

# **Three Essays on ...**

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Elyse Jayne Adamic

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M.A., University of Toronto, 2016

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The following individuals certify that they have read, and recommend to the Faculty of Graduate and Postdoctoral Studies for acceptance, the thesis entitled:

**Three Essays on ...**

submitted by **Elyse Jayne Adamic** in partial fulfillment of the requirements for the degree of **Doctor of Philosophy in Economics**.

**Examining Committee:**

Frederik Noack, Professor, Food and Resource Economics, UBC  
*Supervisor*

Patrick Baylis, Associate Professor, Economics, UBC  
*Supervisory Committee Member*

Sumeet Gulati, Food and Resource Economics, UBC  
*Supervisory Committee Member*

TBA, UBC  
*University Examiner*

TBA, UBC  
*University Examiner*

TBA  
*External Examiner*

# Abstract

The drilling of oil and gas wells creates large upfront economic benefits for drillers, but the economic and environmental costs only appear years or decades later, often long after the original owners of the well are legally required or financially able to repay them. This arrangement creates the potential for economic inefficiency along several dimensions: “judgement-proof” drillers who do not account for such long-run costs in their drilling decision, myopic homeowners who fail to anticipate the capital costs to their land, and neighbors onto whom the environmental costs of drilled, uncapped wells often spill over. Although the possibility of these types of market failures is well-documented, relatively little evidence is available about the magnitude of such costs and the degree to which they persist over time. I investigate the effects of oil and gas wells on housing prices across the complete life-cycle of the well. I consider both whether homeowners with wells on their property suffer long-term property value losses - specifically due to abandoned, non-producing wells - and whether well-plugging, a growing focus of environmental policy, can reclaim those losses. I combine detailed geospatial well location and production data with individual home characteristics and sales in Pennsylvania. I first show that there is a negative effect of active producing wells, consistent with the literature. Inactive wells have an even larger negative effect, and plugging does not fully reverse this loss, suggesting persistent perceptions of risk or environmental degradation. These results support environmental policies that increase setback requirements and strengthen incentives for timely well plugging and land reclamation.

Global overfishing causes substantial economic losses. Individual Transferable Quota (ITQ) systems are seen by economists as a promising solution creating a market mechanism which limits catch to the socially optimal level and ensures fish are caught at the least costs. However, theory suggests that despite increasing overall rents, fishers benefit differently from the ITQ system depending on their skill and outside income option. In this paper, we use the universe of individual level catch and revenue data for Maritime Quebec to quantify the distributional impacts of an ITQ system. We use matching methods to find appropriate control fleets, and then implement a difference-in-difference event-study approach to first look at distributional changes in incomes and effort on the intensive margin and then exit rates on the extensive margin. Overall, we find that fishing incomes increase in response to the introduction of ITQ regulation while fishing effort remains constant. This finding supports the efficiency increasing role of ITQ systems, yet these gains are unequally distributed across the fishery. Where an extra unit of regulation exposure increases incomes of the highest income quartile by around \$1200 there is no significant effect at the lowest income quartile. We further find evidence of substantial quota consolidation. While fishers in the highest income quartile hold initially around 40 percent of

the quota, this share increases within the next 10 year to almost 80 percent. However, this process is not per se inequality increasing, as long as those that leave the fishery face attractive outside options. Using income and employment data from the Canadian census, we show that those fishers that leave the fishery are predominantly from areas with high average incomes and low unemployment rates. Our results therefore suggest that ITQ systems raise fisheries income and that although that these gains are unequally distributed, we provide evidence that the resource incomes do not move away from remote communities and fishers with no income alternatives.

# **Lay Summary**

This dissertation...

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# **List of Abbreviations**



# **Chapter 1**

## **Introduction**

This dissertation...

## **Chapter 2**

# **The Long Term Impacts of Oil and Gas Extraction**

### **2.1 Introduction**

Oil and gas activity is known to generate immediate economic benefits to the surrounding communities through increased employment, higher wages, and improvements to local infrastructure. This holds true for both historical periods of production and for more recent booms, however these gains may come with longer-term costs when firms delay the financial burden of plugging. Mounting evidence associates these orphaned wells to environmental risks, including methane emissions, explosions, groundwater contamination, and land subsidence. At the same time, the sheer scale of the orphan well problem has become more apparent, with tens of thousands of documented wells across the United States with no financially responsible party on record. These environmental and financial burdens that may emerge decades later during the post-production phase are not internalized by the well operators during the drilling decision.

In contrast to active drilling, where the effects are more immediate and visible, abandoned wells represent a more pervasive and less perceptible environmental threat while also far outnumbering producing wells. In response, recent state and federal initiatives, including the 2021 Infrastructure Investment and Jobs Act, have sought to expand plugging efforts. In Pennsylvania alone, more than 90 percent of abandoned wells emit methane, contributing an estimated 5 to 8 percent of the state's total methane emissions (Kang et al., 2021). Furthermore, PADEP tracks over 27,000 wells with no viable owner. Despite growing policy attention, there is limited empirical evidence on the long-term economic consequences of oil and gas wells. This paper uses property market data from Pennsylvania to examine the extent to which legacy environmental hazards are capitalized into housing prices. First, I quantify the long-term effects of oil and gas wells across the life cycle, focusing on wells left unplugged. Second, I assess the extent to which damages may be reversed following plugging. I pay particular attention to the effect of the distance between the home and the well.

While the short-term gains can be wide-spread in the local economy, most enduring risks associated

with abandoned or improperly maintained wells are concentrated among those residents in direct proximity. The externalities associated with oil and gas wells change significantly over the life cycle. For example, in the short-run landowners may benefit from lease payments from active wells while dealing with noise, traffic, and pollution. Over time, as production declines these benefits dissipate, while the risks from improperly maintained or abandoned wells can persist or even intensify. I adopt the hedonic framework where home prices reflect a willingness to pay for environmental quality and disamenities, allowing me to recover the implicit cost that nearby homeowners bear from proximity to hazards created by abandoned wells. This approach follows closely the methodology of Muehlenbachs, Spiller, and Timmins (2015), who study the housing market impacts of shale gas development in Pennsylvania, though I extend the analysis to the post-production phase and focus on the long-term risks posed by unplugged and orphaned wells. However, home prices may not fully capture all disamenities if risks are uncertain, not salient to buyers at the time of purchase, or diffuse such as broader climate impacts. The housing market can only capture local perceived costs.

To study these dynamics, I construct a novel matched dataset of well production histories and property transactions in Pennsylvania over 1980 - 2023. I first identify homes that were exposed to oil and gas activity at the time of sale and then use variation in both distance to wells of given statuses and intensity, or the number of wells within a given radius. I use the production histories to identify status changes of a given well, namely differentiating between inactivity, abandonment, and orphaned in the post-production period. I supplement the production histories with the complete documented inventory of legacy wells, which have remained inactive over the entire period. My empirical strategy captures the cumulative risks associated with prolonged environmental exposure, accounting for intensity, distance, and well age. To address potential endogeneity in well placement and cleanup, I implement an instrumental variables approach.

The results reveal meaningful and persistent effects of historical drilling on property values. Even after remediation, plugged wells within 2 km can be associated with a 2.1% reduction in nearby home prices. This suggests that remediation may not fully eliminate perceived or actual risks. By contrast, abandoned wells also depress property values, though to a lesser degree, and active wells show no consistent impact once finer fixed effects are included. These findings underscore the long-term economic effects of fossil fuel development and provide new evidence to inform environmental liability and remediation policy.

By quantifying the long-term damages imposed on housing markets, this research informs regulatory efforts and highlights the financial burdens associated with legacy environmental risks. I further demonstrate how the orphan well problem is likely to escalate in the absence of intervention by looking at the current stock of active wells in Pennsylvania that are approaching the end of their productive life. Finally, I demonstrate how individual financial burdens can aggregate at the county level over time. These insights are critical for designing more effective policies, which I discuss in the context of bonding requirements, setback limits, and impact fees.

In Section 4.2 I provide a detailed background of the oil and gas industry in Pennsylvania and current regulations. In Section 4.3 I provide an overview of the hedonic method and in Section 4.4 I describe the

data. I present the empirical strategy in Section 2.5 , with results in Section 4.6 . Section 2.7 provides a series of robustness checks. I conclude with a policy discussion in Section 2.8 .

## 2.2 Background and Literature

### 2.2.1 Oil and Gas Drilling in Pennsylvania

Oil and gas extraction has played a significant role in Pennsylvania’s economy since the drilling of the first commercial oil well in the United States in 1859. Over the following century and a half, the industry expanded geographically and technologically, as advances such as fracking and horizontal drilling enabled the extraction of previously inaccessible resources. Many of these early wells were drilled prior to modern regulations and were later abandoned as operators exited or exhausted production. The legacy of this early drilling is still visible today, as modern communities live among a dispersed and aging network of wells with varying production statuses.

The lifecycle of a well includes ing, site preparation, drilling, production and closure. Once an operator identifies a potential hydrocarbon reservoir, they obtain a permit from the Pennsylvania Department of Environmental Protection (PADEP). Historically, Pennsylvania’s oil and gas industry relied on conventional wells, which are drilled vertically, resulting in numerous small-scale operations. However, the mid-2000s saw a rapid shift to unconventional horizontal drilling enabled by advances in hydraulic fracturing which made it economically viable to extract natural gas from the Marcellus Shale. Unconventional wells experience peak production early, while conventional wells tend to be shallower and produce lower quantities of hydrocarbons over a longer period.

During the active production phase, wells extract oil or gas and generate revenue. As a well nears the end of its productive life, operators face decisions about whether to extend production through additional interventions, temporarily idle the well, or plug it. Many older conventional wells transition into “stripper wells,” producing only marginal quantities of hydrocarbons but remaining active to postpone costly closure requirements. Other wells may be temporarily idled as operators wait for favorable market conditions. Once a well is no longer viable, proper plugging and abandonment are required to prevent environmental hazards and regain use of the land. If these are not followed, the well is abandoned.

Pennsylvania’s oil and gas regulations have evolved considerably, reflecting increasing awareness of environmental risks. Early drilling was mostly unregulated, where operators were not required to report the drilling location or plug wells. The Oil and Gas Act of 1984 introduced more stringent permitting requirements and standards for well construction, operation, and plugging. However, enforcement was limited, and many wells drilled before its enactment still remain unaccounted for. Regulatory updates such as Act 13 of 2012, sought to address the unique challenges of shale gas extraction. Act 13 introduced impact fees, stricter well construction standards, and measures to protect water resources. Act 13 also introduced higher bond requirements for producers that use fracking, although these requirements often fall short of covering full plugging costs. Further amendments in 2016 mandated disclosure of chemicals used in hydraulic fracturing and imposed stricter zoning restrictions on oil and gas operations. Despite these regulatory improvements, the stock of unplugged wells is increasing, particularly

during periods of low oil prices when operators face financial distress or bankruptcy. Firms often have limited financial incentives to plug wells, especially when bankruptcy allows them to offload environmental liabilities (Mitchell & Casman, 2011). Boomhower (2019) shows that weak bonding and limited liability protections can lead operators to underinvest in cleanup and exit before remediation is complete. Black, McCoy, and Weber (2018) shows that impact fees—though intended to internalize some external costs—often fall short of addressing long-term environmental liabilities such as unplugged wells.

The persistence of orphan wells reflects historical regulatory inadequacies and underscores their potential economic impacts, including effects on housing markets. Understanding this context is essential for analyzing the economic and policy dimensions of orphan wells.

### 2.2.2 Housing Market and Oil and Gas Activity

The economic literature of the effects of oil and gas development on housing markets has largely focused on active wells.<sup>1</sup> Most notably, Muehlenbachs et al. (2015) estimates the impact of shale gas development in Pennsylvania differentiating between ground-water dependent properties and piped-water properties. They find that properties within 1.5 km of a shale gas well experience a 13% reduction in sales price if they rely on groundwater, reflecting concerns about contamination. In contrast, similar properties with access to piped water show a small positive effect, likely due to lease payments or expected economic gains from development. Boxall, Chan, and McMillan (2005) finds a negative impact of hazardous wells on rural residential properties in Alberta, Canada. Property values are reduced between 4 and 8 percent within 4 km of a facility emitting lethal gases. Gopalakrishnan and Klaiber (2014) find that proximity to shale gas wells consistently diminishes property values in Washington County, Pennsylvania. The losses increase with each additional well, with particularly large losses for agricultural land. Delgado, Guilfoos, and Boslett (2016) only find weak evidence for a few select Pennsylvania counties that are isolated from other resource extraction or large urban areas. In contrast, Balthrop and Hawley (2017) study a densely populated area in Texas and find robust evidence that unconventional wells drilled within 3500 ft of a property reduce property values by 1.5 - 3% with an additional loss from construction. Weber and Hitaj (2015) study the link between shale development and farm real estate values, which reflects the value of the undeveloped land. They find small positive effects, suggesting the leasing potential of the land - any long-term disamenities associated with drilling were not large enough to outweigh the positive effects of gas development. Bennett and Loomis (2015) use a hedonic pricing model to examine the impact of fracked oil and gas wells on housing values in Weld County, Colorado, finding that proximity to wells can have both positive and negative effects depending on the distance and density of development.

While this literature has established effects of active wells, little attention has been given to the impacts of abandoned and orphan wells. My research extends this body of work by quantifying the economic costs of abandoned wells on housing markets, addressing a critical gap in understanding long-term externalities.

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<sup>1</sup>All of these papers use some form of the hedonic method developed by Rosen (1979). I build on the extensive literature using housing market to measure environmental disamenities (Greenstone and Gallagher (2008), Gamper-Rabindran and Timmins (2013), Cassidy, Meeks, and Moore (2023).)

### **2.2.3 Local Economy and Oil and Gas Activity**

The literature on the oil and gas industry also tends to emphasize the benefits that accrue to local economies during periods of high oil and gas extraction. These effects are broad in scope, short and medium run by nature, and are distributed equally among the proximal population.

Feyrer, Mansur, and Sacerdote (2017) tracks the geographic and temporal diffusion of local fracking shocks. They find persistent increases in local wages, royalty payments, and employment at the county and regional level. Maniloff and Mastromonaco (2017) attribute over 500,000 new local jobs to fracking. Komarek (2016) finds that shale gas development in the Marcellus region increased county-level employment by 1.5% to 2.5% and average wages by 1% to 2%, with the largest effects in counties experiencing the most intensive drilling activity. Bartik, Currie, Greenstone, and Knittel (2019) use geological variation and timing in the initiation of fracking and find improvements in various economic indicators but deterioration in local amenities. They calculate an extremely heterogeneous willingness to pay for fracking with a lower bound of zero. Wilson (2022) further explores how mobility patterns respond to local booms.

On the negative side, Cascio and Narayan (2022) documents that low-skilled males will forgo schooling during a fracking boom due to the increase in opportunity cost of human capital investment. Proville et al. (2022) show that marginalized communities are disproportionately exposed to drilling activities, building on the work of Smith and Wills (2018) who document that oil booms can promote regional inequality through benefitting urban populations while leaving behind the rural poor. Zwickl (2019) shows that proximity to fracking activity is not evenly distributed across populations—in Pennsylvania, communities near fracking sites tend to have lower income and education levels, suggesting a degree of environmental inequality in exposure to unconventional oil and gas development. Other negatives can include health Hill (2018), trucking accidents/traffic, and noise.

My research contributes to this literature by introducing a long-run margin of economic cost which contrasts these temporary economic effects associated with active drilling. By examining wells that no longer produce but still impose environmental and financial burdens, I reveal persistent externalities previously underexplored in the housing market literature.

### **2.2.4 Environmental Risks of Abandoned Wells**

While the effects of active wells may be more perceptible to property owners, abandoned wells significantly outnumber producing wells in both number and risk. It is estimated there are over 80,000 documented orphan wells across the country with no solvent owner of record Boutot, Peltz, McVay, and Kang (2022). Harleman, Weber, and Berkowitz (2022) find a significant lack of investment surrounding over half a century of abandoned wells in Pennsylvania compared to land with plugged wells. Nallur, McClung, and Moran (2020) look at the potential to restore ecosystem services in Arkansas following land reclamation.

These studies offer important qualitative and policy insights, yet few have quantified the welfare costs of orphan wells to nearby residents or property markets. Without this economic evidence, policy-makers lack the information needed to weigh the costs of inaction against the benefits of remediation.

## 2.3 Theory

The hedonic pricing method is a standard empirical approach used to estimate the implicit value of individual attributes by decomposing observed prices into the marginal contributions of their characteristics. The hedonic gradient can be interpreted as the marginal willingness to pay for an incremental change in a non-marketed attribute. The hedonic pricing model assumes that the market transaction price  $P_i$  depends on a vector of its characteristics  $X_i$ , including structural features and neighborhood attributes.

$$P_i = f(X_i) + \epsilon_i$$

In the case where there is an evolving environmental component  $E_{it}$  with changing levels of disamenities, we can assume the price  $P_{it}$  equals the present value of an infinite stream of per-period housing utility flows:

$$P_{it} = f(X_i) + f\left(\sum_{\tau=0}^{\infty} \delta^{\tau} E_{it+\tau}\right) + \epsilon_{it}$$

where  $0 < \delta < 1$  is the household's discount factor. Let home  $i$  be in the specified radius of  $J$  wells  $W_{it} = (w_{1t} \dots w_{Jt})$ , such that the total environmental component is equal to the sum of the disamenity of each well weighted by a distance function:

$$E_{it} = f(W_{it}) = \sum_{j=1}^J d(w_{ij}) v(w_{jt})$$

At a given time, the well is defined by one of the mutually exclusive states  $s \in S = \{a, u, p\}$  or active, unplugged, and plugged. Let  $m(s)$  denote the per-period marginal disamenity from having the well in state  $s$ , such that  $v(w_{jt} = s) = m(s)$ . We know have:

$$P_{it} = f(X_i) + f\left(\sum_{j=1}^J \sum_{\tau=0}^{\infty} d(w_{ij}) \delta^{\tau} v(w_{jt})\right) + \epsilon_{it}$$

*Perfect foresight* Suppose households have perfect information about the future path of the well's state  $\{w_{jt+\tau}\}_{\tau \geq 0}$  and treat it as deterministic. For example, suppose it is known that an active well becomes abandoned after  $T_U$  periods, and plugged after  $T_P$  periods, after which it is plugged forever.

Then the present value of disamenities for well  $j$  is:

$$v(w_{jt} = a) = \sum_{k=0}^{T^U-1} \delta^k m(a) + \sum_{k=T^U}^{T^P-1} \delta^k m(u) + \sum_{k=T^P}^{\infty} \delta^k m(p).$$

These sums evaluate to:

$$v(w_{jt} = a) = \frac{1 - \delta^{T^U}}{1 - \delta} m(a) + \frac{\delta^{T^U} - \delta^{T^U+T^P}}{1 - \delta} m(u) + \frac{\delta^{T^U+T^P}}{1 - \delta} m(p).$$

Similar for an unplugged well with a deterministic plugging date:

$$v(w_{jt} = u) = \frac{1 - \delta^{T^P}}{1 - \delta} m(u) + \frac{\delta^{T^U + T^P}}{1 - \delta} m(p).$$

Finally, for a plugged well:

$$v(w_{jt} = p) = \frac{1}{1 - \delta} m(p).$$

Therefore, the valuation of a specific well just depends on the duration in each status, which in turn can be a function of age, operator, and county. A well need not complete its full life cycle if it is known, for example, that it will remain unplugged indefinitely. Therefore, given perfect foresight, the coefficients capture the discounted value of all future disamenities given the current state and the observed transaction price is then:

$$P_{it} = f(X_i) + f(W_{it}) + \epsilon_{it}$$

*Zero foresight* Since the future path of the well's life-cycle is highly uncertain in reality, homeowners instead must form expectations, given the current state at time  $t$  which can be included in the hedonic function:

$$P_{it} = f(X_i) + f(W_{it}) + f(E_{t+1}^\infty(W_{it})) + \epsilon_{it}$$

While location disclosure is mandatory, it can also be assumed homeowners lack well-specific information or knowledge that would help to form expectations over the life-cycle. Consequently, all wells of an observed status within the radius of interest are treated identically. Two types of homeowners can be considered: naive, who would assume the observed status persists forever, and optimistic, who would assume all wells will be plugged within a chosen timeframe. The assumed beliefs will influence the interpretation, yet in either case, the expectations become deterministic, and the hedonic framework still fully captures the discounted stream of future amenities or disamenities:

$$P_{it} = f(X_i) + f(W_{it}) + \epsilon_{it}$$

Finally, the hedonic model assumes equal willingness to pay across individuals and that there is no shift in the hedonic gradient over time. Homeowners across time periods capitalize wells identically, there is no dynamic learning or uncertainty resolution.

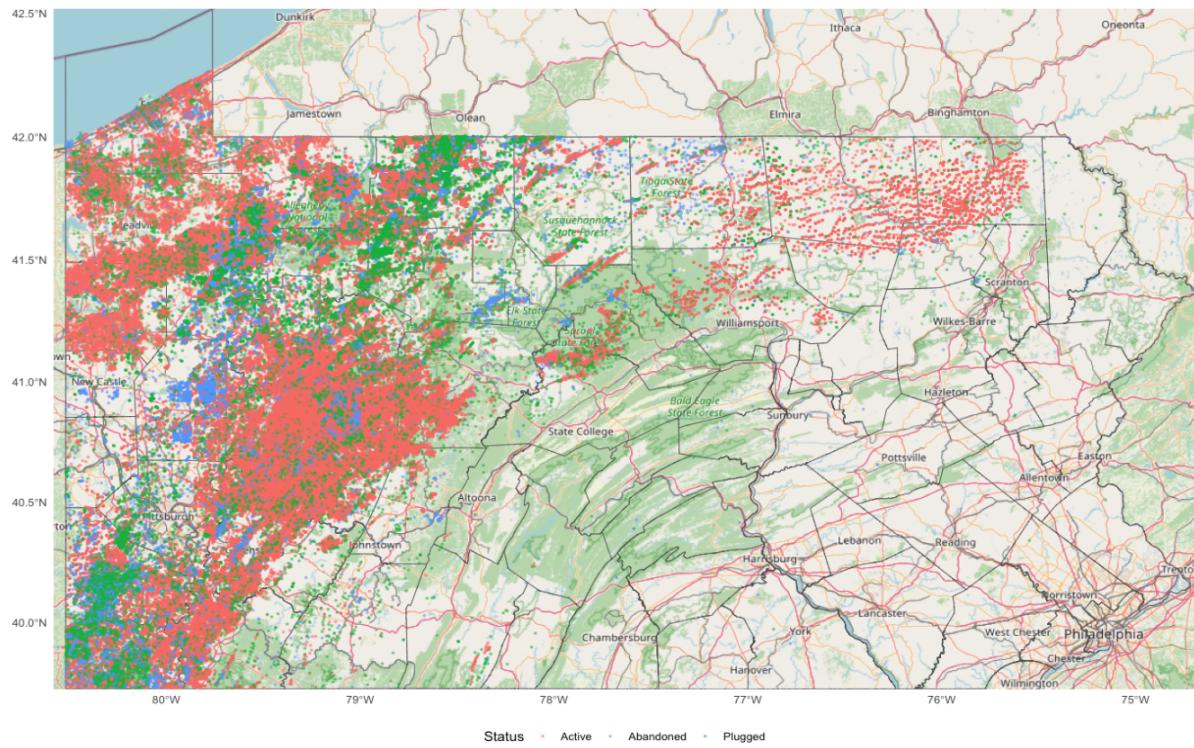
## 2.4 Data

### 2.4.1 Well Data

I compile data on oil and gas wells from several reports provided by the Pennsylvania Department of Environmental Protection (PADEP). The current well inventory identifies all wells known to the DEP. I link this inventory to historical production reports dating back to 1980 to identify the well status at each point in time, as oil and gas operators are required to report production details for each individual well they own. I also use the Plugged Wells Report to get the precise date of plugging when relevant.

Although there exists production evidence for wells not in the current DEP inventory, I choose to omit these in the interest of only addressing wells most likely known to a nearby homeowner. Unknown wells would not be capitalized into home prices and it is probably that only wells known to the DEP would be subject to disclosure laws. However I do include older legacy wells that are in the inventory without a production history. These wells are either orphaned or plugged and I assume they do not change status over my time period of interest. While it is estimated that there are hundreds of thousands of wells that the DEP does not have location information for, I assume these are randomly scattered across the state or unknown to homeowners thus unlikely to bias my estimates. However I can address potential concerns about unobserved well presence through the use of home fixed effects in select specifications, which absorb any time-invariant characteristics.

Prior to 2010, these data are compiled annually, after which they are reported biannually until 2015, and then monthly until the present. These reports include complete information about the location, quantity of resource extracted, type (oil or gas), purpose (extraction, injection, storage), and well configuration (conventional vs. unconventional). Each well is identified using a unique permit number, and for consistency, I aggregate the post-2010 reports to the annual level. I preserve all characteristics and sum the production quantities. I preserve the DEP status which is the status declared by the operator. In any given year the majority of “active” wells do not produce. Given that there are certain disamenities associated with active production, for certain specifications I impute status to see if homeowners respond to production rather than declared status, otherwise I do not use the reported quantity to differentiate between wells. As temporarily inactive wells still have the capacity to produce, all the equipment remains and it is still economical to keep the well alive. From the homeowners perspective, they likely cannot differentiate between these periods. I remove wells with inconsistent or missing latitude and longitude coordinates, as well as wells that were permitted but never spud. Wells are found in 33 Pennsylvania counties as shown in 2.1.

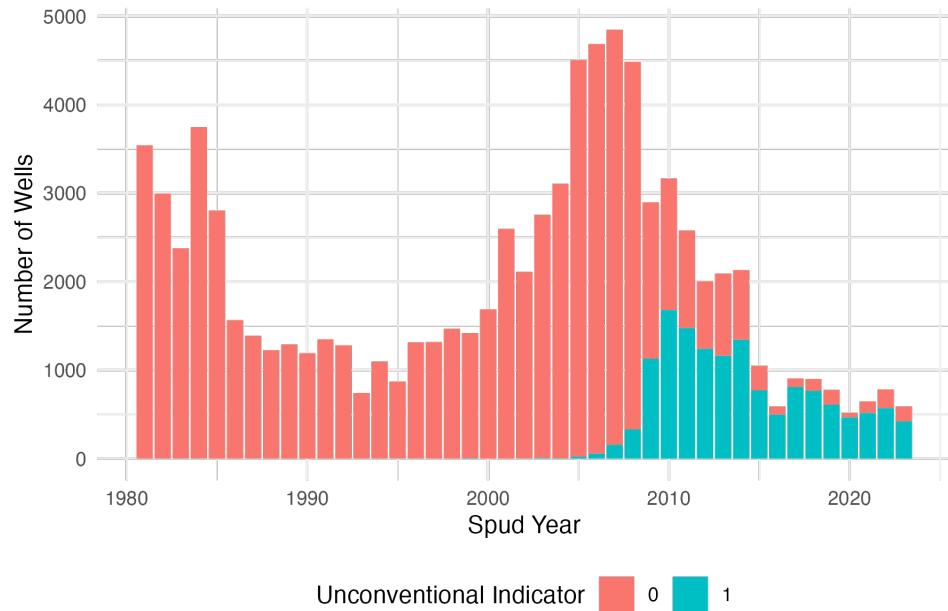


**Figure 2.1:** Oil and Gas Activity in Pennsylvania

This results in a time series of wells across the lifecycle. There is an initial stock of abandoned and plugged wells. Due to sparse observations for many wells in non-producing years, I am often required to impute the status in the following manner. Active wells become abandoned in the years following the last active observation until the plug year, or indefinitely if there is no plug year. Temporarily inactive wells are considered active if there are missing observation years yet produce again. As the inactive status refers to the official regulatory inactive status which operators have to declare, I do not impute that. This is in accordance with terminology used by the DEP. An abandoned well is defined as “a well: (i) that has not been used to produce, extract or inject any gas, petroleum or other liquid within the preceding 12 months; (ii) for which equipment necessary for production, extraction or injection has been removed; or (iii) considered dry and not equipped for production within 60 days after drilling, redrilling or deepening. The term does not include wells granted inactive status.” Wells deemed regulatory inactive are not intended to sit idle for extended periods of time, however this is common in the data and for certain specifications I treat these wells as abandoned. An orphan well is defined as a well abandoned prior to April 18, 1985. While all orphan wells are abandoned, not all abandoned wells are legally classified as orphaned. In practice, however, I do not distinguish between the two in most specifications, as both types of wells represent inactive sites with similar implications for homeowners. Finally, there can often be a long period in between when well is spud and first reports activity. I treat these wells as temporarily inactive unless they never produce, in which case they are deemed abandoned.

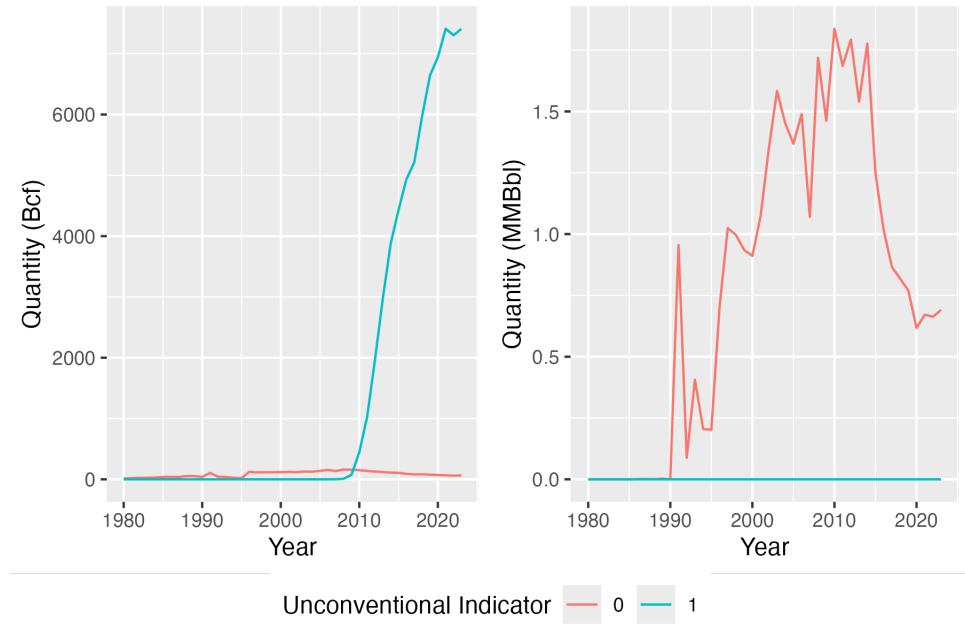
This leaves data on around 175, 000 wells. Figure 2.2 shows spudding over time by type. There are

about 66,000 wells that do not report a spud year. Since these are mainly legacy wells I can assume they were there before my time period of interest. By resource, only 22% are oil compared to 66.7% gas and 7.1% combined. By type, only 6.2 % of wells are unconventional. All unconventional wells are gas, yet these vastly account for the majority of production.

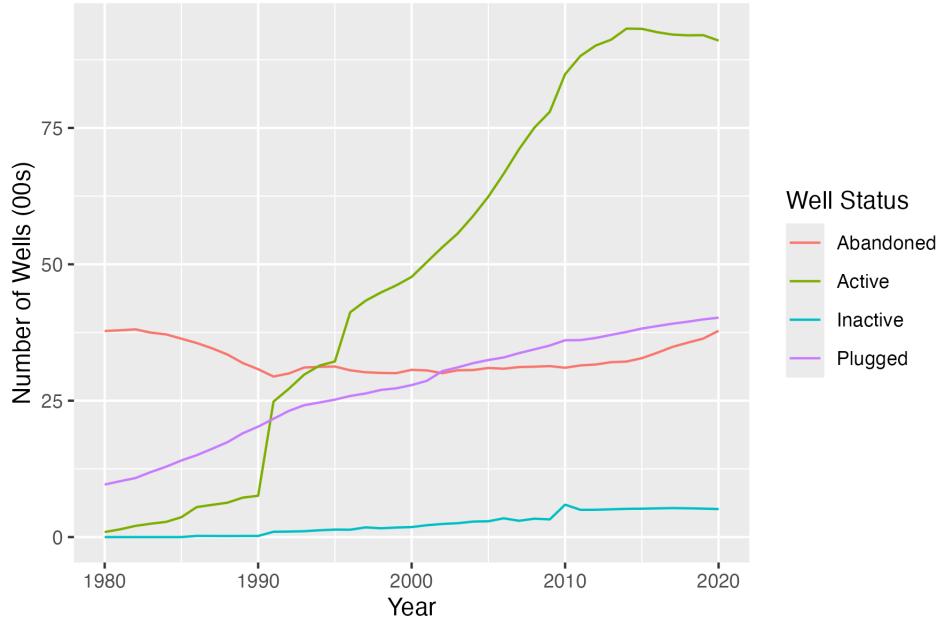


**Figure 2.2:** Wells Spud Over Time by Type

Figure 2.3 lots production over time separately for gas and oil. I converted oil measured in millions of cubic feet to barrels of oil equivalent (BOE). Figure 2.4 plots the number of wells at a given status each year. This is a cumulative count where once a well becomes abandoned, it continues to contribute to the abandonment total in all future years, as opposed to summarizing production reports which are not a complete panel. The count of plugged wells increases over time showing that some abandoned and active wells are being plugged. Inactive refers to the DEP status "Regulatory Inactive", although at any given point a high percentage of active wells are also not producing positive quantity which I selectively treat as inactive.

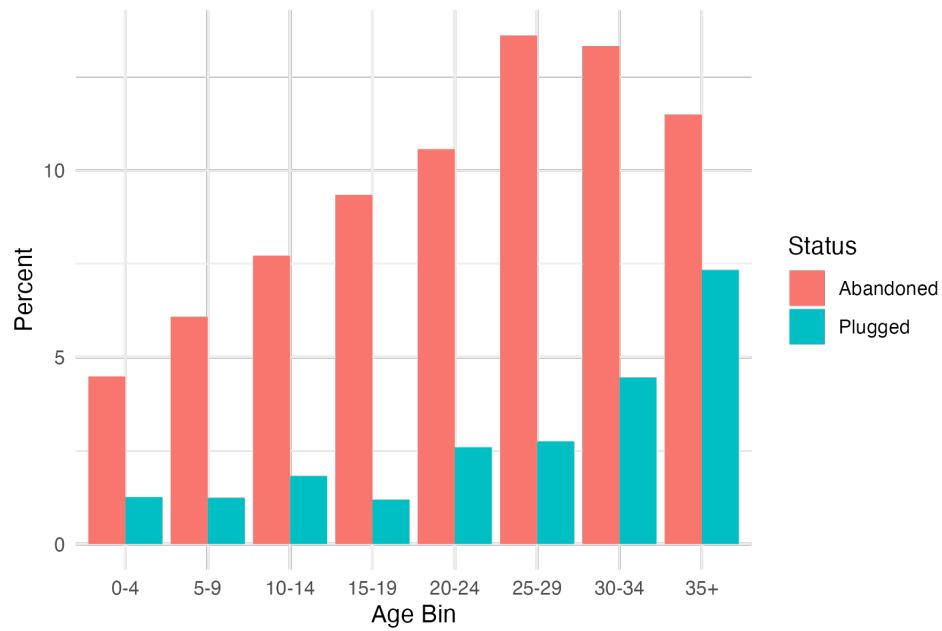


**Figure 2.3:** Production Over Time by Type and Resource

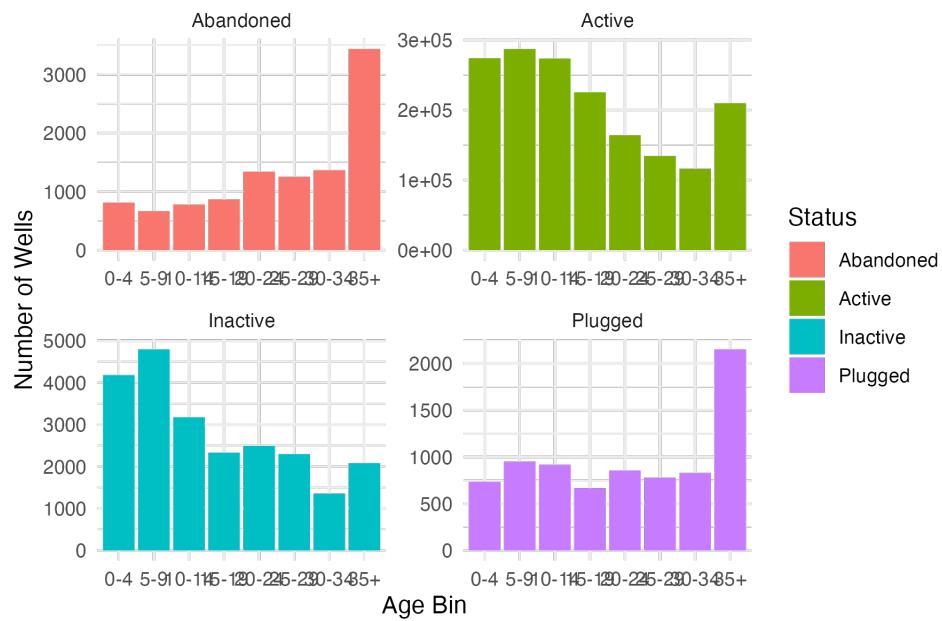


**Figure 2.4:** Well Status Over Time

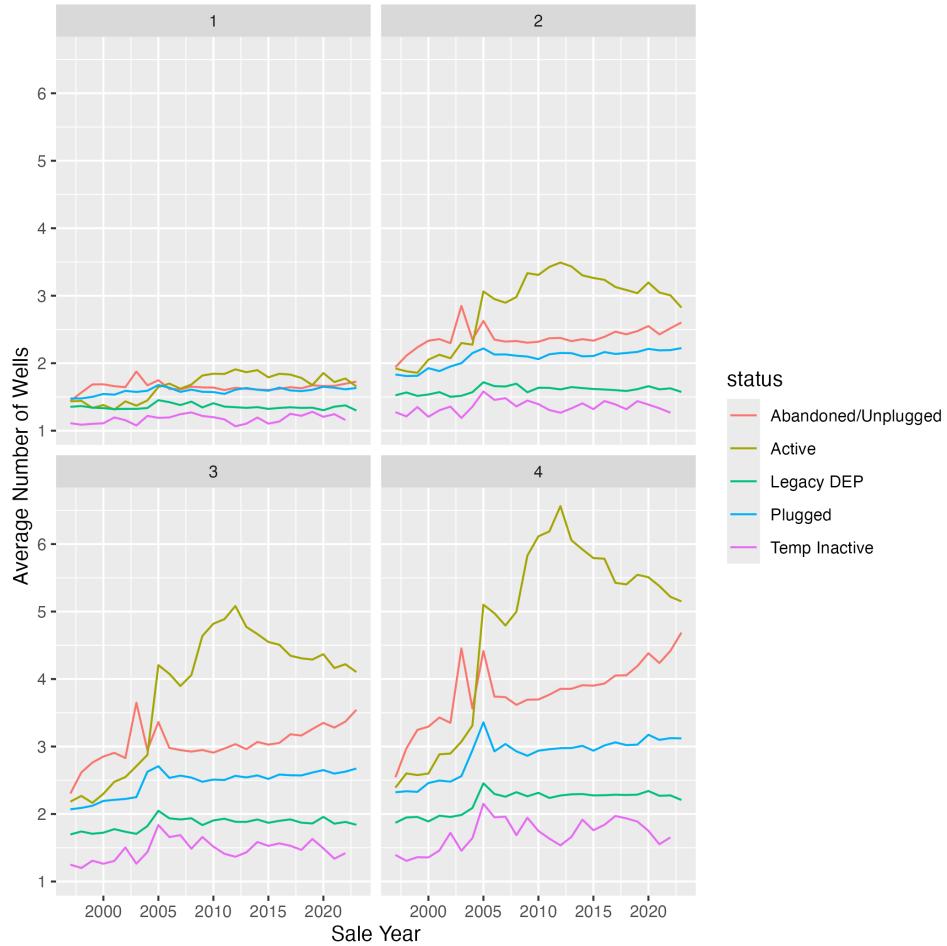
Figures 2.5 and 2.6 display the age-status distribution of wells. These distributions are cumulative: for example, a well observed at age 35 is also counted in all younger age bins. There are wells of all statuses at every age, yet older wells are more likely to be plugged or abandoned. Finally, 2.7 shows the average number of wells in each sale year of for homes that were sold, and at had at least one well of the given status within the given distance bin.



**Figure 2.5:** Age Distribution of Wells



**Figure 2.6:** Age Distribution of Wells by Status



**Figure 2.7:** Number of Wells by Status

#### 2.4.2 Housing Data

Housing market data is obtained from Attom - a nationwide provider of proprietary property data. The data are the universe of housing transactions since 1980, and include property characteristics, along with date of sale and home location. I remove arms-length transactions with low transaction values, as well as homes built to order where the sale year is the same as the built year. I identify single family homes by limiting the number of transactions over the time period, as well as winzering all characteristics. I end up with 938,432 housing market transactions that occurred between 1980 and 2023 with 608,462 homes. The identifying variation comes from homes sold at different times and new wells or existing wells changing status. The same home sold in two different time periods is essentially treated as two separate observations subject to different oil and gas activity, unless I include property fixed effects. Table 2.1 presents summary statistics.

**Table 2.1:** Home Sale Summary Stats

	Mean	SD	Min	Median	Max
<i>Variables</i>					
Price	143	127	10	112	1221
Year Built	1949	35	1700	1952	2022
Lot Size (K sqft)	76	793	0	9.1	261236
Building Size (K sqft)	1.9	237	0	1.4	228602
Bedrooms	2.6	1.4	0	3	122
Bathrooms	1.7	1.2	0	2	99
<i>Counts</i>					
Transactions	929219				
Properties	608886				
Census Tracts	1019				

*Notes:* Sample of homes sold between 1995 and 2023 in Pennsylvania counties that have oil and gas activity. Homes without complete characteristics have been removed and variables have been winzterized to be within reasonable bounds. Homes with more than 100 wells have also been removed.

## 2.5 Empirical Strategy

### 2.5.1 Matching

For each home, I create well counts of each status within a given distance bin. For simplicity I begin with 3 status categories and 4 distance bins. Homes that are in the pure control group have no wells of any status within any distance bin. Homes that are in the treated group have at least one well nearby, or at least one non-zero well count variable. In certain specifications, I adjust the treatment distance cutoff  $r$  so homes with wells exceeding  $r$  km are not included in the treatment. In other specifications I sum the counts distance bins to find the total active wells surrounding a home less than  $r$  km. I can also examine finer distance bins in the case that homeowners are most concerned with wells within the boundaries of their land parcel.

Homes are matched to oil and gas wells using a fixed radius nearest neighbour matching algorithm. I find wells within 2000 meters which are then assigned to distance bins. Since I am working with latitude/longitude points for both wells and homes, I use the Haversine formula to calculate distance. The sample is restricted to homes with no more than 100 wells nearby. Treatment is determined by the proximity to wells, while treatment intensity is determined by the total number of wells nearby.

Treated homes are subject to the effects of well proximity, untreated homes are not. However, homes in the control group should still be in the vicinity of wells in order to belong to the same local economy.

Vicinity effects include local labour market effects such as changes in wages or employment, or changes in local amenities through tax revenues. For this reason, I limit my control group to homes in oil and gas counties and no home is farther than 20km from a well.

I first match the complete set of known wells to all homes with residential property transactions occurring between 1997 and 2023, then reduce the matches to only the wells that were spud at the year of sale. This leaves to be found the status of all of the matched wells in the year of sale. The two easiest cases are in the case I have a production observation in the year of sale in which case I have the status, or the well is plugged prior to the year of sale in which case the well is plugged. This leaves the case where the well exists based on spud year and prior production observations, yet there is no current observation.

I begin by matching the full set of known wells to all residential property transactions occurring between 1997 and 2023. I then restrict the sample to only those wells that were already spudded by the year of each home sale. For each matched well, I require its status in the year of sale, but this year is not always observed in the production history as it is not a balanced panel. Two cases are straightforward: if the well has a recorded production value in the year of sale, I use that to determine its status; if the well was plugged prior to the year of sale, I classify it as plugged. The remaining cases involve wells that were spudded and have prior production history, but no production is reported in the sale year. These require additional logic to assign status.

For the status in a given production year I either impute based on quantity produced or I accept what the DEP recorded. Active wells without production crossing a threshold are deemed "non-producing". Then, all wells without an active observation in the sale year that aren't plugged are essentially inactive/idle. Wells that will become active again are deemed "temporarily inactive" and wells that are never active again are deemed abandoned. This leaves two variations of status that essentially differ on the treatment of non-producing active wells. The results presented below are based on the DEP status rather than production.

I aggregate this status variable into 3 broad levels: active, abandoned, and plugged. I either categorize all non-active statuses (temporarily inactive, regulatory inactive) as abandoned in line with the DEP definition, or include them with active wells. This is to differentiate between historical legacy wells and wells with infrastructure available to produce. I further reduce the sample to homes with less than 100 wells nearby.

Summary stats of matched wells to homes are presented in Table 2.2.

**Table 2.2:** Matching Wells to Homes Summary Stats

Status	Distance Bin	Share of Homes		Number of Wells if Treated			
		Perc. Treated		Mean	SD	Median	Max
Active	0-0.5	0.12		2.11	1.53	2.00	19.00
	0.5-1	0.23		3.90	3.78	2.00	30.00
	1-1.5	0.30		5.43	5.78	3.00	41.00
	1.5-2	0.36		6.82	7.76	4.00	63.00
Inactive	0-0.5	0.20		2.08	1.69	1.00	56.00
	0.5-1	0.39		3.29	3.41	2.00	48.00
	1-1.5	0.50		4.24	4.74	2.00	49.00
	1.5-2	0.59		5.23	5.99	3.00	79.00
Plugged	0-0.5	0.14		1.64	1.38	1.00	43.00
	0.5-1	0.30		2.31	2.16	2.00	41.00
	1-1.5	0.39		2.83	3.13	2.00	48.00
	1.5-2	0.48		3.33	4.35	2.00	68.00

*Notes:* Inactive wells include legacy wells, temporarily inactive, and abandoned wells.

### 2.5.2 Identification

Within our matched sample of homes and wells, several pairwise comparisons are possible. The approach can be illustrated with a simple comparison: a treated home with a single nearby well versus a control home with no wells within proximity. Each such comparison reflects a composite of potential effects. Active wells may provide financial benefits through royalty payments to landowners (+), but also introduce local disamenities and environmental risks (-). When production ceases, these financial benefits stop, and some of the active phase externalities may diminish. However, the well can continue to pose environmental hazards, especially if left unplugged. Unplugged wells can degrade local aesthetics and, when visible, impose further disamenity costs. The comparison between a home near an unplugged well and a control home with no wells thus captures the long-run externalities of oil and gas extraction in the absence of proper plugging practices. Without intervention, unplugged wells remain features of the landscape indefinitely.

Wells in the post-production phase can either be left unaddressed in which case they become officially abandoned, or can be plugged. While I can distinguish between temporarily abandoned wells and historically abandoned legacy wells, such distinctions may be irrelevant from the homeowners perspective - post-production wells could be perceived as abandoned regardless of official status. However, the longer a well remains unplugged, the lower the probability it will be remediated, especially if ownership becomes unclear or the responsible operator becomes insolvent. Whether homeowners incorporate well age or regulatory status into their assessments remains an open empirical question. A properly plugged

well should eliminate environmental risks if all technical and regulatory requirements are satisfied. In this case, any residual impact on housing prices would reflect public perception rather than actual hazard. Therefore the comparison between a home near a plugged well and a control home captures whether homes homes with and without a history of extraction are valued similarly. Comparing these groups provides insight into whether market participants treat remediated well sites as fully restored.

Empirically, essentially all treated homes are located near multiple wells which are designated a status and distance bin.

Treated Home	Control Home	Comparison Captures
Near active producing well	No wells nearby	Net effect of production: royalties (+), disamenities (-)
Near inactive, unplugged well	No wells nearby	Long-run externalities without remediation
Near plugged, inactive well	No wells nearby	Residual effect of fully remediated site (perceived or real)
Near unplugged, inactive well	Near plugged, inactive well	Incremental effect of plugging (policy impact)
Near older legacy well	Near newer unplugged well	Effect of duration of abandonment

### 2.5.3 Baseline Specification

The following specification identifies relationship between residential property values and exposure to oil and gas wells, differentiated by status (Active, Abandoned, Plugged) and  $d$  distance bin: [0–500), [500–1000), [1000–1500), [1500–2000).

$$\ln(\text{price}_{itg}) = \sum_{d=1}^4 \alpha_d A_{ditg} + \sum_{d=1}^4 \alpha_d U_{ditg} + \sum_{d=1}^4 \alpha_d P_{ditg} + \gamma_t + \lambda_g + \mathbf{X}_i + \epsilon_{itg} \quad (2.1)$$

I consider a home  $i$  sold in year  $t$  of geography  $g$ . A range of fixed effects specifications to flexibly control for both spatial and temporal confounders. These can be separate or interacted. Year of sale fixed effects absorb aggregate shocks to the housing market, reflecting macroeconomic trends. I can interact year with county to allow for counties to have different trends over time, due to local demand or labour market policies for example. Month of sale fixed effects capture seasonality in housing prices of demand over the year. Then I introduce some level of geographic fixed effect, either census tract or block. These effects account for time-invariant spatial characteristics, and I am dealing with within-tract variation in well exposure over time. More saturated specifications, such as tract-by-year plus month fixed effects, allow for highly granular control over localized trends in housing prices. I control for characteristics  $\mathbf{X}_i$  in all specifications besides those with property fixed effects. By controlling for observable characteristics, any remaining variation in the housing price can be attributed to unobservables and the surrounding oil and gas activity. The unobservables are accounted for by comparing houses that are otherwise identical across everything except the proximity to wells, achieved through the inclusion of these fixed effects. Characteristics include year built, land square footage, building square footage, number of bedrooms and number of bathrooms.

#### 2.5.4 IV Specification

A potential threat to identification is endogenous well location and status. Conditional on observables and fixed effects, the assignment of a nearby well to a particular status (e.g., active, abandoned, plugged) should not be systematically correlated with omitted factors that also affect property prices, otherwise results could be biased. First, macroeconomic conditions shape the broader landscape of oil and gas wells. High commodity prices create incentives for operators to drill new wells or continue extraction, whereas low prices can render some wells unprofitable, leading to temporary or permanent shutdowns. While these macro conditions may not directly affect local housing markets, they could correlate with broader economic trends that do. This potential confounding can be addressed with year and county (or tract) fixed effects, though trends may differ across counties with varying reliance on the oil and gas sector, in which case county-by-year fixed effects are appropriate. Second, wells approaching the end of their productive life are more likely to be abandoned. Well status is influenced by well-specific characteristics, which may correlate with unobserved characteristics of the local housing market. For example, older neighborhoods with a history of oil and gas activity are more likely to have abandoned or orphan wells. Additionally, operators may selectively plug wells for reasons associated with housing characteristics: wealthier homes may be more likely to be near plugged wells if more responsible operators hold drilling rights, or if regulators prioritize plugging wells that affect larger numbers of residences. Including county fixed effects and detailed housing characteristics mitigates some of these concerns, though unobservables may still remain. Residual endogeneity motivates the use of an instrumental variable design to further isolate plausible exogenous variation. Finally, measurement error presents an additional challenge, particularly in the geolocation of homes and wells, which is fundamental to the matching process. For homes on large parcels, recorded home coordinates may be somewhat arbitrary, potentially introducing imprecision in well proximity measures.

To address this concern, I follow the approach of Shappo (2020), which exploits variation in well abandonment and plugging across counties to instrument for well counts. The instrument is constructed using a shift-share approach. The idea is that, at a given point in time, aggregate county-level conditions such as local economic shocks, changes in regulatory enforcement, or fluctuations in the oil and gas market, determine the probability that any particular well will have a given status. These aggregate “global shifts” are plausibly exogenous to individual housing prices. At the same time, the count of wells near each home captures each home’s exposure, or the local share. By combining these global shifts with local exposure, I can isolate variation in well status that is plausibly exogenous.

For simplicity, I remove the distance bins and consider a regression that uses total well counts within 2km for home  $i$  in geography  $g$  in sale year  $t$ :

$$\ln(price_{igt}) = \beta_1 A_{igt} + \beta_2 U_{igt} + \beta_3 P_{igt} + \gamma_t + \lambda_g + \mathbf{X}_i + \epsilon_{igt}$$

Each of the well counts are considered endogenous regressors. The instrument gives predicted well counts based off of macro conditions instead of actual well counts. Since these are based off of aggregate conditions instead of well/location specific characteristics, these are uncorrelated with housing prices.

Starting with abandoned, the probability a well  $j$  is abandoned is a combination of macro factors

$\phi_{gt}$  (oil and gas prices, general economy, regulations) and well specific factors  $\gamma_{jg}$  (age, type, operator, location):

$$Pr(Status_{jgt} = Abandoned) = \phi_{gt}^A + \gamma_{jg}$$

I estimate this with a linear probability model so the probability a well in a county at a given time is then equal to the macro conditions  $\phi_{ct}$  after removing the well specific factors. First I construct a balanced panel where the independent variable is equal to 1 for any year the well is considered abandoned. This variable is also 0 when well is plugged.

I then recover the fixed effects to get this general predicted status of each well drilled due to global factors. The remaining variation in predicted status reflects local, well-specific factors, which I do not use. Focusing exclusively on the component driven by global factors provides the most general specification to capture the macroeconomic and regulatory environment at the time. This is the most general specification to capture the macro state of the time. This gives a  $Pr(abandoned)_{ct}$  at the year and county level which is equal for all wells in a county at at time. I repeat this process for an indicator if a well was plugged.

Then, to construct the instrument as predicted number of wells, I multiply by the number of wells at  $t - 1$  that could possibly be the status in question in year  $t$ . For abandoned, I consider wells that are active, or currently abandoned. For plugged, I consider wells that are active, abandoned or plugged.

The instrument for abandoned wells then becomes:

$$\hat{U}_{igt} = Pr(Status_{ct} = Abandoned) * (A_{ict-1} + U_{ict-1}) = \phi_{gt}^A * (I_{ict-1} + U_{ict-1})$$

And the instrument for plugged wells:

$$\hat{P}_{igt} = Pr(Status_{ct} = Plugged) * (A_{ict-1} + U_{ict-1} + P_{ict-1}) = \phi_{gt}^P * (I_{ict-1} + U_{ict-1})$$

The first stages are the regression of predicted counts on real counts including controls and other instruments:

$$U_{igt} = \beta^U \hat{U}_{igt} + \alpha^P \hat{P}_{igt} + A_{igt} + \gamma_t + \lambda_g + \mathbf{X}_i + \epsilon_{igt}$$

$$P_{igt} = \beta^P \hat{P}_{igt} + \alpha^U \hat{U}_{igt} + A_{igt} + \gamma_t + \lambda_g + \mathbf{X}_i + \epsilon_{igt}$$

For an instrumental variable to be valid, it must be relevant and satisfy the exclusion restriction. Relevance requires that the instrument—the predicted number of wells based on county-year macro conditions—is strongly correlated with the actual number of wells near a home. In other words, aggregate shifts in well abandonment and plugging at the county level must meaningfully predict local well counts. Exogeneity requires that the instrument affects housing prices only through its effect on the actual number of wells, and not through any other channel. In this context, the predicted number of wells is derived entirely

from county-level macro shocks which are plausibly exogenous to the unobserved determinants of individual housing prices. By relying on the portion of well variation that is driven by these global factors, the instrument isolates changes in well exposure that are unrelated to local housing market shocks.

## 2.6 Results

### 2.6.1 Baseline Specification

In the following results tables, the sample is restricted to homes in oil and gas counties with no more than 100 wells nearby. I have clustered the standard errors at the county x year level, allowing for arbitrary correlation in errors across properties within the same county-year. Columns vary in the fixed effects included in order to account for different sources of unobserved heterogeneity. The first two columns are at the tract level, and the last two columns are at the block level. The temporal fixed effect is either sale year, or I allow for a county specific time trend with sale year x county.

Table 2.3 presents results from the aggregate Equation 2.1. The distance cutoff is 2km in Panel A. and 1km in Panel B. These OLS results show that an additional unplugged well is associated with a 0.1 - 0.3% decline in house prices. The effect is small yet statistically significant. For an average treated home with 12.8 unplugged wells nearby at an average home price of \$142,614, the loss is around \$3650. These results are consistent with the visible disamenity of unplugged wells on the landscape.

**Table 2.3:** Regression Results: Total Unplugged Wells within 2km

	log(Price)			
	(1)	(2)	(3)	(4)
Total Unplugged	-0.001*** (0.000)	-0.001*** (0.000)	-0.003*** (0.000)	-0.002*** (0.000)
Characteristics	Yes	Yes	Yes	Yes
Sale Year	Yes	No	Yes	No
Sale Month	Yes	Yes	Yes	Yes
Tract	Yes	Yes	No	No
County x Sale Year	No	Yes	No	Yes
Block	No	No	Yes	Yes
Observations	719,014	719,014	719,014	719,014
R <sup>2</sup>	0.62	0.62	0.70	0.70

*Notes:* \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Homes with no more than 100 wells nearby. Standard errors are clustered at the census tract or census block level. Active wells refer to wells deemed active by the Department of Environmental Protection (DEP). Abandoned wells include legacy wells and wells that have not been producing for at least 12 months. Plugged wells must have a valid date of plugging prior to the sale year. The distance cutoff is measured in meters.

Table 2.4, my main specification, breaks the aggregate effect down into well status and distance bin. These coefficients represent the percentage change in house price associated with the presence of one additional well of the given status within the distance bin. The comparison is to that of a home with no wells. For active wells, I find little evidence that active wells affect property values within 1.5 km. This could represent a net average effect with some homeowners receiving lease or royalty payments, or with those outside public water service areas bearing the environmental risks and disamenities while those with piped water properties gain, consistent with Muehlenbachs et al. (2015). I find the negative impact of active wells is concentrated in the 1.5-2 km distance bin. For an average treated home with 6.82 number of wells in that distance range, the price decline would be 0.6% per well, or around \$5835.

Abandoned wells show consistently negative effects, particularly in Column (3). An additional abandoned well within 500 meters of the property reduces home prices by 0.7% and the effect diminishes yet persists out to 2 km. The attenuation of these effects in Column (4), which uses county-year fixed effects, suggests that some of the price penalty was driven by county-level shocks correlated with both abandoned well presence and lower housing prices. At the upper bound, a average treated home with 2.08 inactive wells in the closest bin, the price decline would be around \$2076.

Plugged wells are also associated with significant negative effects on property values, suggesting that remediation does not fully restore market value. This may reflect lingering stigma, incomplete land reclamation, or uncertainty about the effectiveness of plugging. Notably, the effects of plugged wells

are larger and diminish less with distance. For an average treated home with 1.64 plugged wells in the closest distance bin, the price decline would be around \$4911.

These estimates can also be additive where in practice homes will be surrounded by a vector of wells within each status distance bin. For example, a treated home with the average number of wells in each bin, would be valued at around \$36,000 less than a home with no wells.

**Table 2.4:** Regression Results: Binned Linear OLS

	log(Price)			
	(1)	(2)	(3)	(4)
<i>Active Wells</i>				
≤ 500	0.001 (0.003)	-0.001 (0.003)	0.001 (0.002)	0.000 (0.002)
500–1000	-0.001 (0.002)	-0.002 (0.002)	-0.001 (0.001)	-0.002** (0.001)
1000–1500	0.001 (0.001)	0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)
1500–2000	-0.003*** (0.001)	-0.003*** (0.001)	-0.006*** (0.001)	-0.006*** (0.001)
<i>Abandoned Wells</i>				
≤ 500	0.001 (0.003)	0.003 (0.003)	-0.007*** (0.002)	-0.002 (0.002)
500–1000	0.001 (0.001)	0.003* (0.001)	-0.003*** (0.001)	0.001 (0.001)
1000–1500	-0.002 (0.001)	-0.001 (0.001)	-0.003*** (0.001)	0.000 (0.001)
1500–2000	-0.001* (0.001)	-0.001 (0.001)	-0.004*** (0.001)	-0.002*** (0.001)
<i>Plugged Wells</i>				
≤ 500	-0.009** (0.004)	-0.007** (0.004)	-0.021*** (0.004)	-0.011*** (0.004)
500–1000	-0.003 (0.002)	-0.001 (0.002)	-0.017*** (0.002)	-0.008*** (0.002)
1000–1500	-0.002 (0.001)	0.000 (0.001)	-0.013*** (0.001)	-0.005*** (0.001)
1500–2000	-0.003** (0.001)	-0.002 (0.001)	-0.010*** (0.002)	-0.004*** (0.001)
Characteristics	Yes	Yes	Yes	Yes
Sale Year	Yes	No	Yes	No
Sale Month	Yes	Yes	Yes	Yes
Tract	Yes	Yes	No	No
County x Sale Year	No	Yes	No	Yes
Block	No	No	Yes	Yes
Observations	719,014	719,014	719,014	719,014

Notes: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Homes with no more than 100 wells nearby. Standard errors are clustered at the county year level. Each panel corresponds to a different well status. The distance cutoff is measured in meters.

Table 2.5 shows the respective coefficients when reducing the sample to repeat sales and including home fixed effects. These estimates come from within-home variation, and isolates the effect of changes in nearby wells on the same home's price, removing confounding from unchanging home or neighborhood features that are potentially not fully captured by the fixed effects. Restricting the sample to repeat sales and including home fixed effects attenuates the estimated coefficients toward zero. Diminishing marginal effects of additional wells contribute to attenuation: in the cross-sectional specification, the coefficient reflects an average across homes with few and many wells, whereas the within-home specification mostly captures small incremental changes for the same property, which tend to have smaller marginal effects.”

Measurement error in both well and property locations may also attenuate estimated effects. For example, historical well coordinates are sometimes imprecise, and parcel centroids do not always reflect the actual position of the home. Such noise in exposure measures makes it harder to detect the true effect of wells, biasing estimates towards zero. Measurement error in well counts could also be a factor that is magnified when using only within-home changes yet still affecting baseline estimates.

In these specifications I treat all wells of a given status as identical, regardless of age. This could be important for plugged wells, where by construction the number of plugged wells can only increase. I explore this concept in Section 2.7.1, where I only allow plugged wells to affect a home for a given number of years. I also explore the assumption that all wells within the first 100 have the same effect.

**Table 2.5:** Regression Results: Repeat Sales Linear OLS

	log(Price)		
	(1)	(2)	(3)
<i>Active Wells</i>			
$\leq 500$	-0.002 (0.005)	-0.001 (0.007)	-0.001 (0.009)
500–1000	-0.004 (0.003)	-0.005 (0.003)	-0.002 (0.003)
1000–1500	-0.006* (0.003)	-0.005 (0.005)	0.002 (0.002)
1500–2000	-0.011* (0.006)	-0.009 (0.007)	-0.001 (0.002)
<i>Abandoned Wells</i>			
$\leq 500$	-0.002 (0.004)	0.005 (0.006)	0.001 (0.007)
500–1000	-0.004 (0.003)	-0.001 (0.002)	0.000 (0.004)
1000–1500	-0.008* (0.004)	-0.004 (0.003)	0.001 (0.005)
1500–2000	-0.012*** (0.004)	-0.007 (0.005)	0.000 (0.002)
<i>Plugged Wells</i>			
$\leq 500$	-0.028* (0.015)	-0.014 (0.021)	-0.007 (0.021)
500–1000	-0.025*** (0.006)	-0.014 (0.010)	-0.010 (0.006)
1000–1500	-0.020** (0.009)	-0.009 (0.010)	-0.002 (0.006)
1500–2000	-0.030** (0.014)	-0.016 (0.018)	-0.003 (0.003)
Property	Yes	Yes	Yes
Sale Year	Yes	No	No
Sale Month	Yes	Yes	Yes
County x Sale Year	No	Yes	No
Tract x Sale Year	No	No	Yes
Observations	719,014	719,014	719,014
R <sup>2</sup>	0.90	0.90	0.92

Notes: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$  Homes with no more than 100 wells nearby. Standard errors are clustered at the census block level. Each panel corresponds to a different well status. The distance cutoff is measured in meters.

## 2.7 Robustness

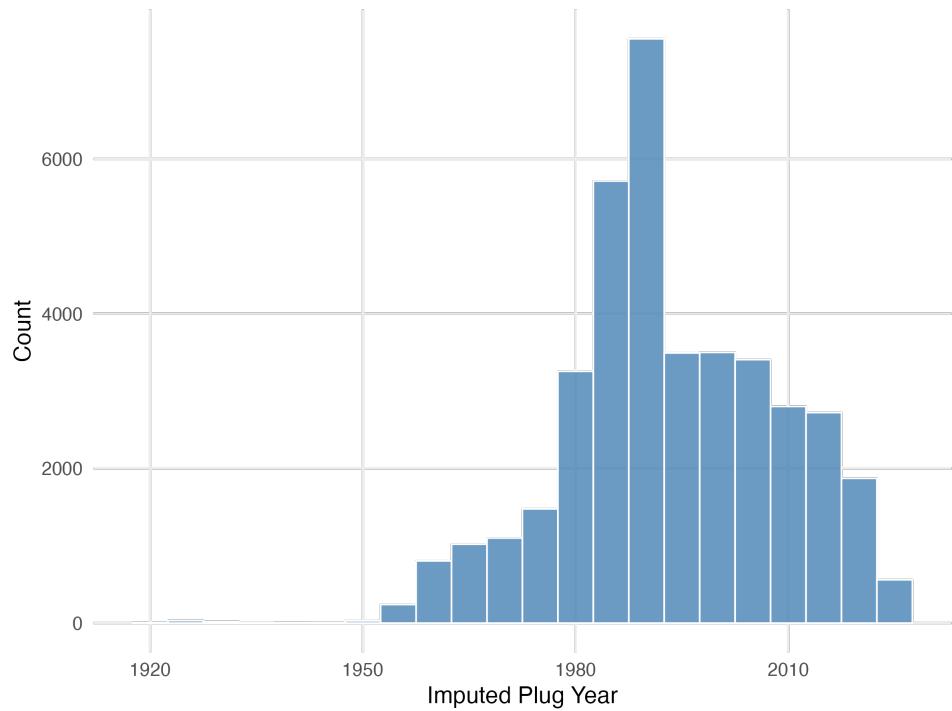
To assess the sensitivity of my main results, I conduct a series of robustness checks that address considerations related to heterogeneous treatment effects, measurement choices, and sample construction.

### 2.7.1 Restricting Plugged Well Exposure Window

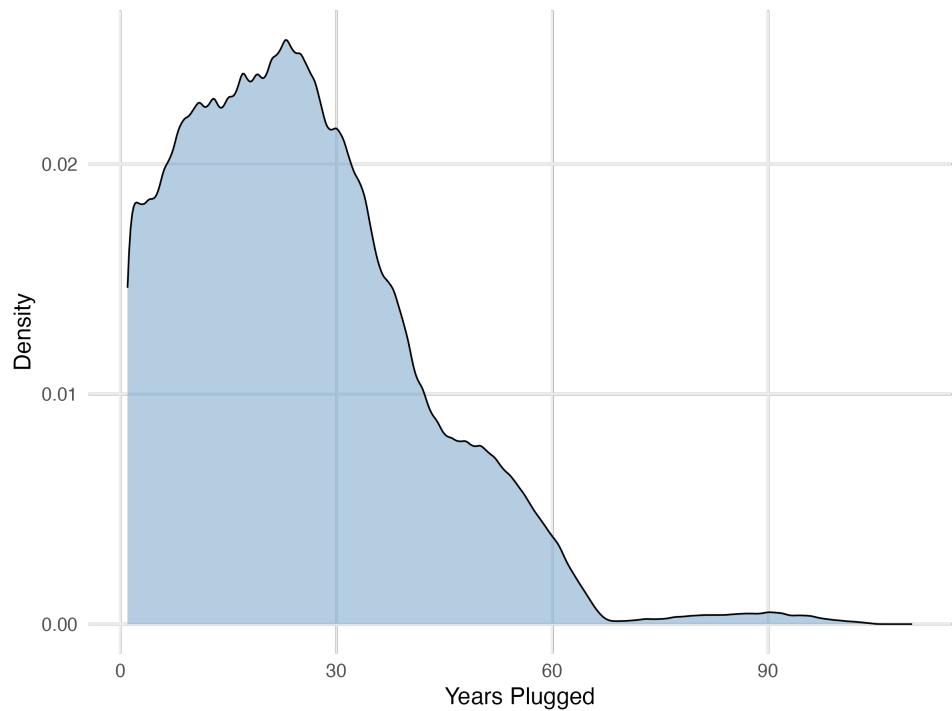
The number of plugged wells near a home can only increase over time by construction, as additional active or abandoned wells are sealed and add to the total. Plugged wells cover an increasing fraction of the land over time. Consequently, once a well is plugged, its potential effect on property values persists indefinitely. However, it is plausible that older plugged wells become less relevant as time passes. Plugged wells may be most salient in the years immediately following remediation, while older wells are less likely to influence buyer perceptions. Since the key question is whether lost property value is possible to recover through land reclamation, this is may be most appropriately captured by focusing on recently plugged wells.

First, for each home  $i$  sold in year  $t$ , I take all plugged wells within 2 km and classify them according to the number of years since plugging. Specifically, I construct counts for three duration bins for well  $s$ :  $d_{st} = (0 - 5], (5 - 15], (15 - 50], (50, \infty)$ . In the case that exact year of plugging is missing, I take the first year the well is reported plugged in the production reports. If the well came from the inventory with no production reports and is plugged, I use the spud year. In the case of a spud year of 1800, I automatically assume the highest duration bin. I show the distribution of these implied plugged years in Figure 2.8 and the distribution of plugging duration in Figure 2.9. Figure 2.9 excludes those wells with a spud year of 1800 to avoid plugging durations of over 200 years. I replace the total plugged count with these variables in my specification, and present the results in Figure 2.10.

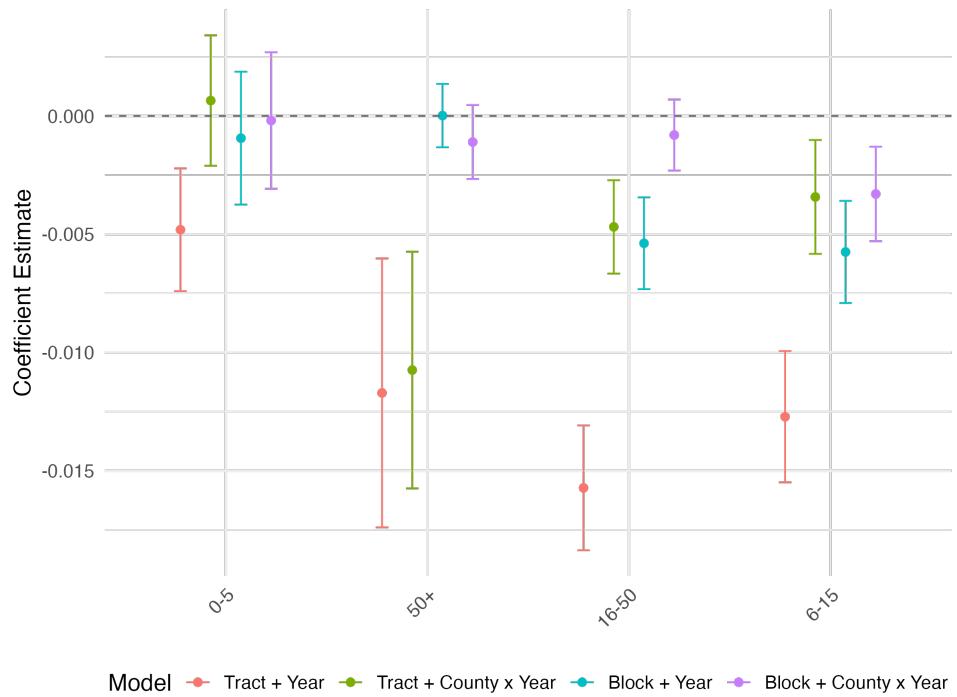
Next, I rerun my main specification while restricting the count of plugged wells to only those plugged within the last ten years. This approach mitigates concerns that long-plugged wells drive the main results. I removes almost 7 million matches including over 40,000 wells. The results are presented in Figure 2.11. In comparison to the full sample, there is no longer the negative effect of plugged wells as expected.



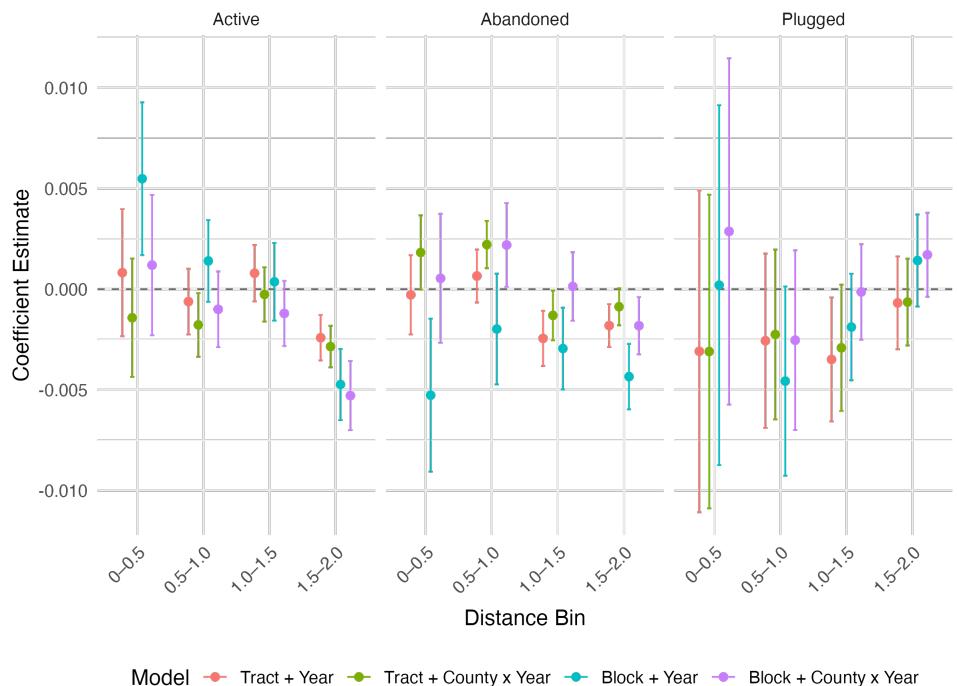
**Figure 2.8:** Distribution of Imputed Plugged Years



**Figure 2.9:** Distribution of Duration of Years Since Plugging



**Figure 2.10:** OLS Results on Duration of Years Plugged



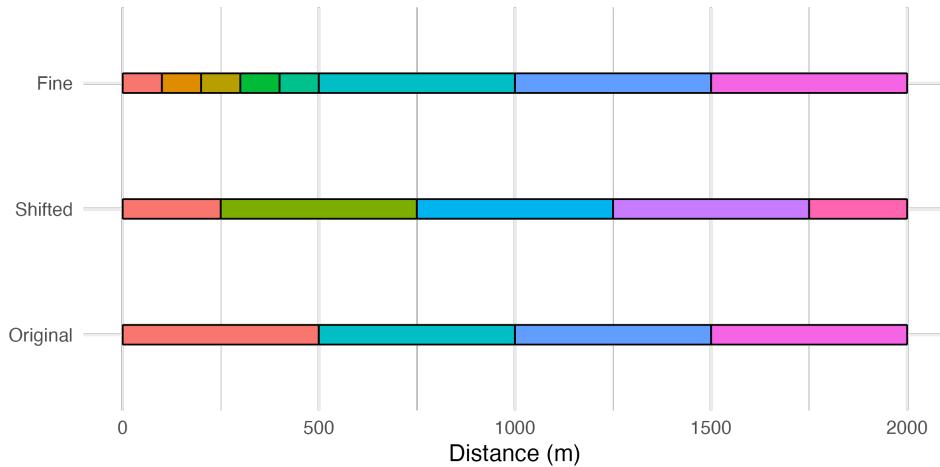
**Figure 2.11:** Baseline Results After Restricting Plugged Well Exposure

### 2.7.2 Alternative Distance Bins

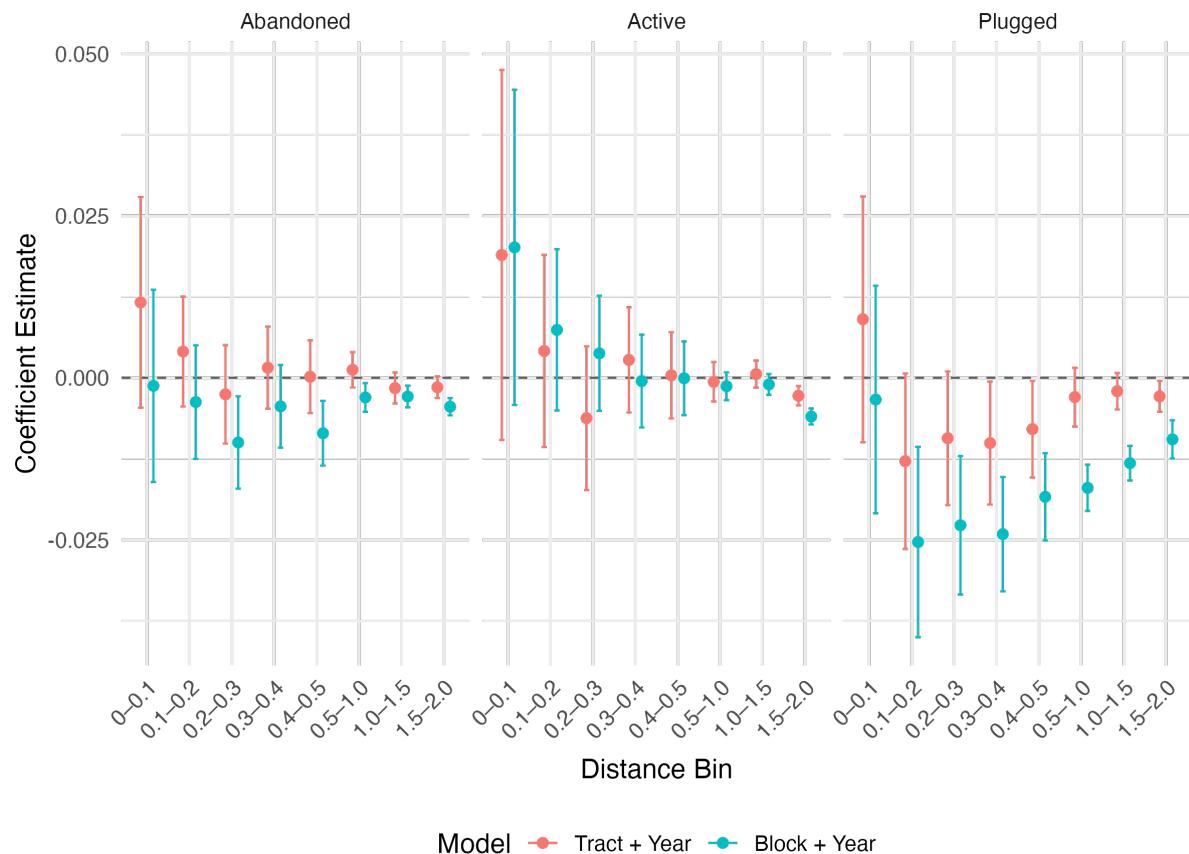
To test whether the price effects of wells are sensitive to arbitrary cutoff choices, I estimate my main specification with alternative distance bin definitions as outlined in Figure 2.12. As the perceived disamenity of wells is likely strongest at very short distances, first I allow for more granularity close to a property with finer distance bins. I split the first bin into 100-meter increments (0 – 100], (100 – 200]...[1500 – 2000], which allows the data to reveal whether price effects decline smoothly with distance or whether there are discrete thresholds at very short ranges. This finer partitioning comes at the cost of reduced precision and noisier estimates, since splitting the data into smaller bins leaves fewer observations in each cell. Next I consider a “shifted” binning scheme designed to test whether results are mechanically driven by the choice of cutoffs. Specifically, I redefine the bins as (0 – 250], (250 – 750], (750 – 1250], (1250 – 1750], (1750 – 2000].

The results of these robustness exercises are reported in Figure 2.13 (finer 100-meter bins) and Figure 2.14 (shifted bins). Across both approaches, the main findings remain consistent with the baseline and there is no evidence of large sensitivity to binning choices, nor do the finer bins reveal strong localized discontinuities just beyond the 0.5 km threshold.

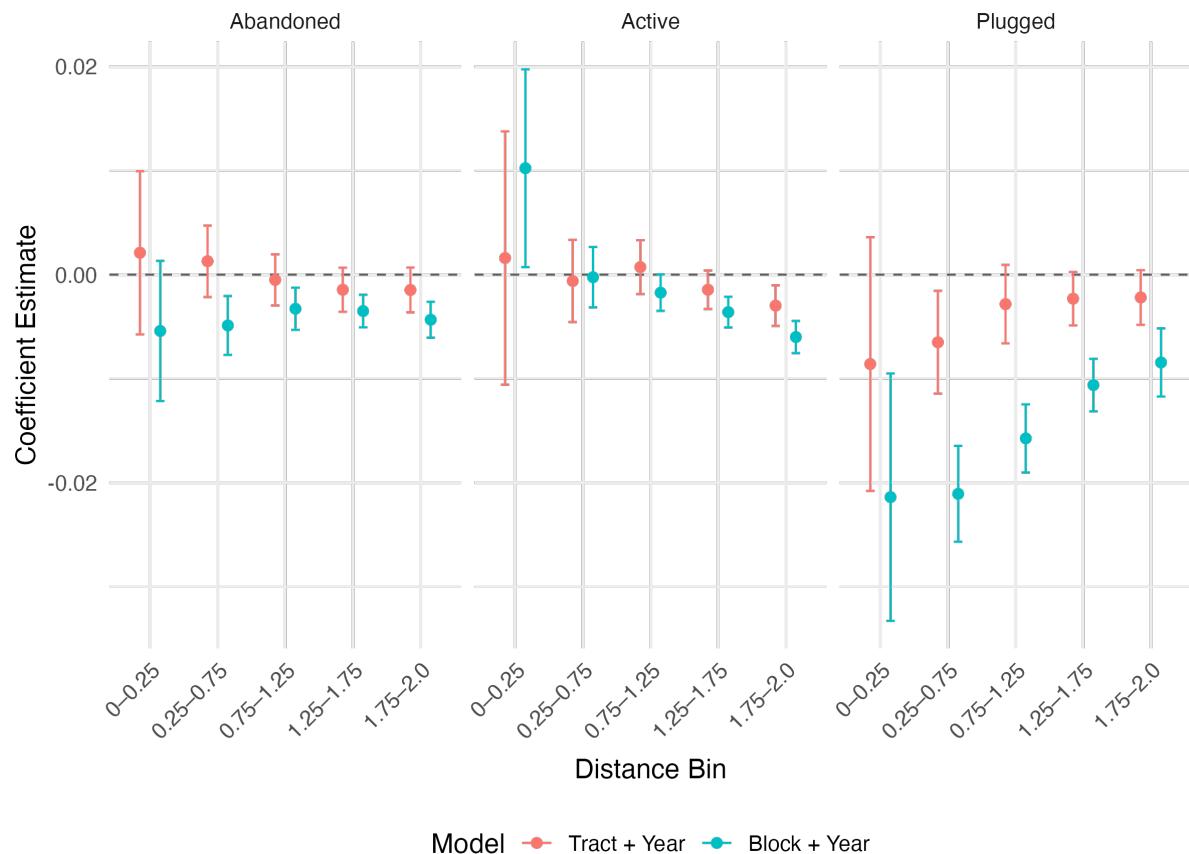
Similarly, I examine wells located directly on parcels. Irregular parcel shapes can result in wells located farther away still being situated on the property, while closer wells may lie just beyond the parcel boundary, as demonstrated in Figure 2.15. While these wells may provide homeowners with lease payments and give a proxy for royalties, they also expose the property to the full intensity of any negative externalities. This is limited to the few counties where parcel-level data is publicly available, where I can spatially join both homes and wells to parcel shapefiles. However, the intersection of sold homes and parcels with a well is very small, resulting in less than 900 direct matches.



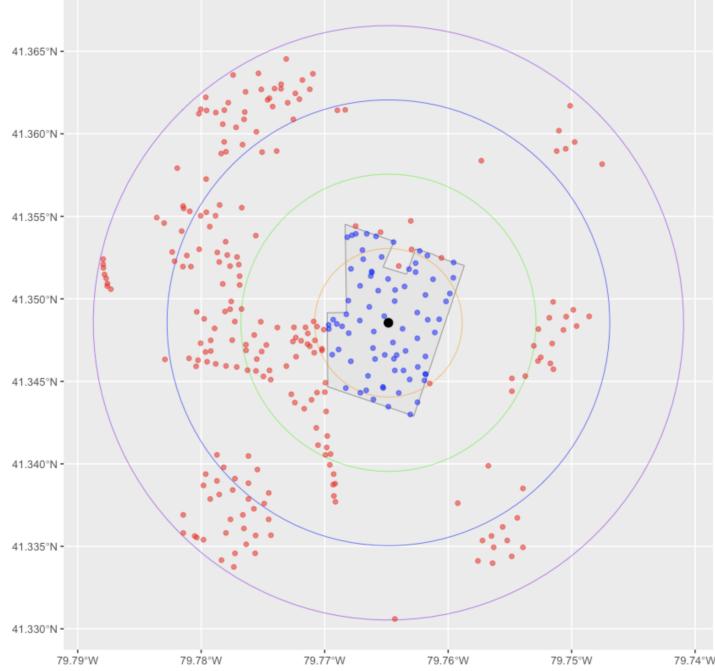
**Figure 2.12:** Comparison of Alternative Distance Bin Definitions



**Figure 2.13:** OLS Estimates with Finer Distance Bins



**Figure 2.14:** OLS Estimates with Shifted Distance Bins



**Figure 2.15:** Parcel Boundary and Distance Bins

### 2.7.3 Linear Treatment Effect

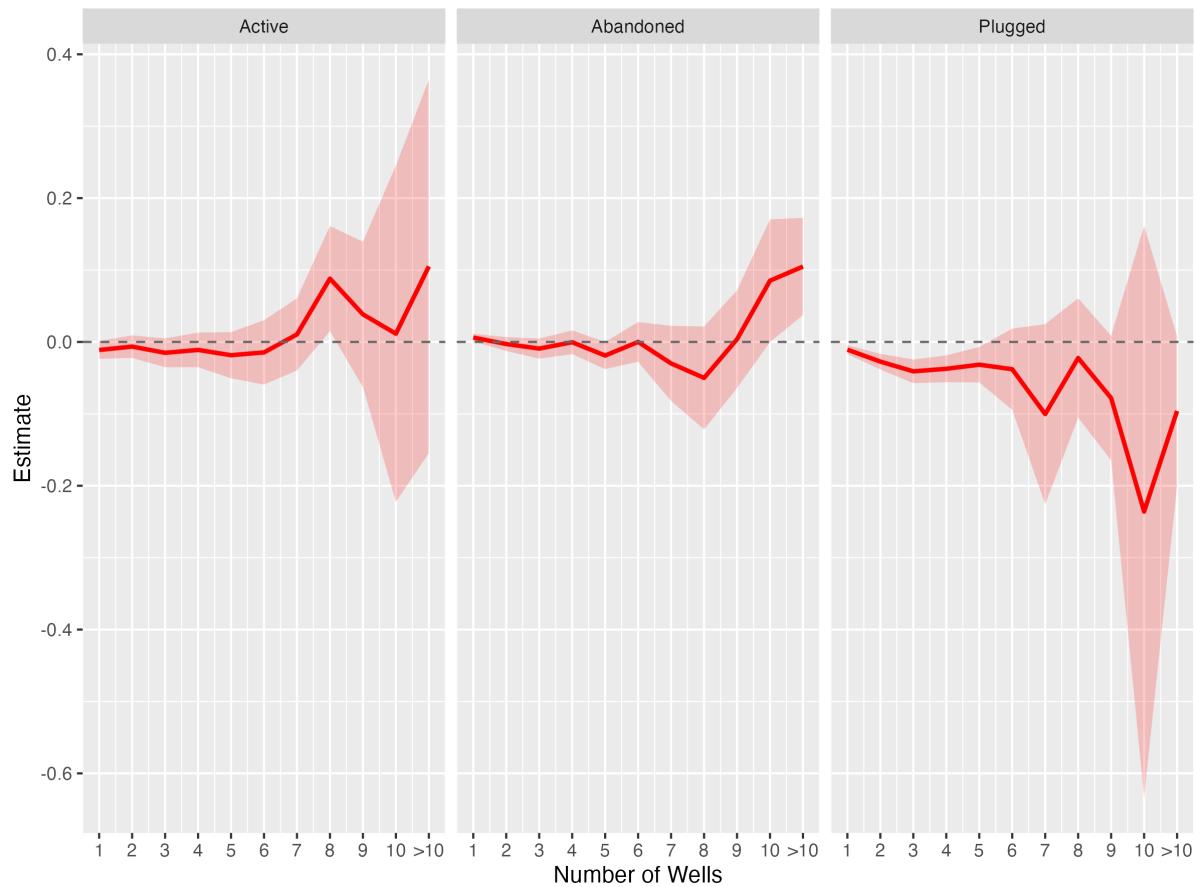
My baseline specification assumes that each additional well (up to 100 wells) of a given status within a given distance bin has the same marginal effect on the property value. Since each well presents the same environmental hazard, I assume the effect of each additional well remains constant. However it is possible the response is non-linear, such as diminishing or compounding effects of additional wells. For example, if the first well represents the largest informational or visual shock to a homeowner, subsequent wells may be perceived as incrementally less consequential, or properties surrounded by an unusually high concentration of wells may be less responsive to well presence. Alternatively, a homeowner may begin to react to the damage after a threshold number of wells is surpassed.

First, I restrict the sample to homes with 25 or fewer nearby wells. These results are unremarkable and shown in Table X. Next, I estimate the following flexible functional form:

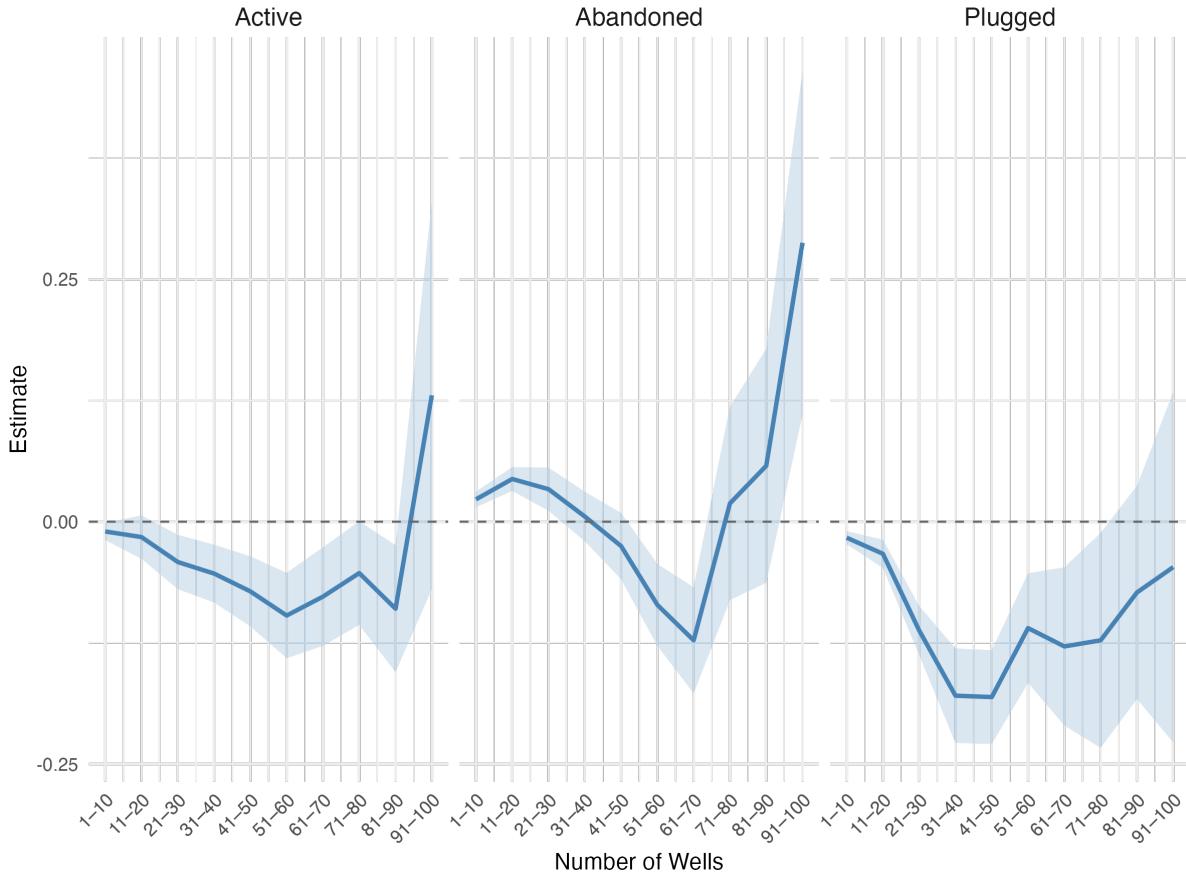
$$\begin{aligned}
 \ln(\text{Price}_{itg}) = & \sum_{k=1}^{10} \beta_k^A \mathbf{1}\{W_{it}^A = k\} + \beta_{>10}^A \mathbf{1}\{W_{it}^A \geq 10\} \\
 & + \sum_{k=1}^{10} \beta_k^U \mathbf{1}\{W_{it}^U = k\} + \beta_{>10}^U \mathbf{1}\{W_{it}^U \geq 10\} \\
 & + \sum_{k=1}^{10} \beta_k^P \mathbf{1}\{W_{it}^P = k\} + \beta_{>10}^P \mathbf{1}\{W_{it}^P \geq 10\} \\
 & + \mathbf{X}_i + \gamma_t + \lambda_g + \varepsilon_{itg}.
 \end{aligned} \tag{2.2}$$

Equation 2.2 regresses log home prices on indicators for exact well counts less than 10, with one

indicator for well counts greater than 10. I also run this specification with indicators for binned well counts in increment of 10 (0-10, 1-20, ..., 91-100). For simplicity, I abstract away from binned distance and look at totals within 2 kilometers. I present these results in Figure 2.16 and Figure 2.17 respectively. These models provide a more detailed picture of how housing markets respond to the spatial intensity of environmental disamenities. These results suggest that the linear functional form is appropriate.



**Figure 2.16:** Regression coefficients of indicators of given number of wells within 500 m



**Figure 2.17:** Regression coefficients of indicators of binned numbers of wells within 2000 m

#### 2.7.4 Subgroup Analysis

In this section I explore various margins of heterogeneity in the treatment effect. If the effect is concentrated within a particular subsample, pooling all observations may attenuate the estimated coefficient toward zero. I benchmark results against the baseline specification described above. Each panel reflects a different set of fixed effects.

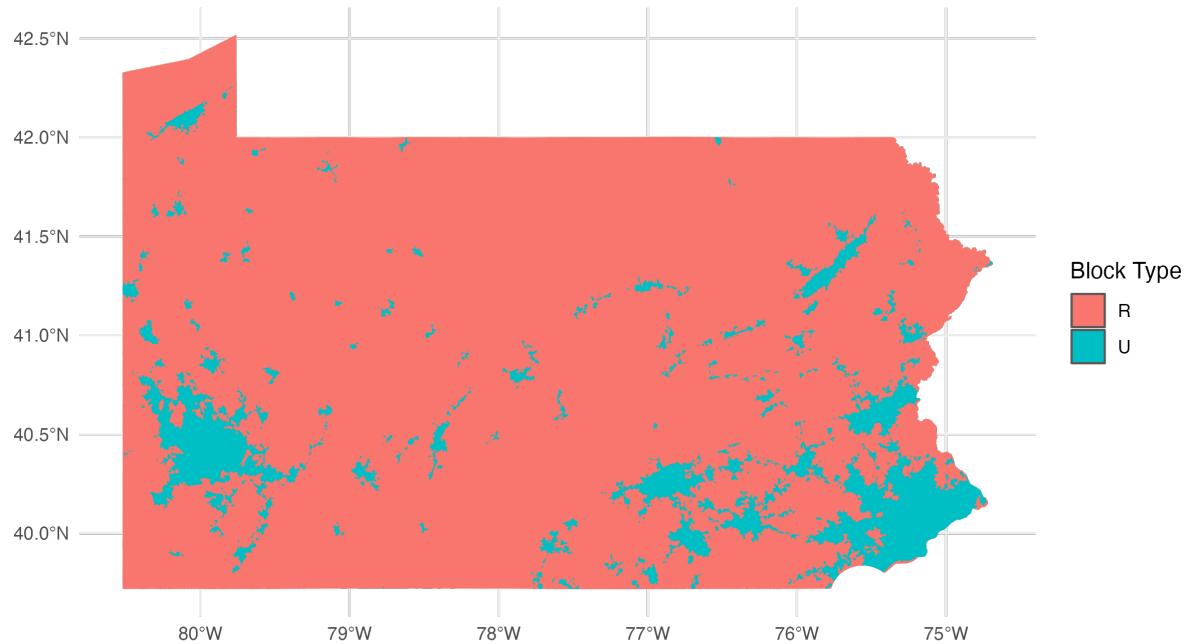
The use of these alternative samples do not alter the underlying identification strategy. In all specifications, I continue to absorb fixed local differences with geographic fixed effects, and I control for common shocks with year fixed effects. The sample splits are instead designed to test whether the estimated effect varies across different margins. I run the baseline regression on these various samples.

*Rural vs. Urban* Oil and gas development interacts differently with rural and urban housing markets, and understanding this variation is essential for assessing the broader economic consequences of extraction. In rural areas, where housing density is low and residents are more directly exposed to drilling activity, wells may represent a salient local disamenity that capitalizes strongly into property values. At the same time, rural economies are often more closely tied to resource industries, which could amplify positive income effects of extraction. In urban areas, by contrast, deeper housing markets and more diversified local economies may buffer households from direct exposure, leading to weaker or more

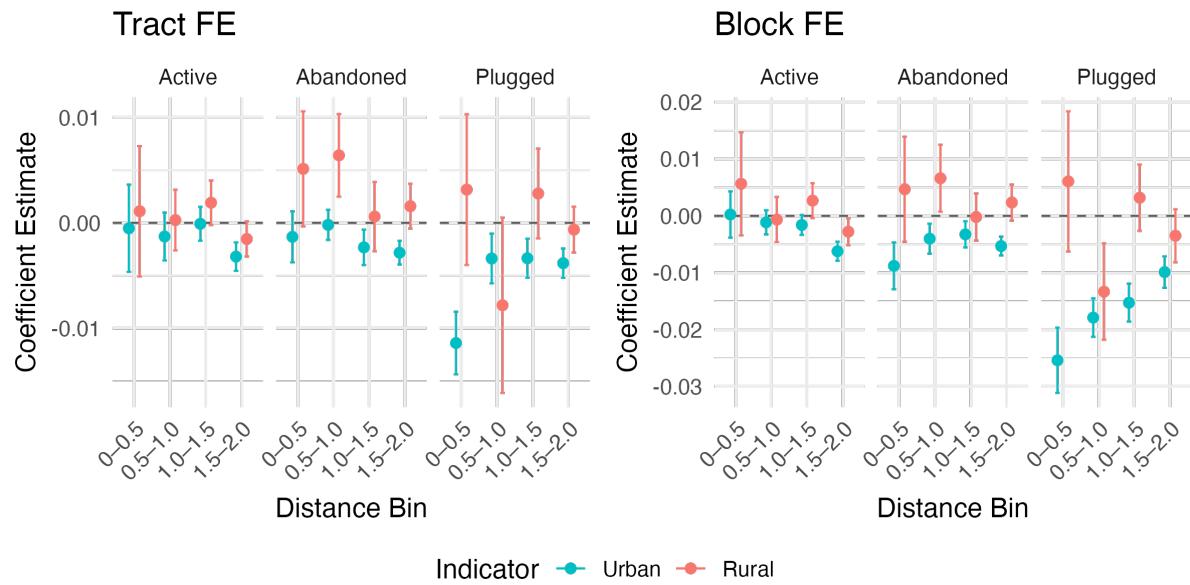
diffuse effects.

I use the Census classification of rural and urban at the block level, defined based on housing units and population. Figure 2.18 shows the 70,741 rural blocks, and 647,932 urban blocks. Figure 2.19 reports the results.

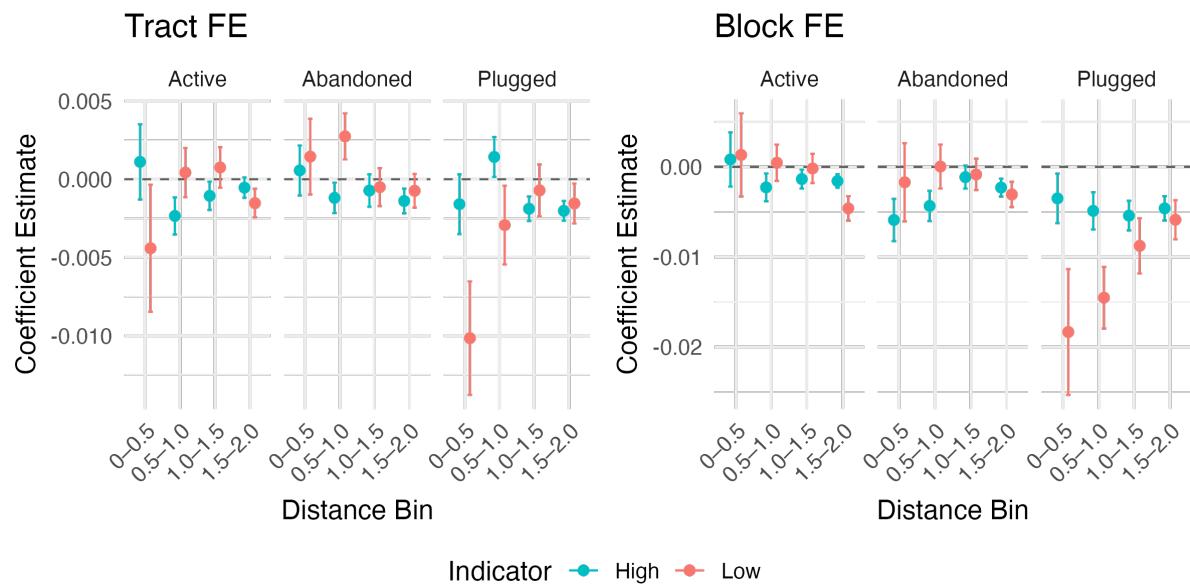
*Top- vs. Bottom-Quartile Homes* Next I split the sample by homes above and below the mean price as property values may respond differently to nearby wells depending on the relative wealth of the home. I also take the top and bottom 25% homes by value. Figure 2.20 and Figure 2.21 reports the results.



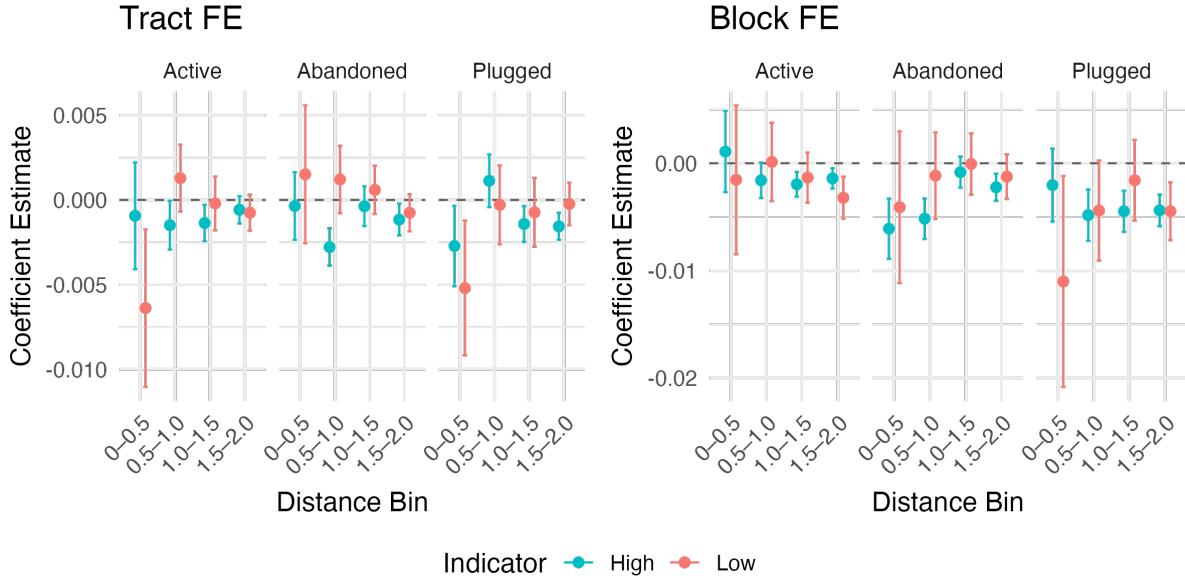
**Figure 2.18:** Rural and Urban Census Blocks



**Figure 2.19:** OLS Estimates with Rural/Urban Sample Split

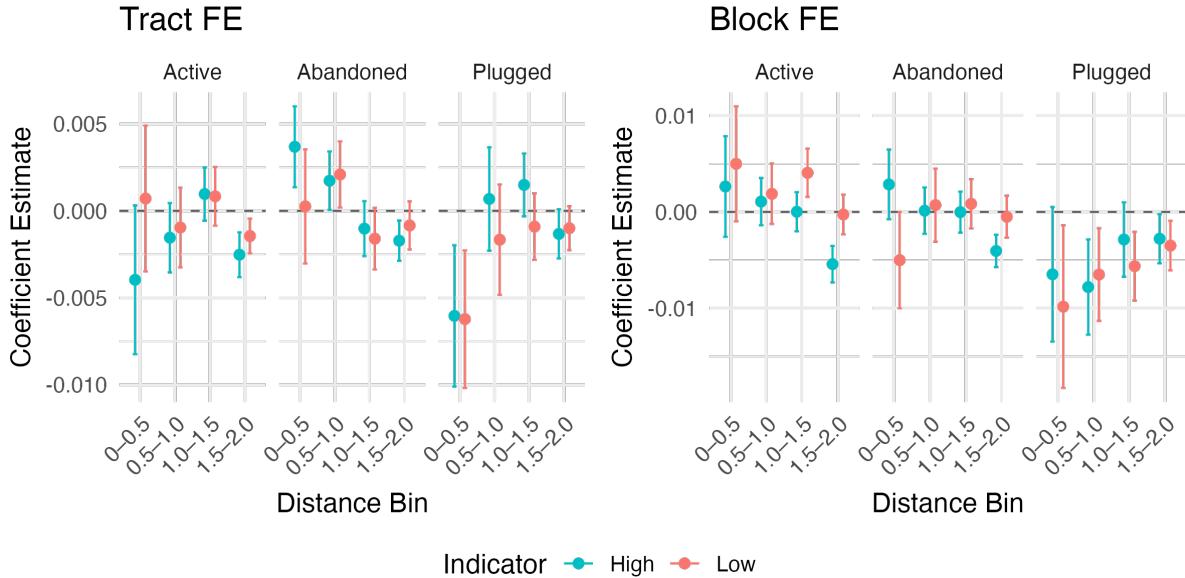


**Figure 2.20:** OLS Estimates with Above/Below Price Mean Sample Split



**Figure 2.21:** OLS Estimates with Top and Bottom Quartile Sample Split

*Pre/Post 2012* To capture potential policy- and industry-driven changes, I also split the sample into pre and post-2012 periods, as the regulatory environment and pace of plugging in Pennsylvania’s oil and gas sector shifted substantially around that time. Figure 2.22 reports the results.



**Figure 2.22:** OLS Estimates with Pre/Post 2012 Sample Split

*Individual County Contributions* To examine whether our results are being driven disproportionately by any single county, I implement a “leave-one-county-out” analysis. In this exercise, I re-estimate our baseline specification repeatedly, each time dropping one county from the sample. This produces a distribution of coefficient estimates that can be compared to the full-sample estimate.

If the estimates remain stable across these iterations, it suggests that our findings are not unduly influenced by outliers or localized dynamics in any particular county. Conversely, large shifts in the coefficients when a given county is removed would indicate that heterogeneity across counties may be important, either because of differences in demographics, housing markets, or regulatory environments.

### 2.7.5 Box-Cox Transformation

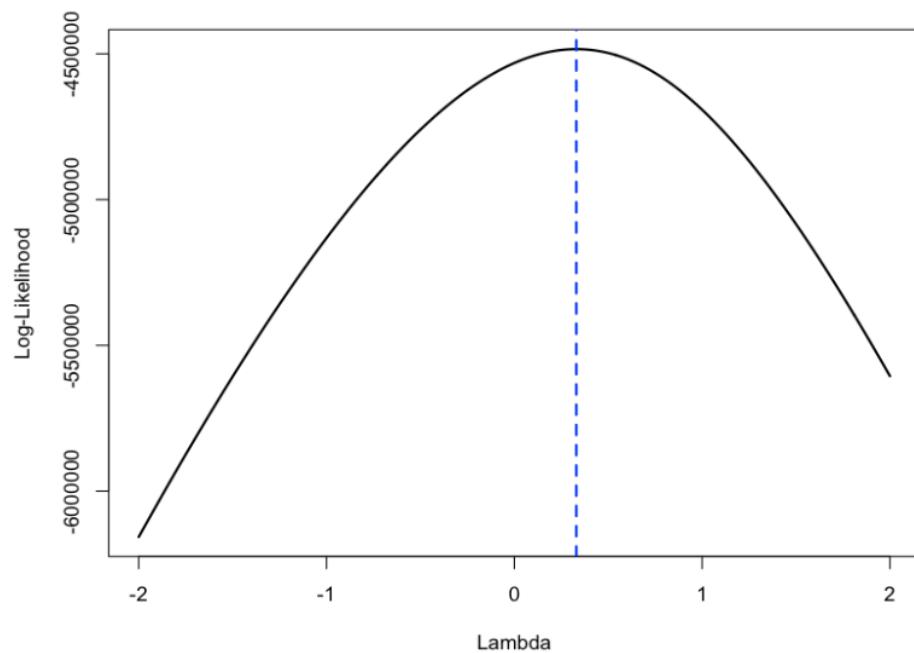
A potential concern with hedonic price models is that the assumed functional form of the dependent variable may not adequately capture the distribution of housing prices, which are typically right-skewed. While the log-linear specification is standard in the literature, I also estimate a Box-Cox transformation to test whether the data favor an alternative functional form.

The Box-Cox transformation of a positive dependent variable  $y$  is defined as

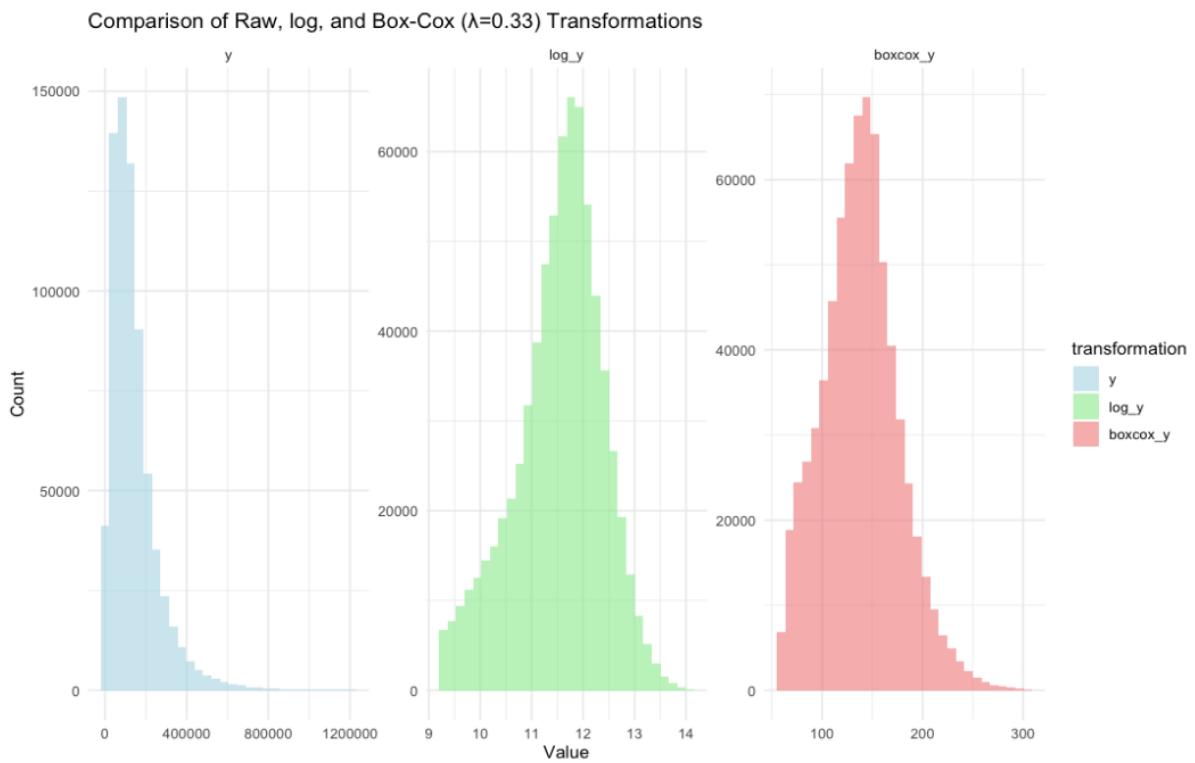
$$y^{(\lambda)} = \begin{cases} \frac{y^\lambda - 1}{\lambda}, & \text{if } \lambda \neq 0, \\ \ln(y), & \text{if } \lambda = 0. \end{cases}$$

The Box-Cox procedure estimates an optimal transformation parameter  $\lambda$  by maximizing the profile log-likelihood of the model, where  $\lambda = 1$  corresponds to the level specification and  $\lambda = 0$  corresponds to the log specification. Intuitively, values of  $\lambda$  between 0 and 1 compress the right tail of the price distribution, stabilizing variance and improving residual normality.

I estimate  $\lambda$  to be approximately 0.33 as shown in Figure 2.23, which lies between the level and log specifications. This suggests that the data modestly prefer a power transformation of housing prices that is less aggressive than the logarithm. Figure 2.24 shows the distribution of home prices under a log and box-cox transformation. However, the substantive results of interest are qualitatively unchanged under this transformation. For ease of interpretation, I present results using the log-linear specification in the main text, and note that the Box-Cox estimates reinforce the robustness of the findings.



**Figure 2.23:** Log-likelihood Function for the Box-Cox parameter  $\lambda$



**Figure 2.24:** Distribution of Home Prices Under Log and Box-Cox Transformations

## 2.8 Discussion

My results have implications for policy design along both the extensive and intensive margins. On the extensive margin, policymakers can limit the accumulation of orphan wells through preventative regulation and improved oversight. On the intensive margin, given the existing landscape of wells - many of which are no longer active - the question becomes how best to mitigate their long-term effects. Three common policy tools in this industry are setback limits, bonding requirements, and impact fees. My estimates show that the economic footprint of oil and gas wells persists well beyond the end of production, suggesting that plugging alone may not fully eliminate their market impact. These findings imply a need for continued policy attention to not only to ensure proper well closure, but also address lingering risks and perceptions that continue to depress nearby property values.

The evidence suggests that current setback requirements may be insufficient to shield homeowners from the physical, environmental, or perceived disamenities associated with nearby wells. Policymakers should consider expanding setback distances for new wells, particularly in residential areas, to account for these long-term costs. In addition, households already located near legacy wells might benefit from disclosure mandates or compensatory mechanisms.

The persistent price penalties associated with plugged wells indicate that the cost of long-term damages may not be fully accounted for in current plugging practices. This supports raising bonding requirements to ensure adequate funding is available not only for technical closure, but also for long-term monitoring and site restoration. Bonding levels should be calibrated to reflect local housing market risks and the cumulative burden of multiple wells in close proximity.

Finally, if homeowners are absorbing part of the legacy costs of drilling through lower property values, impact fees can serve as a redistributive tool. Revenues could be directed toward community compensation funds, local infrastructure, or programs aimed at reducing perceived risks. Moreover, these fees should not be limited to active wells - they could be structured to reflect the enduring externalities left behind even after production ceases.

## 2.9 Conclusion

This paper documents the long-run costs of oil and gas wells that extend far beyond the drilling phase, with important implications for both private landowners and public policy. Using rich geospatial and housing transaction data from Pennsylvania, I show that wells reduce property values not only while they are active but also after they become inactive, and that plugging does not fully reverse these losses. These results suggest that homeowners face persistent risks from the oil and gas production cycle, and that the private market systematically underestimates the future costs of drilling. The inefficiency arises because operators can externalize long-run liabilities, homeowners fail to anticipate the capitalized risk to their land, and nearby residents bear environmental spillovers.

Recently, the Infrastructure Investment and Jobs Act (IIJA) represents a major policy shift by providing Pennsylvania with an estimated \$400 million over the coming decade to accelerate well plugging and site remediation, with initial grants already funding the closure of several hundred wells. The scale of this intervention is unprecedented and long overdue, and its effectiveness will depend on the ability to

identify undocumented wells, prioritize those posing the greatest environmental and health risks, coordinate with landowners and local governments, and build contractor capacity to meet plugging targets. At the same time, persistent challenges including administrative delays in federal disbursement, limited state bonding requirements that allow future orphaning, and political debates over monitoring and reporting obligations. highlight that IIJA funding, while transformative, is not a substitute for deeper regulatory reform aimed at preventing the continued accumulation of liabilities.

This paper highlights the central inefficiency in the lifecycle of oil and gas wells: private actors capture short-run gains, while the public sector and neighboring landowners absorb persistent costs.

## **Chapter 3**

# **The Distributional Consequences of Individual Transferable Quota**

### **3.1 Introduction**

Global fish stocks are declining from over-extraction and an excess of capital, resulting in colossal economic losses (Costello et al., 2016; World Bank, 2017). In recent Canadian history, 50% of the total amount of fish by weight was lost due to overfishing, yet only 18% of critical stocks have plans to support their recovery (Archibald, Rangeley, & McIver, 2020). This is an insufficient pace of change, and the longer this persists the harder it will be to reverse these damages, leading to widespread fishery collapse in the extreme case. Tensions in securing fishing rights between different interest groups are particularly relevant in Canada, as there have been many controversial management decisions that have gained recent attention. In contrast to past insufficient management schemes, individual transferable quotas are seen as a promising solution as they impose property rights and provide a market mechanism for resource allocation (Birkenbach, Kaczan, & Smith, 2017; Branch, 2009; Grafton, 1996). ITQ systems were gradually introduced in Canada starting in the 1990's, transitioning many species away from an open-access competitive regime (McCay, Creed, Finlayson, Apostle, & Mikalsen, 1995). In these regimes, fishers receive quotas for the regulated species based on their historical catch which reflects a portion of the total allowable catch. These quotas can then be traded at a predetermined market price, which theoretically represents the net present value of all future resource rents accruing from that allocation. Ownership therefore supports conservation objectives by creating a direct link between long term stock productivity and the current value derived from extracting the resource (Van Putten, Boschetti, Fulton, Smith, & Thebaud, 2014). This encourages environmental stewardship where fishers view the resource as an asset that delivers long-term economic benefits (Olson, 2011).

Two components of ITQ systems ensure efficiency. The cap on total catches limit aggregate catches to the socially optimal level and the quota trade ensures that fish are caught at least costs (Reimer, Abbott, & Wilen, 2014). Ownership creates incentives for the most efficient operators to purchase additional access rights from the more inefficient operators. Fleet rationalization can produce an additional

efficiency gain, which occurs when these inefficient operators exit the industry altogether, resulting in the exiting of excess capital and concentration of catch among the remaining vessels (Hatcher, 2014). Therefore, internalizing the opportunity cost of removing stocks ideally removes the race to fish and allows for the optimal timing of catch. However, the channels that produce these gains also result in the main concern surrounding these regimes, which is the so-called “efficiency-equity” trade-off. Even if the efficiency gains under property rights will increase the overall value of the fishery, it is unclear who gains and who receives these resource rents, and whether this results in a Pareto improvement (Gunnlaugsson, Saevaldsson, Kristofersson, & Agnarsson, 2020; Guyader & Thebaud, 2001). There are potential negative implications for small-scale harvesters and coastal communities, where these communities are often resource dependent, and the fishing industry provides an important source of employment between harvesting, processing, and aquaculture (Baland & Francois, 2005). The problem is especially severe in remote areas with little access to resource-independent income opportunities. Watson, Reimer, Guettabi, and Haynie (2021) further shows that local resource ownership can even have multiplying effects for generating benefits in other sectors for local economies, so welfare impacts can exist beyond the fishing sector. There are increasing concerns that resource privatization can contribute to rising rural inequalities (Brandt & McEvoy, 2006; Da-Rocha & Sempere, 2017). Equity impacts long term enforcement, and stocks will continue to collapse with opposition if these regulation disproportionately benefit specific capital-rich users.

Here, we investigate the distributional impacts of the introduction of ITQs on economic inequality among resource users. For homogeneous agents, the quota trade does not affect inequality because the sellers are perfectly compensated by the quota buyers for the loss of resource rents. However, with degrees of fisher heterogeneity this is not true since the profits from using the quota are not equally distributed among sellers and buyers (Costello & Deacon, 2007). We allow fishers to differ in both resource-specific productivity and local labour market opportunities. The idea is that efficiency gains from trade may therefore either evolve from a flow of quota to the most skillful fishers or to the areas (of fishers) with the lowest opportunity costs of fishing (Arnason, 2012). These have very different implications, and the distinction is relevant because the loss of quota or fishery access may be especially important in areas with no “outside-option”, or few employment opportunities outside of the fishery. Theoretically, the assumptions of heterogeneity present in the model leads to conflicting predictions. Grainger and Costello (2016) allow for heterogeneity in skill, and find incomes of the wealthy decrease, while Okonkwo and Quaas (2020) allow for heterogeneity in the outside option and find incomes of the poor decrease after the transition to a property rights regime. For Grainger and Costello, the idea is that heterogeneity in skill creates inframarginal rents, which is rent arising from different marginal extraction costs. Since ITQ systems transfer inframarginal rents to resource rents, they show that the incomes of the most productive fishers could decrease. However, Pareto gains could still result from complete grandfathering. For Okonkow and Quaas, the poor are the resource users without a profitable “private project”. The transition to an ITQ system lowers their resource return, although their model is for a completely equal quota allocation.

We quantitatively address this ambiguity by introducing both skill and spatial heterogeneity using

the universe of catch and revenue data for Maritime Quebec provided by the Department of Fisheries and Oceans Canada. We first create a measure of regulation exposure and then use matching methods to find appropriate control fleets. We then implement a difference-in-difference approach to first study distributional changes in incomes and effort on the intensive margin and then exit rates on the extensive margin. Finally, we also look at changes in total quota holdings over time.

In Section 3.2, we introduce the Quebec fishing industry and the specifics of the ITQ regulations introduced over the time period. Section 3.3 provides a brief theoretical model, we describe the data in Section 3.4, and Section 3.5 describes our empirical strategy. Finally, 3.7 presents the results, and we finish with a discussion of the potential limitations of this study and furter research in 3.9.

## 3.2 Background

### 3.2.1 Literature

Income distributions under free access versus private property have most notably been studied by Samuelson (1974) and Weitzman et al. (1974), who find incomes are always higher under open access. Specific to fishery economics, Baland and Francois (2005) first shows that all individuals are worse off due to losing the commons as insurance. Conversely, Baland and Bjorvatn (2013) shows that resource privatization can actually benefit traditional users in the long run due to stock increases, even for short run income losses.

Our paper contributes to multiple branches of the current ITQ literature. First of all, numerous papers study the efficiency gains of quota regimes, and it is fairly well-known that property rights establish a basis for economic benefits. Costello and Deacon (2007)) find that there are efficiency loses if the stock is heterogeneous in density, location or value as the incentives to compete remain and redundant search effort dissipates potential rents. Fox, Grafton, Kirkley, and Squires (2003) provide a method to decompose firm behaviour in the B.C. halibut fishery over time to assess the effects of regulatory changes on profits and productivity. The decomposition indicate that the major benefit from a shift to individual harvesting rights in the industry in 1991 was an increase in output prices and that vessel size restrictions may prevent full efficiency gains. Arnason (2012) discusses the limitations of ITQs, specifically dealing with setting inappropriate TACs and inadequate enforcement. Grafton (1996) distinguishes between technical, allocative, and economic efficiency gains and shows how these gains evolve over time. Brandt (2007) acknowledges the importance of changes in sample composition, namely distinguishing between the exit of excess capital and increased efficiency of individual firms. Pinkerton and Edwards (2009) notably reveal the negative economic impacts of ITQs due to the extent of quota leasing. These papers are primarily theoretical, so we complement these findings with the welfare implications, and whether these established efficiency gains come at the cost of equality.

For distributional impacts, Arnason (2009) finds that ITQs cannot coordinate conflicting interests of extracting and non-extracting users, or fishers and conservationists. Quaas and Stöven (2013) also differentiate between different interest groups to present a theoretical model where maximizing consumer surplus taking into account stock dynamics can explain inefficiently high harvest levels set by public

resource managers. Brandt, 2005 finds no segment of the mid-Atlantic clam fishery was disproportionately affected by ITQs. Da-Rocha and Sempere (2017) calibrate a general equilibrium model with firm dynamics and find revenue inequality increases yet wealth inequality decreases. Doering, Goti, Fricke, and Jantzen (2016) defines the perspectives and instruments of distributive fairness to evaluate ITQ programs. Brandt and McEvoy (2006) finds that the gains depend on vessel gear, home-port and relationship with buyers and that certain vessels will gain relative to others. Olson (2011) provides a broad overview of these social impacts of privatization in the fishery. Guyader and Thebaud (2001) discuss the nature of these distributional conflicts. Gunnlaugsson et al. (2020) study the distribution of resource rent in Icelandic fisheries. They show large rent increase after the first three years of program implementation, and that those who initially received the quotas received windfall gains. Grainger and Costello (2016) also mentions the welfare losses to newcomers, who he shows to prefer an open access regime. As the majority of these papers are descriptive in nature, we will provide a quantitative analysis to this literature. Furthermore, the majority of these papers are empirical assessments of specific species, and due to our data we can study the region as a whole.

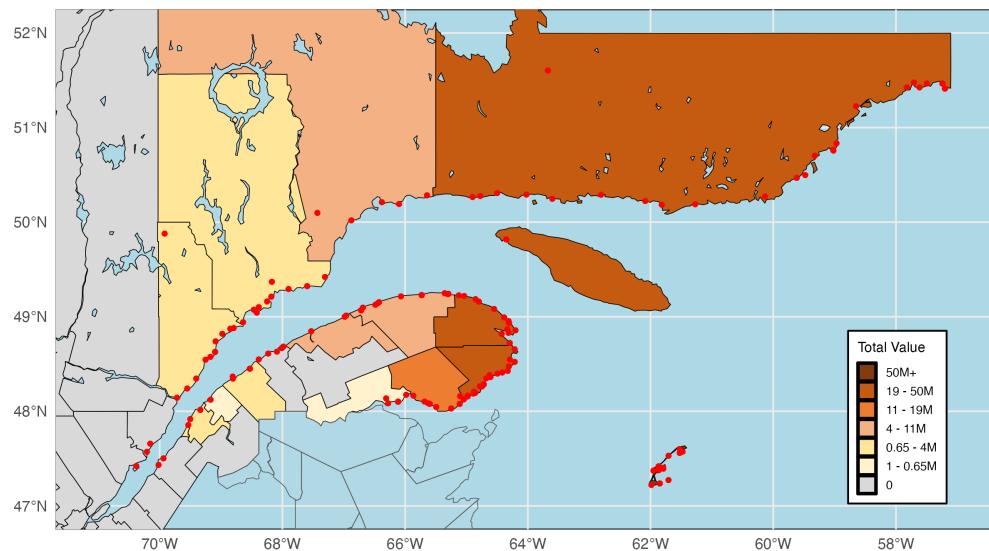
This work can also contribute to the labour market effects of environmental regulations. The aggregate benefits of these regulations often rely on the ability of labour to reallocate to other sectors. There are also very few papers in the fisheries literature that introduces the labour market and the outside option in the analysis of distributional impacts. Reimer et al. (2014) emphasizes how important the fishing industry can be to the local labour market, and Hatcher (2014) discusses changes to worker renumeration in an ITQ system.

### **3.2.2 Socio-economics of Quebec Fishing Industry**

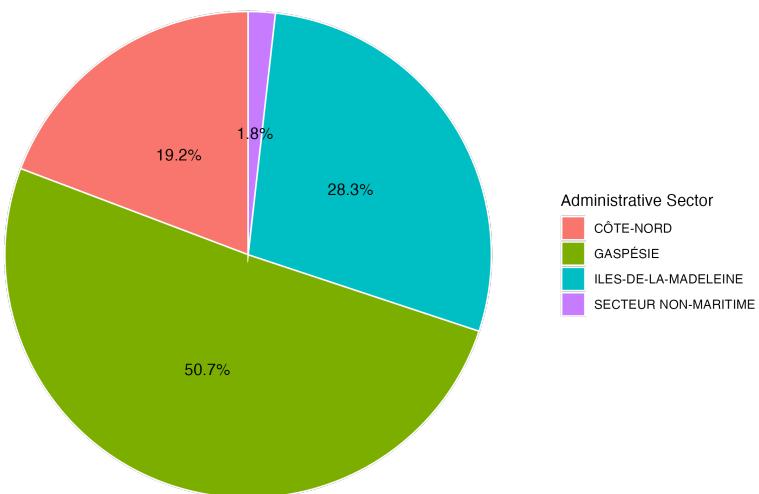
There are three administrative regions in Maritime Quebec: the North Shore, Gaspé-Lower St. Lawrence, and the Magdalen Islands as pictured in Figure 3.1. Maritime Quebec accounts for around 5% of the provincial population (DFO, 2015). The Quebec fishing industry is an ideal setting for this research question as there are over 90 remote resoure-dependent communities. The majority of catch is landed on the Gaspé peninsula, with the largest value of landings accruing to Rivière-au-Renard. Figure 3.2 shows the division of total revenues divison amongst the administrative regions. The three main species landed are snow crab, lobster and shrimp, which accounted for 88% of the total landed value. There are large spatial differences in landed species as well, for example where the Magdalen Islands have the majority of lobster catch where Gaspé-Lower St. Lawrence has the majority of shrimp. The Regional County Municipalities (RCM) are also depicted in Figure 3.1, which is the census division level available for Quebec. In addition to a decreasing population, the unemployment rate for Maritime Quebec is slightly higher than the provincial average.

### **3.2.3 Description of ITQ Regulations**

Fishery management can be broadly classified as with or without quota. Regulations are implemented by the administrative region on fleets for specific areas. Fleets are arbitrarily defined fishers similar in principal species and vessel length. Multiple fleets can fish the same species at the same time, and



**Figure 3.1:** Annual Revenues in Maritime Quebec by Census Sub division (2015)



**Figure 3.2:** Percentage of Total Revenues by Administrative Region in 2003

fleet shares determine the percentage of the total allowable catch (TAC) allocated to each fleet. Quota systems can remain competitive, where all fishers must stop fishing when they collectively reach the TAC or “global quota” set by the regulator. In the case of individual transferrable quotas, quotas reflect each individual’s rights to a portion of the TAC which can be permanently or temporarily transferred. Quotas are initially allocated through a grandfathering system based on historical catch in predetermined base years. The objectives of the regulations range from streamlining fishing operations to creating stability in access to stocks. A successful ITQ regulation should reduce the need for multiple complex regulations and increase the product quality and price through optimizing the market conditions.

Over our time period of interest, we will study two ITQ regulations introduced for Greenland Halibut. First, in 2003 for the Gaspé-Upper Middle North Shore, and then in 2012 for the Lower North Shore for fixed gear vessels less than 19.81m. The management of Greenland halibut is outlined in the Integrated Fishery Management Plan (IFMP) for the species, and the objective has been to stabilize fishing operations. There were also individual quotas introduced in the late 1990s for the Gaspé-Upper Middle North Shore fleet, however these did not become transferable until 2003. The Lower North Shore fleet remained competitive until 2012, although their fleet share is significantly lower. Fishers must be eligible to receive initial quotas through having an active license status and having landings equal to or greater than the “floor”. There is a maximum quota of 3.844% for the 2012 fleet.

Over this time period, there was also an ITQ system introduced for Atlantic Halibut and Cod in 2012, however only 20 fishers were affected so we would not expect to see any aggregate effects. Atlantic Halibut and Cod were also regulated for the Magdalen Islands and the Lower North Shore in 2017-2019, yet this does now allow for a sufficient post period to understand the outcomes. There are also fleets that have been flagged and will begin the conversion process in the future. We may explore using these fleets as control groups. Lobster represents a stable fishery which has remained in a competitive regime over this time period. Snow crab also operates under an ITQ system, however it was converted before our time period.

### 3.3 Conceptual Framework of Regulatory Scenarios

We derive conditions under which an ITQ system increases income inequality compared to open access with these two dimensions of heterogeneity. This model unifies the two main theoretical channels discussed in the literature: heterogeneity in fishery-specific productivity found in Grainger and Costello (2016) and heterogeneity in opportunity cost found in Okonkwo and Quaas (2020).

#### 3.3.1 Setup

There is a continuum of individuals  $i \in [0, 1]$ . Each individual chooses between participating in the fishery or working in an outside labor market. We denote  $L^f$  the share of individuals in the fishing sector and  $L^l$  the share of individuals in the private sector such that  $L^f + L^l = 1$ . Each agent has a private labour market return or “outside option”  $\theta_i \sim N[\bar{\theta}, \bar{\theta}]$  and a skill endowment in the fishery  $\alpha_i \sim N[\underline{\alpha}, \bar{\alpha}]$ . These are drawn independently from continuous distributions  $F_\alpha(\alpha)$  and  $F_\theta(\theta)$ . Higher  $\alpha_i$  implies higher productivity, while higher  $\theta_i$  implies a higher opportunity cost of fishing. Each individual  $i$  belongs

to a geographic location  $l$  such that all individuals within a location face the same outside option, or  $\theta_i = \theta_l, \forall i \in l$ . Each individual can either work in:

1. the fishery, earning profit  $\pi_i = f(\alpha_i)$ , or
2. the private sector, earning income  $w_i = f(\theta_i)$ .

### 3.3.2 Open-Access Regime

Under open access, the total harvest  $H$  and total effort  $E$  are determined by free entry. Aggregate profit is dissipated in equilibrium:

$$\pi_i^{OA} = 0, \quad \forall i \in L^f.$$

Fishers enter until average revenue equals average cost, driving expected profits to zero. The marginal participant is indifferent between fishing and the outside option, so the return from fishing equals the marginal labor-market return. We normalize this outside option to zero,  $\theta_o = 0$ , which sets the marginal worker's income as the reference point. Thus, all individuals with  $\theta_i \leq 0$  participate in the fishery. There are no rents, and income inequality reflects only heterogeneity in outside options.

### 3.3.3 Limited-Access Fishery

In a limited-entry fishery, where the number of participants  $N$  is capped below the open-access level  $N^{LE} < N^{OA}$ . Aggregate effort is therefore constrained, so that average revenue exceeds average cost and positive rents emerge. As total harvest  $H = \sum_i h_i$  is limited, the stock is higher than under open access, leading positive economic rents. With heterogeneity in skill, these rents are distributed unevenly. Following Grainger and Costello (2016), total rents can be decomposed into two parts: a resource rent that accrues to all participants, and an inframarginal rent that is skill-dependent. Aggregate profits are therefore positive and distributed according to individual cost heterogeneity. The degree of income inequality within the fishery under limited access depends on the dispersion of  $\alpha_i$ : when skill differences are small, rents are nearly uniform; when differences are large, the distribution of inframarginal rents is highly skewed toward efficient producers.

The introduction of entry restrictions also changes the relationship between fishing incomes and outside options. Under open access, individuals participate until the marginal fisher is indifferent between fishing and their next-best alternative, such that  $\theta_i \leq 0$  for active fishers. When entry is capped, expected incomes in the fishery exceed this marginal return, so even individuals with relatively high outside options ( $\theta_i > 0$ ) may prefer to enter. This could increase inequality if the excluded individuals are those with lower  $\theta_i$  who can no longer afford to fish as found by Okonkwo and Quaas (2020).

This regime provides a natural benchmark between open access and full property rights. Limited entry generates resource rents but does not internalize them through market prices or tradable rights, so rents remain tied to individual efficiency rather than quota ownership.

### 3.3.4 Privatized (ITQ) Regime

Under an ITQ system, total allowable catch (TAC) is fixed at  $Q$ . Quota shares  $q_i$  are distributed across fishers, with  $\sum_i q_i = \sum_i h_i = Q$ .

Each fisher's profit from harvesting is:

$$\pi_i^{ITQ} = ph_i - c(\alpha_i, h_i) - rq_i,$$

where  $p$  is the price of output,  $r$  is the equilibrium quota rental rate,<sup>1</sup> and  $c_\alpha < 0$  (higher skill reduces cost).<sup>2</sup>

Profit maximizing ensures fishers trade quota until marginal harvesting costs are equalized:

$$p - c_q(\alpha_{i,i}) = r.$$

Here fleet consolidation occurs endogenously through the quota market. Harvest rights reallocate from less efficient to more efficient operators through quota trade until marginal harvesting costs are equalized across all active fishers. This market-driven adjustment achieves the same efficiency outcome as an optimal cap on effort, but through voluntary exchange rather than direct regulation. As inefficient vessels exit and sell their quota, total capacity in the fishery contracts, leading to a smaller but more productive fleet.

Similar to limited access, under ITQs there are positive resource rents due to restricted access and inframarginal rents arising from heterogeneity in fishing skill. However, as shown by Grainger and Costello (2016), an ITQ system transforms the composition of rents: inframarginal rents tied to individual efficiency are converted into uniform resource rents embodied in the quota price. Since the quota market equalizes marginal costs across fishers, the most efficient operators no longer capture large inframarginal gains, and their profits may even decline despite overall increases in aggregate fishery value. This depends on the initial allocation of quotas.

Once again, the ITQ system also changes the relationship between fishing incomes and outside option as profits are available through limited access while exit from the fishery is induced, and the threshold of  $\theta_i$  for fishery participation changes. Note that the degree of heterogeneity in fishing skill endogenously determines the extent of fleet consolidation under ITQs: when cost differences across fishers are large, quota trades reallocate harvest rights toward the most efficient operators, reducing the number of active vessels, whereas when skills are relatively homogeneous, reallocation is limited and the post-reform fleet size remains closer to its pre-reform level.

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<sup>1</sup>The quota rental rate  $r$  can be interpreted as the implicit opportunity cost of holding quota. Even if a fisher owns quota outright and pays no explicit fee, they still face a shadow price equal to what they could earn by leasing or selling it in equilibrium. In this sense,  $r$  represents the market value of access rights, and its capitalization reflects the total resource rent generated under the ITQ system.

<sup>2</sup>Alternatively, one could model heterogeneity in skill as a multiplicative productivity term on revenues, such as  $\alpha_i p q_i$ . Both formulations are equivalent up to a monotonic transformation of  $\alpha_i$ : modeling skill as cost-reducing emphasizes differences in marginal extraction costs, while modeling it as revenue-enhancing emphasizes total factor productivity. The qualitative implications for the equilibrium allocation and the distribution of rents are identical.

### 3.3.5 Distributional Effects

The impact of ITQs on income inequality depends on how skill, outside options, and quota allocation interact in equilibrium.

**Case 1: Inequality increases.** Inequality rises when high-skill fishers ( $\alpha_i$ ) capture a disproportionate share of the rents created by privatization, and when these skills are positively correlated with outside options ( $\theta_i$ ). Formally, inequality increases when

$$\frac{\partial y_i^{ITQ}}{\partial \alpha_i} > \frac{\partial y_i^{pre}}{\partial \alpha_i} \quad \text{and} \quad \text{Cov}(\alpha_i, \theta_i) > 0,$$

and when post-ITQ participation and quota holdings are selective, such that high- $\alpha_i$  and high- $\theta_i$  individuals are more likely to remain active and to hold larger quota shares. In this case, the returns to skill steepen, consolidation concentrates both fishing income and asset income among the most productive and best-located individuals, and inequality in total incomes rises.

**Case 2: Inequality decreases.** Inequality falls when ITQs relax rather than reinforce pre-existing heterogeneity. This occurs if returns to skill flatten because quota trading equalizes marginal costs, or when skill and outside options are weakly or negatively correlated. Formally, inequality decreases when

$$\frac{\partial y_i^{ITQ}}{\partial \alpha_i} < \frac{\partial y_i^{pre}}{\partial \alpha_i} \quad \text{and} \quad \text{Cov}(\alpha_i, \theta_i) \leq 0.$$

In this case, the most efficient fishers may lose some inframarginal rents, while lower-skill or location-disadvantaged fishers gain from higher stock abundance and more stable resource rents. Aggregate inequality declines even if ownership concentrates, provided that incomes at the lower end of the distribution rise proportionally more than those at the top.

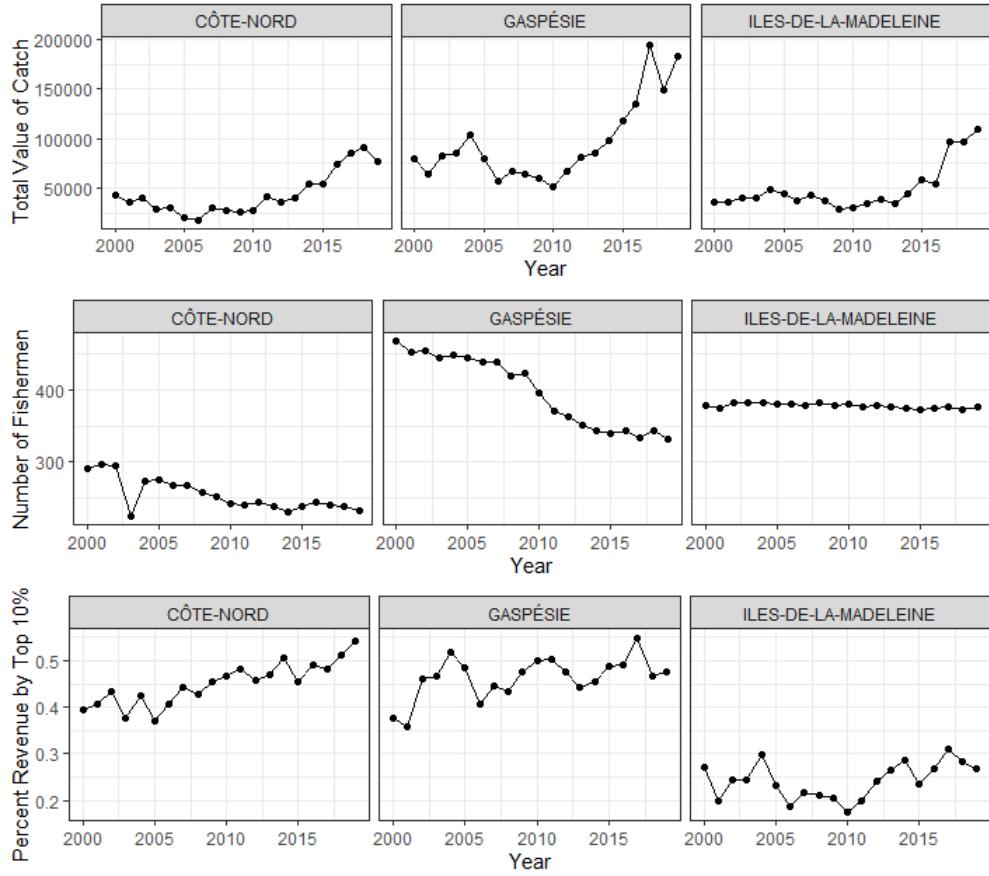
The model highlights that ITQs can generate both efficiency and inequality. Efficiency arises from reallocating production toward the most skillful fishers, yet this can impact income inequality within the fishery and overall when these fishers are systematically located in high-income areas and quotas leave resource-dependent communities. Conversely, if the most productive fishers are already in the low outside option areas, ITQs may provide an equity gain by channeling rents toward poorer areas while fishers who exit do not lose income. Exit is about the relative attractiveness of fishing vs the outside option, conditional on skill.

These predictions motivate the empirical analysis in Section 3.5, which estimates how distributional outcomes in Maritime Quebec evolved across heterogeneous skill groups and local labor markets following ITQ implementation.

## 3.4 Data

### 3.4.1 Fishing Revenues

For fishing revenues, we will exploit the universe of catch and revenue data in Quebec from 2000 - 2019, provided by the Department of Fisheries and Oceans Canada. Each observation is the landed weight and

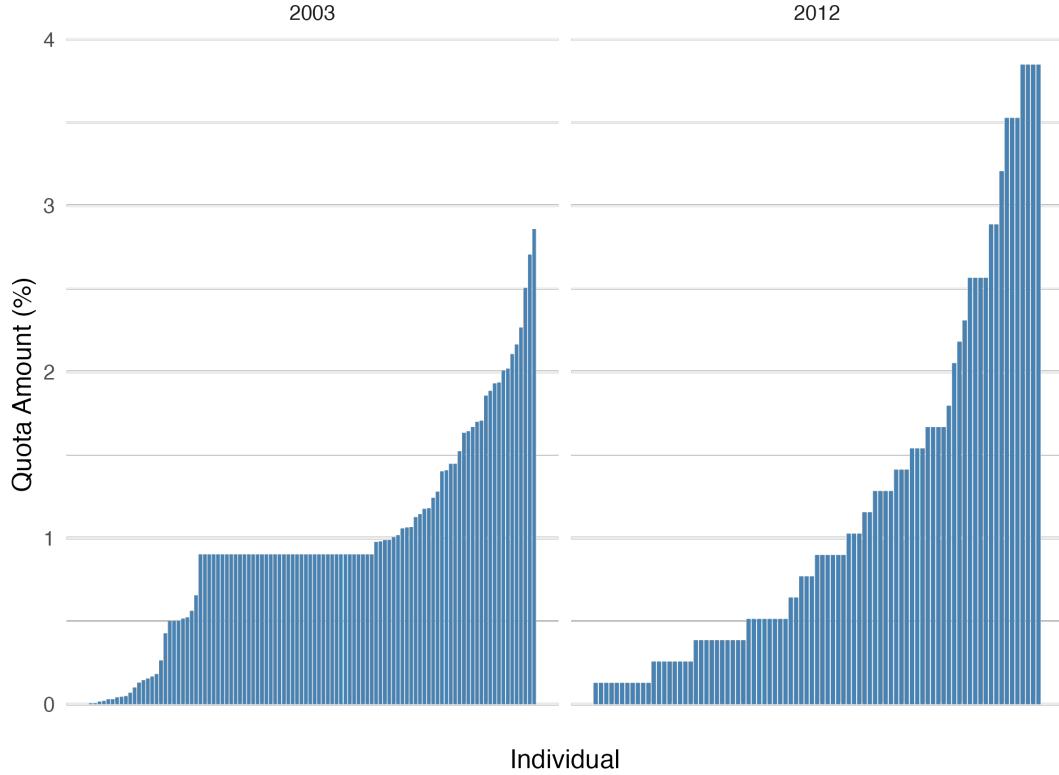


**Figure 3.3:** Trends in Maritime Quebec

value of a specific species caught by an individual on a given trip. In addition, we have location data such as departing and landed community, and vessel characteristics such as length and gear. These data include over 2800 individuals. We first aggregate these data to the individual-year-species level, and then to the individual-year level for regressions. Effort will serve as a proxy for annual costs, and we calculate total days at sea, total operational days, and total number of trips taken per year. We deflate revenues to a 2003 base year. Table 3.1 reports summary statistics.

**Table 3.1:** Summary Statistics: Catch and Revenue Data

	Mean	SD	Min	Median	Max
Revenue (\$1000s)	142	195	0	84	2716
Vessel Length	36	14	0	38	95
Trip Length	28	27	1	17	362
Operational Days	23	20	1	15	180
Number of Trips	18	16	1	12	188
Number of Species	2.4	1.9	1	2	12



**Figure 3.4:** Initial Quota Distribution

### 3.4.2 Quota Holdings

The DFO keeps track of annual individual quota holdings. We define treatment as receiving an initial quota allocation, and this applies to 85 and 87 fishers respectively in the 2003 and 2012 regulated fleets. While there are many individuals who purchase quota over the years, we omit these individuals from the treatment as individuals who select into the program have a different optimizing decision than those who receive free quotas. Initial quota holdings vary from 0.1 - 2 percent of the TAC as shown in Figure 3.4.<sup>3</sup>

### 3.4.3 Local Labour Market Outcomes

I construct measures of local labor market conditions for Maritime Quebec using data from the 2001 Canadian Census. I collect variables for males aged 25 and over to closer resemble the demographics of the fishing industry. For this analysis, I focus on the Census Division (CD) level, which corresponds to Regional County Municipalities (RCMs) in Quebec. This larger geographic area is representative of the “local labour market” available to each fisher. In an alternative specification, I use the disaggregated data at the Census Subdivision (CSD) level, which more closely corresponds to municipalities. To characterize the local labor markets, I compile several indicators of labor market performance. For employment I look at size of the labour force and number of individuals employed and unemployed.

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<sup>3</sup>The DFO do not keep track of quota prices, as this is determined among fishers.

For income, I look at average, median, and standard error of annual earnings. I calculate expected income as average income multiplied by employment rate.

## 3.5 Empirical Strategy: Sample Construction

### 3.5.1 Regulation Exposure

Since different fish stocks are regulated at different points in time, it is common to harvest several regulated and unregulated fish stocks at the same time. In practice, this implies that within a fleet, a regulation will affect all fishers differently. While individuals usually fish one or two main species, the species composition of total revenues are not constant over time and revenues can be volatile based on levels of activity. Therefore we take the average exposure in a baseline period. For the 2003 regulation, we use 2000 - 2002, or 1-3 years prior to the ITQ introduction. For the 2012 regulation, we have a longer period available and use 2006 - 2011.

Exposure is calculated in two ways:

1. Catch-based: the contribution of Greenland halibut to a fisher's total catches during the baseline period. For ease of interpretation, we primarily focus on monetary value, though we also examine percentages.
2. Quota-based: the percentage of initial quotas received, with larger initial allocations indicating higher potential impact from the ITQ.

Fishers are in the treatment group if they receive an initial share of quota, either in 2003 or 2012. We require the fishers to be active in the regulation year for quota-based exposure. Furthermore, treated fishers must catch Greenland Halibut in the baseline period for catch-based exposure. Therefore, certain individuals may be omitted from the treatment group, depending on the measure used. Table 3.2 shows these calculations for the two fleets of interest as a monetary value and percentage of their total catch in the base period. There is significant variation within the fleets where some fishers almost exclusively fish Greenland Halibut, yet the mean exposure is far less than 50% for both fleets. The lower value of exposure from the 2012 fleet is explained by the lower fleet share.

**Table 3.2:** Regulation Exposure

Regulation	N	Mean(% Exp)	Max (% Exp)	Mean(\$ Exp)	Max (\$ Exp)
FG 2003	84	32.28	88.41	22,769.31	67,952.06
FG 2012	61	20.24	64.81	10,049.83	35,764.32

### 3.5.2 Assigning Distribution Quantiles

**Skill Distribution** Fisher skill is defined as the portion of individual revenue that cannot be explained by observable inputs. By estimating individual fixed effects in a revenue regression controlling for these

inputs, we isolate persistent differences across fishers that reflect their underlying ability, experience, or efficiency.

We start with a general production function for individual  $i$  at time  $t$ :

$$\text{Revenue}_{it} = A_i K_{it}^\delta S_{it}^\beta e^{u_{it}}, \quad (3.1)$$

where  $A_{it}$  is total factor productivity capturing efficiency or unobserved skill,  $K_i$  is capital,  $S_{it}$  captures species characteristics, and  $u_{it}$  is an idiosyncratic shock. Taking natural logs gives the standard log-linear form. Specifically, I estimate the following regression using pre-regulation data:

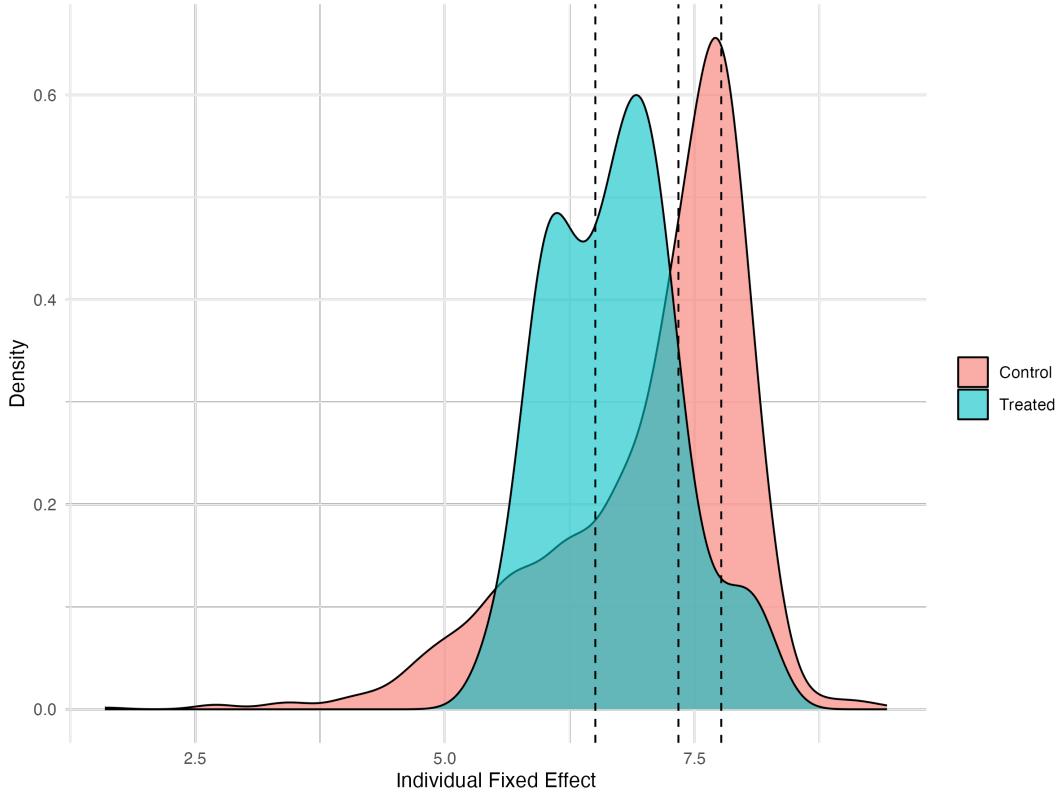
$$\log(\text{revenue}_{it}) = \delta_1 \log(\text{effort}_{it}) + \delta_2 \log(\text{capital}_i) + \beta(\text{species}_{it}) + \gamma_t + \alpha_i + \epsilon_{it}, \quad (3.2)$$

Here  $\alpha_i$  is an individual-specific fixed effect capturing persistent differences in skill across fishers. Effort variables include total number of trips, total operational days, and total days at sea. Capital variables include vessel length and gear. We take the logarithm of these measures to linearize the approximately multiplicative relationship between inputs and revenue. I also include an indicator for main species fished. These fixed effects are then divided into skill groups. This follows Grainger and Costello (2016) where harvest increases in skill. In a robustness check I also use a Best Linear Unbiased Predictor (BLUP) approach through a random-effects model. This shrinks estimates for fishers with few observations toward the population mean, reducing estimation noise and producing a more precise measure of underlying skill, particularly for individuals with sparse data.

The regression is run on all individuals during the base period, and fishers in the treated group tend to be concentrated on the lower end of the distribution of individual fixed effects, as shown in Figure 3.5. The dashed vertical lines indicate the thresholds for four quantiles, however to ensure that both treated and control groups have sufficient numbers of individuals for meaningful comparisons, we simply divide fishers into a low or high-skilled group instead of quartiles.

**Outside Option Distribution** Next, I assign each individual a draw from the outside option distribution. First, I construct a composite “outside option index” using the census variables summarizing income levels, income dispersion, and unemployment. To ensure comparability across measures expressed in different units, each variable is transformed into a standardized z-score by subtracting its mean and dividing by its standard deviation. Again, I take natural logarithms of both average and median income before standardizing, because income variables are highly skewed. I then assign positive signs to measures reflecting stronger labor markets (log average and log median income) and negative signs to those reflecting weaker conditions (standard error of average income and the unemployment rate).

This equal-weighted index expresses local labor market conditions in standard deviation units relative to the mean, with higher values indicating stronger outside options for workers. Finally, I classify regions into quartiles (1–4), where 4 represents the most favorable local labor market conditions. This is an alternative to simply ranking expected income for example. We restrict our ranking of geographic



**Figure 3.5:** Distribution of Individual Fixed Effects for Treatment and Control Groups.

areas to locations with active fishing communities. Average incomes are naturally higher in regions closer to major urban centers along the St. Lawrence, but we assume that high relocation costs and the specialized nature of fishing limit mobility, so local labor market conditions still meaningfully reflect outside options for fishers. The unemployment rate ranges from less than thirty percent to over fifty, and expected income from around \$10,000 to almost \$30,000.

We define a fishers “home port” as the most frequented location of departure<sup>4</sup>. Geographic boundaries and identifiers are obtained from Statistics Canada’s geographic correspondence files, and these communities are linked to their respective Census Division. Since most locations are small fishing communities, the local labour market is defined at the CD or CSD, allowing for movement between nearby communities.

In a robustness test we can randomly assign a location or skill to a given fisher, and our results are upheld if coefficients of interest are statistically insignificant.

### 3.5.3 Control Group: Matching Methods

Our empirical strategy involves comparing the outcomes of the treated individuals to the outcomes of a control group, where the control group individuals are assumed to exhibit the trends of the treated individuals in the absence of the regulation. We use matching methods to reduce our sample to these

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<sup>4</sup>Location of landing was also explored, yet in all cases was identical to the most frequented location of departure.

fishers that represent this valid counterfactual. Unregulated fishers far outnumber regulated fishers, so it is unreasonable to expect they are all representative of potential outcomes. We will match on pre-treatment and time invariant characteristics, which highlight areas of the covariate distribution where there is sufficient overlap between the treatment and control groups. Furthermore, as treated individuals are present in the base years by construction, matching ensures we are not including fishers who enter post-regulation. The goal of the matching is to reduce bias in the estimation of the treatment effect based on selection into the regulation. We run the following regression, which essentially estimates the propensity score.

$$Treat_i = (\overline{revenues})_i + (\overline{effort})_i + (\overline{vessellength})_i + (\#species) + \epsilon_i \quad (3.3)$$

We run two slightly different specifications and variations of nearest neighbour matching. The idea is to calculate the individual “probability of being treated”, and choose individuals that were not exposed to an ITQ regulation but were just as likely to be. For the first, we only include average base year revenues and vessel length and match one control individual to each treatment individual. For the second, we include all covariates noted above, and flexibly match four control units to each treatment. This means that for the same overall number of control individuals, each treated fisher can have a minimum of one and maximum of six matches. This method ensures propensity scores are closer together in the end in the case a treated individual does not have many appropriate matches and another treated individual has many. Since we matched both treatment groups at once, we used 2000-2003 for the average base year characteristics for revenues and effort. In the instances where individuals fish multiple vessels, we calculated the revenue weighed average vessel length. Table 3.3 shows the results of this matching process. We are not concerned about number of species as this includes by-catch. Vessel length is especially important since the regulation is only applied to vessels that do not exceed a certain length.

**Table 3.3:** Matching Method Specifications

	Treatment	Vessel	Revenue	Effort	Num. Species
Method 1	0	40.32	98138.78	26.08	2.45
	1	40.58	98869.05	46.59	5.55
Method 2	0	38.48	93455.31	35.11	3.38
	1	40.58	98869.05	46.59	5.55

## 3.6 Regression Specifications

### 3.6.1 Two-Way Fixed Effects Model

Here we present the baseline specification, which is a two-way fixed effects model exploiting within-individual changes over time and allowing the treatment effect to vary with the intensity of treatment exposure as defined above. It can also be interpreted as a difference-in-differences model with heterogeneous treatment intensity.

We first look at the average effect of the regulation as follows:

$$\log(y_{ijt}) = \beta(1TQ_{jt} * Exp_i) + \gamma_t + \alpha_i + \epsilon_{ijt} \quad (3.4)$$

On the intensive margin, our outcome variables are revenues and effort. On the extensive margin we look at the probability of being active in the fishery. We regress these outcomes on the interaction of our exposure variable with the indicator for the ITQ regulation, which is equal to 0 in the baseline years and 1 in the “post” period. Here  $\beta$  is the coefficient of interest, which represents the additional effect for an extra “unit” of exposure, here referring to an increase of \$1000 of exposure in the base period. We include individual and year fixed effects.

For the distributional impacts, we run the same regression yet now allowing  $\beta$  to differ across the income and outside option distributions:

$$y_{ijqt} = \beta_q \sum_{k=1}^4 \mathbb{1}\{q = k\} (ITQ_{jt} * Exp_i) + \gamma_t + \alpha_i + \epsilon_{ijqt} \quad (3.5)$$

The two main assumptions for identification in this model are: (1) exogenous treatment assignment and (2) unaffected and stable control units. Although ITQ regulations are not randomly assigned, the use of multiple base years to calculate historical catch ensures that fishers cannot strategically alter their behaviour to manipulate initial quota allocations. Even if the policy is anticipated, the timing of implementation is effectively random, given the lengthy administrative process required to establish these regimes.

While control units may be affected through spillover effects or changes in stock abundance, fishers are still subject to fleet shares, where each fleet cannot collectively catch over a pre-defined amount of the total allowable catch. Spillover effects are further mitigated by the fact that control and treatment units are geographically distinct, limiting direct interaction or competition over the same stocks. For unregulated species, this may be violated if treated fishers sell their quotas and begin to fish other species from the portfolios of the control group with a greater intensity. In practice, though, this appears uncommon: sellers of quotas typically exit the fishery altogether, potentially because existing gear investments make it suboptimal to immediately shift effort toward alternative species.

### 3.6.2 Event Study

Next, we adapt the above specifications to an event-study design as is appropriate for our setting with treatment being introduced in two different time periods. These estimates will demonstrate the evolution of the treatment effect over time. We look at 3 periods before the regulation and 6 periods after, as these are the years where we have individuals from both fleets. The specification is as follows, with  $\bar{t}_j$  representing the year of regulation for the two fleets:

$$y_{ijt} = \beta_d \sum_{d=-3, d \neq -1}^6 \mathbb{1}(t - \bar{t}_j = d) * Exp_i + \gamma_t + \alpha_i + \epsilon_{ijt} \quad (3.6)$$

For distributional impacts, we estimate coefficients  $B_{dq}$  by looking at the evolution of the treatment effect for each skill or outside option quantile.

$$y_{ijqt} = \beta_{qd} \sum_{k=1}^4 \sum_{d=-3, d \neq -1}^6 \mathbb{1}\{q = k\} \mathbb{1}(t - \bar{t}_j = d) * Exp_i + \gamma_t + \alpha_i + \epsilon_{ijqt} \quad (3.7)$$

## 3.7 Results

### 3.7.1 Intensive Margin: Revenues and Effort

Here we include our preliminary regression results for the regulation implemented in 2003. The first column includes all fishers, the second uses the preferred matching methods to restrict the sample to a valid counterfactual. Since this is not a balanced panel, fishers will enter and leave the sample, the number of observations is affected by the choice of control group. Table 3.4 demonstrates the average effect of ITQs on revenues among active fishers. We find the average effect of the ITQ regulation on revenues in the post period of an additional \$1 of exposure is between \$1.28 - \$1.58. This represents how revenues increase post-ITQ, as expected.

**Table 3.4:** Intensive Margin Results: 2003 Overall

	Total Revenues		Total Fishing Days	
	(1)	(2)	(3)	(4)
ITQ Exp	1.278*** (0.250)	1.580*** (0.279)	0.000 (0.000)	0.000 (0.000)
Individual FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	21,664	6,360	21,664	6,360
R <sup>2</sup>	0.77	0.71	0.75	0.63

*Notes:* \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

In Table 3.5, we allow this coefficient to differ across the skill distribution to demonstrate the distributional impacts. We find that for the same \$1 increase in the base period, it is the individuals at the lower end of the skill distribution who capture those gains. There is no significant effect for the higher skilled, so it is possible this is a Pareto gain. We find no significant effects on effort, as shown in columns (3) and (4) for total fishing days. It is likely that fishers still experience gains through decreased costs, however it could be through a unobserved margin such as distance traveled. This also suggests

that revenues per effort increase as expected.

**Table 3.5:** Intensive Margin Results: 2003 Skill Distribution

	Total Revenues (1)	Total Fishing Days (2)	Total Revenues (3)	Total Fishing Days (4)
ITQ Exp x Skill: High	-6.197 (6.425)	-4.423 (7.230)	-0.002 (0.004)	-0.002 (0.004)
ITQ Exp x Skill: Low	1.285*** (0.250)	1.581*** (0.279)	0.000 (0.000)	0.000 (0.000)
Individual FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	16,142	6,360	16,142	6,360
R <sup>2</sup>	0.73	0.71	0.74	0.63

*Notes:* \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

In Table 3.6, we allow this coefficient to differ across the distribution of local labour market opportunities. In this case, we find that individuals without a prosperous outside option are those who thrive in the fishery. This suggests quotas are not leaving rural communities.

**Table 3.6:** Intensive Margin Results: 2003 Outside Option Distribution

	Total Revenues (1)	Total Fishing Days (2)	Total Revenues (3)	Total Fishing Days (4)
ITQ Exp x Labour: High	2.039*** (0.519)	2.751*** (0.563)	0.000 (0.000)	0.000 (0.000)
ITQ Exp x Labour: Low	5.491*** (1.391)	6.769*** (1.458)	-0.001 (0.001)	0.000 (0.001)
Individual FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	15,761	6,333	15,761	6,333
R <sup>2</sup>	0.73	0.72	0.74	0.64

*Notes:* \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

For the 2012 regression, we run the same specifications and find null results as shown in Table 3.7 and Table 3.8. This could be explained by lower exposure on average, lower overall fleet share of the

regulated species, or dynamics within the fishery of being regulated second.

For the 2012 regulation, we estimate the same specifications and find no significant effects, shown in Table 3.7 and Table 3.8. This null result may reflect lower average exposure to the policy, a smaller fleet share of the regulated species, or structural dynamics associated with being regulated later in time.

**Table 3.7:** Intensive Margin Results: 2012 Overall

	Total Revenues		Total Fishing Days	
	(1)	(2)	(3)	(4)
ITQ Exp	0.070 (0.439)	0.724 (0.487)	0.000* (0.000)	0.000 (0.000)
Individual FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	21,804	5,099	21,804	5,099
R <sup>2</sup>	0.77	0.72	0.74	0.60

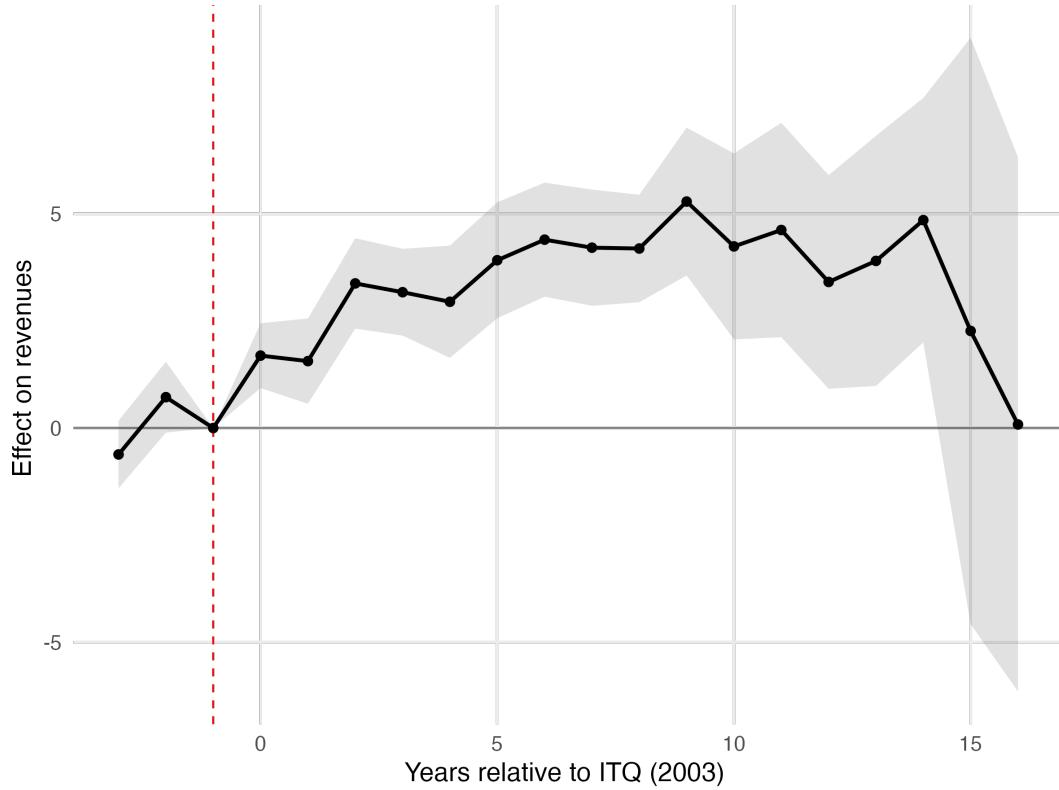
*Notes:* \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

**Table 3.8:** Intensive Margin Results: 2012 Skill Distribution

	Total Revenues		Total Fishing Days	
	(1)	(2)	(3)	(4)
ITQ Exp x Skill: High	-0.134 (0.392)	0.426 (0.517)	0.000 (0.000)	0.000 (0.000)
ITQ Exp x Skill: Low	0.131 (0.525)	0.805 (0.566)	0.001* (0.000)	0.000 (0.000)
Individual FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Observations	19,227	5,099	19,227	5,099
R <sup>2</sup>	0.74	0.72	0.72	0.60

*Notes:* \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

Figure 3.6 presents the event study results, showing how the effect of the regulation develops over time.

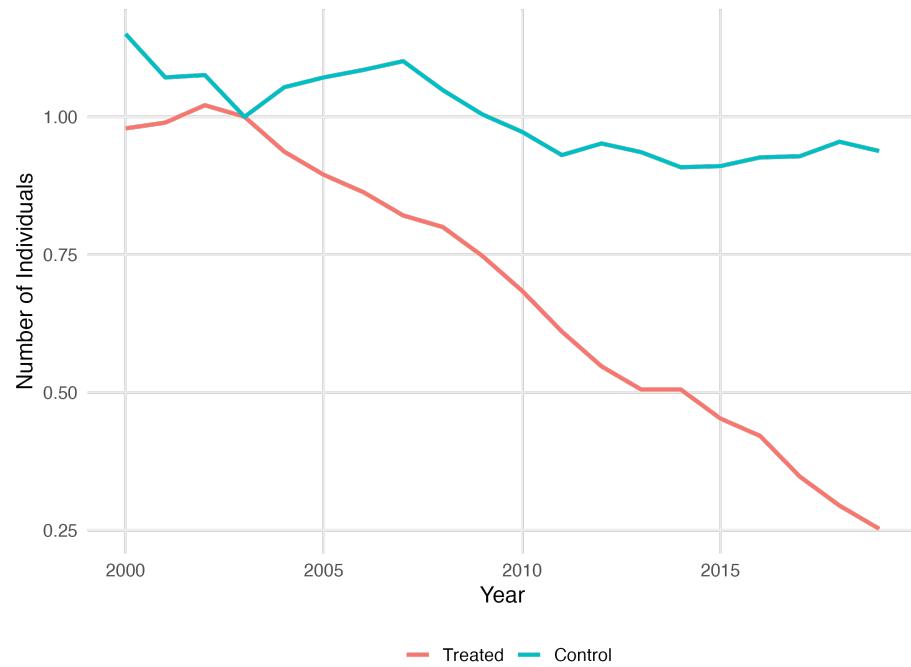


**Figure 3.6:** Event Study Results for 2003 Regression

### 3.7.2 Extensive Margin

Here we present the extensive margin results which examine whether ITQs induce exit from the fishery. When a quota system is introduced, fishers face new incentives: some may choose to sell their quota, capture the lump-sum value, and exit the industry, leading to a concentration of the total allowable catch among those who remain. Figure 3.7 demonstrates the levels of exit in the treatment and control group where the number of individuals in 2003 is normalized to one.

The regression results are presented in Table 3.9. In this analysis, we use a balanced panel where the dependent variable equals one if a fisher is actively fishing in a given year and zero otherwise. Instead of an exposure measure, we interact the treatment indicator with a post-period indicator. Overall, the results show that ITQs induce exit from the fishery, as expected. While the rate of exit is somewhat higher among lower-skilled fishers, it is relatively similar across labor markets. Thus, although there is substantial exit across the skill distribution, it is not disproportionately concentrated in rural areas.

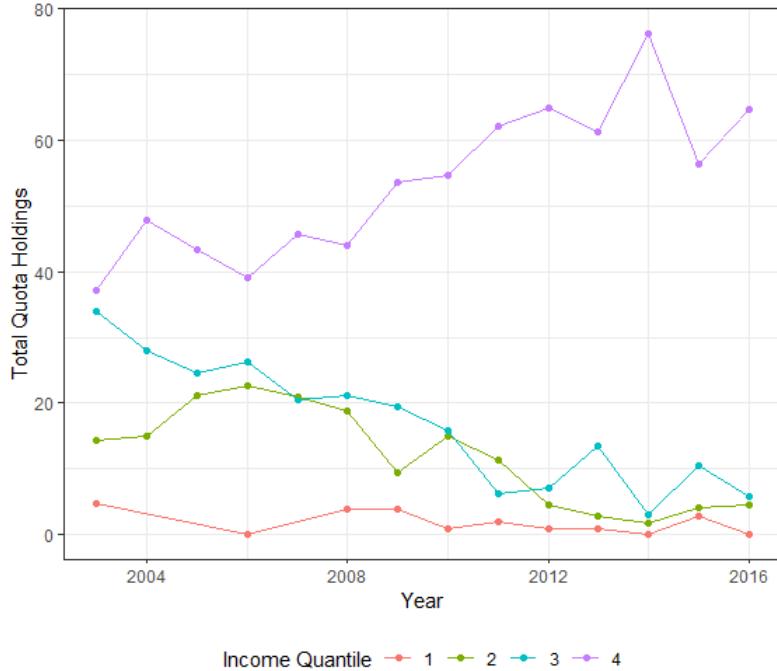


**Figure 3.7:** Number of Active Fishers in Treatment and Control (2003 = 1.00)

**Table 3.9:** Extensive Margin Regression Results

	Active = 1					
	(1)	(2)	(3)	(4)	(5)	(6)
ITQ	-0.335*** (0.034)	-0.059 (0.038)				
ITQ × Skill: High		0.000 (0.110)	0.020 (0.111)			
ITQ × Skill: Low		-0.091** (0.036)	-0.071* (0.039)			
ITQ × Labour: High				-0.358*** (0.090)	-0.177* (0.090)	
ITQ × Labour: Low				-0.356*** (0.067)	-0.102 (0.071)	
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54,100	9,700	27,560	9,700	31,940	4,920
R <sup>2</sup>	0.49	0.59	0.60	0.59	0.50	0.58

Notes: \*  $p < 0.1$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$



**Figure 3.8:** Quota Holdings by Income Quantile

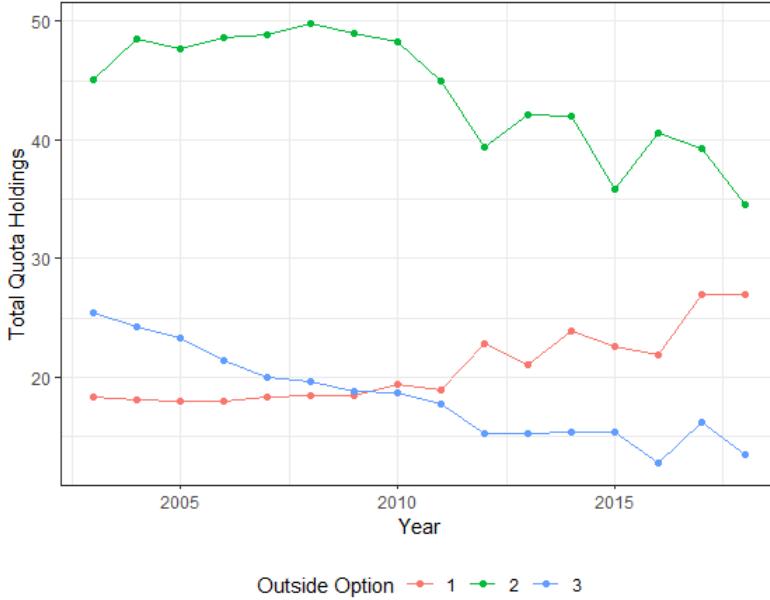
### 3.7.3 Quota Holdings

Next, we look at quota holdings across each distribution across time. In the introduction year, the highest quota percentage held was around 2.5 percent. Over the years this increased to almost 4.5 percent, with many individuals holding over 3 percent. From Figure 3.8 it is very clear that the most skilled purchase and amass quota. While the least skilled did not have a high percentage to begin with, they never acquired any quota. There is a clear negative trend in the two middle bins. From Figure 3.9 we see that fishers with the lowest outside options were also able to amass quota from those with the highest outside options. This suggests that fishing communities did not lose an important source of income and employment.

## 3.8 Alternative Specifications

### 3.8.1 Quantile Regression

The empirical strategy first assigns individuals to discrete distribution bins based on their baseline characteristics, and then estimates separate effects of the ITQ exposure interaction within each bin. The bins are fixed, and the regression captures the average effect within that bin. This shows heterogeneity in treatment effect by type. In contrast, a quantile regression estimates the effect of ITQ exposure at different points of the conditional distribution of revenues, and examines whether the treatment effect differs for low-, median-, or high-outcome individuals. Overall, our approach demonstrates average effects within pre-defined groups, while quantile regression stratifies by the conditional outcome and re-



**Figure 3.9:** Quota Holdings by Labour Market Quantile

veals how the treatment effect varies across that distribution. Quantile regression would reveal whether ITQs disproportionately benefit the highest-earning fishers, for example, but it does not identify which specific individuals receive these gains. For our purposes, tracking the actual fishers who benefit is more important, which is why we focus on skill-based bins.

### 3.9 Discussion

While these results reveal underlying trends from the transition to property rights in the fishery, their broader policy implications remain to be explored. In particular, our findings may be influenced by the cap on quota holdings, which limits consolidation to some extent. This suggests an interesting avenue for extension: we could apply the same analysis to British Columbia fisheries, where no upper bounds on quota exist, to assess whether results differ. We believe our findings are externally valid within the context of Quebec’s ITQ program and likely reflect outcomes for future ITQ implementations in the region. However, the aggregate effects would likely be larger if a more valuable species, representing a greater share of the portfolio, were regulated, as groundfish generally account for a small portion of total catch. Additionally, limited information on quota leasing and prices constrains our understanding of market dynamics. Future work will examine more detailed labor market measures at a finer scale and further investigate the mechanisms underlying our results, guided by our model.

### 3.10 Conclusion

In this paper, we have provided an analysis of the distributional impacts of an individual transferable quota regimes. We leveraged the introduction of a quota system for Greenland Halibut in 2003 for Gaspé–Upper Middle North Shore and then in 2012 for the Lower North Shore. Using a comprehensive

dataset of the universe of catch and revenue data for Maritime Quebec, we contributed an empirical assessment of changes in fishery revenues from ITQs. By allowing fishers to differ along a measure of productivity and their outside option, we look at the effect of ITQs across these distributions to inform who benefits. We find that revenues increase the most for the lowest skill quantiles. While fishers in the lowest skill quantile are also the most likely to leave, this is not concentrated among those without an outside option. This suggests that inequality may actually decrease within the fishery and although small-scale harvesters may exit, remote communities do not experience negative effects. For quota holdings, we find that quota flow towards those at the top of the income distribution and those with the lowest outside option. As more Canadian fisheries move towards ITQ management schemes, quantifying their impacts is crucial in informing policy to limit economic losses, ensure prospering fishing communities, and allow for long-term sustainability of the fishing industry in Canada.

## Chapter 4

# Mapping Risk: Predicting Well Inactivity and the Geography of the Potential Orphan Well Burden

### 4.1 Introduction

Orphan oil and gas wells represent a growing environmental and fiscal liability across the United States. These wells, which have been abandoned by their operators without proper plugging or reclamation, pose serious risks to air, water, and soil quality and impose significant cleanup costs on state governments. Pennsylvania alone is home to more than 300,000 documented wells with tens of thousands are currently classified as orphaned or abandoned and many more are idle or inactive with uncertain futures. The scale of the problem has prompted unprecedented public investment: under the 2021 Bipartisan Infrastructure Law, Pennsylvania received over \$400 million for well-plugging programs. Yet despite these efforts, policymakers still lack credible forecasts of how many additional wells are likely to become orphaned in the coming decades and where those liabilities will arise.

This paper addresses that gap by developing a predictive framework to identify the subset of Pennsylvania's existing wells most at risk of becoming orphaned. Using detailed well-level production and ownership data from the Pennsylvania Department of Environmental Protection (PADEP), I construct a naive, production-based classification of the current well stock. I can aggregate these categories to the operator level to characterize the structure of firm ownership and operational capacity which highlights the concentration of high-risk wells among small, low-production firms. This provides a transparent depiction of the state's aging well portfolio.

Second, I estimate the probability that a given well becomes orphaned within a fixed time horizon, using logistic models that incorporate well age, cumulative production, recent production decline, operator size, drilling vintage, and local geological and regulatory controls. The results indicate that age, operator scale, and production history are strong predictors of orphaning.

Finally, I can map the spatial distribution of these high-risk wells to provide a statewide view of

emerging environmental liabilities. These at-risk wells are disproportionately located in older conventional oil fields in northwestern and southwestern Pennsylvania, rather than in the newer shale-gas regions of the state. I evaluate whether the Act 13 impact fee aligns with these future risks. Since the impact fee is assessed only on active unconventional wells, despite generating substantial revenues, only counties with ongoing shale development benefit. In contrast, the regions most exposed to future orphaning are older conventional areas.

By integrating production-based forecasts of future orphan wells with fiscal data on state and local revenues, this paper quantifies both the environmental and budgetary dimensions of Pennsylvania's orphan-well problem. The findings underscore the need for policy mechanisms that more effectively internalize legacy environmental risks—such as differentiated bonding requirements or risk-adjusted impact fees—so that current extraction more fully accounts for future cleanup obligations. More broadly, the framework developed here offers a scalable approach for other producing states to anticipate and manage long-term liabilities from the fossil fuel industry.

The remainder of the paper is organized as follows. Section 4.2 describes the institutional and policy background of orphan well regulations and the structure of Pennsylvania's Act 13 impact fee. Section 4.4 offers insight into the operators decision to abandon a well. Section 4.4 outlines the data sources and presents descriptive evidence on well life-cycles. Section 4.5 introduces the empirical framework for the naive classification and predicting orphanhood risk. Section 4.6 provides the results and maps the spatial distribution of at-risk wells. Section 4.7 discusses the fiscal alignment and compares the results to the current known landscape of orphan wells and Section 4.8 concludes.

## 4.2 Background

### 4.2.1 Legal Definitions and Well Status Classification in Pennsylvania

A well is considered active when it produces positive quantities of oil or gas, or zero quantity with expected future production. If a well ceases production for twelve consecutive months but remains under an operator's control, it is classified as inactive. Wells that are non-producing and lack an approved inactive status become abandoned. Abandonment may occur for a variety of reasons including economic, technical, or corporate, but it signifies that the well is no longer maintained and may pose environmental risk. Wells have to be properly decommissioned at the end of their useful life. This is the point at which a well is uneconomical, (which is different than just producing no revenue based on future price forecasts, it is much more complicated) This is state specific, but often requires plugging to prevent fluid mitigation, and land restoration. The large upfront cost of decommissioning gives well operators incentive to postpone. Often regulators allow operators indefinite postponement of commissioning allowing operators this indefinite “inactive” status. This means operators try to keep inactive status although the well will never produce again. Within this broader set, Pennsylvania defines “orphan wells” as a specific subset of abandoned wells for which no responsible operator exists and the well was abandoned prior to April 18, 1985. My point here is that the focus is always on orphan wells, but these abandoned wells are the exact same burden, if not more. These wells often change ownership multiple times, ultimately end-

ing up with small or insolvent operators. When maintenance costs or transfer requirements eventually exceed expected revenues, these wells are abandoned.

Discrete regulatory categories of well status offer limited information, as wells lie along a continuous spectrum of production, age, ownership, and operational activity. At one end are active wells that remain under private-firm responsibility; at the other are orphan wells, which represent realized public liabilities. Between these extremes lies a substantial stock of inactive or abandoned wells that are still legally owned by operators but exhibit widely varying maintenance levels and, in many cases, present environmental hazards. Abandoned wells without current production can be the same environmental and fiscal burden as orphan wells, differing only in the state's ability to assign legal responsibility. This paper focuses on the set of active and inactive wells as the universe of potential future liabilities. By classifying these wells according to their probability of transitioning into abandonment or orphanhood, the analysis identifies where Pennsylvania's next generation of environmental liabilities is likely to emerge.

Muehlenbachs (2015) studies well operators in Alberta, Canada, and shows that inactive gas wells are highly unlikely to ever produce again, even in ideal conditions.

#### **4.2.2 Production Profiles and the Changing Composition of Pennsylvania's Well Stock**

The production lifecycle of an oil or gas well follows a characteristic decline pattern that shapes both its economic viability and its eventual environmental legacy. Conventional and unconventional wells differ sharply in the magnitude and timing of that decline, with important implications for the trajectory of orphan-well liabilities in Pennsylvania.

Conventional wells dominated Pennsylvania's drilling landscape for over a century, typically exhibit low initial production rates followed by a gradual exponential decline. Many continue to produce marginal quantities of oil or gas for decades to maintain "active" regulatory status. This long tail of low-output wells is a defining feature of Pennsylvania's legacy conventional sector and underpins much of the states current official orphan-well inventory.

Unconventional wells, by contrast, exhibit a dramatically different production profile. Horizontal drilling and hydraulic fracturing techniques generate very high initial output followed by a steep hyperbolic or harmonic decline. Gas production in the Marcellus and Utica shales typically falls by 60–80 percent within the first two years of operation and stabilizes at a small fraction of peak output after a decade. These wells are capital-intensive but have relatively short productive lifespans; once decline sets in, continued operation is viable only if fixed surface infrastructure and gathering systems are in place. The industry's rapid technological adoption and scale mean that nearly all new wells since 2010 consists of such unconventional gas wells.

This structural shift from long-lived conventional oil wells to short-lived unconventional gas wells has two competing implications for future orphan burdens. On one hand, the shorter economic lifespan of unconventional wells could accelerate the pace of decommissioning, leading to a faster turnover of wells reaching the end of productive life. If operators meet their plugging obligations, this could actually limit the long-run growth of the orphan stock. And the stock of orphans could remain conventional. On the other hand, the sheer number of high-cost, high-decline unconventional wells now

in operation—combined with the likelihood of corporate defaulting creates the potential for a future wave of orphaning once these wells mature. The accelerated decline compresses the window between peak revenue and end-of-life, meaning that economic and regulatory decisions about plugging will arise much sooner than for the conventional wells of the past.

From a policy perspective, Pennsylvania’s historical legacy ensures that the current orphan problem is concentrated in older conventional fields, while the emerging risk lies with newer unconventional gas wells that may reach the end of their productive lives within the next twenty years. The temporal and spatial overlap of these two regimes—legacy oil in the northwest and modern gas in the northeast and southwest—means that the state faces a dual challenge: managing a backlog of century-old liabilities while anticipating a shorter-cycle wave of future ones. Understanding the contrasting production dynamics of these well types is therefore essential for forecasting both the timing and geography of Pennsylvania’s long-run environmental burden.

#### **4.2.3 Fiscal Policy**

Act 13 of 2012 reshaped the fiscal treatment of unconventional gas development in Pennsylvania. Rather than adopting a conventional severance tax on the value or volume of extracted gas, the legislature created an annual “impact fee” levied on each unconventional well that is drilled or producing in a given year. In contrast to severance taxes, which are typically levied as an ad valorem percentage of the value of oil and gas at the wellhead or as a specific tax per unit of production, impact fees are more concerned with the existence of the well. The fee is set in a schedule that depends on well age and the annual average natural gas price, with higher fees in early years and declining obligations as wells age. Impact fee revenues are distributed according to a specific formula, with allocations based on the number of unconventional wells located within each jurisdiction, adjusted for population and other factors. The remaining share is deposited into several state-level funds, including the Marcellus Legacy Fund and various environmental, infrastructure, and emergency-response programs. Distributions began in 2012 and have fluctuated with drilling activity and gas prices, but cumulatively have exceeded \$1.4 billion in their first seven years. In recent years, annual collections have been on the order of \$150–\$250 million.

The impact fee on unconventional wells is assessed annually for only the first fifteen years after a well is spud. After year fifteen, the fee expires entirely, even if the well remains unplugged, produces no gas, or later becomes orphaned. As a result, a substantial share of aging wells continue to impose potential future costs on the state without contributing further revenue, strengthening the case for identifying high-risk wells well before they reach the end of the fee schedule.

A separate but related instrument is well bonding, which is intended to ensure that operators internalize at least a portion of future plugging and reclamation costs. Under Pennsylvania law, operators must post bonds that vary by well type and operator scale. For conventional wells, firms may post a relatively modest per-well bond (e.g., \$2,500 per well) or a blanket bond covering all wells up to a capped amount, while for unconventional wells the required bond depends on total wellbore length and the number of wells operated, with statutory caps that keep total bonding obligations well below estimated plugging costs. Recent analyses have concluded that these bond amounts fall far short of the expected costs of

plugging and site restoration, particularly for older conventional wells, implying substantial residual risk for taxpayers if operators default or dissolve.

Therefore, the impact fee concentrates revenue flows in counties with recent shale gas development, largely in northeastern and southwestern Pennsylvania. Legacy conventional regions, where the current stock of orphan and abandoned wells is highest, receive relatively little Act 13 revenue because they host few unconventional wells. Bonding requirements, meanwhile, are too low and too loosely enforced to guarantee full cost recovery in the event of widespread operator default.

This paper addresses the spatial and temporal aspects of this fiscal policy. First, by forecasting which active and inactive wells are most likely to become orphaned, it provides a forward-looking measure of expected environmental liabilities at the county level. Second, by comparing these expected liabilities to historical and contemporaneous Act 13 allocations, it assesses the degree of spatial misalignment between where the state collects drilling-related revenues and where long-run cleanup costs will fall.

### 4.3 Theory of Decommissioning

Wells remain idle or producing marginal amounts long after they have ceased to be economically viable. Decommissioning laws are necessary in the presence of externalities, where unplugged or poorly maintained wells create substantial private and social costs. For other operators, they can depress reservoir pressure and reduce the productivity of neighboring wells. For the broader population, they contaminate groundwater, leak methane, and depress nearby property values. Operators have strong incentives to delay plugging, as decommissioning is a large, irreversible expenditure. Postponing it preserves both the opportunity cost of funds and the option value associated with waiting for price increases or technological changes. Therefore, delay is may be privately optimal for the operator but socially costly through environmental risks, foregone land uses, and heightened probability that liabilities ultimately fall on the state.

Building on the framework of Weber et al. (2021) to identify a production threshold that identifies wells past their economic life, I introduce a simple model that characterizes the operator decision. This perspective informs my analysis, as I use this threshold to both identify and predict uneconomic wells.

For a given well  $i$  at time  $t$ , a well faces price  $p_t$ . Production value is revenue  $p_t * q_{it}$ . There are fixed costs  $F_{it}$  and variable operating costs which are a function of quantity  $C_{it}(q_{it})$ . The annual impact fee is an example of a fixed cost. There is a one time plugging fee of  $P_i$ . Operators discount future revenues by  $\beta$  and  $V_{it}$  is the continuation value of keeping the well unplugged. Each period the operator chooses to keep the well active and producing  $q_{it}$ , idle with  $q_{it} = 0$ , or plug the well.

**Active** Given an operator chooses to operate, revenues are

$$\pi_{it}^A = p_t * q_{it} - C_{it}(q_{it}) - F_{it}$$

A breakeven production value  $Q^*$  can be defined such that producing  $q_{it} < Q^*$  leads to negative revenues. Given that any non-zero production is sufficient to maintain active status, operators may

choose to operate at a loss if they anticipate more favourable conditions:

$$p_t * q_{it} - C_{it}(q_{it}) - F_{it} + \beta V_{it} \geq -P_i$$

**Idle** As the well nears the end of its life, variable costs can increase if it is harder to extract the diminishing resource. Hence the revenues may not cover the variable costs, yet the operator may choose to incur the fixed costs to avoid plugging:

$$-F_{it} + \beta V_{it} \geq -P_i$$

Leaving a well unplugged also leaves the option open to produce in the future. Wells that remain idle indefinitely are functionally abandoned, but regulatory frameworks can permit this status without triggering decommissioning.

**Plug** Plugging generates no revenue and eliminates all future revenue opportunities, the operator pays  $P_i$  and  $V_{i,t+1} = 0$ .

Essentially this can be summarized with the following value function:

$$V_{it} = \max \left\{ \pi_{it}^A + \beta V_{i,t+1}, \pi_{it}^{Idle} + \beta V_{i,t+1}, -P_i \right\}.$$

Taken together, the model clarifies the incentives underlying operator's decisions. First, higher plugging costs unambiguously reduce the likelihood of decommissioning. Second, higher current prices raise the value of keeping a well nominally active for the current and future revenues, making operators more likely to continue producing small quantities rather than initiate plugging. Finally, greater optimism about future conditions from anticipated higher prices, falling operating costs, or regulatory leniency, increases the continuation value of the well and further slows decommissioning.

In practice, the economic life of a well varies substantially across operators and locations because the cost function is highly well-specific and non-linear in age. Well characteristics and technology shape the variable costs of extracting additional resource reserves and a price that is economical for one well may be greatly uneconomic for another. My empirical model effectively identifies the condition under which the operator's best response will be to abandon the well.

Note this simplified framework abstracts from the choice of quantity. In a fully specified extraction model, output in each period would be determined by an intertemporal optimization problem balancing current extraction against the value of leaving the resource in the ground. This would be a Hotelling model describing the optimal extraction path of a finite resource. Here, I simply modeling the discrete status choice in a first stage. The second stage could determine the optimal production level conditional on the chosen operating state.

## 4.4 Data

### 4.4.1 Oil and Gas Production Reports

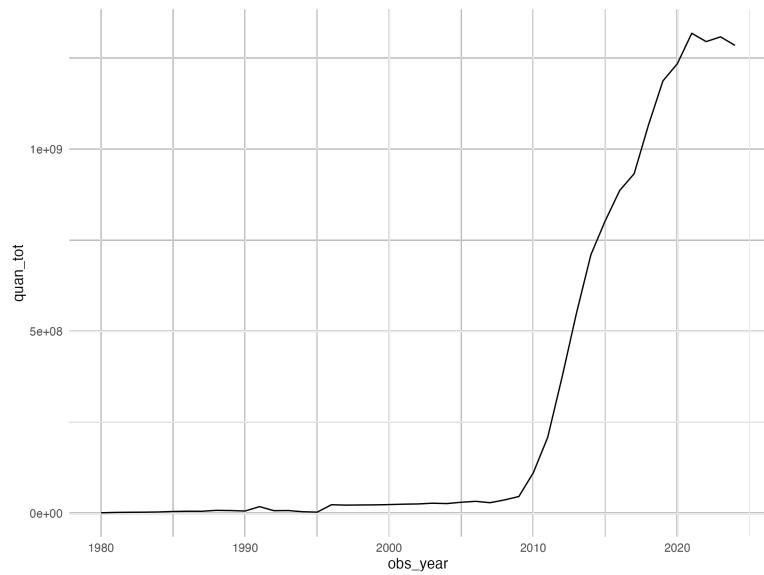
The oil and gas production data comes from Pennsylvania's Department of Environmental Protection (PADEP). I build on the compiled dataset constructed in Chapter 1, which aggregates and merges annual, semi-annual, and monthly production reports over 1980 - 2024. I balance the panel with the assumption that any year after the spud year in which a well is missing a production observation is sitting idle unless a plugging year is stated. I restrict the sample to unplugged oil, gas, or combined oil and gas wells. As natural gas is reported in thousand cubic feet (MCF) and oil in barrels, I natural gas quantity to barrels of oil equivalent (BOE) which allows direct comparison of production volumes across wells and operators. Unless otherwise stated, all quantities are in units of BOE. Each well in a given year can be described using well-specific characteristics (e.g. type, configuration, age), production variables summarizing current and historical activity, and operator characteristics constructed by aggregating and tracking the production of all wells managed by that operator. These variables are all constructed from the annual production recorded for each well and are described in detail in Table 4.1.

The majority of wells are non-producing at some point over the period of interest. Production decline is defined as the percentage change in production relative to a previous period. This measure becomes undefined when the lagged value is zero, however this could represent a transition from 0 to 0 or 0 to any amount of positive production. While these two cases are very different - either persistent inactivity or reactivation - here the distinction does not matter since periods of lagged zero production do not provide meaningful information on a well's depletion trajectory. Only when a well is producing does a percentage decline meaningfully signal diminishing reservoir pressure or resource exhaustion. I recode these values to zero so that the observations are retained in the regression.

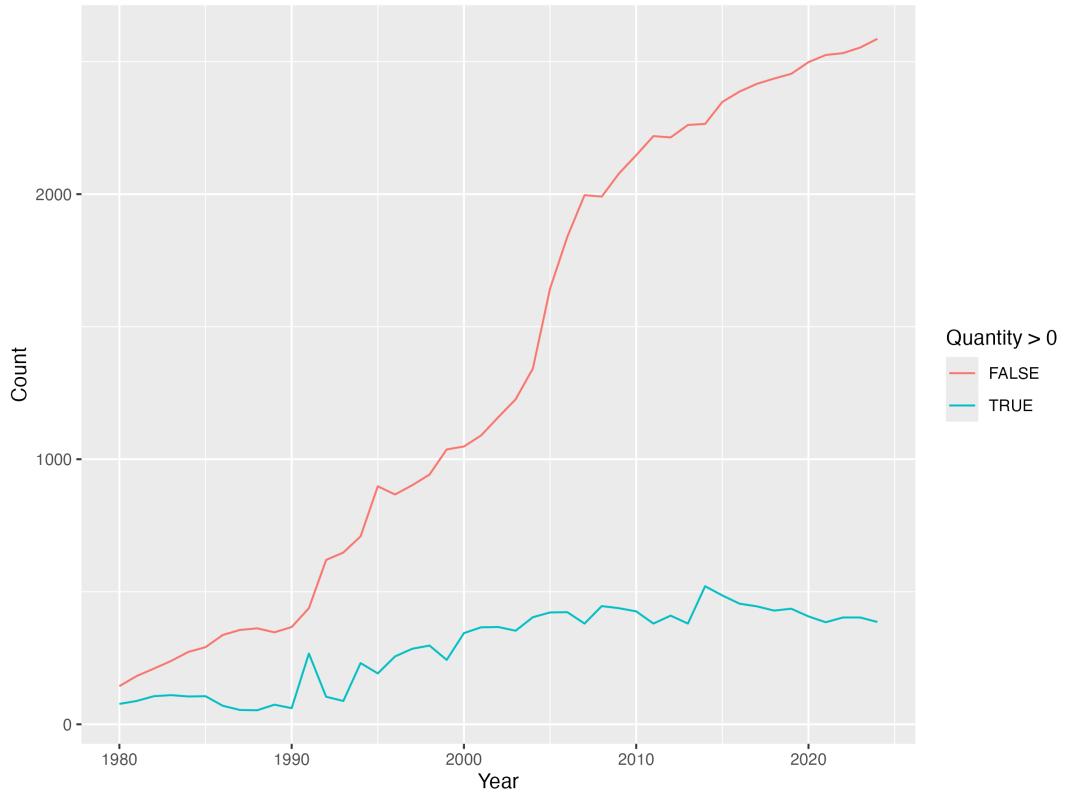
Overall, production variables capture the key dimensions of a well's lifecycle and provide the foundation for the predictive analysis that follows. Figure 4.1 shows total production over the time period.

Operators are of particular importance as the behavior and operational capacity of firms ultimately determine whether wells are maintained, transferred, plugged, or abandoned. Tracking operator characteristics over time (e.g. how many wells they own, how many of each status, production intensity) provides insight into both their economic viability. Operators managing large, actively producing portfolios are more likely to have the resources to comply with plugging obligations, whereas small or declining operators face greater bankruptcy risk and may leave wells orphaned. There are over 3700 unique operators over time, yet in any given year a larger number of them do not own producing wells as shown in Figure 4.2. This is a defining feature of Pennsylvania's oil and gas industry.

Unconventional wells exhibit a markedly different production profile than older, conventional wells: they generate extremely high initial output followed by a steep, predictable decline, whereas conventional wells tend to produce at lower but more stable rates over time. This contrast reflects the broader evolution of Pennsylvania's oil and gas industry. For more than a century, all drilling in the state was conventional and vertical, characterized by small operators and long-lived, low-output wells. Beginning around 2008, however, horizontal drilling and hydraulic fracturing in the Marcellus and Utica



**Figure 4.1:** Total Production Over Time



**Figure 4.2:** Operator Count Over Time

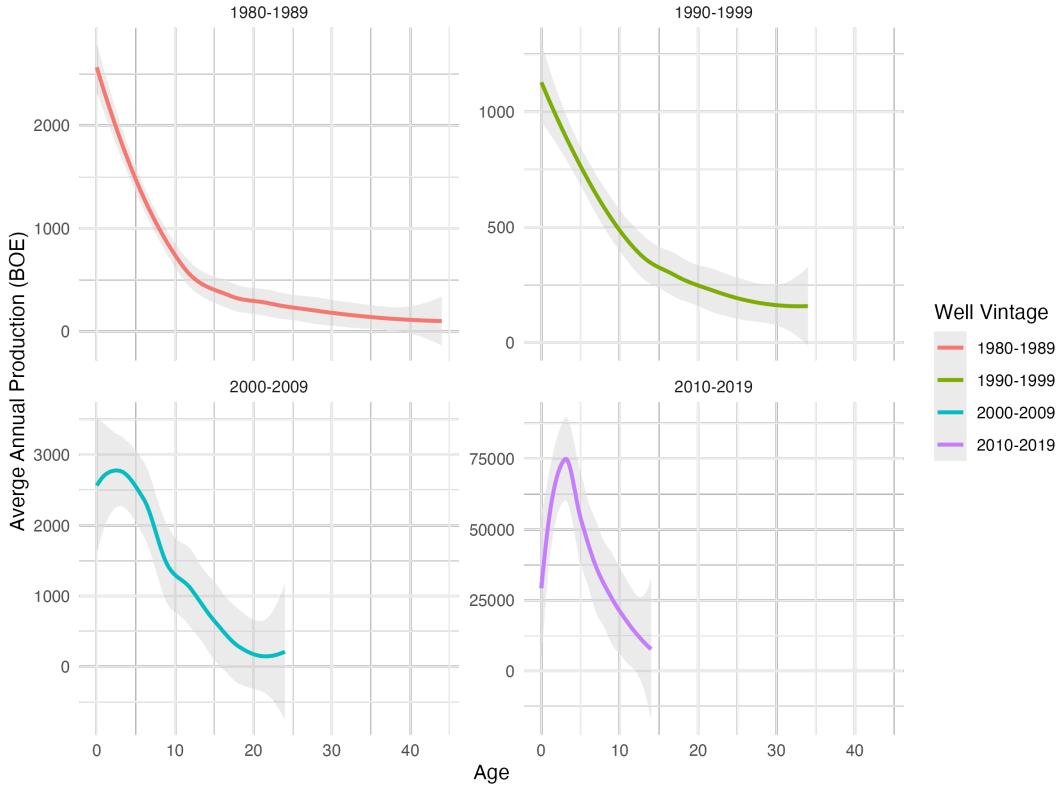
**Table 4.1:** Variables for Classification and Prediction

Variable	Description
<i>Well Characteristics</i>	
Unconventional	Unconventional indicator
<i>Age Variables</i>	
Age	Well age in years
Number of Productive Years	Number of years since first production
<i>Production Variables</i>	
Annual Production	Annual oil or gas production in BOE
Daily Production	Average oil or gas production per day in BOE
Production Days	Total oil or gas production days in the year
Production Decline	% change in production from previous year
Cumulative Production	Sum of production up to date
Total Production (5 yr.)	Total production over previous 5 years
Non-Zero Production (5 yr.)	Number of non-zero production years over previous 5 years
<i>Operator Characteristics</i>	
Number of Wells	Annual number of wells operated
Total Quantity	Total annual quantity (BOE) over all wells operated
Total Quantity (5 yr.)	Total production by operator over previous 5 years
Percentile	Annual rank of an operator's production among producing operators
Number of High-Producing Wells	Total annual active well count
Number of Low-Producing Wells	Total annual marginal well count
Number of Idle/Zero Production Wells	Total annual idle well count
Number of Orphan Wells	Total annual orphan well count

formations transformed the industry, with unconventional wells now dominating new development and driving the state's production levels. As a result, today's landscape reflects an aging stock of legacy conventional wells and a newer, highly productive generation of horizontal shale wells as demonstrated in Figure 4.3. Given the compressed production cycle of unconventional wells, the question is whether they will progress to non-viable status sooner, potentially accelerating the rate at which they are abandoned, or whether recent plugging efforts have successfully slowed the accumulation of new orphan wells, leaving older, legacy wells as the primary contributors to the remaining burden.

#### 4.4.2 Act 13 Impact Fee Data

To examine the spatial distribution of revenues, I compile annual impact fee collection and disbursement data from the Pennsylvania PUC. The dataset provides total fee payments by operator and detailed



**Figure 4.3:** Average Annual Production by Well Vintage

county and municipality level allocations by year since 2012. Each jurisdiction's allocation is linked to the number of unconventional wells located within its boundaries. I aggregate these data to the county-year level to measure total revenue received and shares of allocations directed to environmental, infrastructure, and legacy programs.

## 4.5 Empirical Strategy

### 4.5.1 Naive Classification

For a naive classification of the current stock of unplugged wells, I develop a rough screen for wells following Boomhower, Shybut, and DeCillis (2018). I assign a well to one of the following categories: likely already orphaned, high risk of becoming orphan, marginal, idle, and active. First of all, I take all wells with zero production over the last five years. If the operator also has no production over the last five years, the well is assumed to be orphan. If the operator has positive production, but the average production rate over all wells is less than 5 BOE/day and primarily operates marginal or idle wells, the well is classified as a high risk of becoming orphan. The remaining wells are classified using current production. Marginal wells are those between 1 and 5 BOE per day, and idle wells are less than 1 BOE per day with many completely inactive producing 0. High-producing wells with over 5 BOE per day are considered active. Daily output is the preferred measure of production intensity, since wells that

produce at high rates for only part of the year can appear low-producing in the annual sum. However, because many wells have incomplete or missing data on production days, I also construct an annual production classification using a threshold of 1825 BOE per year (equivalent to 5 BOE per day) to ensure comparability across wells with less reliable operating-day records.

Weber et al. (2021) also do a threshold analysis for conventional natural gas wells in Pennsylvania. They estimate a breakeven production threshold by comparing well level operating costs with future gas prices. Using the highest projected gas prices and no variable operating costs, they find that wells producing below 0.5 Mcf/day are uneconomical even under these highly optimistic assumptions. In a secondary classification, I use this much more stringent threshold which translates to approximately 0.01 BOE per day and represents an absolute lower bound on economic viability. This provides a much stricter screen for wells at high risk of abandonment and helps bound the number of wells for which the state is likely to bear future decommissioning liability.

#### 4.5.2 Logit Model

The naive classification labels wells based on recent production patterns and is inherently descriptive. While it provides an informative picture of the current landscape, it offers little insight into which active or inactive wells are likely to become future liabilities. To forecast Pennsylvania's future orphan-well burden, I estimate a predictive model that uses the full production history data to relate current well characteristics to the probability of abandonment within the next five years.

I use historical patterns in production profiles, decline trajectories, and operator attributes of likely orphan wells to predict future patterns. While the DEP maintains an inventory of verified legacy orphan and abandoned wells, these records lack production histories and therefore provide little basis for predicting future orphan-well risk. However these wells contribute to the overall plugging burden and fall under state responsibility so when explicitly stated I will incorporate counts into the overall estimates of orphaned wells alongside my model-based predictions.

First, I create a binary indicator  $Y_{it}$  equal to one if the well becomes abandoned in the next five years of the observation year. This model is conditional on being observed for the past 5 years for certain explanatory variables and for the future 5 years for the dependent variable so the first and last four observations per well are omitted. This essentially restricts the sample to 1984 - 2019<sup>1</sup>.

Then I estimate a logistic regression that maps well-level and operator-level covariates to the probability of near-term abandonment. The covariates as outlined above include production attributes that are known to correlate with well retirement decisions: well age, recent annual production decline, cumulative lifetime production, daily output, five-year production history, and operator characteristics such as size and well status portfolio. Note year or county fixed effects are not included as that would absorb the cross-sectional variation essential for forecasting. Since the objective is to identify structural drivers of orphan risk rather than short-run market dynamics, I also exclude resource prices from the baseline specification, yet will explore in an alternative specification. Specifically, I estimate the following:

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<sup>1</sup>If a well is spud in a later year, the first four years of production still need to be removed.

$$\begin{aligned}\Pr(Y_{it+5}) = & \beta_0 + \beta_1 \text{Age}_{it} + \beta_2 \text{Decline}_{it} + \beta_3 \log(\text{CumProd}_{it}) \\ & + \beta_4 \log(\text{Prod5yr}_{it}) + \beta_5 \text{DailyProd}_{it} + \beta_6 \text{SmallOp}_{it} + \epsilon_{it}.\end{aligned}$$

I apply the estimated coefficients to all active and inactive wells in 2024, generating well-level predicted probabilities of orphan status in the next five years. These predicted risks form the foundation of the subsequent mapping and aggregation analysis. These probabilities range from near zero for recent unconventional wells operated by large firms to substantially higher values for older, low-producing conventional wells managed by small operators.

This approach fully reflects uncertainty, incorporates the joint influence of age, decline patterns, operator characteristics, and production history, and avoids arbitrary threshold choices present in the naive classification. It also makes the estimates additive and comparable across regions enabling a direct link between expected future liabilities and current policy instruments.

#### 4.5.3 County Level Aggregation

The predicted probabilities generated by the logistic model provide a well-level measure of near-term abandonment risk. To translate these individual predictions into a statewide assessment of Pennsylvania's future orphan-well burden, I aggregate the well-level probabilities to the county level and map the resulting spatial distribution. This section presents the geographic distribution of predicted risk.

$$ExpectedOrphans_c = \sum_{i \in c} p_{it+5}$$

## 4.6 Results

### 4.6.1 Naive Classification

I present the results of this naive classification for 2024 in Table 4.2. The four categories demonstrate different operational profiles. Current active wells are overwhelmingly horizontal (98 percent), relatively young with an average age of 9.65 years, and produce substantial volumes, averaging over 100,000 BOE and 360 BOE per day. By construction marginal wells average fewer than 2 BOE per day, while idle wells produce virtually nothing by construction. These wells are considerably older, with mean ages of over 25 years. Wells that are likely orphan are the oldest in the inventory with an average of 32 years and have the longest operational histories.

Although the naive classification is primarily descriptive, it offers simple forward-looking insights. Idle and marginal wells are substantially older and produce far less than active wells, and together represent more than 75,000 wells statewide. If even 5-10 percent of these wells follow the same trajectory as current orphan wells. Pennsylvania could face 3,000-7,500 additional orphan wells in the coming decade. Age profiles also suggest substantial future risk as idle and marginal wells are only a few years younger than today's orphan wells. Finally, large numbers of wells already produce less than 1 BOE/

**Table 4.2:** Naive Classification of 2024

Status	N	% Horiz.	Annual	Daily	Total 5-Year	Age	Prod. Yrs.
Likely orphan	14,689	2.41	0.00	0.00	0.00	33.21	27.43
Idle	65,057	0.81	99.40	0.29	227.38	28.23	24.47
Marginal	9,927	3.18	532.54	1.64	641.64	25.74	23.67
Active	11,831	97.98	106945.25	362.49	86951.90	9.65	9.38

*Notes:* Columns (2) and (3) use raw well counts. Columns (4) - (6) refer to average production in BOE among wells of the given status. Column (7) refers to average years since spud year, while column (8) is average years since first production.

day, a threshold at which wells historically exhibit high abandonment rates. These naive projections underscore the scale of potential future liabilities and motivate the more formal predictive modeling approach that will use this information.

I present operator summary statistics in Table 4.3 which use the naive classification and reveal an interesting industry structure in Pennsylvania. The group of operators with above-median production is small at 369 firms, but on average they manage more than 230 wells each and account for virtually all statewide production. Nearly 90 percent have at least one idle well, over half manage marginal wells, yet only a quarter hold high-producing wells. Importantly, 51 percent of them also have at least one well that has not produced over the past five years suggesting a likely orphan well if the producer could not be held liable. The below-median production operators average fewer than five wells and overwhelmingly consisting of single-well entities where 264 firms own exactly one well. Their production volumes are negligible, and nearly all of them operate exclusively idle wells. The zero-production operators represent small legacy operators that collectively manage wells with no measurable output. These firms own an average of 5–6 wells and 90 percent of these operators have a likely orphan well. This underscores the strong association between very small operators, aging conventional wells, and abandoned infrastructure.

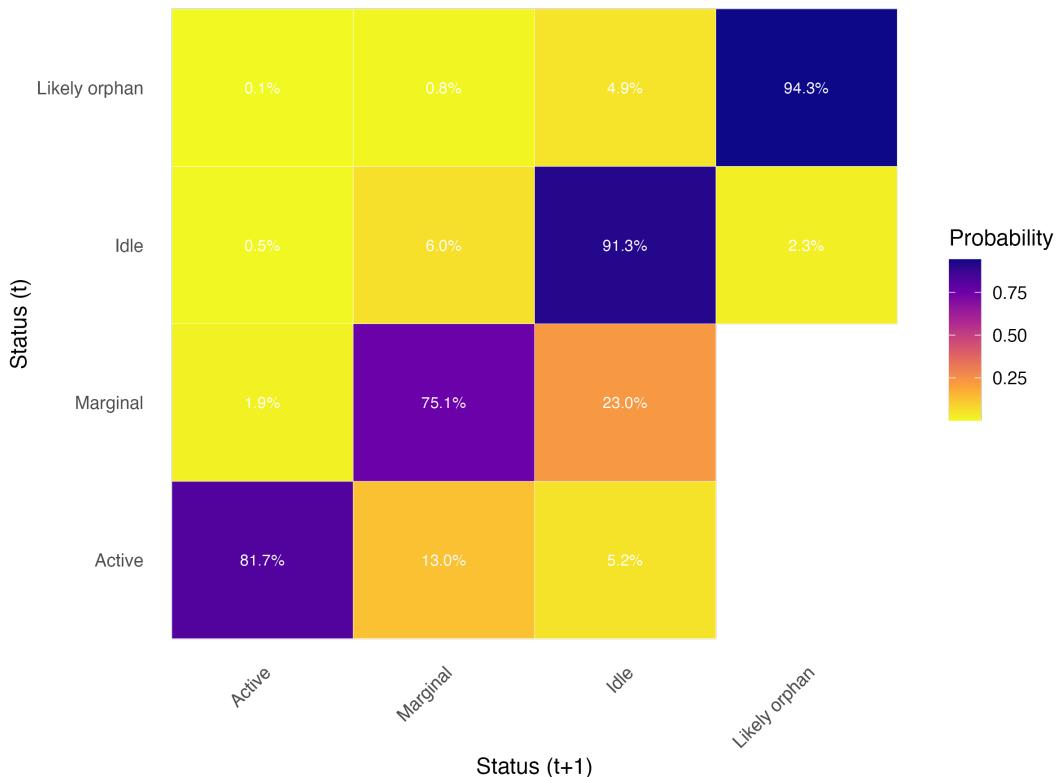
Taken together, these patterns show that Pennsylvania’s future orphan well burden is highly concentrated among the thousands of very small, very low-production operators who collectively manage the bulk of aging, nonproducing wells, while nearly all economically meaningful production is concentrated among a few hundred large operators.

Again, the results above classify wells in 2004. I can also use this classification for all wells over time. Figure 4.4 shows how wells transition between states and highlight the strong persistence of well conditions over time with movement reflecting declining production. However the transition matrix underscores that historical status alone has limited predictive content for identifying future orphan-well risk, reinforcing the need for a modeling framework that incorporates richer well-level and operator-level characteristics.

**Table 4.3:** Operator Summary Stats for 2024

Stat	large	small	zero
Number of Operators	363.00	363.00	2246.00
Mean Number of Wells	243.13	4.54	5.16
Number of Wells = 1	23.00	263.00	1593.00
Total (1000 BOE)	3517.94	0.03	0.00
% Have Orphan Well	51.52	6.89	92.30
% Have Idle Well	90.08	100.00	9.17
% Have Marginal Well	53.17	0.00	0.00
% Have Active Well	24.24	0.00	0.00
% Only Idle	22.87	93.11	7.70

*Notes:* Above (below) median refer to operators with annual quantity in the top (bottom) half, and zero production refer to operators with zero annual quantity.



**Figure 4.4:** Transition Matrix

**Table 4.4:** Results from Logistic Regression

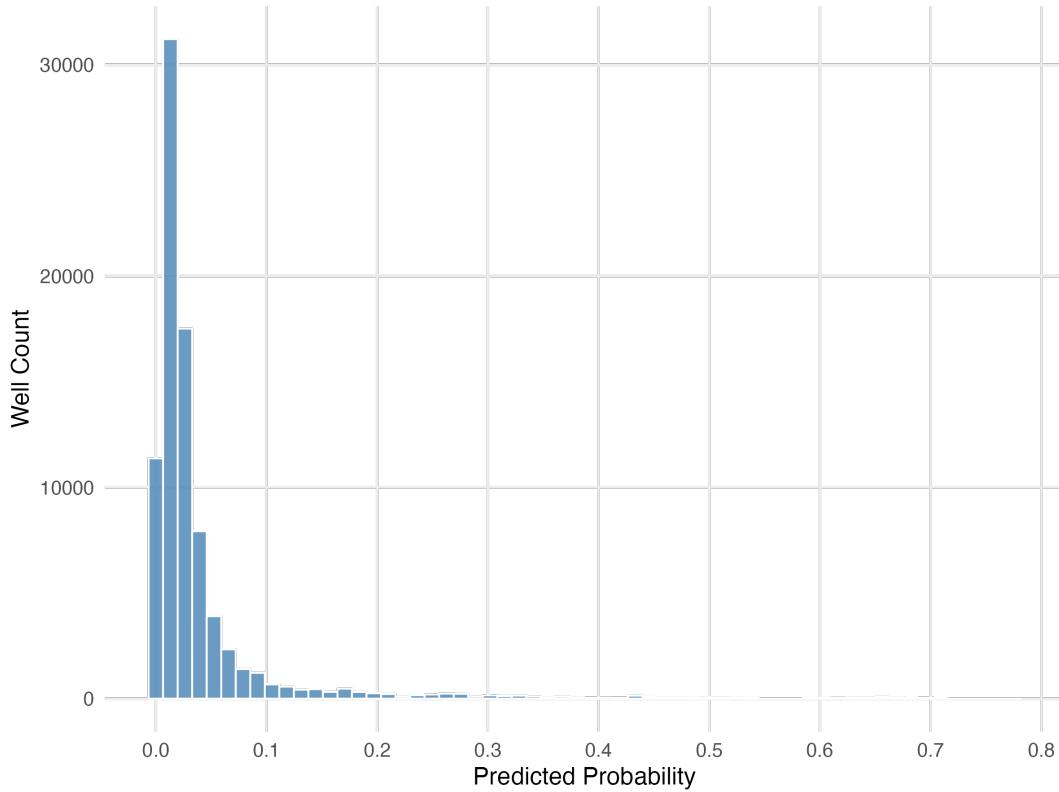
	(Orphan in 5 Years = 1)
	(1)
Well age	0.003*** (0.000)
Production years	-0.017*** (0.001)
One-year production decline (%)	-0.003*** (0.000)
Log cumulative production	-0.012*** (0.004)
Log 5-year production	-0.404*** (0.004)
Mean Daily production	-0.009*** (0.002)
Operator active-well count	-0.001*** (0.000)
Operator production percentile	-2.023*** (0.012)
Observations	1,248,444

*Notes:* Standard errors in parentheses. \* $p < 0.10$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

#### 4.6.2 Prediction for 2024

Table 4.4 reports the logistic regression estimates linking well and operator characteristics to the probability of becoming “likely orphaned” within five years. The signs of the coefficients are consistent with expected patterns in well life cycles. Wells with greater age, fewer recent production observations, and steeper production declines exhibit sharply higher abandonment risk. Higher cumulative and recent production are strongly protective, reflecting that productive wells are rarely left idle long enough to orphan. Operator characteristics also matter: wells owned by smaller operators face systematically higher near-term abandonment risk. Unconventional wells have markedly lower predicted orphan risk, consistent with their younger age and higher annual output.

The predictive model is then used to forecast orphaning risk for the current inventory of wells in 2024. Using the characteristics of each active or inactive well and the coefficients from the logit equation, the model yields a well-specific probability of becoming orphaned within the next five years. Logistic regression estimates effects in terms of log-odds, which are not directly interpretable as probabilities. After estimating the model, I apply the logistic inverse-link function to transform the linear predictor into a probability between zero and one, yielding a well-level measure of the chance that the well becomes orphaned within five years. These predicted risks summarize the combined information contained in production trends, operational intensity, operator features, and geological controls, provid-



**Figure 4.5:** Predicted Probabilities for all Wells

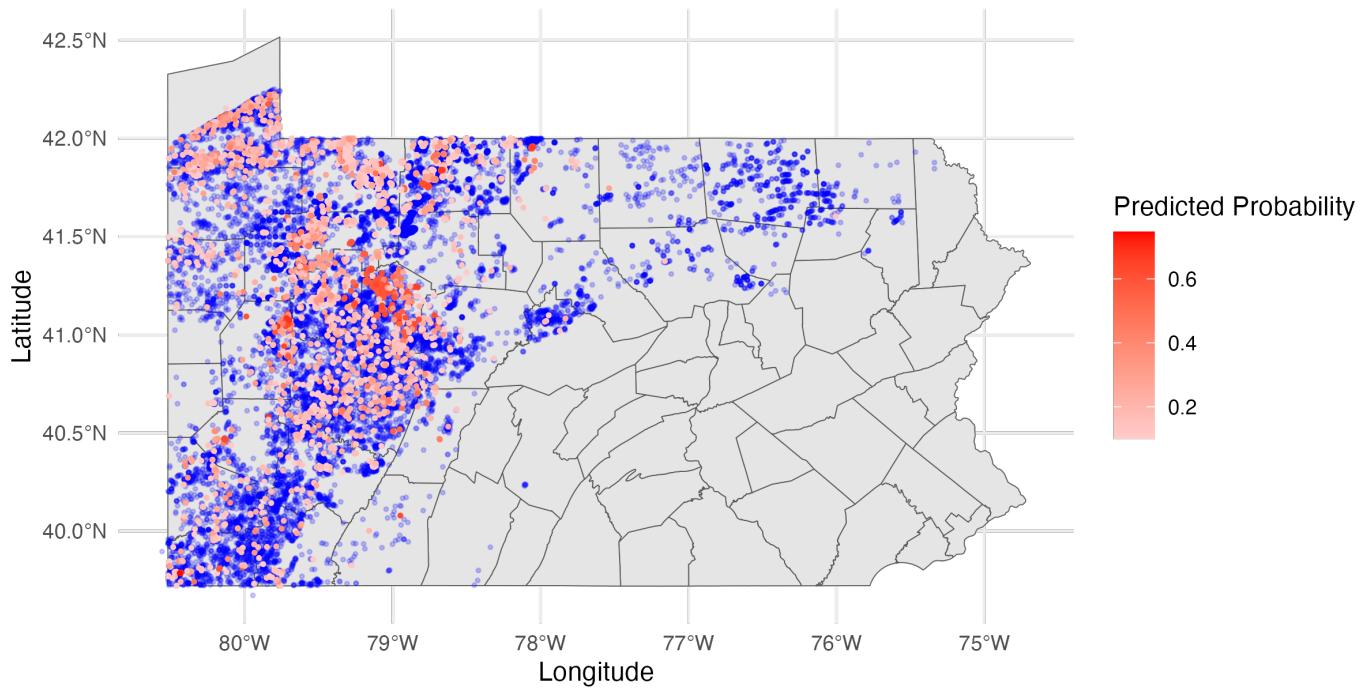
**Table 4.5:** Prediction based on Logit Results

Status 2024	Mean	Max	Std. Dev.	Future Expected Orphans
Idle	0.051	0.774	0.084	3238.508
Marginal	0.018	0.298	0.038	170.645
Active	0.001	0.081	0.003	7.056

*Notes:* Predicted probabilities between 0 and 1 calculated from the logit model for each well based on model characteristics.

ing a forward-looking measure of each well's vulnerability to abandonment. I present the distribution of predicted probabilities in ???. While the majority of wells have a low chance of abandonment, the probability is non-zero.

In Table 4.5 I summarize the logit results by my previous classification. Current high-producing wells have the lowest probability of abandonment, highlighting how it they are managed by the largest operators with little risk of bankruptcy. Idle wells have the highest probability as expected due to the persistence of low output and smaller operators. Overall, within the next five years the expected number of additional orphans added to the current legacy burden is over 3400.



**Figure 4.6:** Future Orphan Well Burden across Pennsylvania

#### 4.6.3 Spatial Aggregation

Figure 4.6 maps the spatial distribution of current “likely” orphans and expected orphans based on these predicted probabilities. Current orphan wells can be thought of as having a probability equal to one of remaining an orphan well, and all other unplugged wells have a range of probabilities.

As expected, the projected orphan-well burden is highest in counties with extensive drilling activity, simply reflecting the larger underlying stock of wells. This baseline pattern is not surprising: regions with dense historical development necessarily contain more wells at risk. However, the spatial concentration of the most likely future orphans are not uniformly distributed but rather clustered in specific parts of the conventional drilling region.

## 4.7 Discussion

### 4.7.1 Fiscal Alignment under Act 13

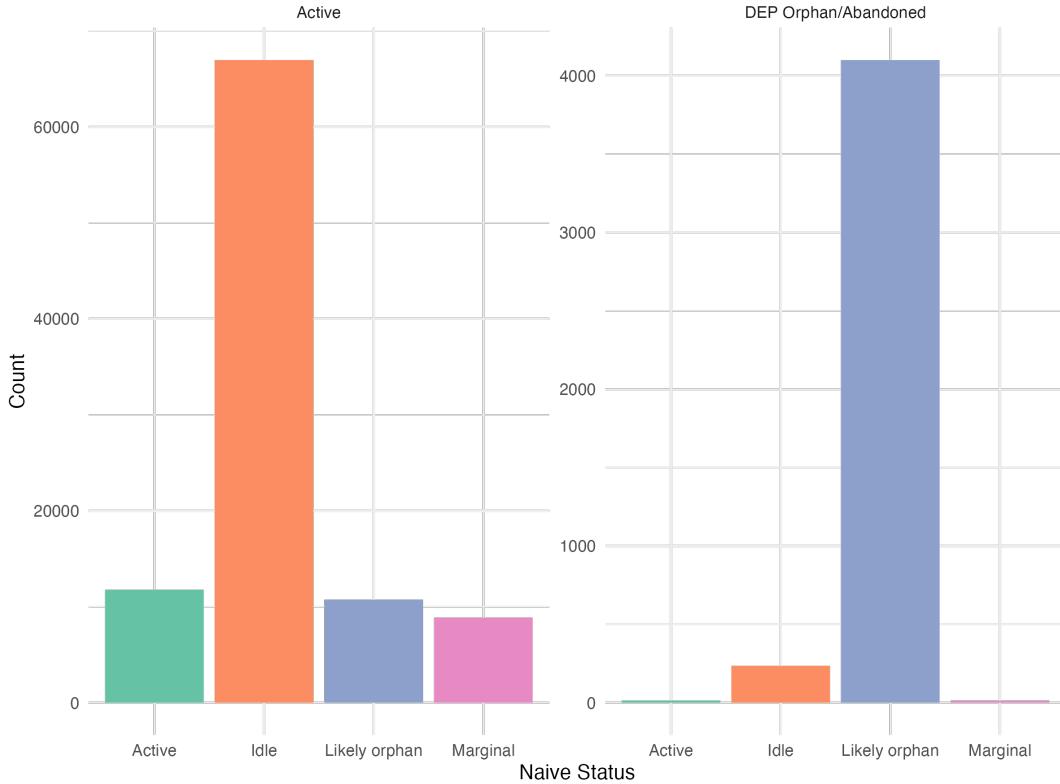
Although the impact fee was originally designed to address short-run externalities associated with unconventional drilling, comparing these revenues to the long-term orphan-well liabilities remains informative. The contrast highlights potential mismatches between where short-term revenues are generated and where long-term remediation burdens ultimately fall. The distribution of fee revenues is tied to the location and timing of active unconventional wells, with counties such as Washington, Susquehanna, Bradford, and Greene receiving the largest annual allocations. However, the predictive results show that the expected future orphan burden is concentrated in a completely different part of the state. Northwestern counties—McKean, Venango, Warren, Forest, and Clarion—harbor the oldest and least productive conventional wells, and therefore accumulate the highest predicted probabilities of abandonment in the coming years. Yet these counties receive little, if any, impact fee revenue because they host very few unconventional wells. The result is a policy mechanism that steers substantial funding toward counties with robust shale activity, where wells are newer, better capitalized, and at low risk of orphaning while the counties facing the highest remediation costs are disproportionately left without dedicated fiscal resources. Together, the predictive orphan-risk analysis and the geographic distribution of impact fee revenues suggest that Pennsylvania’s existing funding framework is ill-suited to address the long-term costs well abandonment. A dedicated policy mechanism for long-term environmental liabilities is needed to ensure adequate and sustainable funding for orphan-well remediation. Effective policy must align funding streams with the spatial and temporal distribution of those liabilities.

### 4.7.2 Comparison to DEP Inventory

Here I compare my results to the official DEP Inventory which contains data on all current and legacy wells known to the DEP. A comparison of the official reported status and the production-based naive classification reveals large inconsistencies in wells recorded as “Active” and how wells actually behave. A significant number of these wells exhibit production patterns far more consistent with idle or even orphan wells. Among wells recorded as Active, fewer than 12,000 also appear as Active under the naive production-based classification. In contrast, more than 66,000 DEP Active wells are classified as Idle, and an additional 10,700 are classified as Likely Orphan wells producing zero output over the past five years. Taken together, over four-fifths of wells labeled Active by DEP show little or no recent production, suggesting that the operational meaning of “active” in regulatory records diverges sharply from the economic reality of well behavior.

This mismatch most likely reflects structural features of Pennsylvania’s regulatory regime where operators face limited pressure to either produce from or properly decommission non-producing wells, and many wells remain in a nominally “active” status long after production has ceased.

If DEP records define tens of thousands of wells as Active despite negligible output, the formal inventory dramatically overstates the operational viability of the state’s well stock and understates both the scale and urgency of long-term liabilities. Figure 4.8 shows what the likely landscape of abandoned



**Figure 4.7:** Naive status distribution of DEP Inventory Categories

wells actually looks like compared to the DEP categories. The DEP abandoned and orphan lists remain small relative to the much larger pool of wells that meet behavioral criteria for abandonment but are not administratively recognized as such.

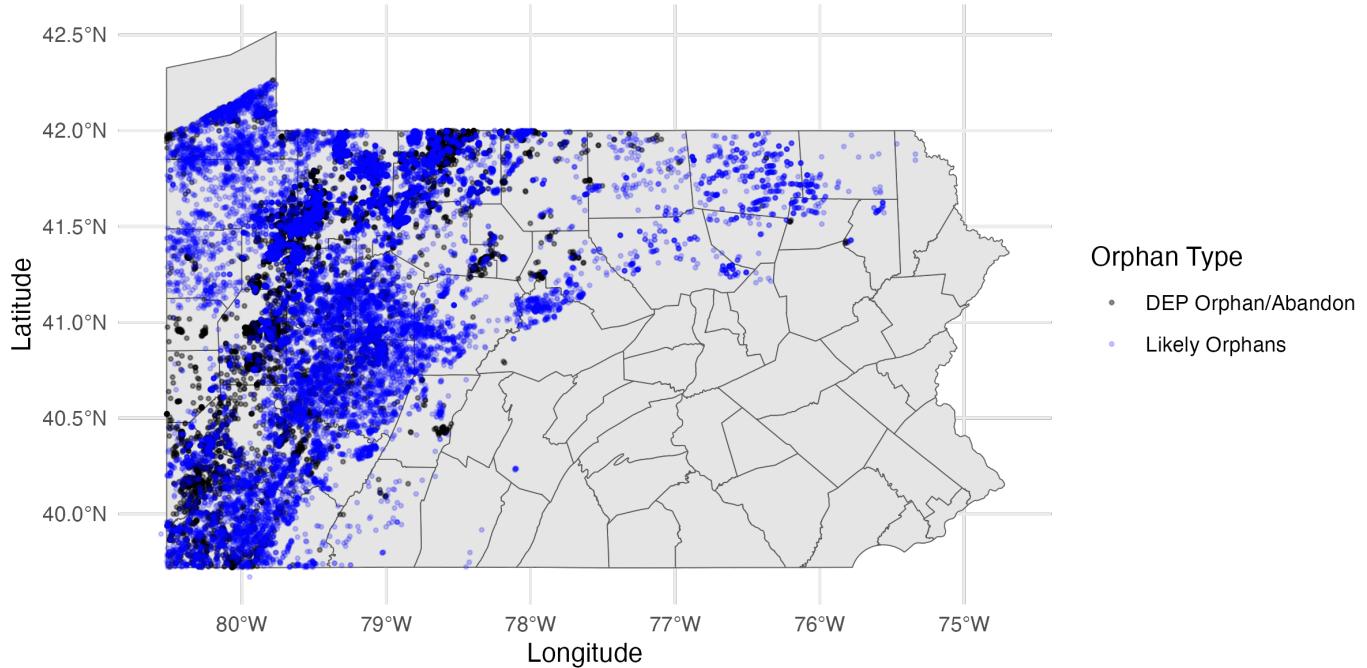
Using the predictive probabilities among these wells in the DEP “Active” category, the expected number of orphan wells that could ultimately be added to the burden within five years is between 10,000 and 15,000. The lower bound comes from summing the predictive probabilities across all wells, and the upper bound gives all wells classified as “likely orphan’s” a probability of one. Together, these comparisons underscore that Pennsylvania’s regulatory inventory substantially understates the scale of its non-producing well problem.

#### 4.7.3 Short and Long Run Forecasts of Well Abandonment

In addition to the baseline five year prediction window, I examine how abandonment risk evolves under alternative time horizons, namely one and ten years.

### 4.8 Conclusion

This paper develops a forward-looking assessment of Pennsylvania’s orphan well liabilities by linking detailed production histories, operator characteristics, and regulatory classifications to the probability that currently active or inactive wells will become orphaned in the near future. Although the predictive



**Figure 4.8:** DEP Orphan and Abandoned Wells vs. “Likely Orphan” Classification

model sharpens the identification of wells at highest risk of abandonment, the broader implications of the analysis are ultimately structural rather than statistical. The core patterns uncovered by the model align closely with intuitive features of well life cycles: long-idle, low-production, and aging conventional wells exhibit the highest abandonment risk, while recent unconventional wells operated by large firms rarely approach orphanhood in the short run. In this sense, sophisticated prediction validates that Pennsylvania’s abandoned well problem is driven not by failures among active, high-producing wells, but by the vast, persistent stock of legacy wells that have effectively ceased to be economically viable which are not recognized by the DEP. By quantifying the expected number of orphan wells embedded in the current well inventory, this paper highlights the extent to which Pennsylvania’s long-term environmental liabilities stem from wells that are, for all practical purposes, already orphaned but not administratively recognized as such.

The fiscal analysis further reveals a structural misalignment between the geography of future liabilities and the distribution of revenues under Act 13. Impact-fee collections are concentrated in counties

with ongoing unconventional development, while the burden of future orphaning lies predominantly in older conventional regions that receive little fee revenue. This divergence between short-run revenue flows and long-run cleanup costs implies that Pennsylvania's existing fiscal architecture internalizes immediate drilling externalities but leaves intertemporal environmental liabilities largely unfunded. Addressing this gap will require complementary policy mechanisms.

Taken together, the findings demonstrate that credible forecasts of orphan-well risk are feasible using naive classifications and predictive models, but the deeper value lies in demonstrating the scale and geography of a longstanding legacy problem. Predictive frameworks of this kind can help policymakers anticipate emerging liabilities, target resources effectively, and design fiscal institutions that better align revenue collection with long-term environmental responsibility.

# **Chapter 5**

# **Conclusion**

Fill in conclusion here.

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