index with a half-mile radius ($herf$) as the variable of interest. These results are presented in table **??** and include lease-level fixed effects.

Moran-I statistics for both oil and natural gas show significant evidence of spatial autocorrelation.[4] Because the productivity of a lease is driven by geological characteristics, which are unobserved in the dataset but likely to be highly correlated over space, it is expected that the residuals are positively correlated in space. According to OLS specifications for both oil and natural gas, drilling another well on the lease tends to increase production, but at a diminishing rate (the square term is insignificant). The affect of the number of wells on the lease is estimated less precisely in the GLS specification–the standard errors are larger and the coefficients are not distinguishable from zero. The age of the latest well on the lease does not meaningfully impact lease-level production. Water injection enhances oil recovery, but does not have a statistically noticeable affect on natural gas recovery. Gas injection is negatively correlated with oil recovery, and has little effect on gas recovery when controlling for spatial autocorrelation in the GLS specification. It appears then, that gas injection is not very successful *across* leases in secondary recovery in Slaughter field.

The variable of interest in the specification is the local Herfindahl concentration index. As the concentration index falls, the rights to the resource *in situ* become less secure, and the producer should extract at a higher rate. We, therefore, expect a negative correlation between concentration and lease-level extraction, and indeed this is what table 15 indicates. It can be argued that concentration is endogenous because naturally more productive areas face fiercer competition and thus lower concentra-

[4] The Moran statistics are calculated with the same inverse distance weight matrix used in the statistical models of the next sections.

tion.[5] By explicitly accounting for how the unobserved productivity is correlated in space through the GLS specification, I hope to attenuate some of these problems; and yet concentration is a choice variable for the economic agents involved. Therefore in the rest of the paper, I use a different strategy to uncover a race to extract. Treating the structure of ownership as predetermined, I investigate how neighbor's pumping affects own extraction. With no strategic interaction, the estimated effect should be negative. A race to extract will manifest itself as a positive correlation between neighbor's extraction and own extraction.

5.1 Cross sectional model, single inverse distance weight matrix, no injection

The initial cross sectional model I estimate is

$$y_i = \lambda * \sum w_{ij} y_j + \alpha + \beta_1 depth_i + \beta_2 wcnt_i + \beta_3 wcnt_i^2 + \beta_4 age_i + \beta_5 wtr_i + \epsilon_i \quad (3)$$

where the weights are given by the inverse of distance between leases i and j. The spillover parameter of interest is λ; estimates can be found in tables 2-5. The dependent variables I consider are the log of month lease-level oil and natural gas production. Independent variables are *depth*, the total depth of the most recent well completed on the lease; *wcnt*, the number of active producing wells on the lease (and its square); *age*, the time since the most recent well was completed; *wtr*, the

[5] It could just as easily be the case that it is the more productive areas that are monopolized by one owner; but this bias works in my favor, with the parameter for concentration taking a lower bound to the true value.

amount of water produced on the lease that month, a proxy for whether the lease is constrained by disposal.

Tables 2-5 present regression results of the model for the month of January in 1990, 1995, 2000, and 2005. The columns entitled "OLS" present results for equation 3. The "GLS" column omits the variables for spatial dependence, but allows errors to be correlated according to the same inverse distance weight matrix. The column "2SLS" is estimated according to equation 3, but with y_j instrumented with $w_{ij} * X_j$, with $X_j = \{depth_j, wcnt_j, wcnt_j^2, age_j, wtr_j\}$. Finally, the "GS2SLS" column presents results from the model given by equation 1.

There are two parameters of particular interest in Table 2 and Table 3 . λ, the parameter for the spatial autoregressive lag, conflates the geophysical and strategic effects of neighbor's extraction. As mentioned earlier, the geophysical effects are expected to be wholly negative: own extraction causes a cone of depression to extend out from the well and causes oil to migrate from nearby leases, reducing production at other nearby leases. Everyone knows this, and so neighbors react by extracting at a higher rate to counteract the affects of the nearby pumping. In this case the strategic effect is positive and may be large enough to countervail the negative geophysical effects. The other parameter, ρ, measures the spatial autocorrelation of the errors. *A priori*, it is expected that $\rho > 0$ because it captures unobserved geological variables which are positively correlated through space.

Conditional on inverse distance weighting, I find consistent evidence of positive spatial autocorrelation in errors. Assuming that unobserved geological productivity is spatially correlated, these estimates are immanently reasonable. The parameter for the spatial autoregressive lag (λ) is also positive and significant across specifications. This indicates an increase in neighbors' production (or a diminution in the distance to neighbor's lease) results in an increase in own oil production, which is consistent with a race to extract.

The story for lease level natural gas production is not as clear cut. Estimates for the coefficient on spatial autoregressive lag (λ) and spatial autoregressive error (ρ) are not as close across specifications or cross-sections. There is no evidence of autocorrelation of errors in 1990; the coefficient is positive and significant thereafter. The preferred specification for measuring λ is the GS2SLS estimate, which is negative and significant in 1995 but statistically non-distinguishable from zero in all other years.

Cross sectional models may be flawed because it is unlikely that the independent variables used in estimation are truly exogenous. Take for example the variable *wcnt*. It is easy to imagine that $E(wcnt_i * \epsilon_i) \neq 0$: if a lease is especially productive, or the lease owner expects that it will be, then more wells may be drilled. It is possible to control for these unobserved lease-level time invariant productivity differences by pooling the data and estimating the model adding fixed effects.

5.2 Cross sectional model: simultaneous inverse distance weight matrices, with injection

In this model the weight matrices differ according to whether plots are operated by the same owners or different owners. Weights are given as the inverse distance when two plots have a common operator (the "friendly" weight matrix); similarly they are also give as the inverse distance when two plots have different operators (the "unfriendly" weight matrix). Results from these regressions are presented in tables 6-9 for Slaughter field.

Focusing first on GS2SLS specifications of oil production in Slaughter Field, there does not appear to be a clear pattern in the relationship between λ_F and λ_U; friendly spillovers are positive and significant across years, larger than unfriendly spillovers in 1990 and equal to unfriendly spillovers in 2005. There is evidence that the errors are strongly correlated over space. There is also significant autocorrelation in Slaughter gas production. Friendly spillovers are positive and significant in 1990; no other spillover parameters are significant at the 95% confidence level, and point estimates between friendly spillovers and unfriendly spillovers are close.

5.3 Panel Model, single inverse distance weight matrix, no injection

Table 10 presents fixed effects estimated for the pooled data. The fixed effects models for lease-level gas production indicate positive and significant spatial autocorrelation in the time-varying aspect of the errors. There is also evidence of a race to extract in natural gas production, as the estimates for λ are positive and stable, although the preferred GS2SLS estimate is insignificant.

Turning to the oil results, it is apparent that the OLS and 2SLS estimation yield parameter estimates for λ that are positive and significant and very close to previous cross-sectional estimates. The parameter for the spatial autocorrelation in errors (ρ) is a third to half the size of estimates in Tables 2 and 3. This difference cannot be wholly attributed to the importance of lease fixed effects in controlling for spatial autocorrelation,[6] nevertheless, it is expected for the error to attenuate because fixed effects diminishes the unexplained variation in the model. What is striking is the insignificance of λ in the GS2SLS specification when controlling for lease-level fixed effects.

There are two ways to interpret the insignificance. The first is that the spatial dependence in production is a statistical illusion. Cross sectional GS2SLS estimation is not powerful enough to properly distinguish true production spillovers from time invariant differences in lease productivities. But going deeper, fixed effects estimation differences out the variation in ownership structures, which are precisely the effects that I seek to isolate.

5.4 Panel model, separate inverse distance weights by ownership, no injection

To isolate the spillovers that result from different ownership structures, I estimate the fixed effects models in two specifications which differ in the weight matrix used. In particular, I separately estimate

$$\begin{aligned} y &= X\beta_i + \lambda_i W_i y + u \\ u_i &= \rho_i M u_i + \epsilon_i \end{aligned} \tag{4}$$

[6] The models have different regressors. The variable *depth* is time invariant and cannot be used in fixed-effect specification.

where $i = \{F, U\}$ indexes the weight matrix to be used in the specification. M represents the inverse distance weighting matrix used previously. W_F represents the inverse distance weights, but take values only when the neighboring leases are produced by a common operator (*i.e.*, the weights take values only for "friendly" leases.) Similarly, W_U takes inverse distance values when neighboring leases do no share a common operator (the leases are said to be "unfriendly") *A priori*, we would expect leases with common owners to more fully account for the spillovers in production , so that $\lambda_F < \lambda_U$. Equation 4 thus provides a testable hypothesis.

Result from estimation of models with weight matrices given according to Equation 4 are given in Tables 11 and 12. Again, the preferred specification is GS2SLS. For oil production, the parameter measuring the spatial spillover among friendly wells is positive and statistically significant. What is surprising is that the parameter for friendly spillover is larger and significantly different than the parameter for unfriendly spillovers (which is not significantly different from 0). Results are qualitatively similar for natural gas production. Combined, these results seem to indicate that leases under common stewardship are more likely to engage in a race to extract.

One plausible explanation for the unexpected results is that no account has been made for how injection impacts recovery. Injection is more likely and more effective when contiguous leases are controlled by a common operator. If these types of leases are more successful in injection, then recovery across the leases may be highly correlated, contributing to what looks like spatial dependence. Moreover, the impact of injection will not be swept up with lease-level fixed effects because injection varies over time. This can be tested for by adding injection into the model. The variables for injection are defined as the sum of injection that occurred within a half-mile radius of the well within the past year.

5.5 Panel model, simultaneous inverse distance weights by ownership, with injection

The next model I estimate is

$$\begin{aligned} y &= X\beta + \lambda_F W_F y + \lambda_U W_U y + u \\ u &= \rho M u + \epsilon. \end{aligned} \tag{5}$$

Tables 13 and 14 present estimations controlling for gas and water injection for the spillover parameters λ_F and λ_U for oil and gas, respectively. This model is slightly different from equation 4 in that the effect of spillovers from friendly wells is estimated in the same model as spillovers from unfriendly wells. In the columns labeled "GS2SLS" in both tables 13 and 14 we see evidence of a race to extract, in that the spillover estimate for unfriendly wells comes up as positive and significant, and is larger than the estimate for the spillover from friendly wells. Take for example table 13. The spillovers from nearby leases managed by the same operator is insignificantly different from zero, evidence that the operator is fully accounting for the externality in production. Meanwhile, the spillover from unfriendly wells is significant and positive. After controlling for spatial autocorrelation, this indicates that when a neighboring competing operator increases production, you also tend to increase production–a classic race to extract.

5.6 Panel model, simultaneous inverse distance weights by ownership and well age, with injection

We observe that there is a large "positive" spillover when neighboring wells are owned by competing operators– evidence of a race to extract. However, it is possible that it is not ownership per se that drives the results. Well age is an important variable to consider in modeling reservoir dynamics. Young wells are likely to have much more capacity to communicate with neighboring wells, than comparatively older wells, simply because, all things being equal, younger wells will be in higher energy parts of the reservoir and more potential for drawdown. To test for this, I allow the spillover parameter to be vary across wells of different ages, and these parameters are allowed to be different for both friendly and unfriendly operators. The model I estimate is

$$\begin{aligned} y &= X\beta + \textstyle\sum_a (\lambda_{F,a} W_F y_a + \lambda_{U,a} W_U y_a) + u \\ u &= \rho M u + \epsilon. \end{aligned} \tag{6}$$

Production at neighboring wells, y_a has been separated into 4 vectors depending on what age bin production falls. I arbitrarily choose 4 bins, so that each production been of well age represents a quartile, $a \in 1, 2, 3, 4$. We expect that the spillover parameter should decline with as neighboring wells increase in age. The decline occurs for two reasons. First, since the neighboring wells are older, there is likely less capacity at those wells for drawdown because with time the pressure in the surrounding reservoir and at the well face tends toward equilibrium. Second, it is reasonable to expect that the age of wells is correlated across space; therefore, when neighboring wells are older, it is likely that your own well is older, and that you have less capacity to adjust own production, although this effect would be accounted for to some degree by the linear term in age. Results for regressions with oil as the dependent variable are in table 6, while gas results are in table **??**.

Looking first at results for oil, the Moran-I statistic indicates significant positive spatial autocorrelation in the errors, making inference on the OLS parameters untenable. After controlling for other covariates an, an extra day of production (*age*) does not meaningfully affect oil production. The OLS and GS2SLS specifications also indicate that gas injection is negatively correlated with production when controlling for spillovers; however, local gas injection is positive in the GLS specification while local water injection is negative and statistically significant. The instability of the parameter estimates for injection is likely due to to the complex spatial dynamics of the reservoir. A sudden within drop off in production could precipitate a local within increase in injection to compensate; a positive relationship is also easy to explain. The countervailing pressures in injection explain why estimates are not significant in the GS2SLS specification. The specifications for oil do pick up significant positive autocorrelation in oil production between leases.

Results for explanatory variables for natural gas are similar to those for oil. The age of the well does not seem to significantly impact production; the number of wells on the lease increases production, although the negative square term, indicates that this is at a decreasing rate. Injection is generally insignificant. Injection is likely to be even more difficult to identify with gas production, since produced gas can be re-injected into the reservoir. The Moran-I statistic on the OLS regression indicates negative spatial correlation, while the GLS and GS2SLS specification pick up the expected positive spatial autocorrelation in errors.

The parameters for spatial autoregressive lag are graphed in figure 10 for oil and figure 11 for gas. The older the age of the neighboring well the more the spillover parameter should attenuate, and so we see a negative slope in the graphs in both cases. Additionally, there should be more of a race to extract when wells are owned by competing (”unfriendly”) operators, and so we would expect that the unfriendly line lies above the friendly line on the graphs. This is generally the case for oil, with the exception being spillovers from wells within the first quartile of age. Unlike oil the spillovers parameters for natural gas are, with the exception of the first period, negative, here the friendly spillover tends to lie above estimates for unfriendly spillovers, and is closer to zero. Pinning down the interpretation of the spillover parameter requires a full spatial dynamic model of joint resource recovery, as well as controls for cumulative recovery, which is not attempted at present.

6 Conclusion

The spatial interaction between wells is an important consideration in efficiently draining oil an natural gas from expansive underground reservoirs. Yet previous research has shown that the present structure of lease-ownership in Texas impedes efficient field development because rights to the resources *in situ* are not fully delineated. This insecurity perverts economic incentives so that the resources are extracted too quickly, with too much of the rents depleted by costly excess capital.

This paper exploits recent advances in spatial econometrics to quantify the production spillovers between leases. Results show evidence of a race to extract across a variety of specifications. The most extensive model show that after controlling for injection and fixed effects, consolidated ownership reduces spillovers and tends to slow the rate of extraction as compared to areas where ownership is highly fractured. These results are directly in line with economic theory.

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Table 1: Summary Statistics (Slaughter)

Full Sample variable	Obs.	Mean	Std. Dev.	Min	Max
log gas	61427	6.00	3.75	0	14.3
log oil	61427	8.07	2.19	0	13.5
log water	61427	7.81	5.30	0	15.1
GOR	61427	-2.06	3.07	-12.53	9.9
age	61427	6324.72	7100.95	0	39870.0
age sq	61427	9.04E+07	1.75E+08	0	1.59E+09
well count	61427	28.04	48.21	1	652.0
well count sq.	61427	3110.75	10426.54	1	425104.0
total depth	430431	608.42	1721.06	0	12384.0
lease acreage	421938	3507.56	2803.63	0	8684.3
Regression Sample					
log gas	387	6.37	3.16	0	14.0
log oil	387	7.54	2.25	0	12.5
log water	387	8.01	4.76	0	14.3
GOR	387	-1.17	2.15	-9.25	5.4
age	387	8384.34	7521.19	0	36862.0
age sq	387	1.27E+08	2.16E+08	0	1.36E+09
well count	387	23.39	41.65	1	243.0
well count sq.	387	2276.80	7588.24	1	59049.0
total depth	6125	306.90	1290.07	0	10700.0
lease acreage	6055	3673.79	2834.06	0	8684.3

Notes: This table reports summary statistics tests for the HPDI data available for Slaughter field in the top panel, and for the regression sample in the bottom panel. The regression sample represents a subsample of production data for the month of January in 1990, 1995, 2000, and 2005. Note that injection observations far outnumber production observations because injection is reported at the well level. In all regressions, injection is summed over the past year within a half mile of each production observation. Log gas, log oil, and log water are log of one plus monthly lease level gas, oil and water production, respectively. Water and oil production are reported in log barrels, while gas is reported in log thousand cubic feet. GOR is gas to oil ratio, which is also logged. Age is the age of the most recent well drilled on the lease. Well count is the number of active producing wells on the lease. Total depth is the total depth of the most recently completed well on the lease. Lease acreage is the only variable not provided by HPDI, it is taken from the Texas Railroad Commission and measures the area of the lease.

Table 2: Oil Cross Section 1990s, Slaughter Field

	1990				1995			
	OLS	GLS	2SLS	GS2SLS	OLS	GLS	2SLS	GS2SLS
constant	3.34709	3.47369	3.35367	2.38126	2.33943	2.24115	2.31813	2.10240
	0.10525	1.50365	0.47453	1.07251	0.10799	1.56704	0.49387	0.99411
depth	0.00002	-0.00001	0.00002	0.00010	0.00002	0.00012	0.00002	-0.00006
	0.00002	0.00038	0.00005	0.00013	0.00002	0.00031	0.00006	0.00015
wcnt	0.06014	0.05663	0.06011	0.06699	0.05399	0.05220	0.05424	0.06537
	0.00217	0.07442	0.00831	0.01746	0.00218	0.03522	0.00810	0.01470
wcnt2	-0.01851	-0.01347	-0.01850	-0.02161	-0.01894	-0.01920	-0.01906	-0.02292
	0.00125	0.03774	0.00419	0.00900	0.00131	0.01686	0.00405	0.00725
age	-0.00002	-0.00010	-0.00002	0.00001	0.00000	-0.00005	0.00000	0.00001
	0.00001	0.00012	0.00002	0.00004	0.00001	0.00007	0.00002	0.00003
wtr	0.16650	0.21082	0.16653	0.22752	0.27921	0.37018	0.27837	0.24650
	0.01178	0.14719	0.02373	0.03654	0.01137	0.18829	0.03165	0.05007
λ	0.00208		0.00207	0.00203	0.00206		0.00209	0.00260
	0.00009		0.00029	0.00032	0.00010		0.00028	0.00032
moran	133.63				-18.67			
ρ		0.07031		0.06860		0.06860		0.06445
		0.00454		0.00450		0.00482		0.00393

Notes: The table presents results for cross-sectional regressions with logged lease level oil production as the dependent variable. The columns entitled "OLS" present results for equation 3. The "GLS" column omits the variables for spatial dependence, but allows errors to be correlated according to the same inverse distance weight matrix. The column "2SLS" is estimated according to equation 3, but with y_j instrumented with $w_{ij} * X_j$, with $X_j = \{depth_j, wcnt_j, wcnt_j^2, age_j, wtr_j\}$. Finally, the "GS2SLS" column presents results from the model given by equation 1. Independent variables are *depth*, the total depth of the most recent well completed on the lease; *wcnt*, the number of active producing wells on the lease (and its square); *age*, the time since the most recent well was completed; *wtr*, the amount of water produced on the lease that month, a proxy for whether the lease is constrained by disposal. λ is the parameter estimate for the spatial autoregressive lag; ρ is the parameter for the spatial autoregressive error. The model is estimated using a single inverse-distance spatial weighting matrix.Standard errors are reported on the line underneath coefficient estimates.

Table 3: Oil Cross Section 2000s, Slaughter Field

	2000				2005			
	OLS	GLS	2SLS	GS2SLS	OLS	GLS	2SLS	GS2SLS
constant	3.62138	3.66083	3.60804	3.71260	3.09252	4.09500	3.07114	4.19248
	0.07343	2.19179	0.36951	1.31357	0.09461	1.58374	0.44899	1.41697
depth	-0.00005	0.00016	-0.00005	-0.00010	-0.00006	0.00003	-0.00006	-0.00023
	0.00001	0.00022	0.00004	0.00016	0.00002	0.00027	0.00006	0.00017
wcnt	0.06319	0.06457	0.06338	0.06816	0.06085	0.06450	0.06127	0.06503
	0.00157	0.03040	0.00619	0.01579	0.00206	0.04805	0.00820	0.01747
wcnt2	-0.02084	-0.02216	-0.02093	-0.02260	-0.02064	-0.02103	-0.02083	-0.02209
	0.00098	0.01682	0.00318	0.00804	0.00131	0.02116	0.00430	0.00914
age	0.00000	-0.00002	0.00000	0.00002	0.00001	-0.00002	0.00001	0.00001
	0.00001	0.00004	0.00001	0.00003	0.00001	0.00005	0.00001	0.00003
wtr	0.17133	0.21460	0.17075	0.16103	0.21090	0.22758	0.20942	0.15728
	0.00787	0.08493	0.02433	0.06265	0.00991	0.16120	0.03041	0.06483
λ	0.00180		0.00182	0.00184	0.00188		0.00193	0.00200
	0.00007		0.00020	0.00032	0.00010		0.00026	0.00037
moran	-81.27				-143.92			
ρ		0.10359		0.09997		0.10645		0.09375
		0.00907		0.00844		0.01193		0.00949

Notes: The table presents results for cross-sectional regressions with logged lease level oil production as the dependent variable. The columns entitled "OLS" present results for equation 3. The "GLS" column omits the variables for spatial dependence, but allows errors to be correlated according to the same inverse distance weight matrix. The column "2SLS" is estimated according to equation 3, but with y_j instrumented with $w_{ij} * X_j$, with $X_j = \{depth_j, wcnt_j, wcnt_j^2, age_j, wtr_j\}$. Finally, the "GS2SLS" column presents results from the model given by equation 1. Independent variables are *depth*, the total depth of the most recent well completed on the lease; *wcnt*, the number of active producing wells on the lease (and its square); *age*, the time since the most recent well was completed; *wtr*, the amount of water produced on the lease that month, a proxy for whether the lease is constrained by disposal. λ is the parameter estimate for the spatial autoregressive lag; ρ is the parameter for the spatial autoregressive error. The model is estimated using a single inverse-distance spatial weighting matrix. Standard errors are reported on the line underneath coefficient estimates.

Table 4: Gas Cross Section 1990s, Slaughter Field

	1990				1995			
	OLS	GLS	2SLS	GS2SLS	OLS	GLS	2SLS	GS2SLS
constant	5.08840	6.04701	5.33505	5.33505	4.16513	7.66914	4.18287	4.10589
	0.17169	2.48669	0.85614	0.85614	0.16510	3.18929	0.81855	1.14052
depth	-0.00019	-0.00020	-0.00019	-0.00019	-0.00016	-0.00069	-0.00016	-0.00018
	0.00003	0.00039	0.00008	0.00008	0.00003	0.00034	0.00009	0.00012
wcnt	0.05905	0.05511	0.05803	0.05803	0.04403	0.08769	0.04386	0.03640
	0.00354	0.06272	0.01359	0.01359	0.00334	0.05953	0.01271	0.01428
wcnt2	-0.01426	-0.01227	-0.01375	-0.01375	-0.01175	-0.03117	-0.01166	-0.00944
	0.00203	0.03166	0.00686	0.00686	0.00200	0.02986	0.00635	0.00710
age	0.00000	0.00000	0.00000	0.00000	0.00000	-0.00006	0.00001	0.00001
	0.00002	0.00012	0.00003	0.00003	0.00002	0.00015	0.00003	0.00003
wtr	0.10430	0.10959	0.10566	0.10566	0.36653	0.12877	0.36717	0.45718
	0.01921	0.18206	0.03880	0.03880	0.01739	0.15279	0.04979	0.04969
λ	0.00093		0.00069	0.00069	-0.00058		-0.00060	-0.00116
	0.00017		0.00065	0.00065	0.00019		0.00066	0.00092
moran	886.0685				230.246			
ρ		0		0		0.039063		0.039063
		0.001583		0.001575		0.002681		0.002889

Notes: The table presents results for cross-sectional regressions with logged lease level gas production as the dependent variable. The columns entitled "OLS" present results for equation 3. The "GLS" column omits the variables for spatial dependence, but allows errors to be correlated according to the same inverse distance weight matrix. The column "2SLS" is estimated according to equation 3, but with y_j instrumented with $w_{ij} * X_j$, with $X_j = \{depth_j, wcnt_j, wcnt_j^2, age_j, wtr_j\}$. Finally, the "GS2SLS" column presents results from the model given by equation 1. Independent variables are *depth*, the total depth of the most recent well completed on the lease; *wcnt*, the number of active producing wells on the lease (and its square); *age*, the time since the most recent well was completed; *wtr*, the amount of water produced on the lease that month, a proxy for whether the lease is constrained by disposal. λ is the parameter estimate for the spatial autoregressive lag; ρ is the parameter for the spatial autoregressive error. The model is estimated using a single inverse-distance spatial weighting matrix.Standard errors are reported on the line underneath coefficient estimates.

Table 5: Gas Cross Section 2000s, Slaughter Field

	2000				2005			
	OLS	GLS	2SLS	GS2SLS	OLS	GLS	2SLS	GS2SLS
constant	2.91982	6.83444	3.09420	1.64463	2.67971	1.44926	2.68422	2.02392
	0.21505	6.81210	1.13448	1.35258	0.20795	4.52562	1.02424	1.36226
depth	-0.00033	-0.00095	-0.00032	-0.00020	-0.00031	-0.00050	-0.00031	-0.00026
	0.00004	0.00101	0.00013	0.00015	0.00004	0.00083	0.00012	0.00015
wcnt	0.06411	0.16550	0.06183	0.04621	0.05851	0.15736	0.05844	0.04801
	0.00460	0.11331	0.01865	0.01902	0.00454	0.09710	0.01835	0.01917
wcnt2	-0.01755	-0.05379	-0.01645	-0.01077	-0.01829	-0.06283	-0.01825	-0.01576
	0.00286	0.05352	0.00958	0.00978	0.00288	0.05035	0.00965	0.01007
age	0.00002	-0.00021	0.00002	0.00004	0.00000	-0.00018	0.00000	0.00001
	0.00002	0.00019	0.00003	0.00003	0.00002	0.00015	0.00003	0.00003
wtr	0.32342	0.05458	0.33313	0.44646	0.33085	0.57627	0.33116	0.43741
	0.02304	0.36198	0.07483	0.07024	0.02177	0.33291	0.06923	0.06972
λ	0.00109		0.00071	0.00053	0.00122		0.00121	0.00077
	0.00029		0.00094	0.00080	0.00028		0.00088	0.00079
moran	385.3884				-23.2705			
ρ		0.046875		0.0625		0.0625		0.064453
		0.004149		0.00413		0.009473		0.009104

Notes: The table presents results for cross-sectional regressions with logged lease level gas production as the dependent variable. The columns entitled "OLS" present results for equation 3. The "GLS" column omits the variables for spatial dependence, but allows errors to be correlated according to the same inverse distance weight matrix. The column "2SLS" is estimated according to equation 3, but with y_j instrumented with $w_{ij} * X_j$, with $X_j = \{depth_j, wcnt_j, wcnt_j^2, age_j, wtr_j\}$. Finally, the "GS2SLS" column presents results from the model given by equation 1. Independent variables are *depth*, the total depth of the most recent well completed on the lease; *wcnt*, the number of active producing wells on the lease (and its square); *age*, the time since the most recent well was completed; *wtr*, the amount of water produced on the lease that month, a proxy for whether the lease is constrained by disposal. λ is the parameter estimate for the spatial autoregressive lag; ρ is the parameter for the spatial autoregressive error. The model is estimated using a single inverse-distance spatial weighting matrix. Standard errors are reported on the line underneath coefficient estimates.

Table 6: Oil Cross Section 1990s, Simultaneous Weighting With Injection, Slaughter Field

	1990				1995			
	OLS	GLS	2SLS	GS2LS	OLS	GLS	2SLS	GS2LS
constant	1.9607	5.0210	1.9436	2.2188	0.6648	6.2060	0.6643	-1.3133
	0.1020	66.3668	1.0139	1.7090	0.1051	3.6279	0.9744	1.9199
depth	0.0000	0.0003	0.0000	0.0001	0.0000	0.0002	0.0000	0.0000
	0.0000	0.0011	0.0001	0.0000	0.0000	0.0003	0.0001	0.0001
wcnt	0.0585	0.1042	0.0587	0.0427	0.0518	0.0523	0.0519	0.0507
	0.0021	0.1180	0.0082	0.0098	0.0021	0.0499	0.0080	0.0120
wcnt2	-0.0183	-0.0434	-0.0184	-0.0104	-0.0180	-0.0168	-0.0182	-0.0167
	0.0012	0.0603	0.0041	0.0048	0.0013	0.0234	0.0040	0.0056
age	0.0000	-0.0001	0.0000	-0.0001	0.0000	0.0000	0.0000	0.0000
	0.0000	0.0002	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
wtr	0.1517	-0.1417	0.1517	0.1745	0.2664	0.3231	0.2673	0.2058
	0.0114	0.2428	0.0237	0.0273	0.0111	0.2149	0.0330	0.0348
ginj	-0.0126	0.1306	-0.0139	0.0215	-0.0129	0.0290	-0.0143	-0.0919
	0.0060	0.9996	0.0319	0.0905	0.0063	0.0852	0.0299	0.1017
winj	0.1226	-0.4219	0.1222	0.1172	0.1305	-0.2057	0.1290	0.3349
	0.0055	4.3554	0.0723	0.1613	0.0058	0.2723	0.0721	0.1813
λ_F	0.0031		0.0031	0.0027	0.0015		0.0014	0.0015
	0.0005		0.0007	0.0005	0.0005		0.0007	0.0007
λ_U	0.0013		0.0014	0.0009	0.0018		0.0019	0.0019
	0.0001		0.0005	0.0004	0.0001		0.0004	0.0006
Moran	-196.0741				-384.9071			
ρ		-0.2342		0.2197		0.1185		0.1284
		0.0358		0.0390		0.0247		0.0119

Notes: The table presents results for cross-sectional regressions with logged lease level oil production as the dependent variable and separate inverse distance spatial weight matrices given according to whether neighboring leases are under common ownership. λ_F is the estimated spatial autoregressive coefficient for the weight matrix that takes inverse distance values when leases have a common operator; λ_U is the estimated spatial autoregressive coefficient for the weight matrix that takes inverse distance values when leases have competing operators. The canonical model is given by equation 4. The column labeled "OLS" presents results when no instrumentation is made for the spatially lagged dependent variable, and no spatial structure is assumed in the errors; "GLS" is a specification, where the errors are assumed to be spatially autocorrelated; the column "2SLS" instruments for endogenous production with WX; "GS2SLS" instruments for endogenous production, and assume the errors to be spatially autocorrelated. Independent variables are *depth*, the total depth of the most recent well completed on the lease; *wcnt*, the number of active producing wells on the lease (and its square); *age*, the time since the most recent well was completed; *wtr*, the amount of water produced on the lease that month, a proxy for whether the lease is constrained by disposal; *winj* is water injected within a half-mile of the lease in the past year; *ginj* is the gas injected within a half mile of the producing lease in the past year; ρ is the parameter for the spatial autoregressive error. Standard errors are reported on the line underneath coefficient estimates.

Table 7: Oil Cross Section 2000s, Simultaneous Weighting With Injection, Slaughter Field

	2000				2005			
	OLS	GLS	2SLS	GS2LS	OLS	GLS	2SLS	GS2LS
constant	3.3091	6.1262	3.3109	4.6510	3.0190	3.6612	3.0241	3.4066
	0.0703	22.6531	0.7142	1.0283	0.0921	25.1143	0.9348	1.6542
depth	0.0000	-0.0001	0.0000	-0.0001	0.0000	-0.0002	0.0000	-0.0002
	0.0000	0.0017	0.0000	0.0000	0.0000	0.0011	0.0001	0.0001
wcnt	0.0623	0.0744	0.0624	0.0751	0.0604	0.0635	0.0605	0.0623
	0.0015	0.1980	0.0060	0.0098	0.0020	0.1960	0.0082	0.0134
wcnt2	-0.0204	-0.0243	-0.0205	-0.0258	-0.0204	-0.0154	-0.0205	-0.0205
	0.0009	0.0986	0.0031	0.0048	0.0013	0.0973	0.0043	0.0068
age	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	0.0000	0.0003	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000
wtr	0.1578	0.0466	0.1583	0.1603	0.2010	0.0290	0.2007	0.1706
	0.0075	0.6192	0.0250	0.0267	0.0096	0.6674	0.0318	0.0302
ginj	0.0364	0.0563	0.0357	0.0626	0.0445	0.0083	0.0438	0.0217
	0.0041	0.6383	0.0196	0.0407	0.0054	0.4588	0.0258	0.0709
winj	0.0136	-0.1567	0.0129	-0.1025	-0.0087	0.0262	-0.0093	0.0192
	0.0038	1.6269	0.0501	0.0936	0.0050	1.5744	0.0650	0.1394
λ_F	0.0019		0.0019	0.0012	0.0019		0.0019	0.0017
	0.0003		0.0005	0.0004	0.0004		0.0007	0.0007
λ_U	0.0012		0.0012	0.0019	0.0013		0.0013	0.0017
	0.0001		0.0003	0.0004	0.0001		0.0004	0.0004
Moran	-300.4290				-238.6740			
ρ		0.2524		0.2254		0.1980		0.1828
		0.0383		0.0281		0.0229		0.0445

Notes: The table presents results for cross-sectional regressions with logged lease level oil production as the dependent variable and separate inverse distance spatial weight matrices given according to whether neighboring leases are under common ownership. λ_F is the estimated spatial autoregressive coefficient for the weight matrix that takes inverse distance values when leases have a common operator; λ_U is the estimated spatial autoregressive coefficient for the weight matrix that takes inverse distance values when leases have competing operators. The canonical model is given by equation 4. The column labeled "OLS" presents results when no instrumentation is made for the spatially lagged dependent variable, and no spatial structure is assumed in the errors; "GLS" is a specification, where the errors are assumed to be spatially autocorrelated; the column "2SLS" instruments for endogenous production with WX; "GS2SLS" instruments for endogenous production, and assume the errors to be spatially autocorrelated. Independent variables are *depth*, the total depth of the most recent well completed on the lease; *wcnt*, the number of active producing wells on the lease (and its square); *age*, the time since the most recent well was completed; *wtr*, the amount of water produced on the lease that month, a proxy for whether the lease is constrained by disposal; *winj* is water injected within a half-mile of the lease in the past year; *ginj* is the gas injected within a half mile of the producing lease in the past year; ρ is the parameter for the spatial autoregressive error. Standard errors are reported on the line underneath coefficient estimates.

Table 8: Gas Cross Section 1990s, Simultaneous Weighting With Injection, Slaughter Field

	1990				1995			
	OLS	GLS	2SLS	GS2LS	OLS	GLS	2SLS	GS2LS
constant	8.9812	9.2607	8.9959	9.4893	6.7562	11.8219	6.7586	2.8660
	0.1630	12.0000	1.7000	2.0200	0.1560	11.6000	1.4900	3.3200
depth	-0.0002	-0.0002	-0.0002	-0.0002	-0.0001	-0.0002	-0.0001	0.0000
	0.0000	0.0004	0.0001	0.0001	0.0000	0.0005	0.0001	0.0001
wcnt	0.0619	0.0901	0.0615	0.0477	0.0420	0.0729	0.0419	0.0324
	0.0034	0.0632	0.0131	0.0151	0.0032	0.0635	0.0122	0.0144
wcnt2	-0.0161	-0.0296	-0.0159	-0.0093	-0.0099	-0.0254	-0.0099	-0.0069
	0.0019	0.0362	0.0066	0.0075	0.0019	0.0292	0.0061	0.0071
age	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	0.0000	0.0001	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000
wtr	0.0968	0.0710	0.0986	0.1560	0.3490	0.2400	0.3480	0.4930
	0.0182	0.0983	0.0381	0.0420	0.0165	0.2060	0.0506	0.0550
ginj	0.1330	0.0104	0.1330	0.1220	0.1220	0.1540	0.1220	-0.0417
	0.0096	0.1890	0.0527	0.0826	0.0093	0.1280	0.0464	0.1560
winj	-0.2550	-0.2590	-0.2580	-0.1840	-0.1720	-0.4670	-0.1720	0.0463
	0.0088	0.7610	0.1160	0.1550	0.0086	0.6770	0.1080	0.2900
λ_F	0.0029		0.0026	0.0045	0.0009		0.0009	0.0006
	0.0008		0.0012	0.0020	0.0009		0.0012	0.0015
λ_U	-0.0010		-0.0009	-0.0035	-0.0028		-0.0028	-0.0017
	0.0002		0.0010	0.0016	0.0002		0.0011	0.0013
Moran	372.3171				-21.1776			
ρ		0.0313		0.0313		0.0549		0.0625
		0.0014		0.0014		0.0058		0.0054

Notes: The table presents results for cross-sectional regressions with logged lease level gas production as the dependent variable and separate inverse distance spatial weight matrices given according to whether neighboring leases are under common ownership. λ_F is the estimated spatial autoregressive coefficient for the weight matrix that takes inverse distance values when leases have a common operator; λ_U is the estimated spatial autoregressive coefficient for the weight matrix that takes inverse distance values when leases have competing operators. The canonical model is given by equation 4. The column labeled "OLS" presents results when no instrumentation is made for the spatially lagged dependent variable, and no spatial structure is assumed in the errors; "GLS" is a specification, where the errors are assumed to be spatially autocorrelated; the column "2SLS" instruments for endogenous production with WX; "GS2SLS" instruments for endogenous production, and assume the errors to be spatially autocorrelated. Independent variables are *depth*, the total depth of the most recent well completed on the lease; *wcnt*, the number of active producing wells on the lease (and its square); *age*, the time since the most recent well was completed; *wtr*, the amount of water produced on the lease that month, a proxy for whether the lease is constrained by disposal; *winj* is water injected within a half-mile of the lease in the past year; *ginj* is the gas injected within a half mile of the producing lease in the past year; ρ is the parameter for the spatial autoregressive error. Standard errors are reported on the line underneath coefficient estimates.

Table 9: Gas Cross Section 2000s, Simultaneous Weighting With Injection, Slaughter Field

	2000				2005			
	OLS	GLS	2SLS	GS2LS	OLS	GLS	2SLS	GS2LS
constant	7.8646	9.4236	7.8815	7.2907	5.9010	4.1532	5.8947	5.0717
	0.2035	19.6447	2.0801	3.3982	0.1964	19.1210	2.0026	3.3064
depth	-0.0003	-0.0005	-0.0003	-0.0003	-0.0002	-0.0001	-0.0002	-0.0003
	0.0000	0.0006	0.0001	0.0001	0.0000	0.0007	0.0001	0.0001
wcnt	0.0687	0.1288	0.0674	0.0574	0.0660	0.0739	0.0661	0.0549
	0.0044	0.0641	0.0178	0.0181	0.0043	0.1117	0.0178	0.0198
wcnt2	-0.0187	-0.0523	-0.0181	-0.0159	-0.0208	-0.0252	-0.0210	-0.0189
	0.0027	0.0390	0.0091	0.0092	0.0027	0.0510	0.0092	0.0103
age	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	0.0000	0.0002	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000
wtr	0.3076	0.4992	0.3113	0.4265	0.2836	0.2790	0.2863	0.4187
	0.0218	0.2953	0.0753	0.0620	0.0206	0.3668	0.0710	0.0545
ginj	0.1303	0.2120	0.1352	0.0335	0.1386	0.0748	0.1348	0.0597
	0.0120	0.1453	0.0574	0.1266	0.0116	0.1918	0.0559	0.1356
winj	-0.3547	-0.5107	-0.3516	-0.3854	-0.2242	-0.0765	-0.2290	-0.2054
	0.0111	1.0820	0.1459	0.2743	0.0107	1.0798	0.1405	0.2748
λ_F	0.0033		0.0031	0.0024	0.0036		0.0035	0.0015
	0.0011		0.0017	0.0014	0.0011		0.0017	0.0014
λ_U	-0.0007		-0.0010	0.0025	-0.0015		-0.0012	0.0011
	0.0003		0.0015	0.0013	0.0003		0.0014	0.0011
Moran	155.3594				-142.3822			
ρ		0.0686		0.0803		0.1232		0.1073
		0.0059		0.0058		0.0134		0.0227

Notes: The table presents results for cross-sectional regressions with logged lease level gas production as the dependent variable and separate inverse distance spatial weight matrices given according to whether neighboring leases are under common ownership. λ_F is the estimated spatial autoregressive coefficient for the weight matrix that takes inverse distance values when leases have a common operator; λ_U is the estimated spatial autoregressive coefficient for the weight matrix that takes inverse distance values when leases have competing operators. The canonical model is given by equation 4. The column labeled "OLS" presents results when no instrumentation is made for the spatially lagged dependent variable, and no spatial structure is assumed in the errors; "GLS" is a specification, where the errors are assumed to be spatially autocorrelated; the column "2SLS" instruments for endogenous production with WX; "GS2SLS" instruments for endogenous production, and assume the errors to be spatially autocorrelated. Independent variables are *depth*, the total depth of the most recent well completed on the lease; *wcnt*, the number of active producing wells on the lease (and its square); *age*, the time since the most recent well was completed; *wtr*, the amount of water produced on the lease that month, a proxy for whether the lease is constrained by disposal; *winj* is water injected within a half-mile of the lease in the past year; *ginj* is the gas injected within a half mile of the producing lease in the past year; ρ is the parameter for the spatial autoregressive error. Standard errors are reported on the line underneath coefficient estimates.

Table 10: Fixed Effects Panel Regressions

	Oil				Gas			
	OLS	GLS	2SLS	GS2SLS	OLS	GLS	2SLS	GS2SLS
constant	3.9159	5.4011	3.3475	6.0533	3.1392	4.4618	2.8723	3.1834
	0.0592	0.5177	0.2123	1.9024	0.0967	0.6800	0.3486	0.9923
wcnt	0.0883	0.0902	0.0930	0.0741	0.0938	0.0262	0.0958	0.0874
	0.0012	0.0192	0.0047	0.0288	0.0020	0.0286	0.0079	0.0101
wcnt2	-0.0333	-0.0445	-0.0346	-0.0293	-0.0349	-0.0026	-0.0354	-0.0301
	0.0008	0.0106	0.0022	0.0134	0.0012	0.0135	0.0037	0.0046
age	2.69E-05	-1.77E-05	2.75E-05	1.25E-05	5.75E-05	8.17E-05	5.64E-05	5.26E-06
	5.40E-06	4.01E-05	8.26E-06	7.00E-05	8.83E-06	5.85E-05	1.40E-05	1.91E-05
wtr	1.12E-06	5.55E-06	6.37E-07	2.31E-06	2.26E-06	6.48E-06	2.03E-06	4.86E-07
	2.51E-07	2.54E-06	5.75E-07	2.57E-06	4.10E-07	2.51E-06	9.69E-07	1.14E-06
λ	0.0020		0.0026	0.0003	0.0014		0.0017	0.0018
	0.0001		0.0002	0.0019	0.0001		0.0004	0.0010
moran	5049.4790				7359.2500			
ρ		0.0313		0.0313		0.0156		0.0156
		0.0010		0.0011		0.0004		0.0005

Table 11: Fixed Effects, Separate Weighting: Oil

	Friendly			Unfriendly		
	OLS	2SLS	GS2SLS	OLS	2SLS	GS2SLS
constant	5.6175	5.6309	5.6309	4.3534	4.1100	5.4825
	0.0615	0.1124	0.1124	0.0644	0.2586	1.6967
wcnt	0.0789	0.0787	0.0787	0.0829	0.0846	0.0714
	0.0013	0.0050	0.0050	0.0014	0.0054	0.0207
wcnt2	-0.0294	-0.0293	-0.0293	-0.0323	-0.0328	-0.0303
	0.0008	0.0024	0.0024	0.0008	0.0025	0.0099
age	2.92E-06	3.68E-06	3.68E-06	3.57E-05	3.73E-05	-9.02E-06
	5.61E-06	9.35E-06	9.35E-06	5.88E-06	9.51E-06	4.49E-05
wtr	1.58E-06	1.63E-06	1.63E-06	1.90E-06	1.75E-06	2.03E-06
	2.61E-07	6.22E-07	6.22E-07	2.74E-07	6.43E-07	2.23E-06
λ	0.0042	0.0041	0.0041	0.0017	0.0020	0.0011
	0.0003	0.0004	0.0004	0.0001	0.0002	0.0017
moran	5163.204			6276.67		
ρ			0			0.03125
			0.001416			0.000859

Table 12: Fixed Effects, Separate Weighting: Gas

	Friendly			Unfriendly		
	OLS	2SLS	GS2SLS	OLS	2SLS	GS2SLS
constant	3.8227	3.8838	4.0070	4.6325	4.3195	5.0673
	0.0888	0.1620	0.1664	0.0982	0.3978	0.7723
wcnt	0.0944	0.0931	0.0901	0.0833	0.0852	0.0858
	0.0019	0.0073	0.0069	0.0021	0.0080	0.0099
wcnt2	-0.0335	-0.0334	-0.0323	-0.0319	-0.0325	-0.0327
	0.0011	0.0035	0.0032	0.0012	0.0038	0.0046
age	3.05E-05	3.51E-05	2.58E-05	6.08E-05	6.17E-05	2.84E-05
	8.11E-06	1.38E-05	1.29E-05	8.97E-06	1.43E-05	1.82E-05
wtr	1.57E-06	1.81E-06	1.54E-06	3.46E-06	3.28E-06	1.82E-06
	3.77E-07	9.11E-07	8.53E-07	4.17E-07	9.76E-07	1.14E-06
λ	0.0060	0.0051	0.0069	-0.0005	-0.0001	-0.0007
	0.0005	0.0007	0.0016	0.0001	0.0005	0.0009
moran	5395			7552		
ρ			0.0156			0.0156
			0.0005			0.0005

Table 13: Fixed Effects, Simultaneous Weighting: Oil

	OLS	GLS	2SLS	GS2SLS
constant	-0.0098	-0.0144	-0.0104	-0.0151
	0.0149	0.2356	0.0154	0.0060
wcnt	0.0130	0.1402	0.0130	0.0160
	0.0034	0.0398	0.0057	0.0135
wcnt2	-0.0076	-0.0498	-0.0076	-0.0117
	0.0016	0.0140	0.0026	0.0061
age	0.0000	0.0000	0.0000	0.0000
	0.0000	0.0000	0.0000	0.0000
wtr	0.5428	0.1363	0.5432	0.3350
	0.0337	0.1382	0.0365	0.0516
ginj	-0.0069	0.0710	-0.0070	-0.0237
	0.0026	0.0202	0.0057	0.0089
winj	0.0093	-0.0694	0.0091	0.0149
	0.0021	0.0129	0.0048	0.0075
λ_F	0.0087		0.0070	-0.0061
	0.0016		0.0026	0.0053
λ_U	0.0041		0.0043	0.0056
	0.0004		0.0006	0.0008
moran	201.3414			
ρ		0.1206		0.0938
		0.0054		0.0035

Table 14: Fixed Effects, Simultaneous Weighting: Gas

	OLS	GLS	2SLS	GS2SLS
constant	-0.013	-0.858	-0.019	-0.009
	0.057	0.293	0.057	0.019
wcnt	0.051	0.217	0.051	0.054
	0.013	0.044	0.021	0.025
wcnt2	-0.022	-0.036	-0.023	-0.019
	0.006	0.020	0.010	0.011
age	0.000	0.000	0.000	0.000
	0.000	0.000	0.000	0.000
wtr	0.871	1.354	0.847	0.543
	0.129	0.408	0.136	0.111
ginj	-0.023	0.051	-0.022	0.008
	0.010	0.074	0.021	0.021
winj	0.011	-0.107	0.010	-0.013
	0.008	0.052	0.018	0.017
λ_F	0.007		0.004	0.010
	0.004		0.006	0.007
λ_U	0.004		0.005	0.004
	0.001		0.002	0.001
moran	-685.593			
ρ		0.068		0.045
		0.003		0.002

Table 15: Regression on Local Herfindahl Index

	liq		gas	
	OLS	GLS	OLS	GLS
constant	0.0000	0.1262	0.0000	-0.0870
	0.0169	0.0645	0.0573	0.1340
wcnt	0.0139	0.0188	0.0523	-0.0061
	0.0039	0.0339	0.0133	0.0998
wcnt2	-0.0062	0.0151	-0.0202	0.0212
	0.0018	0.0152	0.0062	0.0440
age	-0.0001	0.0000	-0.0001	0.0001
	0.0000	0.0000	0.0000	0.0001
wtr	0.5920	0.6180	0.9354	1.6088
	0.0383	0.1319	0.1302	0.4158
ginj	-0.0106	-0.0454	-0.0264	0.0606
	0.0029	0.0188	0.0099	0.0487
winj	0.0074	0.0367	0.0044	-0.0269
	0.0024	0.0193	0.0083	0.0511
herf	-1.4696	-4.3574	-2.8451	-19.1496
	0.5710	2.9428	1.9396	9.5801
moran	10990.7500		1351.1970	
ρ		0.0376		0.0391
		0.0019		0.0013

Table 16: Oil Spillover by Age

	OLS	GLS	2SLS	GS2SLS
constant	0.0052	0.2362	-0.0123	0.0069
	0.0147	0.3114	0.0204	0.0084
wcnt	0.0137	0.1526	0.0129	0.0214
	0.0034	0.0440	0.0057	0.0168
wcnt2	-0.0079	-0.0482	-0.0079	-0.0150
	0.0016	0.0170	0.0026	0.0071
age	0.0000	0.0000	0.0000	0.0000
	0.0000	0.0000	0.0000	0.0000
wtr	0.5333	0.5301	0.5419	0.0058
	0.0333	0.1880	0.0380	0.0022
ginj	-0.0066	0.0592	-0.0073	-0.0129
	0.0025	0.0309	0.0057	0.0097
winj	0.0091	-0.0558	0.0076	0.0124
	0.0021	0.0237	0.0049	0.0081
λ_{F1}	0.0088		-0.0047	0.0302
	0.0016		0.0072	0.0049
λ_{F2}	0.0711		0.0046	-0.0002
	0.0572		0.0004	0.0003
λ_{F3}	-0.5457		-0.0002	0.0002
	0.5325		0.0002	0.0001
λ_{F4}	-0.6970		-0.0005	0.0000
	0.8834		0.0001	0.0000
λ_{U1}	0.0037		0.0057	0.0045
	0.0004		0.0011	0.0008
λ_{U2}	0.0320		0.0103	0.0247
	0.0084		0.0269	0.0160
λ_{U3}	-0.0609		-0.0044	0.0008
	0.2087		0.0013	0.0007
λ_{U4}	-0.0535		0.0125	0.0012
	0.1293		0.0009	0.0006
moran	317.9857			
ρ		0.1250		0.1170
		0.0053		0.0040

Table 17: Gas Spillover by Age

	OLS	GLS	2SLS	GS2SLS
constant	0.0185	-2.3327	-0.0114	-0.0605
	0.0558	1.3353	0.0460	0.0267
wcnt	0.0491	-0.8593	0.0506	0.0554
	0.0129	0.1637	0.0212	0.0256
wcnt2	-0.0219	0.1199	-0.0229	-0.0161
	0.0060	0.0717	0.0098	0.0113
age	0.0000	-0.0001	0.0000	0.0000
	0.0000	0.0001	0.0000	0.0000
wtr	0.8644	-0.3713	0.8499	0.0532
	0.1267	1.3790	0.1415	0.0222
ginj	-0.0259	0.0109	-0.0229	0.0235
	0.0097	0.2275	0.0211	0.0224
winj	0.0145	0.1186	0.0101	-0.0287
	0.0081	0.1581	0.0176	0.0179
λ_{F1}	0.0059		0.0011	0.0115
	0.0040		0.0137	0.0081
λ_{F2}	0.0055		0.0138	-0.0203
	0.1369		0.0025	0.0083
λ_{F3}	-0.1013		0.0011	-0.0031
	0.6226		0.0008	0.0013
λ_{F4}	-0.0370		0.0105	-0.0217
	0.1455		0.0072	0.0108
λ_{U1}	0.0007		0.0048	0.0089
	0.0012		0.0027	0.0020
λ_{U2}	0.0464		0.0109	-0.0203
	0.0144		0.0499	0.0281
λ_{U3}	0.2683		-0.0145	-0.0162
	0.2439		0.0052	0.0068
λ_{U4}	0.0692		0.0170	-0.0962
	0.0441		0.0350	0.0490
moran	-725.9618			
ρ		0.09375		0.046875
		0.004000141		0.00171428

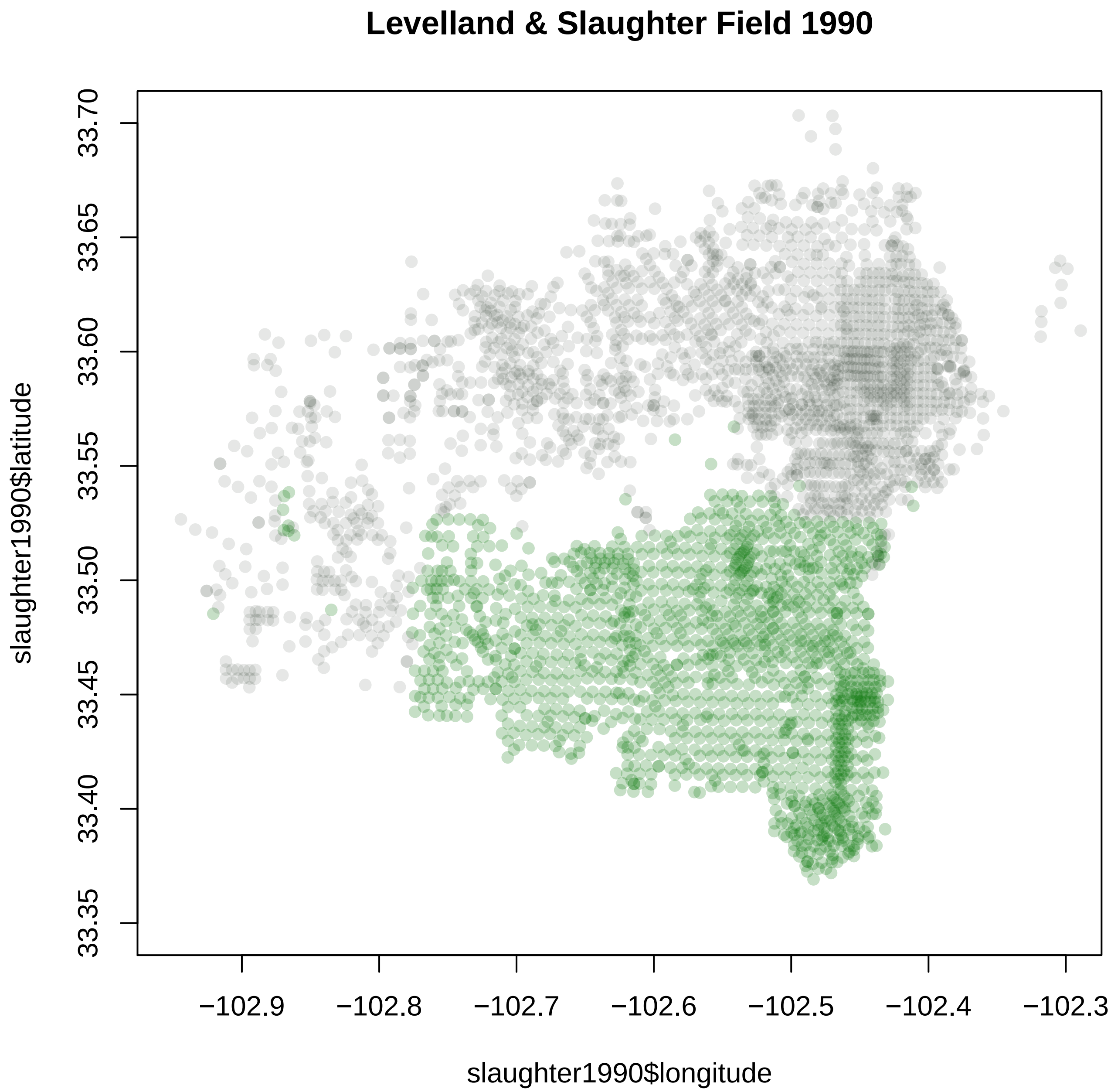

Figure 1: *Well locations.* Slaughter field is in green. To the north in gray is Levelland field which is geologically similar, but separated from Slaughter by an anhydrite salt dome.

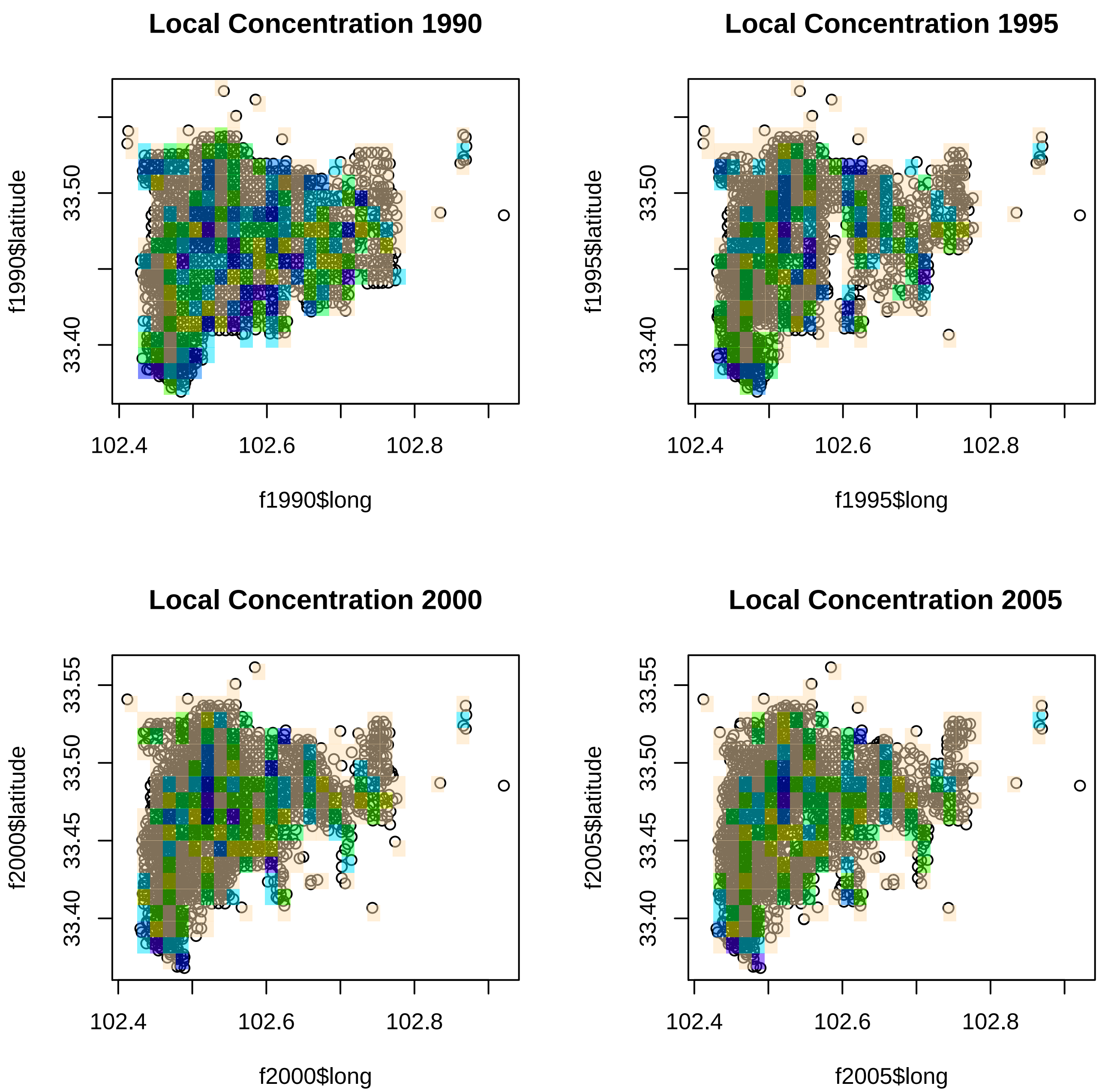

Figure 2: *Local Herfindal Concentration Index: Slaughter Field.* Herfindahl concentration index computed for each cell in a 30 x 30 grid. Lighter colors indicate higher ownership concentration.

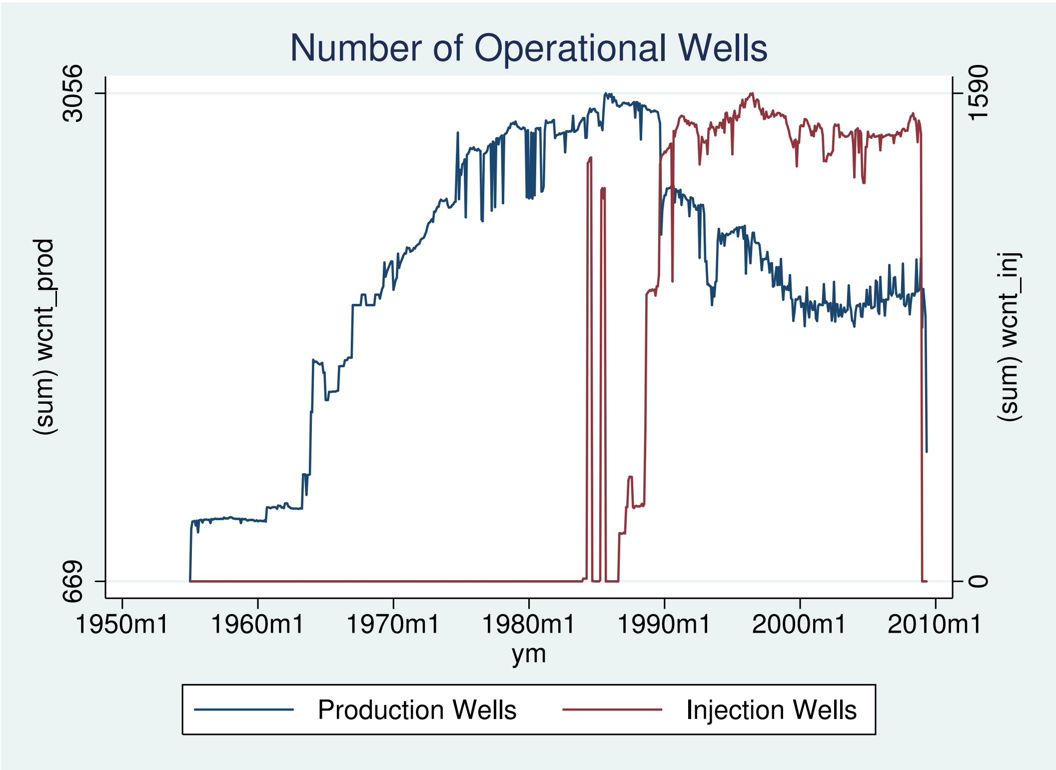

Figure 3: *Total Wells in Production: Slaughter Field.*

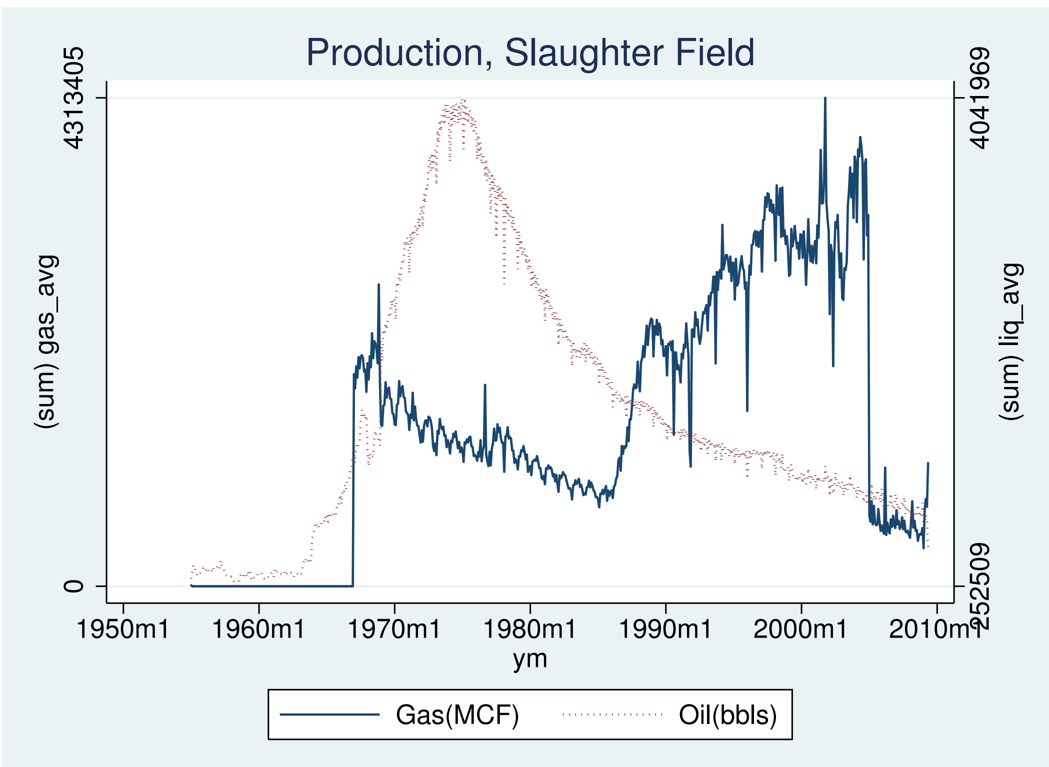

Figure 4: *Aggregate Production: Slaughter Field.*

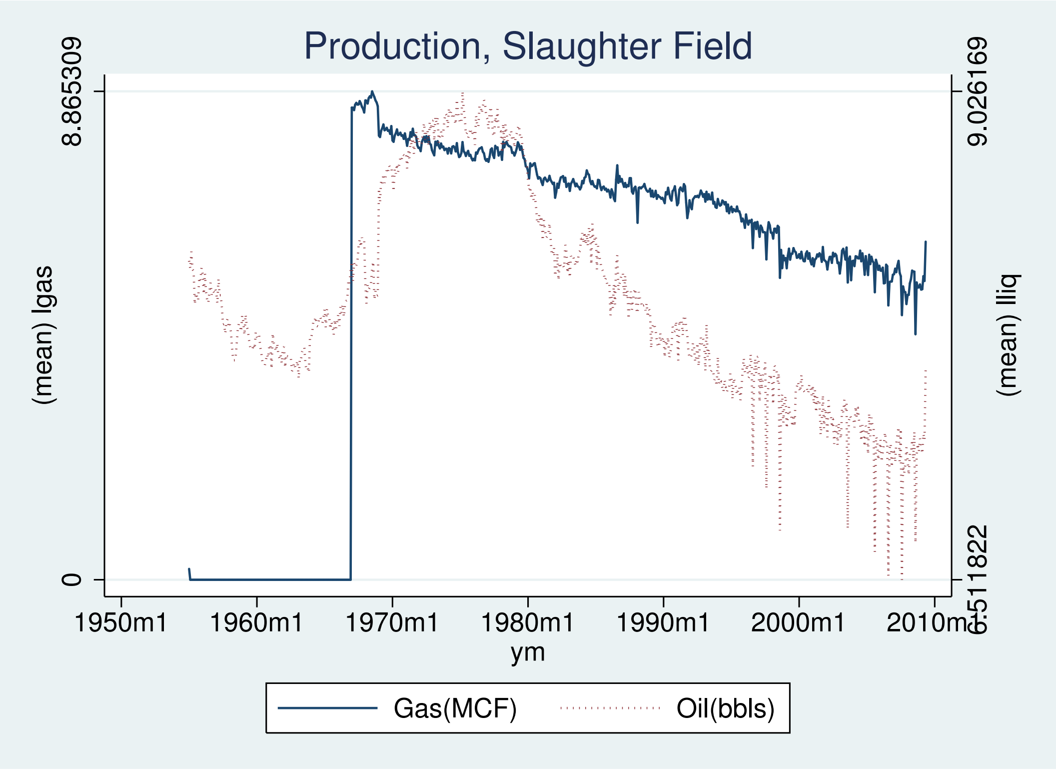

Figure 5: *Log of Well Average Production: Slaughter Field.*

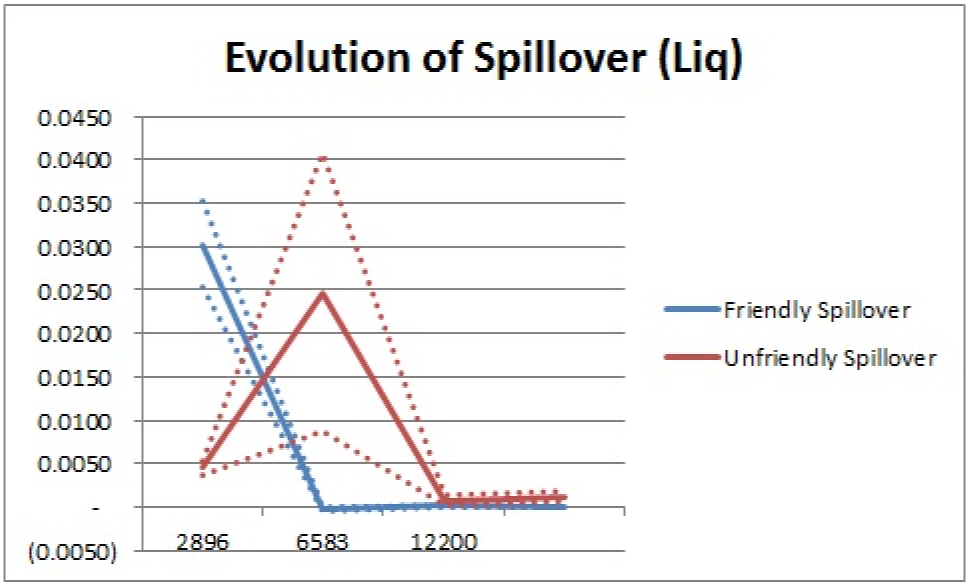

Figure 6: Table Plotted

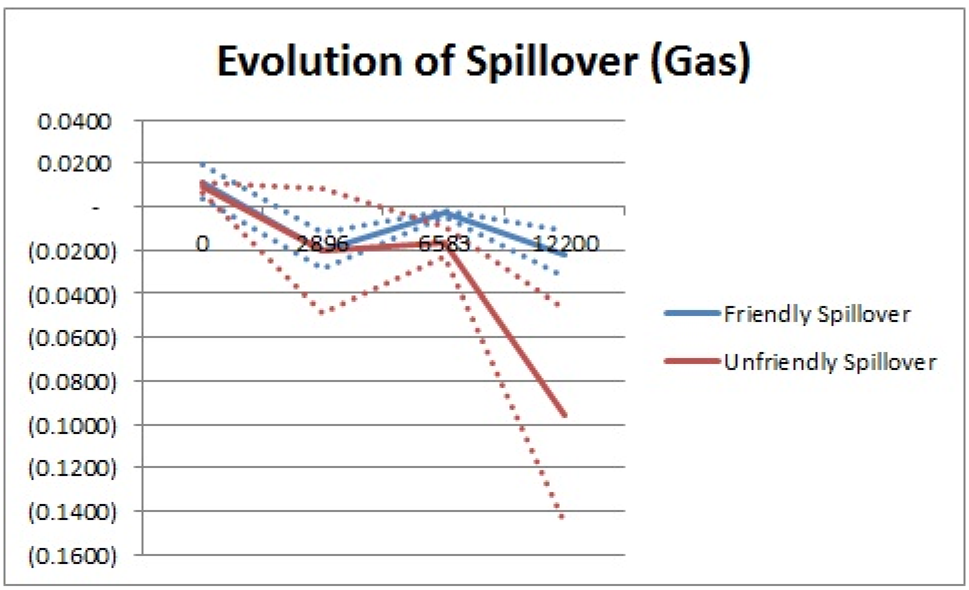

Figure 7: Table Plotted