Tolerance of the Side Effects? Hedonic Pricing Analysis of Housing in the Permian Basin

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Picture A: Landscape view across schoolyard with pumpjacks in background. Source: Google Map view of Denver City, TX downloaded July 13, 2023

Picture B: Aerial view of city and surrounding area with wellpad areas in white. Source: Google Map view of Denver City, TX downloaded July 13, 2023

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Executive Summary

While oil was first discovered in the Permian Basin in the early 1920s (Vertress, 2019), the most recent production boom began in 2010. Lasting now more than a dozen years, the boom has been driven by changes in production technology that allowed producers to apply unconventional oil and gas (UO&G) technology (horizontal drilling and hydraulic fracturing) with the layered geology of the Permian Basin (Maniloff & Mastromonaco, 2017; Popova, 2020; Popova & Long, 2021). In relative terms, the boom in the Permian, composed of parts of New Mexico (NM) and Texas (TX), represents one of the most cost-effective and productive oil fields in the world. The boom has generated significant in-migration, employment, earnings, and tax revenues. Currently, the oil and gas (O&G) industry constitutes an estimated 8% of U.S. GDP (Pricewaterhouse Coopers, 2021). For TX and NM, the O&G industry contributed 10.8% and 11.1% of each state's 2022 GDP, respectively, driven significantly by the Permian boom (Bureau of Economic Analysis, 2023). NM is highly reliant on the industry as it contributes approximately 35% of state budget revenue (NMOGA, 2021).

Played out over time, the policy context of a boom centers on balancing the benefits of increased earnings, employment, and public revenues against the environmental damages from UO&G development (Maniloff & Mastromonaco, 2017), and whether there is any localized "resource curse" attached to future economic development in the extractive region. As part of that larger context and given that housing markets aggregate and monetize the preferences of buyers and sellers, as well as capitalize present values, changes in housing prices due to UO&G development are important reflections of the community perceptions of these tradeoffs in benefits and damages (Krupnick & Egarthe, 2017).

The objective of this analysis is to examine whether and to what degree some of the effects of the boom, such as well drilling and associated environmental effects, are being capitalized into the regional housing market. To econometrically isolate such effects on housing values, while controlling for other factors, the hedonic pricing method (HPM) is employed. A sample of more than 6,000 individual residential properties are collected for a nine-month period in 2022-2023, drawn from both the 55 counties of the Permian, and a set of 18 control counties in eastern NM and western TX. Since both are sales price non-disclosure states, houses listed for sale on Zillow are webscraped to obtain estimated price and structural housing characteristics (e.g., bedrooms, bathrooms). Each residential property is geolocated and paired with location attributes (e.g., population density, public water availability, unemployment rates) from the Census Bureau and other governmental data sources. Spatial data is collected on environmental effects (air quality, and earthquakes) connected to the boom in unconventional (UO&G) development. This includes unique modeling results (Goodkind et al., 2023), to isolate both fine particulate matter ($PM_{2.5}$) concentrations, as well as the increment attributable to O&G production. Spatially detailed data on more than 220,000 (active) wells is obtained from both NM and TX and used to generate well count density measures for various buffers around each house. Lastly, the analysis is unique in treating the region wholistically (both NM and TX) with a carefully selected set of control counties.

From this initial analysis, key econometric findings from estimated hedonic price functions are:

- While there has been significant in-migration and positive earnings effects over the last decade in the Permian, with related housing market pressures (Collins, 2021), sampled homes in the Permian are listed 22-24% less on average than in control counties.
- Manufactured homes represent about only one in twenty of listings overall (and in each of the control and Permian counties samples). They are shown to be a significant negative determinant of house values; but this reduction in value is 45% in the control counties versus only 22% in the Permian.
- With respect to potential negative externalities on listed prices, results demonstrate that effects are either greatly reduced inside the Permian, relative to the control counties, or have no significant effect. The latter case includes the frequency of earthquakes.
- Evidence of how the Permian region may be *tolerating the side effects* of the UO&G boom is seen in the well density results. Overall sample results show that increased well density within 2 km of a house has a negative effect on the listed price, but the effect is greatly muted inside the Permian. For the control counties with an average of less than one well near each house, the negative effective is -0.82% for an additional well ($2,951 reduction evaluated at median price for sub-sample). In contrast, for the Permian counties with an average of about 15 wells near each house, the estimated effect of well density on the listed price is -0.12% for an additional well -$293 reduction evaluated at median price for sub-sample). When modeling the Permian counties sub-sample separately, results cannot reject the null hypothesis that well density has no effect on listed price.
- Using recent regional research (Goodkind et al., 2023) allows the unique ability to isolate the change in the air quality attributable to O&G. $PM_{2.5}$ concentrations in the region originating from all sources are found to be a statistically significant negative amenity for housing values in the Permian, with modest marginal effect. [The area is within attainment status for federal air quality standards for $PM_{2.5}$.] However, the change in air pollution ($\Delta PM_{2.5}$) *specifically attributable* to O&G production in the Permian is *not* shown to be a statistically significant determinant of housing values in the Permian.
- Controlling for homes within a public water service boundary (i.e., likely to be on piped water), results show this indicator variable to always be a significant positive determinant of listed price (e.g., 4.5-5% higher in the full sample, but roughly 3% in Permian counties versus 7% in control counties). Further results show that density of injection and disposal wells—of particular concern for water pollution risks with UO&G—is not a significant externality when controlling for whether a house is within an area with piped water (roughly 85% in either sample).

Econometric results investigating the residential housing market in the Permian are consistent with the argument that a region with significant prior exposure to conventional O&G development, and now highly dependent on UO&G production, may exhibit a tolerance of the side effects. The paper closes with a discussion of policy implications—e.g., public data availability (including housing sales price disclosure), environmental monitoring, legacy environmental costs, risks of a localized resource curse, and potential mitigation measures.

1. Introduction

> "It feels like this (ban) is just another chance for Santa Fe elites to push policy for political reasons, instead of looking for input from those living in that area."
>
> State Senator David Gallegos (R-District 41 [Eddy and Lea Counties]) (McKay, 2023)

Understanding trade-offs between environmental effects and income generation (including public revenue from royalties, leases, and taxes) in an oil and gas (O&G) production boom is complicated and made more so by differing regional perspectives. There is inherent complexity in weighing the costs and benefits of a boom (Covert & Sweeney, 2023). Such complexity is reflected in responses to recent regulatory action by the state of New Mexico (state capitol in Santa Fe) affecting the O&G leases so prevalent in southeastern NM (part of the Permian Basin). Driven by technological changes connected to hydraulic fracking, and massive capital investment into the region (Collins, 2021), O&G production has been booming in the Permian Basin for the last decade (Ball & Lowy, 2018; Popova & Long, 2021; Thompson, 2022).

On June 1st, 2023, NM State Lands Commissioner Stephanie Garcia Richard signed an executive order banning new O&G leases on state trust lands, within one mile of a school (McKay, 2023). Pertaining only to state lands (not federal, tribal, or private), the order was expected to affect more than 100 schools in NM's portion of the Permian. The order came with a directive to assess environmental compliance for existing O&G wells on state lands near schools. Through the commissioner, the order reflects concern by the State to protect against a presumed negative environmental externality—significant economic damages not accounted for in a transaction (e.g., an O&G lease). The expressed purpose was to "protect children's health" (McKay, 2023). Separate from concerns over broader climate damages from greenhouse gases, from both the production and consumption of O&G, such health damages from O&G extraction and transport are connected to air pollution emissions (e.g., Ozone and $PM_{2.5}$). Recently, Goodkind et al. (2023) estimated the monetary damages from $PM_{2.5}$ emissions by isolating emissions attributable to O&G production in the Permian. Such external health effects have been found elsewhere for fracking booms (see Collins, 2021). As noted by Covert and Sweeney (2023):

> There is now robust evidence of large negative externalities from fracking... These costs, most of which are local, must be evaluated against the (ideally local) benefits generated by fracking.

As elsewhere (e.g., Ericson et al., 2020), the juxtaposition of relative tradeoffs—financial vs. environmental—is clear in New Mexico. The moratorium was described as just the first step in reducing environmental impacts near schools. Extending concern from schools and children to where people live more generally, a spokesperson for the NM Environment Department concurrently said that current state rules on air pollution emissions (e.g., ozone precursors) from O&G required "enhanced monitoring around occupied dwellings." (McKay, 2023). [1] Such

[1] The benefit-cost tradeoffs play out spatially between buildings and the density and distribution of well drilling for hydraulic fracking. Spatial setbacks are a common regulatory tool for attempting to reduce exposure and mitigate some of the localized environmental effects of O&G development (air, water and noise pollution, industrial accidents etc.). They can be implemented for schools, residences, parks, protected sites etc. To wit, as the state of

concern came while O&G production was near record annual highs in the ongoing boom in the Permian Basin (McKay, 2023). As the state of NM moved forward with plans to transition to renewable energy resources,[2] the associated public revenues from royalties, leases and taxes on O&G extraction and production was estimated to account for roughly 40% of state public finance revenues (McKay, 2023).

Generally, the June 2023 NM new-lease moratorium near schools was supported by the environmental community and questioned by the O&G industry (McKay, 2023); the logic of the setback distance was questioned against potential loss of O&G revenues for the state (Editorial Board, Albuquerque Journal, 2023). As reflected in the epigraph, public sentiment in southeastern NM would not necessarily be supportive of additional environmental regulation of O&G activities in an extraction intensive region like the Permian. As noted in a recent review, there is accumulating evidence (e.g., Campbell et al., 2020) that communities deeply connected to O&G "tolerate the side effects" (i.e., negative externalities). As Collins (2021, p. 20) summarizes:

> [C]ommunities with a high economic reliance on oil and gas production tended to have a strong attachment to the industry, with many residents willing to accept a substantial degree of negative externalities in exchange for the economic benefits generated by oil and gas activity in the area – and often, for them personally or family and friends.

Against this context, with sometimes highly vocal public discourse, we explore an empirical question: How are environmental effects being capitalized (or not) into regional housing markets in the booming Permian Basin? Housing markets, both permanent and temporary, have been significantly impacted by the O&G production boom in the Permian (Collins, 2021). With a restricted focus on the market for more permanent dwellings, the objective of this study is to investigate the relative effects of economic and environmental factors on housing markets in the Permian Basin (southeastern NM and western Texas (TX)). Complicating our investigation is both NM and TX are real estate sales price non-disclosure states (i.e., not publicly available information). Using a unique data set of individual house values and characteristics, matched with a wide variety of geospatial data, we pursue this objective using the hedonic pricing method (HPM). Data is collected across the 55 counties defined as in the Permian Basin and a selected control set of 18 nearby regional counties outside the production basin. The HPM allows econometric decomposition of observed variation in house values to estimate the marginal implicit value of various environmental effects (e.g., seismic activity, well density and air pollution emissions).

NM announced their ban on new leases on state withing one mile of schools (McKay, 2023), the federal Department of Interior announced a withdrawal from O&G leasing of public lands within a 10-mile radius of Chaco Culture National Historic Park in New Mexico (U.S. Department of Interior, 2023). Standard O&G setbacks from buildings vary across states but tend to be 200-1000 ft (Ericson et al., 2020). In TX, OG setbacks are 200 ft, while in NM these are administered at the local or county level (Ericson et al., 2020). Ericson et al. (2020) examine the foregone revenues of resource unavailability of setbacks for recent CO proposals, they estimate that expanding from a 500 ft to a 2,500 ft O&G setback from buildings would generate $4.4B in revenue losses over 10 years in CO.

[2] NM's Energy Transition Act of 2019 sets renewable energy standards of 50% (80%) by 2030 (2040) for NM electricity providers (Senate Bill 489, 2019).

Preliminary econometric results are consistent with the argument that regions that are highly dependent on O&G production activities, develop or exhibit a tolerance of the side effects, i.e. no evidence of a significant negative effect in the Permian Basin is seen for earthquakes, well density, or the change in air pollution (i.e., $PM_{2.5}$) attributable to oil and gas production. This conclusion is stable across a variety of robustness checks.

2. Background Information

2.1. Background on the Oil and Gas Boom in the Permian Basin

Southeastern New Mexico and West Texas house the Permian Basin (“the basin”), a major oil and natural gas producing area encompassing over 81,000 square miles (The County Information Program, Texas Association of Counties, 2020; U.S. Census Bureau, 2021). The basin takes its name from the Permian geological era that occurred over 250 million years ago (Dancy, 2018). The area is currently the largest oil producing region in the U.S. (U.S. Energy Information Administration (EIA), 2023a). As of April 2022, the basin produced 43.6% of the nation’s crude oil and 16.7% of natural gas output (Federal Reserve Bank of Dallas, 2022). This starkly contrasts to 2008 levels when the Permian produced only 16.4% of the country’s oil and 7.1% of the natural gas (Gilmer & James, 2008). For comparison, in the June 2023 Energy Information Administration’s productivity report the Permian produces over 5 million barrels of oil (bbl) daily while the second highest U.S. basin, the Bakken Basin in Montana and North Dakota produces 1.2 million bbl daily (EIA, 2023b).

Oil was first discovered in the Permian in the early 1920s (Vertress, 2019). The most recent large production boom began roughly in 2010-2012. With consistent growth over more than a decade, the Permian is currently considered one of the most prolific unconventional oil and gas producing regions in the world (Popova & Long, 2021). While an umbrella term, we follow Maniloff and Mastromonaco (2017) in referring to *unconventional* oil and gas (UO&G) development as targeting oil and natural gas deposited in formations that require the use of horizontal drilling and hydraulic fracturing (or fracking) for profitable production.

The boom in UO&G production in the Permian (and elsewhere in the US) has been spurred by technological advances in horizontal drilling (including significant increases in number and length of the horizontal laterals),[3] cluster drilling (multiple wells at one pad), and hydraulic fracturing, combined with improved geologic understanding (subsurface delineation). Together these factors opened "economic extraction from low permeability reservoirs” (Popova & Long, 2021). Further, because of the underlying geologic structure, production in the basin lowers operational costs and allows for more efficient infrastructure as a single well can be used for oil and gas (Chevron, 2023). The basin contains three main smaller basins: the Midland, Central, and Delaware Basins which over time have developed many sedimentary layers (Popova, 2020). Further as noted by Popova and Long (2021) the basin is advantaged by "better access to oilfield services, and its proximity to U.S. Gulf Coast refineries and export facilities."

[3] Horizontal well length in the Permian averaged roughly 3,800 feet in 2010 and now averages over 10,000 feet (US Energy Information Administration, 2022).

As shown in Figures 1 and 2, natural gas production in the Permian has nearly quadrupled since 2010 (3.9x) while oil production has more than quadrupled (4.1x). Revenue has also grown over the course of the boom as shown in Figure 3. As of June 2021, the Midland and Delaware Basins combined for nearly 45,000 producing wells, of which over 80% use fracking (EIA, 2021).[4] Data collection for this study revealed more than 220,000 active wells across the Permian Basin (TX and NM). In 2022, the average breakeven price for creating a new well was $52 per barrel while the average oil trading price was $94.79 (Federal Reserve Bank of Dallas, 2022; EIA, 2023c). When the spot price exceeds the breakeven price businesses can make money (Domonoske, 2023), and it looks like there are significant reserves for this to continue. Looking forward, in 2018 the U.S. Geological Survey estimated at least 46.3 billion barrels of oil (bbl) and 281 trillion cubic feet (TCF) remained to be extracted (Gaswirth et al., 2018).

The boom has driven population increases in the region. In both New Mexico and Texas, the populations in the Permian Basin counties[5] has grown at least 15% since the 2010 census (Hedden, 2021; Texas Association of Counties, 2023; author's calculations). This increase in workers has also shifted demand and impacted housing availability (for both temporary and permanent supply) (Collins, 2021). For example, in 2019 the Midland, TX median house price was almost three times the median house price elsewhere in Texas, for reference this only falls behind Austin real estate prices (Hiller, 2019; Wethe et al., 2022). To help accommodate the influx of temporary workers, companies have created "man camps" which provide group housing for O&G workers (Adams-Heard, 2018). These camps add additional environmental pressures and have sewage problems due to inadequate dumping facilities (KRQE, 2019).

While the UO&G development boom has shifted housing demand in the Permian, it has also boosted earnings (see section 2.2), thus housing affordability in the region must be seen in context. First, much of this demand is absorbed by temporary housing supply (e.g., expansive RV and trailer lots; long-term motel room rentals, etc.) (see Collins, 2021). While not the focus of our analysis, this important slice of housing remains significantly under investigated.

Second, in terms of more permanent housing, using the Goldman Sachs Housing Affordability Index, where above 100 indicates the average family could afford a mortgage (given area incomes, house prices and mortgage rates), the region has generally remained *affordable*. More specifically, over the period from pre-boom to present (January 2009 to mid-2023) for the metro areas in our geographic focus, the Permian Counties and our 18 Control Counties, have had a housing affordability index that has remained significantly above 100, and well above the national average the entire duration; this holds true for all the TX metros in our counties (Lubbock, TX, Midlands, TX, Odessa, TX, Abilene, TX [in a control county]) while Las Cruces, NM [in a control county] more closely matches the national average over the period, using the Goldman Sachs Housing Affordability Index (see: Walker, 2021; Boschma et al., 2023).

2.2. Economic Impacts of Oil and Gas Booms

There are multiple mechanisms through which O&G development impacts local economies: wages, business incomes, jobs, and government revenue (Feyrer et al., 2017; Lee, 2015;

[4] For a visual representation of the increase in well density in the region see Popova and Long (2022).
[5] See Appendix A for the county list.

Maniloff & Mastromonaco, 2017; Sarkar, 2023; The Perryman Group, 2020; Wang, 2020). While we do not seek to capture every impact, we offer the following as an outline of impacts O&G booms have had historically and what is currently happening in the Permian Basin.

Nationwide, Feyrer et al. (2017) find that for every million dollars of extracted O&G, counties generate $66,000 in wages and 0.78 jobs. Feyrer et al. (2017) additionally measure spillover effects to neighboring counties and estimate neighboring counties within the same region as the new production get $243,000 in wages and 2.49 jobs. For all shale formations in the U.S., Lee (2015) estimates O&G employment grew 66% from 2009-2014. In line with this, Maniloff and Mastromonaco (2017) find wages in O&G counties are 7.5-28.6% higher than non-boom counties.

Pricewaterhouse Coopers (2021) summarize the impact of the O&G industry on the U.S. economy. They find the industry contributes $1.7 trillion in value added, equating to nearly 8% of U.S. GDP. State level, the Bureau of Economic Analysis finds the contribution from O&G to NM and TX's 2022 state GDP at 11.1 and 10.8%, respectively (Bureau of Economic Analysis, 2023). In 2021, the New Mexico Oil and Gas Association estimated the industry contributed $2.96 billion annually to the NM budget, or 35% (NMOGA, 2021). While in Texas the Perryman Group found the industry contributed $163.8 billion in gross product (10% of the TX economy in 2020).

Employment in O&G in the New Mexico boom is highly susceptible to price fluctuations of O&G (Moskowitz, 2022). NAICS 21 is the code used by the U.S. Bureau of Labor Statistics (U.S. BLS) to capture employees in the mining, quarrying, and oil and gas extraction sector (U.S. BLS, 2023). Moskowitz (2022) found that from 2014-2016 when oil prices dropped from over $100 per barrel to $40 per barrel, employment in NAICS 21 dropped from roughly 27,000 to 19,000 in NM. In 2015, Texas saw O&G jobs decrease 20% compared to 2014 numbers (Phillips, 2016). By 2019, the American Petroleum Institute estimated NM's share of direct and indirect employment from O&G to be 10.2% of state employment while in Texas the value is 13.9% (PricewaterhouseCoopers, 2021).

Wang (2020) assesses the employment and income effects of O&G within the Permian. Their models use 67 counties with those outside the Permian all bordering the basin. For employment levels their models show for every 1 million bbl there are 113-131 direct jobs and 54-70 indirect jobs. For income effects, their specifications estimate that for every 1 million bbls there are $462-$504/job of direct impacts and $284-$331/job of indirect impacts.

In addition to the positive impacts, some studies have found the economic boom is not sustainable long term or comes with a variety of external costs. Haggerty et al. (2014) find over a 30-year period in six western states (including NM) that the counties that participated the most in the 1980 conventional O&G boom had decreasing per capita income when they had a higher-than-average share of their income from O&G, after adjusting all dollar amounts to 2012. They also found crime rates increased and the percentage of the population with a college degree decreased as specialization in O&G increased (Haggerty et al., 2014). Collins (2021) found traffic fatalities in the Delaware Basin were more than double the statewide average per 100,000 people through 2019. However, Sarkar (2023) has mixed results finding no effect of well completion on accidents in the Permian Basin but well spudding increases accidents potentially due to different vehicles being required at different stages.[6] Traffic infrastructure deteriorates more quickly during a boom than it otherwise would under normal conditions, as roads and bridges are put under unplanned strains (Klasic et al., 2022), thus raising public infrastructure costs.

To measure the Permian's reliance on the O&G industry, we calculate the location quotient changes and wage growth for within the Permian Basin and the remainder of the state. Location quotients are used by the U.S. BLS to measure the concentration of employees in a specific sector compared to the national average (U.S. BLS, 2022). In 2009, the location quotient for NAICS 21 employees in NM was 4.45 and in 2022 grew to 6.87. This value means NM has 6.87 times the concentration of people in NAICS 21 than the U.S. average. For Texas over the same period the concentration decreased from 4.45 to 4.05.

Using the same data, Figures 4 and 5 present county level location quotients for 2009 and 2022, respectively. Zooming into the Permian Basin, the graphic shifts darker by 2022 (i.e., more O&G employment relative to the U.S.). From Table 1, panel A the average Permian location quotient for NAICS 21 is 26.48 in 2022 up from 19.77 in 2009; the concentration of employees in NAICS 21 in 2022 was ~26 times that of the U.S. average. In comparison, non-Permian counties have a location quotient of 8.05. These values also show the Permian was exposed to the O&G industry prior to the UO&G boom as they were already more heavily concentrated in O&G than the U.S.

Additionally, Table 1 panels B and C show the change in annual wages from 2009 to 2022, in constant dollars. The all-industry[7] annual wage change was $10,798 for Permian counties while counties outside the Permian had wage increases averaging $7,137. In comparison, the annual wage increase in NAICS 21 averaged $13,514 for within the Permian and $9,196 outside the basin. Further investigation is needed to compare the oil and gas industry to all other industries, exclusive of oil and gas, to evaluate if spillovers are happening in line with conclusions from Feyrer et al. (2017).

2.3. Background on Hedonic Pricing Method

A heterogenous good is denoted by its marked variation in quality and attributes, where we would expect the price to vary greatly as the quality and bundle of attributes varies. The hedonic pricing method (HPM) attempts to econometrically decompose this observed variation in price and isolate the effect of the contribution of one or more attributes of interest. HPM analyses have been commonly applied in environmental economics and other fields since the 1970s (Freeman et al., 2014; Taylor, 2017). While frequently applied to housing markets, HPM can be applied to any heterogeneous good.[8] There are numerous studies on the effects of air and water pollution and other environmental disamenities on residential housing markets. There are also prior applications investigating the effects of O&G production booms on nearby housing markets.

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[6] Well spudding is the beginning stages of well development when drilling starts (Kansas Geological Survey, 2001).

[7] All-industry wages include all NAICS codes.

[8] Non-housing related examples of HPM studies, with a focus on the southwestern US and Rocky Mountain region, include: Pitts et al. (2012) for the outfitter market for trout fishing; Fonner and Berrens (2014) for lift tickets for Alpine ski areas; and Little and Berrens (2008) for big game hunting permits.

Before reviewing these studies, background is provided on the practical issue of selecting a price or value variable, given its importance in this study and applied analyses generally.

2.3.a. Selection of the Price or Value Variable in an HPM Analysis

Table 2 describes a select range of different price or value measures commonly used in HPM studies. It focuses on sales prices or estimates of market values, which reflect the capitalized present value of the asset, rather than rental rates (also sometimes used in HPM studies). We use Table 2 to help describe the process for selecting a dependent variable in this study, given availability and constraints. We use vectors to indicate variable category, superscripts to denote the individual variable name, and subscripts to indicate geographic level. This selection of dependent variable also must be done in the context of connecting to data on the explanatory variables (as discussed in Tables 3-6). For example, if price/value information is aggregated at a given geographic unit (median price for a census tract), then explanatory variables can only be matched at that scale or larger.

The "gold standard" for selecting the dependent variable in building an HPM data set is a publicly available, observed sales price (P) for each individual house (h), P_h. Where available, this is always the preferred data, because it conveys an actual market transaction at the micro-level. From an expansive literature, select HPM examples include: Dealy et al. (2017); Joshi et al. (2020 and in press). Examples from nearby southwestern (AZ) and Rocky Mountain (CO) sales price disclosure states include Izon et al (2016), He et al. (2017), and Price et al. (2010).

However, the core issue for this investigation of housing in the Permian is that both NM and TX are sales price non-disclosure states.[9] Multiple listing service (MLS) data is proprietary to the private Realtor Board ® in any given location, and sales price information is not publicly available at county offices. Even if select released MLS information was obtained for a given city, county, or metropolitan area, it would likely not be matched across the two-state basin (with more than 50 applicable counties). For further discussion of the policy issues surrounding non-disclosure, see Berrens and McKee (2004). As a practical matter, investigating housing in the booming Permian Basin region requires pursuing alternatives to P_h.

While not commonly used, assessed values (V_h^A) can work in the absence of other alternatives, especially when working with a single county, and a known approximation to market rate (e.g., the assessor target staying within a certain percentage, e.g., 85%). Kalhour et al. (2018) provide an HPM example using (V_h^A) for studying wildfire effects in a single NM county. But as a first discarded alternative, assessed values, V_h^A, are generally too variable from market values, especially when assessment practices are not standardized across counties; this is in addition to what would be costly collection logistics for the 50 plus counties of the Permian Basin.

Next, there are various survey-based US Census Bureau products; these are not observed prices but rather respondent perception of the market value of their residence.[10] Further, these are

[9] In disclosure states local governments publicly share sales prices of homes. Additionally, non-disclosure states include Alaska, Montana, North Dakota, Idaho, Wyoming, Utah, Kansas, Louisiana, Mississippi, and some Missouri counties (Taylor, 2019).

[10] Census products follow a hierarchy defined as nation, regions, divisions, states, counties, census tracts, block groups, and census blocks ((U.S. Census Bureau, 2020). Census tracts are designed to be relatively unchanging to

either: (i) aggregated median values ($medV_g^S$) for a Census unit (e.g., tract or block group), which lack detailed housing characteristics, and cannot be matched with micro-level geospatial information; or (ii) if at the individual residence level (micro-level) (V_h^A), they lack an address and cannot be matched to other geospatial information. Their advantage is that they are standardized, and are available over time (e.g., over the length of the oil and gas production boom in the Permian Basin). In addition to being based on a measure of central tendency, their disadvantage is the lack of the ability to combine with micro-level data on the attributes (explanatory variables). There are a variety of NM and southwestern HPM examples, using these Census-based survey samples. An example of the use of $medV_g^S$ is found in Izon et al. (2010), while Hand et al. (2008) is example of the use of V_h^A. Extending such use out nationally, the use of $medV_g^S$ is found in Koirala et al. (2014), while Jafari et al. (2017) is an example of the use of V_h^A. Especially for the case of $medV_g^S$, at the census block group level, and extended over a long-time frame (e.g., before the production boom to the present), this represents one option for the Permian. But it lacks granular data.

Stepping back, our interest is in relating micro-level geospatial information on O&G production activities, and unique environmental quality variables (e.g., air pollution, seismic activity, etc.), with individual housing prices, while controlling for individual housing characteristics. Given all this, our data collection choice was to focus on two other alternatives: available list price information (P_h^{LIST}) and Zillow price estimates or "Zestimates" (P_h^Z).[11] Since list prices might be collected in a variety of ways, to be consistent we collect both pieces of information from the Zillow website. We only collect information on houses that are considered for sale, or on the market. Website information about a housing unit might contain both pieces, but list prices, P_h^{LIST}, are much more available than P_h^Z (i.e., larger available sample). To implement our objectives, we proceed with using both Zillow-collected variables as alternative estimates, in the absence of observed market prices for housing in the full Permian Basin.

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allow for comparisons over time and contain 1,200-8,000 people. Block groups are subdivisions of tracts and contain 600-3,000 people generally (U.S. Census Bureau, 2022).

[11] The Zestimate is described as generated from a proprietary model that accounts for public data, multiple listing service (MLS) data, user-submitted data, location information, and market trends (Zillow, 2023). To be clear there are other available micro-level property sales value estimate data, that appear to be similarly generated, which can be purchased from commercial vendors (e.g., CoreLogic). In a nondisclosure state, the issue becomes one of purchasing such data, or webscraping from Zillow or another real estate alternative (e.g., Realtor.com, Redfin, etc.). For a NM example using the purchased CoreLogic data, see Fitch et al. (2023), investigating housing effects of forest treatments. Notably, their only house characteristics are house size, age and lot size, and they attempt no HPM econometric analysis. Their geographic focus is for part of the East Mountain area in NM (i.e., Cedar Crest, Sandia Park and Tijeras), which contains approximately 10,000 people and perhaps 5,000 single family residences (see: https://www.city-data.com/neighborhood/East-Mountain-Coalition-Tijeras-NM.html). Fitch et al. (2023) list 10,925 sales values for 2010-2019, which would imply the average home selling more than twice on average in the decade (prior to any unusual Covid effects) or 1,092.5 sales annually (or 0.21 sales per capita annually). The entire Albuquerque metropolitan statistical area had 10,712 single family home sales in 2022, with a population of 915,927 (or about 0.011 sales per capita). There were roughly 5.34 million home sales in the US in 2019, with a population of approximately 330 million (or about 0.016 per capita sales annually). Given that there appear to be perhaps an order of magnitude higher count of sales values than there would have been actual transactions in study area for Fitch et al (2023), this seems to point that the CoreLogic data are more likely to be all point estimates of value in the period (e.g., any time a mortgage, re-mortgage, lien, foreclosure, ad valorem tax update, delinquency etc. occurs with an attached value estimate) rather than actual sales transaction values.

2.3.b. Review of HPM Studies Using Zillow Price Data

Zillow-collected price estimates were used in a variety of HPM studies over the last decade. Select studies are reviewed briefly below. In some cases, these studies used individual-level house list price (P_h^{LIST}) or Zestimate (P_h^Z) information, and others used a Zillow generated index (e.g., median for a census tract, similar to $medV_g^S$). As an early example of the latter, in an HPM application to O&G activity in the Barnett Shale area (west of Dallas/Ft Worth), Weber et al. (2016), used the median Zillow Home Value Index (ZHVI) for a census tract ($medV_{tract}^{ZHVI}$); they find that a $1 increase in the O&G tax base increases home values $0.15 (p. 610). Similarly, Fekrazad (2019) uses the V_{ZIP}^{ZHVI} at the zip code level and finds housing prices in areas with high risk of earthquakes have list prices 6% lower than those with low risk (p. 105).

For a brief window of several years (2016-2018), a number of HPMs leveraged access to individual house level list price (P_h^{LIST}) and Zestimates (P_h^Z) (with housing characteristics) under the Zillow Transaction and Assessment Dataset (ZTRAX); but the program ended enrollment in 2018 (Bechard, 2020; *Important Notice: ZTRAX Program Ending*, 2018; Nolte et al., 2021). For example, using ZTRAX, Dong and Lang (2022) used P_h to examine the impact of views of offshore wind energy on housing prices and find no impact of turbine visibility on houses. More recently, Christensen et al. (2023) use the ZTRAX and P_h to examine exposure to the Flint, Michigan water crisis to study impacts on the housing market; they find the total value of the impact on housing values to be $520 million.

In addition to micro-level Zillow data, aggregate data can also be obtained. Holt and Borsuk (2020) use Zillow data capturing the median price per square foot for a given (n) neighborhood ($medV_n^{SQFT}$) to value the impact of greenspaces on home values across 5,000 neighborhoods in 44 states. Their analysis finds parks and tree shade positively influence a neighborhood's median price per square foot with amenity value increasing with income (Holt & Borsuk, 2020). Kay et al. (2014) use HPM and Zillow data at the block group level, $medV_{bg}^S$, to show property values in New Jersey increase as proximity to transit stations decrease; simply, transit stations are an amenity rather than a disamenity for their selection of eight NJ train stations. An additional disamenity is increased distance from NYC stations.

Similar to this study, Sohn et al. (2020) collect individual house-level Zillow Zestimates (P_h^Z) and housing characteristics to measure the impact of housing proximity to retention and detention ponds in a Houston, TX neighborhood on P_h^Z. They find retention ponds positively impact housing values while detention ponds negatively impact values (Sohn et al., 2020). In discussing the quality of the Zestimate, Sohn et al. (2020) note previous research finds a median margin of error of 7.8% when compared with P_h (Hagerty, 2007, as cited in Sohn et al. 2020). And correlation with the Fiserv Case Shiller Weiss Index[12], a key housing index tracker, to be 0.9 (Mian & Sufi, 2009, as cited in Sohn et al. 2020).

[12] The Fiserv Case Shiller Weiss Indices were acquired by CoreLogic in 2013 and are currently known as the S&P CoreLogic /Case-Shiller Indices (Reuters Staff, 2013)

2.3.c. Review of Prior HPM Housing Studies on the Effects of Oil and Gas Booms

O&G development can bring positive effects to communities, with increases in local employment and earnings, but also a variety of negative consequences.

In addition to housing pressures, a variety of environmental and health consequences are connected to O&G booms. The O&G industry is a global industry, but the effects are felt at regional and local levels too (Adgate et al., 2014). Global considerations include climate change and global warming from the production, transport and especially the burning of fossils fuels (Adgate et al., 2014). Fracking produces carbon dioxide, methane, and other pollutants that contribute to global warming (Leahy, 2019). Regionally, fracking contributes to increases in particulate matter ($PM_{2.5}$ and PM_{10}), nitrogen oxides (NO_x), and other compounds that can lead to respiratory and cardiovascular issues (Fann et al., 2018; Gonzalez et al., 2022; Kerkvliet & Morton, 2017). Locally, the population is subject to increased traffic and potential water contamination (Adgate et al., 2014). At the well site level there is risk of chemical spills and other workplace hazards (Adgate et al., 2014). Finally, there is evidence that the common practice of reinjection of the produced water is connected to increased risk of seismic activity (e.g., Ellsworth, 2013; Folger and Tiemann, 2016; Horton, 2012; Rogers and Malkiel, 1978).

Given the complex mix of goods and bads that an O&G boom can bring, housing markets are useful indicators of community preferences, and how various effects get capitalized (Krupnick & Echarte, 2017). Unsurprisingly, there are a significant number of HPM studies on the effects of proximity or density (typically within 1 or 2 km) of O&G wells, with a focus on hydraulic fracking, shale gas, and UO&G boom areas (e.g., PA, CO). However, with the sales price non-disclosure status in both NM and TX, there is an absence of HPM studies in the Permian.

From the array of applications of HPM to O&G development more generally, results of selected studies are summarized in Table 7. Proximity to the nearest well is used across multiple studies under the framework that production creates negative externalities and subsequently negatively impacts housing values (Balthrop & Hawley, 2017; Gopalakrishnan & Klaiber, 2013; He et al., 2017; Lee & Whitacre, 2021; Muehlenbachs et al., 2015). Results of the studies are mixed suggesting variation across geographic areas. In addition to proximity of wells, seismic activity has been connected to injection wells and studies have consistently found negative impacts to home values with increased seismicity (Ferreira et al., 2018; Gibbons et al., 2021; Metz et al., 2017). While air pollution effects of O&G development have been identified as important (e.g., Kerkvliet and Morton, 2020), few studies use HPM connected to air quality changes specifically attributable to O&G. An exception, Boxall et al. (2005) use HPM to measure the impact of sour gas production on housing prices.

There are other important gaps in the HPM studies to date, including: the need for improved efforts for controlling the absence or presence of piped water, and the inability to match a house sale with information about any private lease royalties from attached mineral rights. However, various reviews of housing market effects (e.g., Krupnick and Echarte, 2017; and Loomis and Haefele, 2017; Kerkvliet and Morton, 2020) make clear that that there can be pathways for *both* positive and negative effects from UO&G development in a boom region. The challenge for HPM applications is to attempt to disentangle these effects.

2.4. Oil and Gas Production Impacts on Air Quality

The National Ambient Air Quality Standards (NAAQS) are set by the U.S. Environmental Protection Agency (EPA) under authority of the Clean Air Act (US EPA, 2014). The NAAQS cover six criteria pollutants including carbon monoxide, lead, nitrogen dioxide (NO_2), ozone, particle pollution ($PM_{2.5}$ and PM_{10}), and sulfur dioxide (SO_2) (US EPA, 2014). While ozone has health impacts, Goodkind et al. (2022) find ozone in NM is primarily driven by pollution in other states and would be difficult to for policy makers to enforce regulations outside of those already in place. $PM_{2.5}$ and its precursors (discussed below) can originate directly from O&G production and thus lie within the realm of control for both NM and TX regulators. Additionally, using data from Goodkind et al. (2023), allows for the isolation of air quality changes due to O&G production emissions.

Air pollution is a byproduct of O&G production. $PM_{2.5}$ is particulate matter with a diameter less than 2.5 micrometers ($PM_{2.5}$), measured as micrograms per cubic meter of air (µg/m^3) (New York Department of Health, 2018; US EPA, 2016). $PM_{2.5}$ can occur naturally (i.e. dust) or can be created through human activity as primary $PM_{2.5}$ or a precursor pollutant. Precursor pollutants of $PM_{2.5}$ include volatile organic compounds (VOCs), nitrogen oxides (NO_x), sulfur dioxide (SO_2), and ammonia (NH_3) (Close, 2021). $PM_{2.5}$ is regulated by the EPA under the Clean Air Act of 1970 (U.S. EPA, 2016). Areas are categorized as nonattainment when their $PM_{2.5}$ levels exceed 12 µg/m^3 over a three-year average (U.S. EPA, 2014). The primary NAAQS standards are designed to “provide public health protection” (U.S. EPA, 2014).

Previous studies find $PM_{2.5}$ causes significant health effects including low birth weight, asthma, and cardiovascular problems through mechanisms such as metabolic activation and inflammatory responses (Dockery et al., 1993; Dominici et al., 2006; Erfanian & Collins, 2020; Olstrup et al. 2022; Stafoggia et al., 2023; Wright et al., 2021). Dockery et al. (1993) provides one of the earliest papers on the connection between the size of particulate matter and associated health outcomes in the seminal “Harvard Six Cities Study.” According to Cao et al. (2013) additional work by Dockery (2006, as cited in Cao et al., 2013) and Chow et al. (2006, as cited in Cao et al., 2013) provided the foundation for adding $PM_{2.5}$ to the NAAQS rather than the existing “total suspended particulates” category the EPA was using.

Generally, particulate matter increases premature mortality risk across all populations (Zanobetti and Schwartz, 2009), however, Olstrup et al. (2022) finds elevated risk among the young (<14 years) and the elderly (65+). This is in line with the meta-analysis results from Fan et al. (2015) that found increased $PM_{2.5}$ levels correspond with increased emergency room visits and are elevated for children. Di et al. (2017) using Medicare data on an older population finds higher $PM_{2.5}$ levels increase risk of mortality. Lelieveld et al. (2015) find outdoor air pollution from $PM_{2.5}$ contributes to 3.3 million premature deaths globally with the potential for that value to double by 2050. Problematic to the study of air quality is the inherent mobility of pollutants. Dedoussi et al. (2020) measure air quality and the transportation across state lines and found 41% of premature mortality from a state’s emissions occur outside the state.

Further, air quality has been incorporated into HPM analyses since the 1970s when PM_{10} was a common measurement of air quality (Graves et al., 1988; Smith & Huang, 1995). Neill et al. (2007) found negative impacts of PM_{10} on Las Vegas housing prices. Singh et al. (2018) used

HPM with proximity to the Salton Sea and air quality as variables of interest. Using property transactions within 10 miles of the sea they find a \$595 decrease in value with each additional 1 km the property is closer to the sea and a 1% increase in PM_{10} decreased values by \$1,140. Nam et al. (2013) finds a 10% decrease in PM_{10} has a marginal willingness to pay of \$187-\$243 per month. Using $PM_{2.5}$ Nam et al. (2022) find a 1 unit increase in $PM_{2.5}$ decreases property values by 3.7%.

In connection to pollution from O&G activities, Loomis and Haefele (2017) estimate the health damages from fracking induced external damages from $PM_{2.5}$ and its precursors at over \$17.5 billion (2015\$) annually for 14 states in their study. However, this estimate excludes pollution from oil wells that are fracked making the estimate more of a lower bound. More recently, Buonocore et al. (2023) estimated the damages of the health impacts from 2016 O&G production; they find $PM_{2.5}$, NO_2, and ozone caused an estimated 7,500 premature deaths and 410,000 asthma exacerbations.

However, even given these high external costs over the period 1981 to 2016, the general overall trend in air pollution for $PM_{2.5}$ concentrations across the U.S has notably declined, although regional disparities remain (Colmer et al., 2020). This trend, however, has stagnated most recently due to wildfire-driven smoke (Burke et al., 2022). The latter point emphasizes consideration of sources on local effects (or receptors), because $PM_{2.5}$ is carried by prevailing wind patterns. There is recent literature investigating source-receptor models (Goodkind et al., 2019a, 2019b; Heo et al., 2017; Van Dingenen et al., 2018). Given that $PM_{2.5}$ in the Permian may be spread across the basin by diverse sources (e.g., Metropolitan areas in the southwestern US, wildfires etc.), parsing out the air quality changes attributable to O&G production in the Permian provides a way to measure consumer sentiment of those both inside and outside the basin regarding the environmental externalities they face.

This analysis is the first HPM to analyze the separate effects of general $PM_{2.5}$ concentrations (satellite sourced), and the separate air quality change in $PM_{2.5}$ attributable to O&G production activities. This isolation of the $PM_{2.5}$ attributable to O&G emissions originating from the Permian Basin combines the 2017 National Emissions Inventory and the InMAP Source-Receptor Matrix (ISRM) (Goodkind et al., 2023). Van Donkelaar et al. (2021) provide data on $PM_{2.5}$ from satellites, modeling, and ground level measurements. The National Emissions Inventory (NEI) is conducted every three years and reports emissions by industry either as point sources or nonpoint sources aggregated at the county level (U.S. EPA, 2022). The ISRM uses estimates of emissions from a source and estimates the corresponding change in $PM_{2.5}$ concentrations at receptor locations (Goodkind et al., 2019a, 2019b). The resulting dataset provides Census block group $PM_{2.5}$ concentrations (Q_{bg}^{PM}) and the $PM_{2.5}$ concentration change attributable to O&G activity ($Q_{bg}^{\Delta PM}$).

The satellite derived $PM_{2.5}$ concentration estimates fill the gap on air quality measurements, especially for rural areas of NM and TX where few monitors exist. Monitoring stations in both TX and NM are managed at the state level. The New Mexico Environment Department (NMED) currently has only two air quality monitors in the Permian Basin of which only the Hobbs monitor actively measures $PM_{2.5}$ (New Mexico Environment Department, 2023). The Texas Commission on Environmental Quality (TCEQ) manages eight monitoring stations in the

Permian Basin and only the Lubbock County and Odessa Gonzales monitors capture $PM_{2.5}$ (TCEQ, 2023).[13]

3. Conceptual Framework

For any heterogenous good, its observable quality attributes are varying. The hedonic pricing method (HPM) can be used to econometrically decompose observed price variation in any heterogeneous good, and thereby isolate the effects of any individual attribute. As focused on here, HPM has been widely applied to residential housing and property markets for almost five decades (Rosen 1974; Palmquist, 1989). The simplifying assumption is that a household (h) chooses a single residence. It is also assumed that the choice of residence is based on a bundle (or vector) of housing attributes (A), that households maximize their utility (U) and have limited income (M). Then, based on Rosen's (1974) model, and following closely Chakraborty et al. (2023), the household utility maximization problem over the choice of C and A can be given as.

$$\max_{C,A} U = f(C, A) \quad \text{subject to: } C + P(A) = M \tag{1}$$

Where C is a composite numeraire good (with a price of one by definition) and P is the price of a residential housing unit. To maintain a certain utility level ($\breve{U}$), the amount that household budgets for A will be $\Omega = M - P(A)$, and the problem becomes: $\breve{U} = f(M - \Omega, A)$; where Ω is the bid function for the household's maximum willingness to pay as a function of their target utility, income level, and varying housing attributes: $\Omega = \left(M, A, \breve{U}\right)$

Theoretically, the hedonic price function is defined as the envelope of a set of individual bid curves, and a set of supply-side offer curves, for housing units (see Taylor, 2017, p. 239). Applied HPM analyses typically start with regressing a selected price measure as a function of selected attributes (e.g., Michelson and Tully, 2018). The derivative of this hedonic price function with respect to any individual attribute is referred to as the marginal implicit price (MIP) of the attribute and represents the marginal willingness to pay for a unit change in the attribute. Further, if the market price for heterogeneous houses reflects the present value of the expected net benefit stream from this asset, and if variation in a given attribute is found to statistically significantly affect the price or value, then it is commonly said that the underlying attribute (e.g., distance to a highway) is being capitalized into the housing market, either positively or negatively.

For our HPM application we assume that price is a function of the residential housing unit's structural characteristics, location characteristics, and environmental quality characteristics. As noted by various sources, (e.g., Dinan and Miranowski, 1989; Taylor, 2017), an OLS linear regression may create bias in forcing linearly additive effects for any attribute. As commonly used in applied studies, the log-linear function can be given as follows:

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[13] The other six TX Permian Basin monitoring stations (with nearest city in parentheses) are: Lubbock County (Lubbock), Big Spring Midway (Midland), Midland Avalon Drive (Midland), Goldsmith Street (Odessa), Odessa Westmark Street (Odessa), Odessa-Hays Elementary School (Odessa), Odessa Gonzales (Odessa), Abilene Industrial Boulevard (Abilene) (TCEQ, 2023).

$$\ln(P) = \delta + \alpha S + \beta L + \lambda Q + \varepsilon \tag{2}$$

Where $\ln(P)$ is the natural log of the price of the residential housing unit in dollars; S is a vector of structural housing unit characteristics (e.g., age, size, number of rooms) $S = \{s^1, s^2, \dots s^i, \dots s^n\}$; L is a vector of location characteristics $L = \{l^1, l^2, \dots l^i, \dots l^n\}$ (e.g., population density, racial makeup, or rural/urban status); Q is a vector of environmental quality characteristics $Q = \{q^1, q^2, \dots q^i, \dots q^n\}$; ε is the mean zero error term; δ is the intercept, and α, β, and λ are the corresponding conformable vectors of estimable coefficients.

To extend the price function, in equation (2), to our context and the focus on the Permian Basin, and the effects of O&G production activities, we isolate O&G well measures from other locational characteristics as the vector $W = \{w^1, w^2, \dots w^i, \dots w^n\}$. This might be a scalar, but could include various types of well counts or measures within a location, thus γ is a conformable vector of estimable coefficients, as shown below:

$$\ln(P) = \delta + \alpha S + \beta L + \lambda Q + \gamma W + \varepsilon \tag{3}$$

Given the log-linear price function, in equation (3), the marginal implicit price, for any individual attribute, say q^i is:

$$\frac{\partial P}{\partial q^i} = \lambda^i \cdot P \tag{4}$$

The estimated value quantifies the marginal implicit price of a change in the attribute. Further, for the log-linear function, $100 \times \lambda^i$ can be interpreted as the percentage change in housing value given a one-unit change in the corresponding attribute.

Next, we transition to describing the data used in estimating the semi-log hedonic price function, in equation (3), and calculating MIPs, in equation (4). Note that if we subscripted the unit of observations in equation (3), ideally as much information as possible will be at the micro-level of the individual house h (e.g., P_h, and S_h^1, S_h^2, etc.). However, available information for individual attributes may vary in spatial definition. For example, there may be variation in locational characteristics at, say, the census tract or county level, and variation in the environmental quality characteristics (e.g., distance or density). In all cases, we have endeavored to use the smallest unit of available information.

4. Data Collection

Data is collected at multiple geographic levels (county, block group, and the house or dwelling unit) and comes from a variety of sources. Using address information, each house is geo-referenced and then connected to a variety of geospatial information, at varying scales. Using the generic price function (equation 3), data is categorized by the vector capturing the variable. Variables are both named (in all caps) and given a shorter notation, which follows X_{geo}^{VAR} where *X* is the referenced vector, *VAR* represents the variable, and *geo* is the geographical level the variable is measured or collected at. In this section, we briefly describe the data, while more detailed information on collection, any transformation and units, etc. is provided in Tables 3-6 and 8. Table 8 provides our two alternative dependent variables (ln P_h^{LIST} and ln P_h^{Z}); Table 3 provides the structural (S) housing characteristics; Table 4 provides the locational (L) characteristics; Table 5 provides the select environmental quality (Q) variables); and Table 6 provides the well (W) characteristics.

Observations on houses are limited to those listed for sale on Zillow in the roughly nine-month period between 21 September 2022 and 31 May 2023. Each housing unit is first webscraped using Webscraper.io, a freely accessible tool, which pulls publicly available information from internet websites in bulk and exports chosen information into tabular format (*Webscraper.io*, 2023). Applying the webscraping tool used on Zillow data captures the list price (P_h^{LIST}), the Zillow Zestimate (P_h^{Z}), an address, and a select set of structural characteristics (S). The properties used in the analysis were categorized as "for sale" on Zillow and filtered to have at least one bedroom and one bathroom.

One limitation of this process is not all characteristics of each unit are scraped without error each time. The tool relies on the information being in the same section of the webpage each use and if the information is not there the scraper returns null values. Or if information shifts to another portion of the page whatever is in the original location is pulled. Thus, while we collected a wide variety of housing characteristics, given missing data, co-linearity, etc., Table 3 provides a parsimonious set. This is similar to what is provided in Tables 4, 5, and 6.

Additionally, due to the sales price non-disclosure issue discussed above, we emphasize that P_h^{LIST} and P_h^{Z} are not values of transactions that have occurred. P_h^{LIST} is chosen between realtors and sellers while P_h^{Z} is calculated using a proprietary formula that incorporates information from the Multiple Listing Service (MLS), public information, and Zillow users (Zillow, 2023). P_h^{Z} is only calculated when an area has enough market activity to lead to valid valuation calculations, which tends to be rarer in many rural areas in the Permian Basin. To give some sense of accuracy, a sale-to-list-price ratio captures how far the sale price is from the listed price. From September 2022-April 2023 NM averaged a sale-to-list-price ratio of 98.3% while TX averaged 97.4% (Redfin, 2023a, 2023b). Given these values, on average, P_h^{LIST} is slightly higher than P_h so we should view P_h^{LIST} as an upward bound on P_h. Where both observations are available for a housing unit, the correlation between P_h^{LIST} and P_h is 0.99 in our data.

After webscraping housing units, each unit is geolocated using ArcMap to obtain precise latitudes and longitudes. A map of all the houses with a list price (LISTPRICE) is shown in Figure 6 and the subset of those with a ZESTIMATE are in Figure 7. Houses with an undisclosed address are assigned to the city center of the given city. This imputation was applied to 0.3% of the data (19 of 6,808 houses). Using map layers for each variable we match locational (L), environmental (Q), and well data (W) to the housing unit. All specifications use the natural log of the dependent variable (ln P_h^{LIST} or ln P_h^{Z}) to decrease the skewness of the variable.

Our final full dataset includes 6,808 homes with P_h^{LIST} and 2,956 homes with P_h^{Z}. It is important to note however that in arriving at the final usable econometric samples, not all housing units have each variable, so some observations are excluded based on which variables are included in each specification.

4.1. Structural Characteristics

Structural characteristics collected via webscraping include: the number of bedrooms (S_h^{BED}), bathrooms (S_h^{BATH}), the house's square feet (S_h^{SQFT}), house type (S_h^{MANU}), age (S_h^{AGE}), central air conditioning (S_h^{AC}), garages ($S_h^{MULTI-GAR}$), and property lot size (S_h^{LOT}). Due to high collinearity between variables not all can be used together. $S_h^{MULTI-GAR}$ indicates whether the housing unit has multiple garages (1 = yes, 0 otherwise). Manufactured homes are often relatively common in boom areas, and we control for here. S_h^{MANU} is binary variable determined by the Zillow listing representing whether a home is a manufactured home (yes = 1, 0 otherwise). All structural variables are described in further detail in Table 3.

4.2. Location Characteristics

In addition to individual housing data, local demographic and economic characteristics provide information about who lives in the area and what their job prospects may be. While we cannot match individual characteristics of homeowners to each house, we can use the geocoded housing units to attach census data at varying levels to each property.

The most recent pre-pandemic 5-year American Community Survey (ACS) Data (2015-2019) is used at the block group level (b) for the percentage of the population who are white ($L_b^{PCT-WHITE}$), the median household income ($L_b^{MED-HINC}$), and the population density per square kilometer ($L_b^{POP-DENS}$). Block groups are the smallest level of detail for these variables without losing observations.

Unemployment data at the census block group level is unavailable in the 5-year ACS data. Instead, to account for the labor market conditions during the period the housing units are listed, unemployment rates are used from each state's respective employment agency (New Mexico Workforce Connection, 2023; Texas Laborforce Commission, 2023). Local Area Unemployment Statistics (LAUS) are obtained at the county level and averaged over March 2022-February 2023 to calculate L_c^{AVG-UE}. The data is the most up-to-date source that covers the area at the same general time the houses were for sale. Each county has a percentage of people unemployed which helps reflect conditions of the local economy.

Housing prices and their associated water source have been shown to be susceptible to impacts from O&G production activity, including in areas of hydraulic fracking booms (Balthrop & Hawley, 2017; Gopalakrishnan & Klaiber, 2013; Mothorpe & Wyman, 2021; Muehlenbachs et al., 2012, 2015). Through the hydraulic fracturing process water is injected into the well site to extract more gas, which potentially contaminates the water source for a house in the local area (Hill & Ma, 2017). While we do not have standardized, geographically dense water quality measures across the region, we do have data on O&G injection wells (discussed below).[14] Further, the one standardized water measure is whether a house is on a public system, and thus

[14] While multiple studies find water contamination in the Permian Basin, Hildenbrand et al. (2016) outline the complications associated with identifying UO&G as the cause of the contaminants (Backstrom, 2019; Rodriguez et al., 2020). Limitations include but aren't restricted to a lack of baseline measurements prior to the UO&G boom and the confounding exposure to conventional O&G for years.

subject to state and federal drinking water standards.[15] L_h^{PW} represents whether a house is on public water or not based on shapefiles of each state's public water areas from the Texas Water Development Board and the Office of the State Engineer (NM) (Office of the State Engineer, 2022; Texas Water Development Board, 2023). Homes outside public water service boundaries are on water systems not managed by a public agency and are assumed to have less monitoring and potentially be at higher risk for pollutants due to fracking. A map of the public water systems in both states is shown in Figure 8.

As noted earlier, a set of control counties were selected using the process outlined in Appendix A. There are 55 Permian Basin counties and 18 counties in the control set. In creating the controls, we sought counties that differ greatly (i.e., more than an order of magnitude), on average, from Permian counties in their exposure to O&G production but were similar on average statistically for a set of socio-economic/demographic characteristics. $L_{cty}^{PERMIAN}$ indicates the county is in the Permian Basin as defined by the Dallas Federal Reserve (Federal Reserve Bank of Dallas, n.d.).

4.3. O&G Well Variables

A focus of this HPM analysis is on the collection of well data. Of note there are both conventional and unconventional oil and gas wells active in the Permian; but the supermajority (>80%) are for UO&G. So, while the region is predominately characterized by UO&G, we make no distinction in our well data collection. While this was a pragmatic research choice, this is not likely to be a difference parsed by the housing market. Further, individual well *production* amounts are proprietary knowledge that are not publicly accessible, except at aggregated county level production amounts.[16] However, detailed, geo-referenced well information is available. NM maintains a database of all wells and well types through the NM Oil and Gas Division's Geospatial Hub (Livengood, 2023). The TX database is maintained by the Railroad Commission of Texas (Railroad Commission of Texas, 2021). Each state provides maps of individual geolocated well locations and well types. Importantly, all wells included in the study are *active* wells. In addition to leaving out inactive wells, this selection distinguishes the analysis from studies (e.g., He et al., 2017) that are based on well permit data (where many permitted sites might never be drilled), and subject to criticism (e.g., Kerkvliet and Morton, 2020). Information was collected on a wide variety of wells (e.g., seven types in NM and 85 types in TX), and then collapsed into two exclusive sets: (i) injection and disposal wells; (ii) oil and gas wells; and then combined into (iii) the total active wells. Table 6 contains more detail on the creation of the variables.

Like Balthrop and Hawley (2017), Lee and Whitacre (2021), we focus on the density of wells near a house as an exposure to O&G production, rather than, say, distance to the nearest well. Using buffers of 0.5 km, 1 km, 2 km, 5 km, and 10 km around the housing unit, wells of each type are counted within each ring. Figure 9 shows an example of how well counts are generated. Figure 10 shows the locations of oil and gas wells within the selection region or near the border

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[15] The Safe Drinking Water Act managed by the U. S. Environmental Protection Agency (EPA) sets drinking water quality limits on over 90 contaminants including both chemical and microbial (U.S. EPA, 2015).
[16] These aggregated county totals were only used in this analysis in helping select the set of control counties relative the Permian Basin counties (see Appendix A).

in case homes were near county borders. Figure 11 shows the injection and disposal wells. Figure 12 shows the wells over a magnified area in the basin. Consistent with prior HPM studies on the effects of UO&G development, the econometric analysis focuses on well density measures within either 1 km (0.62 mile) or 2 km (1.24 miles) of a house.

4.4. Environmental Effects Variables

A boom in unconventional O&G development (UO&G)—horizontal and hydraulic fracking—brings with it a density of development activities, and associated concerns with environmental externalities (e.g., pollution and emission, industrial hazards etc.). Production activity can impact the local environment through multiple pathways but can often be concentrated in area or co-linear. This analysis focuses on: (i) seismic activity; and (ii) air quality measures.

Human-induced increases in seismic activity have been documented for areas exposed to UO&G activity (Ellsworth, 2013; Folger & Tiemann, 2016; Foulger et al., 2018), including in the Permian Basin (Skoumal & Trugman, 2021; van der Elst et al., 2013). Following Metz et al. (2017) for their HPM analysis in Oklahoma, two earthquake variables are specified for capturing the presence of seismic activity Q_h^{SA3} and Q_h^{SA1} around a home. Q_h^{SA3} indicates whether an earthquake above 3.0 on the Richter scale occurred within 10 km of the property from January 1, 2010 to April 4, 2023. Q_h^{SA1} indicates whether 50 earthquakes above 1.0 on the Richter scale occurred within 10 km of the property over the same period. Additionally, variables measuring the quantity of earthquakes over this same period over magnitude 1 and over magnitude 3 around a home were also created and are shown in Figure 13.

$PM_{2.5}$ represents a critical local air pollution measure due to the associated health impacts outlined in section 2.4. $PM_{2.5}$ can have a wide variety of sources, including being blown into a region from distant activities (urban centers, wildfires, etc.). A unique feature of this study is the ability to distinguish between overall $PM_{2.5}$ concentrations and the $PM_{2.5}$ concentration changes due to oil and gas production in the Permian Basin. With respect to the latter, the air quality of the region is susceptible to environmental toxins during the extraction and transportation process associated with O&G activities. $PM_{2.5}$ concentrations (Q_{bg}^{PM}) and $PM_{2.5}$ concentration changes due to oil and gas ($Q_{bg}^{\Delta PM}$) were collected from datasets from van Donkelaar et al. (2021) and analysis by Goodkind et al. (2023) at the census block group level. Additional information on Q_{bg}^{PM} and $Q_{bg}^{\Delta PM}$ can be found in Table 5. Figures 14 (general $PM_{2.5}$ concentrations) and 15 ($PM_{2.5}$ concentrations changes attributable to O&G production) show the air quality variables spatially.

4.5. Summary Statistics

Tables 9-13 show the mean, median and standard deviation for each variable broken down by variable category (P, S, L, Q, and W), and separated out for Permian counties, control counties and the combined values. As shown in Table 9, for the price variables the control group has significantly higher list price (P_h^{LIST}) and Zestimate (P_h^Z) values than the Permian. The median value for a Permian home has a P_h^{LIST} of \$244,900 while the median value for a home in the control group is \$359,900 (46% higher); the same difference in medians for the Zestimate (P_h^Z) is \$232,197 to 3\$63,050 (56% higher).

In Table 10, number of bedrooms (S_h^{BED}) and square footage of the home (S_h^{SQFT}) have similar values between the two groups with a combined average of 2,122 square feet and 2.3 bedrooms. Roughly 5% of both samples are manufactured homes. The Permian counties, perhaps surprisingly, represent an older housing stock. The median age (AGE) is 39 years old overall, with the median age of homes in the Permian at 43 years versus 28 years in the control counties. The median lot size, S_h^{LOT}, is 0.24 acres overall (0.22 in the Permian versus 0.32 in the control group), with vary large variation in this measure (for both groups), as select residential properties are quite large.

Table 11 shows most of the homes are in urban areas as defined by the census (towns or cities of more than 5,000 people). The sample is primarily composed of properties within TX (more than 75% overall, and more than 80% of Permian houses are in TX counties). The median distance to a highway or principal arterial road (L_h^{DIST}) is shorter in the Permian sample (0.75 km versus 1.25 km), which is in line with having more homes in the URBAN category. Median household income (MED-HINC) is higher in the Permian block groups (median value of $71K versus $65K), but per capita income (PC-INC) is similar between the Permian and the control. The average unemployment rate in the county corresponding to a home (L_c^{AVG-UE}) is higher in the control counties (median value of 5.1%) versus the Permian counties (median value of 4.5%). Most homes are within the boundaries of public water systems, with 84% in the Permian counties and 87% in the set of control counties.

Counts of active well data in Table 12 demonstrate the whole region is exposed to active wells but the Permian counties counts are substantially higher on average than in control county group (almost 16 times more total wells per house on average). Well densities are also shown to be highly variable around a home, with the standard deviations at least twice as large as the mean, in all comparisons in Table 12. The medians for well counts are all zero which means that more than half of houses in the sample do not have any wells within 2 km. When there are active wells next to a home in the Permian, there tends to be a lot of them (i.e., more than a dozen). But active wells in the control counties are a rarity (averaging less than one within 2 km of a home). In relative terms, the average Permian home has 1.71 injection and disposal wells (INJ&DISP-2KM), 12.94 O&G wells (O&G-2KM), and 14.65 total wells (ALLWELLS-2KM) within a radius of 2 km. In contrast, the control homes average 0.05 INJ&DISP-2KM, 0.88 O&G-2KM, and 0.93 ALLWELLS-2KM. It is important to note in our well data that O&G is being used generally here (we are not distinguishing conventional oil and gas wells from unconventional oil and gas wells, which constitute a supermajority of all wells).

Finally, because Table 12 is focused on well density around homes, it does not provide the total volume of all active wells in the region (e.g., broken out by type, and by Permian versus the control counties group). For the 55 counties of the Permian Basin, with 81,742 square miles of land, we identified 221,964 active wells (with 21,466 injection and disposal wells (9.7%) and 200,498 oil and gas wells (90.3%)), or 2.72 active well per square mile, on average. In contrast, for the 18 control counties, with 27,762 square miles of land, we identified 2,057 active wells (with 83 injection and disposal wells (4.0%) and 1,974 oil and gas wells (96.0%)), or 0.07 active wells per square mile, on average.

Regarding environmental variables, Table 13 captures seismic activity and air quality measures. The concern with earthquakes is that UO&G and in particular disposal wells will cause human-induced changes in seismic activity (Metz et al., 2017). As noted by Metz et al. (2017, p. 86): "Given consumer theory, and assuming households are mobile, one would expect that homes in 'high risk areas' (those that have witnessed more earthquakes) would be priced lower than equivalent homes in lower-risk areas."; i.e., seismic activity in a high-risk area is expected to be a negative externality.

As shown, exposure to seismic activity for a home is much larger in the Permian than in the control county group, but there is still large variation across homes in the Permian sample. For example, for the quantity or count of earthquakes above magnitude 1.0 within 10 km of a home (Q_h^{EQ1}) over 2010-2013, there is a mean of 13.3 with a relatively large standard deviation of 31.5 in the Permian, compared to a mean of 0.03 earthquakes with a standard deviation of 0.2 in the control counties group. Turning to the quantity or count over the boom period of magnitude 3.0 or greater earthquakes (Q_h^{EQ3}), where people really start to feel effects, the mean for a home in the Permian is 1.4 (with a large standard deviation of 3.6), versus a mean of near zero in the control counties group. For comparison, Metz et al. (2017) found significant negative effects in an Oklahoma HPM study from UO&G development, where their measure of a seismically active region was 50 or more earthquakes of magnitude >1.0 within the period 2010-2015. As noted by others (e.g., Collins, 2021) to date the Permian in general does not appear to have experienced the same level of seismic activity (e.g., relative to Oklahoma).

Turning to the air pollution variables in Table 13, as based on satellite data and matched to a census block group, the variable PM2.5 (Q_b^{PM}) is highly similar between the control sample and the Permian sample; with means and medians the same concentration of 5.9 µg/m^3 (both areas are well within the NAAQS standard of 12 µg/m^3).Where the two sample areas differ is in the change in $PM_{2.5}$ in a given block group attributable to oil and gas production ($Q_b^{\Delta PM}$); for the Permian sample, this average was 2.2 µg/m^3(with a large standard deviation of 3.27) versus 0.24 µg/m^3 (with much smaller standard deviation of 0.22). So, while the increment in 2017 due to oil and gas production was not enough alone to push areas into nonattainment, it did create significant change that was highly variable across block groups. Finally, it is important to note that $Q_b^{\Delta PM}$ does not indicate whether the change is due to conventional O&G or UO&G.

5. Econometric Modeling Approach

Given the study objectives and available data, the econometric modeling approach follows equation (5) below in implementing log-linear hedonic price functions for various model specifications. Given the much larger sample available, the focus is on using the list price variable, P_h^{LIST}. Given that price estimates were collected over a nearly 9-month period (with significant change in mortgage rates over the period), monthly fixed effects, ϕ_t, are included in all models. Further, robust standard errors are used, clustered at the census block group, b, level.

Our base model specifications include a set of housing and structural (S) characteristics, and locational (L) characteristics that initially performed well and avoided multicollinearity concerns (as checked with variance inflation factors [VIFs]). This base model was implemented with and without inclusion of a dummy indicator variable ($L_c^{PERMIAN}$) of whether a housing unit was located in one of Permian counties or one of the selected control counties:

$$\ln P_{hbct}^{LIST} = \delta + \alpha_1 S_h^{SQFT} + \alpha_2 S_h^{MANU} + \alpha_3 S_h^{AGE} + \alpha_4 S_h^{LOT} + \alpha_5 S_h^{BED} + \alpha_6 S_h^{MULTI-GAR} + \alpha_7 S_h^{AC} + \beta_1 L_h^{DIST} + \beta_2 L_b^{MED-HINC} + \beta_3 L_b^{PCT-WHITE} + \beta_4 L_b^{POP-DENS} + \beta_5 L_c^{AVG-UE} + \beta_6 L_h^{PW} + \beta_7 L_c^{PERMIAN} + \phi_t + \epsilon_{hbct} \tag{5}$$

Where h indicates the individual house, in block group b, in county c, at time t. All subsequent models include the same variables for vector S and L, except for $L_c^{PERMIAN}$, which is the indicator variable that is added and removed in various specifications.

To evaluate the effects of wells and earthquakes, we added model specifications with a single variable of interest (equation (6)), and then with an interaction with $L_c^{PERMIAN}$ (equation (7)). This is shown for the example of all active wells within 2 km of a house (Table 14, model 3):

$$\ln P_{hbct}^{LIST} = \delta + \alpha S + \beta L + \gamma_1 W_h^{WELL2} + \phi_t + \epsilon_{hbct} \tag{6}$$

$$\ln P_{hbct}^{LIST} = \delta + \alpha S + \beta L + \gamma_1 W_h^{WELL2} + \nu_1 (L_c^{PERMIAN} \times W_h^{WELL2}) + \phi_t + \epsilon_{hbct} \tag{7}$$

where the interaction term, $L_j^{PERMIAN} \times W_h^{WELL2}$, allows comparison of the effects of proximal well density on the price of housing units inside the Permian Basin counties compared to the control counties. The coefficient ν_1 measures the impact of W_h^{WELL2} within the Permian Basin. Since many of the collected variables both within and across the W and Q vectors are highly correlated, our general strategy, with select exceptions, is to examine these individually for the initial results.

We assess the marginal implicit prices (MIPs) for our focal variables. In the log-linear hedonic price function, the MIP for a continuous variable using W_h^{WELL2} as an example is given as:

$$\frac{\partial P_{hbct}^{LIST}}{\partial W_h^{WELL2}} = \gamma_1 \times P_{hbct}^{LIST} \tag{8}$$

which can be interpreted as the percentage change in the housing unit price with a one-unit change in the explanatory variable of interest (W_h^{WELL2}). For a dummy indicator variable, the MIP is adjusted as follows, $100(e^{beta} - 1)$, and provides the percentage change in the housing unit in the presence of the indicator variable (Taylor, 2017). Finally, for a variable of interest interacted with PERMIAN, the MIP is given as:

$$\frac{\partial P_{hbct}^{LIST}}{\partial W_h^{WELL2}} = \left(\gamma_1 + \nu_1 L_j^{PERMIAN}\right) \times P_{hbct}^{LIST} \tag{9}$$

When $L_j^{PERMIAN} = 1$, the MIP is:

$$\frac{\partial P_{hbct}^{LIST}}{\partial W_h^{WELL2}} = (\gamma_1 + \nu_1) \times P_{hbct}^{LIST} \tag{10}$$

In terms of *a priori* hypotheses, the standard expectation from a classic environmental economics perspective is that proximal density of active wells around a housing unit, the presence or magnitude of seismic activity (with the concern of human induction by UO&G development), and measures of localized air pollution (e.g., $PM_{2.5}$) would all be potential negative externalities and reduce house prices. Thus, using the example of the density of all active wells within 2 km, against the null of no effect ($\gamma_1 = 0$), the alternative hypothesis would be: $\gamma_1 \neq 0$. The question raised in the **Introduction**, and the mixed results found in prior HPM studies, is whether there might be a greater *tolerance of the side effects* in the Permian.

Tolerating the potential negative externality would be shown by calculating the net effect of the variable of interest, say, well density W_h^{WELL2}. Focusing on the Permian basin counties, ($L_c^{PERMIAN} = 1$), if the main effect (γ_1) plus the interaction effect (ν_1) is not statistically different from zero or greater than 0; this would provide evidence of tolerance in the Permian counties; further, if $\gamma_1 < 0$ and statistically significant (representing the case in the control counties), but if there was a greatly reduced effect ($\gamma_1 + \nu_1$), then this would support the conclusions that consumers in the Permian are tolerating what is viewed as a negative externality in the control counties.

Finally, the modeling approach or strategy includes the following robustness checks. First, we break out the Permian and control counties into split samples to allow examination of various model specifications separately for each set. Here we can directly compare the two samples, say, the estimation on the sign and significance of γ_1 from equation (6) for the hypothesis on well density effects. Second, P_h^{LIST} is replaced with P_h^{Z}, with the smaller available samples for the Zillow Zestimate. Third, the use of robust standard errors with clustering at the census tract level is replaced with spatial HAC errors, or Conley standard errors (Conley, 1999). Fourth, as final robustness check, a set of econometric models are estimated focusing on isolating injection and disposal wells as a potential negative externality. This is examined including an interaction term with public water (PUBWATER) for the overall sample, and separately for each of the subsamples. Absent a significant water quality monitoring network across our sampling region, a proxy is the subset of wells that present UO&G water contamination risks, which includes injection and disposal wells.

6. Econometric Results and Analysis

Econometric modeling results for the hedonic price functions, all in log-linear form, are presented in Tables 14 through 22. All econometric analysis was completed using Stata 17. From a general perspective, the econometric analysis shows that the ln P_h^{LIST} models generally fit well, with R^2 measures ranging from around 0.6 to 0.7, and structural and location variables having expected signs and generally significant.[17]

All model specifications include month fixed effects, and with the exception of Tables 20 and 21 use clustered standard errors at the block group level. From the vector of possible structural variables collected, S, after evaluating correlations and collinearity, the final set used in all specifications include: S_h^{SQFT}, S_h^{MANU}, S_h^{AGE}, S_h^{LOT}, S_h^{BED}, $S_h^{MULTI-GAR}$, and S_h^{AC}. Similarly, the

[17] In converting percentage effects into dollars, marginal implicit prices are calculated at the *median* price measure for the appropriate sample or sub-sample.

set of location characteristics consistent across all models include: L_h^{DIST}, $L_b^{MED-HINC}$, $L_b^{PCT-WHITE}$, $L_b^{POP-DENS}$, L_c^{AVG-UE}, and L_h^{PW}.

Table 14 presents the baseline models 1 and 2, (the *S* and *L* vectors of variables, with and without and indicator variable for the Permian Basin) while models 3 and 4 add total active well data within 2 km of a home (ALLWELLS-2KM) and 1 km (ALLWELLS-1KM). Table 15 builds on Table 14 and incorporates extended models with environmental variables. The remaining tables contain robustness checks. Table 16 presents modeling results using the subsample of houses from the Permian counties only, while Table 17 uses the subsample of houses from the control counties only. Tables 18 and 19 replicate 14 and 15 but use the natural log of the Zestimate ($\ln P_h^Z$) as the dependent variable. Returning to $\ln P_h^{LIST}$ as the dependent variable, Tables 20 and 21 contain results using Conley standard errors to correct for potential spatial autocorrelation.[18] As a final robustness check, Table 22 presents results when attempting to isolate special concerns with water contamination (focusing on the subset of active injection and disposal wells, and interacting the presence of public water supply).

6.1. Full Sample Results

Using the overall sample, across all models in Table 14 and 15 an additional square foot of living space is shown to significantly increase the listed price of a home by 0.03%, which is stable across samples. When using the overall sample median P_h^{LIST} this equates to \$82.5/sqft, or \$127.5/sqft at the mean value. Also significant at the 0.001 level, manufactured homes, MANU, are listed 26-29% less than non-manufactured homes; using the midpoint (27.5%), for the overall sample this equates to ~\$76,000 lower list price for the median home or ~\$116,000 for the mean. Estimated coefficients on MULTI-GARAGE and ACCENTRAL are both consistently and significantly positive (0.001 level) across all specifications and range from 7-9% (or ~\$22,000 for the median home and ~\$34,000 for mean list price home, evaluated at 8%) for having multiple garages to 12.8-15.8% (or ~\$39,000 for the median home and ~\$61,000 for mean list price home, evaluated at 14.3%) for having "central" in the air conditioning description. Finally, an additional BEDROOM significantly increases the listed price by 4.5-6% (or ~\$14,000 for the median home and ~\$22,000 for mean list price home, evaluated at 5.25%). As measures of construct validity, these all appear to line up well with market evidence.

In both tables, the average unemployment rate in the county corresponding to a home (AVG-UE) is a statistically significant (0.001 level) and negative determinant of the listed price of a home. Increases in employment are expected to be a positive demand shifter for home values. The magnitude of the effect across model specifications in Table 14 and 15 shows that an additional percentage point reduction in AVG-UE increases the listed price of a home by about 8-10% (except for the Table 15, model 2, which has collinearity issues). Estimated coefficients on DIST are positive and significant (0.05 level) across both tables indicating the farther a house is from a main road (highway or principal arterial road) the higher the listed price. Although they have small marginal effects (< 1%), the Census block group characteristics of median household

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[18] Spatial autocorrelation means the error terms in our regressions are correlated with houses that are geographically close to them. This correlation violates a basic econometric assumption when using OLS and we attempt to correct for the potential violation using the Conley standard errors with a Stata package (reg2hdfespatial) that treats houses within a specified distance of each other as being related.

income and percentage white, MED-HINC and PCT-WHITE, are each significant (0.01 level) and positive determinants in Table 14 and 15. This is consistent with prior research findings (e.g., Howell and Korver-Glenn, 2020). Population density in the Census block group corresponding with a home (POP-DENS) is a negative and significant (0.001 level) determinant across all models in Tables 14 and 15, consistent with Acolin et al. (2022).

Whether a home is within the service boundary of a public water system (PUBWATER) is interpreted as likely indicator that the house is on piped water. The estimated coefficient on PUBWATER is positive and significant (at either the 0.01 or 0.05 level) in the full sample results indicating consumers value access to public water. The average of the estimated coefficients is 0.0475, corresponding to a $13,062 effect on the median listed home in the overall sample. The estimated coefficient on PERMIAN indicates that homes are valued ~28% less in the Permian versus houses in the control counties.

All of the above results on the structural (S) and locational (L) characteristics are consonant with either observed market evidence or prior research. From here the discussion of results turns to possible negative externalities: well density, air pollution and earthquakes.

The well density variables are included Table 14 models 3-4 and Table 15 models 3-4, which focus on well density with 2 km of a house. Density within 1 km (Table 14 model 4) produces similar results on sign and significance, and 2 km (1.24 miles) density is a common measure in HPM studies on UO&G. Only Table 15 model 4 contains the Permian counties indicator variable (PERMIAN). For all the models the effect of an additional well within 2 km is negative and significant (0.01 or 0.05 level). However, in Table 15, model 4 the interaction term PERMIAN × ALLWELLS-2KM is positive and significant and similar in magnitude to the negative coefficient on ALLWELLS-2KM. When combined, this greatly mutes the comparable effect; the result is a small net negative effect of -0.12% for an additional well; this equates to a marginal implicit price of -$293 for an additional well, evaluated at the median listed price in the Permian counties sample. This compares to -0.82% or a marginal implicit price of -$2,951 for an additional well, evaluated at the median listed price for the control county sample houses. However, Table 15, model 4 exceeds the VIF cutoff of 10, indicating multicollinearity, for ALLWELLS-2KM and the interaction with PERMIAN. This problem is addressed in the robustness checks using separate subsamples for Permian and controls. For perspective, the percentage effect of an additional well in the control counties, with an average of less than one proximal well with 2 km, is roughly 7 times larger (or 10 times larger translated into marginal implicit price effects for median priced homes in the different samples) than in the Permian Basin counties where there are almost 15 proximal wells within 2 km of the home on average. This supports the general hypothesis that the housing market within the Permian Basin may be much more tolerant of active well density than in the control counties.

Table 15 extends model specifications to include the air pollution ($PM_{2.5}$) variables. Model 1 includes both PM2.5 and ΔPM2.5. In model 1, only ΔPM2.5 is negative and significant (0.001 level) implying in this specification it is a negative externality. However, when the PERMIAN indicator variable is included as an interaction term with each of the air pollution measures in model 2, both the estimated coefficients for PM2.5 and ΔPM2.5 are negative and significant. For houses in the Permian the net effect is -0.0064 for ΔPM2.5, (i.e., the negative effect is muted in the Permian). However, the concern here is that in model 2, the VIF greatly exceeds the commonly recommended cutoff of 10 indicating multicollinearity (as caused by the interaction term with both PM2.5 and ΔPM2.5) and raises questions about the conclusion. Alternatively, as discussed later, a robustness check is pursued where the interaction term is dropped and separate models for each sample are used to investigate air pollution effects.

Continuing with Table 15, in models 5 and 6 the potential earthquake effect is investigated, using the count of earthquakes greater than magnitude 1 within 10 km of a home since 2010. While the estimated coefficient is negative and significant (0.10 level) in model 5, the inclusion of the interaction term in model 6 makes both variables insignificant. Also concerning here in model 6 is the VIF exceeds 10 indicating multicollinearity (caused by EQS-MAG1 the interaction term with PERMIAN). Discussed later, a robustness check is pursued where the interaction term is dropped and separate models for each sample are used to investigate earthquake effects.

There is no evidence that this earthquake measure (like that used in other HPM studies) is a significant determinant of listed prices for homes in the Permian Basin (or the control counties).

6.2. Subsample Results

As a first robustness check, econometric models are applied separately to the Permian counties sample (Table 16) and control counties sample (Table 17), which demonstrate a very similar range of R^2 measures for goodness of fit. To start, results for the estimated coefficients on the variables SQFT, AGE, and BEDROOMS in the separate samples are similar in sign, significance, and magnitude to the overall sample.

For a number of variables, while the sign and significance do not change, and regardless if the effect is positive or negative on the listed price, there is a much more muted (smaller in percentage effect on price) for homes in the Permian counties sample relative to the control county sample.

The estimated negative and significant (0.001 level) price effect of a manufactured home (MANU) differs starkly between the two samples. There is roughly a 57% reduction in the list price associated with a manufactured home in the control county sample (Table 17), but a much more muted effect—less than half the size—of roughly 25% in the Permian counties sample (Table 16). Other variables with stronger negative impacts in the control county sample are AVG-UE and POP-DENS.

The estimated positive and significant (0.001 level) price effect of being located within a public water system (PUBWATER) differs between the two samples. The effect on the listed price is about 3.5% in the Permian sample (Table 16), but this more than doubles in the control county sample at about 6.5% . Other variables with stronger positive impacts in the control county sample are ACCENTRAL, MED-HINC and PCT-WHITE.

Turning to the investigation of potential negative externalities, as shown in Table 17 well density within 2 km of a home has a negative and significant (0.10 level) effect of -0.73% on the listed price in the control counties; at the median home price in the sample, this equates to a marginal implicit price of -$2,627 for an additional well. The evidence supports the hypothesis of well density as a negative externality. However, for the Permian counties sample (Table 16), the null hypothesis of no effect cannot be rejected; the estimated coefficient on ALLWELLS-2KM is not significantly different from zero.

Additionally, the air pollution variables PM2.5 and ΔPM2.5 are included in model 2 for each of Tables 16 and 17. For the Permian counties sample, the estimated coefficient on PM2.5 has a statistically significant negative effect with a marginal implicit price of -$5,633. This is the first evidence of a negative externality in the Permian counties sample. However, the change in $PM_{2.5}$ specifically attributable to oil and gas production in the Permian (ΔPM2.5) has no significant effect; the null hypothesis cannot be rejected. In contrast, the estimated coefficient on PM2.5 has no effect in the control counties group while ΔPM2.5 has a strong and statistically significant negative effect. To summarize, while there is evidence of a negative externality from air pollution emissions on the homes within the Permian Basin, it is not from oil and gas production in the Basin.

Finally, there is no evidence in either the Permian counties sample (Table 16) or the control counties sample (Table 17) of any significant externality on listed price of home from the earthquake measure.

In conclusion, the subsample modeling results are consistent with the housing market in the Permian exhibiting a tolerance of the side effects from oil and gas production.

6.3. Zestimate Results

As a second robustness check, Tables 18 and 19 present results from log-linear price functions when replacing the listed price ($\ln P_h^{LIST}$) dependent variable with the Zestimate ($\ln P_h^Z$), and then replicating prior modeling. The structural and location variables maintain their signs but estimated coefficients for a few variables, including LOTACRES, BEDROOMS, DIST, and PUBWATER, lose their significance in Table 18 and in some models in Table 19.

In Table 19 ALLWELLS-2KM is only a significant negative determinant in model 3 when PERMIAN is excluded. The air pollution variables PM2.5 and ΔPM2.5 are significant and negative in model 2 but the interactions with PERMIAN are positive (and greatly mute their effect in the Permian Basin). The interactions combined with the main effects estimate indicate that in the Permian a one unit increase in PM2.5 (which corresponds with an approximately 16.7% increase in the mean concentrations in the Permian) leads to a 2.46% increase in home values while a 1 unit increase in ΔPM2.5 is associated with a less than 1% decrease in the Zestimate price, P_h^Z.[19] Finally, there is no evidence of a significant negative externality due to seismic activity. Again, the models with the PERMIAN interactions show evidence of a high VIF.

In summary, the general pattern of conclusions (e.g., tolerance of the side effects within the Permian) is robust to using the Zestimate ($\ln P_h^Z$) as the dependent variable.

[19] Again, while STATA did not reject the model due to multicollinearity, there are concerns with a VIF>10 for this model with interaction terms for between the air pollution variables and the indicator variable for the Permian Basin. While not presented here, split sample analyses draw qualitatively similar conclusions when using $\ln P_h^Z$ as dependent variable in place of $\ln P_h^{LIST}$.

6.4. Conley Standard Errors

As a third robustness check, Tables 20 and 21 present modeling results with ln P_h^{LIST} as the dependent variable and replacing the clustered standard errors with Conley standard errors (Conley, 1999). This allows a correction for potential spatial autocorrelation. Across different model specifications, initial results indicate similar signs and magnitudes on estimated coefficients as in Tables 14 and 15. In summary, there is no alteration in the general pattern of conclusions (e.g., tolerance of the side effects of UO&G within the Permian).

6.5. Piped Water and Water Contamination Risks from Injection and Disposal Wells

A special concern in reviews of HPM studies on UO&G development effects is failing to correct for piped water (which mitigates concerns with water pollution). Absent a significant water quality monitoring network across our entire sampling region, a proxy is the subset of wells that present particular UO&G water contamination risks. This includes injection and disposal wells. Prior studies have found these wells to be important to look at in the context of public water (Balthrop & Hawley, 2017; Gopalakrishnan & Klaiber, 2013; Mothorpe & Wyman, 2021; Muehlenbachs et al., 2012, 2015). Thus, as a final robustness check, Table 22 presents econometric results that focus on isolating injection and disposal wells as a potential negative externality. This is examined including an interaction term with public water (PUBWATER) for the overall sample, and separately for each of the subsamples. Note that injection and disposal wells are extremely rare in the control county sample; the variable INJ&DISP-2KM has an average density within 2 km around a house of 0.05 (standard deviation of 0.26) in the control counties sample, versus an average of 1.71 (standard deviation of 7.58) in the Permian counties sample. There are only 83 injection and disposal wells in the more than 21,000 square miles of our control counties.

Consistent with prior results, all specifications in Table 22 have significant and positive values for whether a house is within the boundaries of a public water supply system (PUBWATER). For the overall sample (model 1), the inclusion of a density variable for injection and disposal wells (INJ&DISP-2KM) has a significant (0.001 level) and negative effect. Continuing with the overall sample (model 2), when an interaction term is added (PUBWATER × INJ&DISP-2KM) the effect of well density is not significantly different from zero. The implication is that conditional on a house being on piped water, the potential negative externality of an additional injection and disposal well is eliminated. When looking at the split samples (model 3 is the control county sample and model 4 is the Permian counties sample), this same general conclusion holds. Absent being on piped water, the density of injection and disposal wells has no effect in the Permian Basin but is a negative externality in the control counties.

Again, results from this robustness check fit within the general pattern that the Permian Basin exhibits a tolerance for the side effects of UO&G activities.

7. Discussion and Conclusions

Boosted by technological change (Popova & Long, 2022) and massive capital investment into the region (Collins, 2021),[20] the Permian Basin has experienced more than a decade long boom in UO&G development in addition to existing O&G activity, with predictions for extending significantly (Gaswirth et al., 2018). In addition to the boosts in employment, various earnings (Maniloff & Mastromonaco, 2017) and economic multiplier or spillover effects in the region (Bown et al, 2016; Feyrer et al. 2017; Wang, 2020), taxes and royalties from O&G and UO&G development on public lands generate significant public revenue that is distributed more broadly outside the region. For example, recent estimates indicate that roughly 30% of the annual general fund (or annual operating budget for all state entities), and 40% of annual total public finance revenues in NM comes from general O&G development (McKay, 2023; Sarkar, 2023).

It is imperative to focus on the region that is generating these benefits and try to understand what is happening economically, and to the environment, both in the near and long term. From the many possible dimensions of effects (e.g., transportation systems, labor markets, net-migration, public health, air and water quality, etc.), this investigation analyzes an important current cross-sectional slice of the housing market in the Permian Basin. Specifically, the objective of this analysis was to employ the hedonic pricing method (HPM) to econometrically decompose the effects of various attributes on permanent residences. Arguably, the boom has extended long enough to have capitalized effects, including any possible negative environmental externalities.

In their recent research review, Krupnick and Echarte (2017, p. 1) note:

> Changes in housing prices as a result of unconventional oil and gas development are useful indicators of community perceptions about the benefits and damages of such development, as they aggregate and monetize the preferences of home buyers and sellers.

Unsurprisingly, there are a significant number of HPM studies on the effects of proximity or density (typically within 1 or 2 km) of O&G wells, with a focus on hydraulic fracking, shale gas, and UO&G development boom areas (e.g., PA, CO). But there is a paucity of HPM studies in the Permian Basin. Sales price non-disclosure clearly complicates research efforts to apply HPM in states like NM and TX (Berrens & McKee, 2004; Bollum, 2021; Kalfrin, 2021; Williams, 2021).[21] To overcome that hurdle, this analysis employs webscraping of microlevel Zillow list price and Zestimate information (and housing characteristics) for 2022-2023, and matches that

[20] Collins (2021) documents more than $80 billion capital investments in upstream UO&D development in the Permian Basin for the period 2016-2018, which is described as unprecedented in the industry in terms of scale and velocity.

[21] The authors are not aware of any published, peer-reviewed HPM property studies for NM using individual house level publicly available sales price data (although it's certainly possible that a local Realtor Board ® could have released such information in some case). For further discussion of a possible recent case with purchased proprietary data see footnote 14. But this case is not for the Permian. For TX, there are several HPM studies of UO&G of note. Weber et al. (2016) use the ZILLOW median price index data for Zip codes (over 10+years), and focus on Barnett Shale play in TX (counties west of Dalllas/Ft. Worth, but not connected to the Permian Basin), Also for the Barnett Shale region, Balthrop and Haley (2017) do use individual level sales prices for their HPM; This large sample urban-focused study for a single county covering (Tarrant) Ft. Worth uses individual sale level MLS data – so the presumption is this was released by local Realtor Board ®, with the data appearing to be 4-5 years old. But neither of these are for the Permian.

with a variety of geospatial information, at varying scales. This includes controlling for a variety of Census based information (e.g., population density), and county-level unemployment. In addition to geo-located well information of varying (highly correlated) types, we collected environmental variables on seismic activity, and air pollution ($PM_{2.5}$ from satellite data). On the latter, we make use of state-of-the-art source-receptor modeling (InMAP) and the recent analysis by Goodkind et al. (2023) to isolate the change in $PM_{2.5}$ attributable to conventional and unconventional O&G sources.

Various reviews of housing market effects (e.g., Krupnick and Echarte, 2017; and Loomis and Haefele, 2017) make clear that that there can be pathways for *both* positive and negative effects from UO&G development in a boom region. HPM applications must attempt to disentangle these effects. To help do that, this analysis of the Permian Basin (55 counties) selected a set of 18 control counties in eastern NM and western TX (but outside the Permian), which were similar for a set of Census-based socio-economic/demographic variables (evaluated for 2009 and 2019) but highly dissimilar in their exposure to, and economic reliance on county-level O&G production (i.e., an order of magnitude difference).

Our modeling strategy focuses on the use of available list price information P_h^{LIST} as the dependent variable, which has a much larger available sample than the Zillow values estimate of Zestimate, P_h^Z. However, the two measures are shown to be highly correlated, and as a robustness check, results from both are qualitatively very similar.

The econometric analysis show that the P_h^{LIST} models generally fit well, with R^2 measures ranging from around 0.6 to 0.7, and structural and location variables having expected signs and generally significant. For example, the median valued manufactured home was anywhere from roughly 25% to >50% lower valued (with the lower percentage effect inside the Permian counties), and the presence of piped water was shown to always be a significant positive determinant of housing value varying across the range of 3% to 7% (with the lower percentage effect inside the Permian). Like other HPM studies of UO&G development (e.g., Bennett and Loomis, 2015 and He et al., 2017), we control for the unemployment rate in a county and show it to be significantly negative, i.e., this is consistent with positive employment changes (and income effects) shifting housing demand and raising the expected price.

Controlling for fixed effects by month of data collection (2022-2023), the otherwise cross-sectional econometric analysis focuses on three sets of variables that would be hypothesized to have *negative externality effects* on house prices. Due to high multicollinearity both within sets and across some sets, our strategy was to generally select and evaluate these externalities separately.

The first potential negative externality investigated is local air pollution in the form of emissions of $PM_{2.5}$, and separately for the change in $PM_{2.5}$ attributable to O&G production in the Permian. To start, these two variables are evaluated together in model specifications. In the full sample model (with Permian interaction terms), results show that negative air pollution effects are greatly muted in the Permian Counties. But this model raised multicollinearity concerns. Thus, turning to the split samples, when evaluating for the Permian counties and the control counties samples separately, results show that background $PM_{2.5}$ (which may be coming from sources outside region) is a significant negative externality for the Permian Counties, but the isolated effect of the change in $PM_{2.5}$ specifically attributable to O&G production in the Basin is not significantly different from zero. In contrast, this change in $PM_{2.5}$ attributable to O&G production is a significant negative amenity in the control county sample, where some of them lie in the path of prevailing wind distribution, as shown by Goodkind et al. (2023). So, while O&G production pollution is causing a negative externality in the regional housing market, it is not doing so specifically in the Permian itself (rather it is spilling into some nearby counties).

The second potential negative externality investigated is seismic activity, where following from recent HPM research (Cheung et al., 2018; Metz et al., 2017; Mothorpe & Wyman, 2021) we use GIS to create four separate variables. We find no evidence of a significant negative effect on housing prices in the Permian from seismic activity (the count of earthquakes since 2010 of magnitude 1 or greater).

The third expected negative externality measure investigated, as focused on in HPM research into UO&G development, was well density. Data was collected on various types of active wells (totaling more than 220,000) and combined with GIS to create well count densities within both 1 km and 2 km concentric circles of a house (consistent with prior studies). Across our main approaches and all robustness checks, for both 2 km and 1 km densities, the evidence supports the argument that the effect of well density proximal to a house is greatly muted if not eliminated (e.g., in the split sample case) in the Permian Counties (in contrast to the control counties).

As a general conclusion, the econometric results provide evidence that for the UO&G boom in the Permian, housing markets may reflect a kind of *tolerance for the side effects*. Environmental externalities are either eliminated or greatly reduced in their marginal implicit price effects. We evaluate both with a combined sample, and with separate modeling for the Permian and Control counties samples. This tolerance outcome is especially clear for measures of the density of total active wells surrounding a residence, which has been a primary focus of prior HPM studies.

To help put in context, Goodkind et al. (2023) show significant monetized damages from the health effects of changes in $PM_{2.5}$ (inside and especially outside the region) attributable to UO&G activities; yet the region overall is not shown to be out of attainment with federal $PM_{2.5}$ emissions standards. Likewise, human induced seismic activity in the Permian may not be as significant yet as observed for UO&G development elsewhere (e.g., Oklahoma) (Cheung et al., 2018; Mothorpe & Wyman, 2021). Not to diminish their importance, but there appears to be a relative tolerance at their current levels as they are capitalized into Permian housing markets. Such evidence is consistent with arguments that in this extraction-intensive region, residents may have a kind of tolerance for the side effects, as the region experiences significant gains in employment, earnings, and tax revenues from UO&G development (Sarkar, 2023).

Our evidence of increased tolerance for the side effects for counties within the Permian Basin is consistent with various pieces of information; this includes some surveys (e.g., Bouchet et al., 2018) and expressed public/political sentiment from within O&G development areas (e.g., as noted in our Introduction). Of note, Paydar et al. (2016) find that state adoption of significant impact fees for UO&G activities, and redistributed back to counties and municipalities in Pennsylvania (PA) increased expressed public support within regions that received significant revenues. Campbell et al. (2020) find that for Oklahoma survey respondents while induced seismicity from deep well re-injection of produced water has “catalyzed pushback against oil and gas development," risk perceptions are shaped by family considerations (employment connections), community context, exposure level and immediacy. Perhaps, most convincingly, it is also supported by 2018 precinct-level voting analysis for shale gas development in Colorado (CO) (Raimi et al., 2020). CO's failed Proposition 112 would have imposed very large setback requirements on new O&G activity. Raimi et al. (2020) show that partisan affiliation correlated strongly with support for O&G development. Further, voters in precincts with higher O&G activity were more supportive of O&G development (but varying with the rate of development).

The important caveat about our results is that what holds now may not hold going forward (e.g., as critical thresholds are passed). Further, it is possible that many public health concerns may be poorly understood, and therefore are not being capitalized into housing markets.

There are also limitations to our HPM analysis, beyond the absence of direct sales price information. To date, two general gaps in the HPM literature on UO&G development effects are: (i) the sometimes absence of controls for piped water; and (ii) private lease royalty information. While we do not have detailed water quality information for houses, we control for the presence of a public water systems (i.e., which we presume correlates with piped water) and show it to always be a significant positive determinant of housing value. However, a limitation of our analysis is the absence of any detailed control for UO&G production royalties from private mineral leases attached to any of the houses in our collected sample. On private lands, this lease information is proprietary and can be significant (see Brown et al., 2016; Covert and Sweeney, 2023). Its absence remains a general gap in the HPM literature for UO&G effects.

It is possible that a decade plus into the boom for many news sales these lease royalties or claims may be separated and no longer appurtenant to the property (see Metz et al., 2027). But lease payments to property owners is certainly a possible mechanism or avenue for the observed tolerance of side effects. Similarly, He et al. (2017) characterize such royalty payments, offered by producing UO&G firms as an implicit Coasian bargaining mechanism for offsetting possible externality effects. Another possible mechanism facilitating a tolerance for side effects is if a growing or disproportionate share of house sales are moved into medium- or shorter-term rental markets (i.e., a large share of buyers never expect to live in the house they buy). We have not explored this question.

There is clearly room for additional refinements in the analyses, including exploring additional price determinants. One example is alternative pollution measures. A second example is pursuing avenues for incorporating information about lease royalties. While matching information to specific land parcels is unlikely, it may be possible gather more aggregated information (e.g., county totals). Since many royalty owners are known to commonly leave a location, this suggests other more general indicators in a boom area like the owner occupancy rate in a census unit. Finally, while likely to be correlated with median household income, crime and school ratings are additional possibilities. These explorations are left to future research. However, it is important to try to place the current evidence in context and discuss its policy relevance.

The general policy context is well characterized by Maniloff and Mastromonaco (2017, pg. 62):

> Local and regional policy makers (and in some cases, voters) must balance the potential local environmental risks of extracting the oil and gas contained in shale with the potential local economic gains that might accrue from increased industry employment, upward pressure on local incomes, and extraction royalty payments.

Part of this balancing is respecting local community self-determination, and the inherent tension between broader efforts to transition to renewable energy sources against sometimes local interest to protect economic development of nonrenewable energy resources in their region.[22]

More broadly, even when significant elements of a community are disposed towards supporting UO&G development, there is a policy case for a public obligation to help manage and mitigate the health, environmental and community impacts (Wang, 2020). This argument is underlined by arguments that there are significant regional spillover effects from the economic benefits (Wang, 2020), and that all state and US residents are benefiting economically to some degree from the moving wave of the post-1990s UO&G development revolution, with its upward pressure on state and national economies (IHS, 2013; Maniloff & Mastromonaco, 2017). However, in addition to the broader climate damages of continued reliance on fossil fuels, that boom can come with localized costs and damages.

Morton and Kerkvliet (2013) and Morton et al. (2015 as cited in, Morton and Kerkvliet, 2020) promote the notion of responsible oil and gas development, which includes managing the rate of activities and mitigating negative impacts, including future ones. Of particular concern is when the boom goes away for a region. As various sources have explored, there is the potential for a *resource curse*, where the resource rich region is left with reduced *ex post* economic development resulting from the intensive focus on the extractive industry (see Collins, 2021; Haggerty et al., 2014). The concern with any region experiencing a boom in UO&G production is the bust that can come when the boom goes away. In contrast to Haggerty et al. (2014), recent evidence does not support the presence of a resource curse on economic measures due to the UO&G development boom to date in the US, where the broader economy may be too diversified (Maniloff and Mastromonaco, 2017; Solarin, 2020). This does not rule out that a *localized resource curse* might not be observed in a more regional context like the Permian (Collins, 2021), when the entire region only contains about 1.3 million people. Further, we argue that a particular concern with a dense well-field region is any social and environmental *legacy costs* after the production plays out.

To help prevent such legacy costs, in addition to spatial setbacks as discussed in the Introduction, policy or regulatory tools can include greater use of specific impact fees, increased penalties for spills, and higher bonding requirements for decommissioning wells, etc. While beyond the scope of this analysis, there are important inter-related research threads on:

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[22] This notion of community self-determination, and its complexity, returns us to the issue of spatial setbacks from the **Introduction** section. As a current example, in the June 2023 case of a 10-mile buffer around Chaco Canyon in northwestern NM (and the San Juan Basin), the federal government was clearly caught off guard by the clash between tribal interests. Some lessees objected to losing their right to lease their lands within the buffer (Boetel and Montoya Bryan, 2023).

(i) the environmental legacy externalities and significant decommissioning costs of wells, which are often under-bonded (Raimi et al., 2021; Weber et al., 2021; Kaiser, 2023)
(ii) the emergent environmental justice questions surrounding UO&G development, and what communities bear any disproportionate costs (e.g., Kroepsch et al., 2019; Johnston et al., 2020; Black et al., 2021; Clark et al., 2021; Lieberman-Cribben et al, 2022; Proville et al., 2022; Fry et al. 2023).

With respect to equity, there is also the broader question of how the public revenues (e.g., the various taxes, leases on state lands, and royalty payments from O&G production on public lands) are distributed, especially back to the resource extraction intensive communities themselves (see Sarkar, 2023). Relatedly, there is the question of how collected public revenues are used to improve monitoring (e.g., air and water quality, industrial spills, roadway accidents, citizen complaint records, etc.) and ensuring public data availability requirements.

For the case of NM, we highlight that given that real estate property sales are subject to market-based taxation under the NM state constitution, there is a clear public nexus in making property sales prices public information (Berrens & McKee, 2004).[23] Arguments in defense of sales price non-disclosure center on privacy protection (see discussions in Morey, 2010; Bollum, 2021; Kalfrin, 2021; Williams, 2021). Arguments against protecting non-disclosure include potential tax revenue leakages, tax inequities, basic market efficiency (reducing uncertainty and maximizing producer and consumer surplus) and optimizing private sector investment response in adding new supply. Stiglitz (2003) argues that information dispersion is a key role for government, as this information shapes economic behavior and choices. With respect to moving to mandating full public disclosure for real estate sales prices, the argument can be made that public interest outweighs privacy concerns.[24] The boom-and-bust context of UO&G development (e.g., the magnitude and velocity of capital investment in the Permian Basin) likely only exacerbates the effects of asymmetric information.

States vary in the *degree* to which they implement real estate sales price non-disclosure (Dornfest et al., 2019). Thus, it is important to note that in NM, post 2004 (see Berrens and McKee, 2004; and Bollum, 2021), changes in state law required that a real estate sales deed must be recorded with the county assessor's office and can be used in setting tax assessments. This disclosure to the county assessor includes all economic components that affects the sale (and thus presumably would include mineral lease information). However, this sales price information is not allowed to be *publicly available*, in fact it is mandated that it not be (see Bollum, 2021). As a recommended policy change, one can imagine a compromise middle ground where an avenue is created so that state university researchers and other public employees might be allowed access

[23] A similar argument can be made be made with respect to water in NM, where water resources are publicly owned under the state constitution, with use rights permitted. While improved water transfers are touted as an important flexibility mechanism, water transfer prices are not public, thus inhibiting efficiency and responses to scarcity.

[24] In the exogenous shock of an O&G development boom there will be housing market effects, and thus property assessments and ad valorem tax revenues effects. To wit, property taxes commonly constitute a large share of county revenues, and evidence on tolerance of side effects might mean the property values are not being negatively affected; however, on the counter side, sales price non-disclosure likely leads to tax revenue leakages (see Berrens and McKee, 2004; Morey, 2010; Bollum, 2021)

to property sales records for research purposes. Various federal census products commonly manage such access and restrictions.

Local governments and regions will continue to wrestle with how to affect the magnitude and rate of UO&G development. Communities may well come to different answers, and levels of tolerance. Economists and other researchers can play a role in providing information about past and expected effects. To help inform public deliberations, ideally, future multi-year, GIS-based housing market analyses, in UO&G activity areas and elsewhere, would be able to use publicly available sales price data, tracked over time and matched to detailed housing characteristics, along with a much denser web of public information on air and water quality monitoring, etc. Variables that might change across a boom (traffic, road accidents, fatalities, crime, temporal variation in human induced seismic activity, etc.) could be connected to housing markets.

8. References

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9. Figures

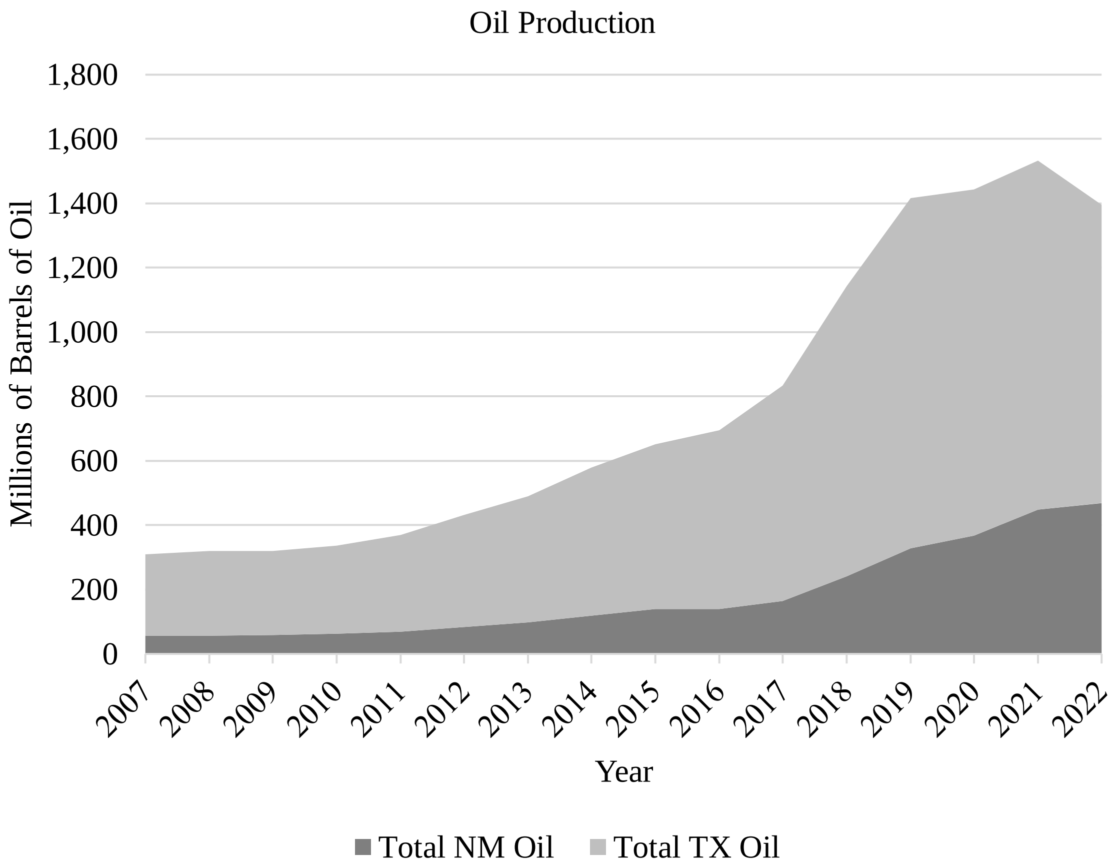


Figure 1: Oil production in the Permian Basin in millions of barrels of oil. Sources: NM Oil Conservation Division (2023), Texas Railroad Commission (2023), and authors' calculations.

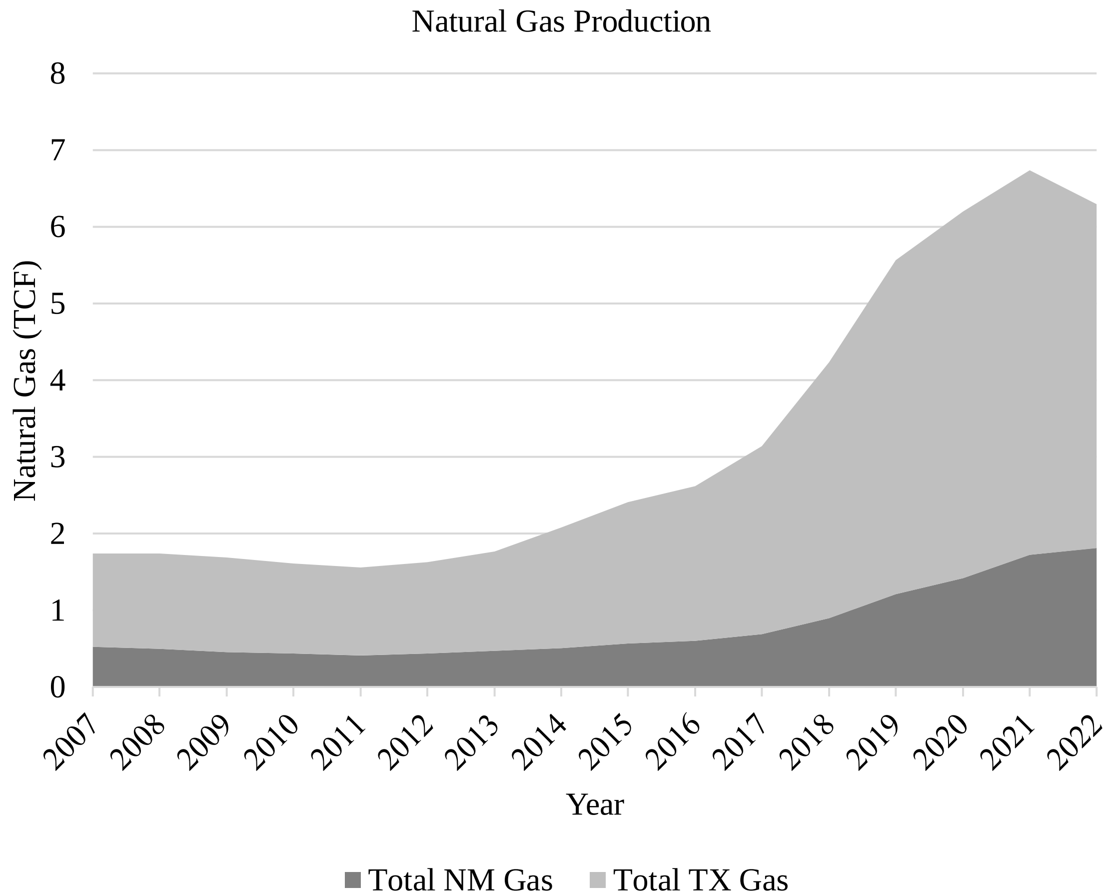


Figure 2: Natural gas production in the Permian Basin in trillions of cubic feet (TCF). Sources: NM Oil Conservation Division (2023), Texas Railroad Commission (2023), and authors' calculations.

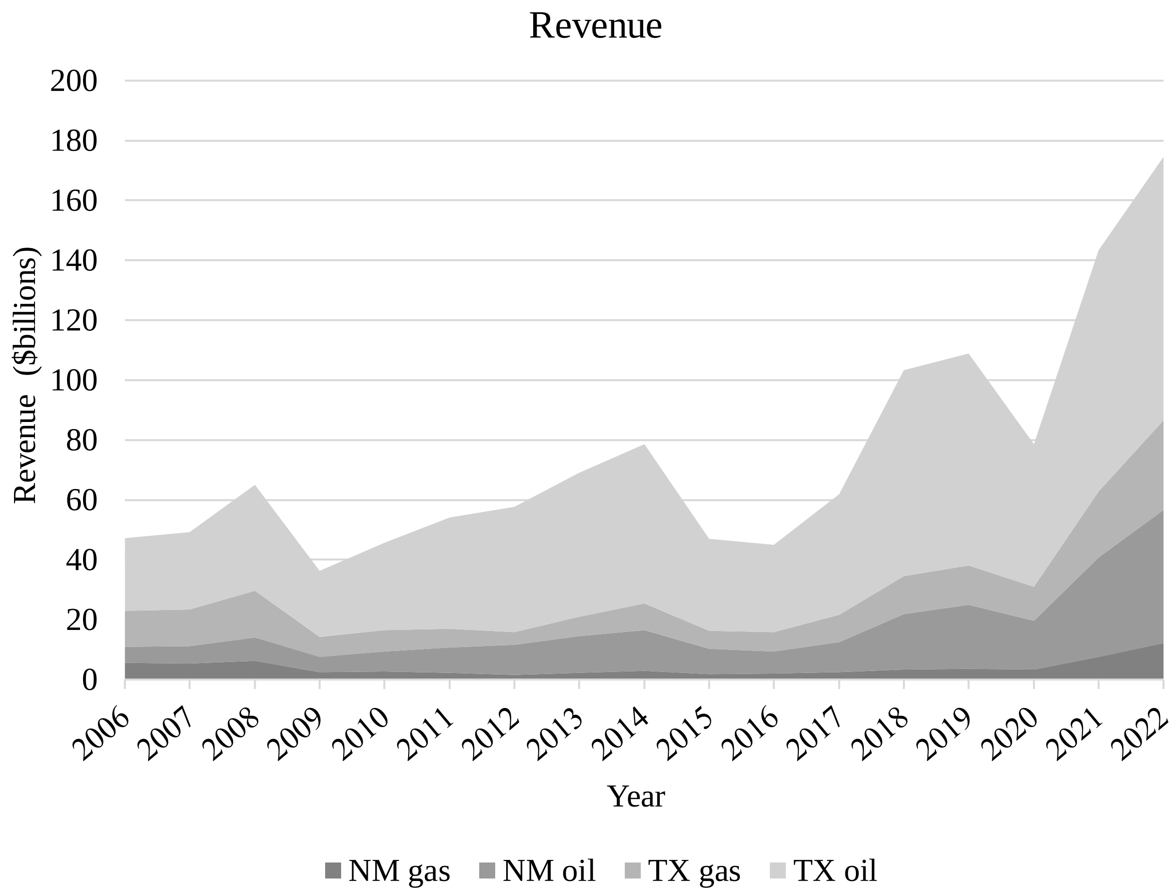


Figure 3: Annual Revenue from oil and gas produced in the Permian Basin. Note: All dollar amounts adjusted to 2022. Sources: NM Oil Conservation Division, the Railroad Commission of Texas, American Institute for Economic Research, U.S. EIA (2023c. 2023d) and authors' calculations.

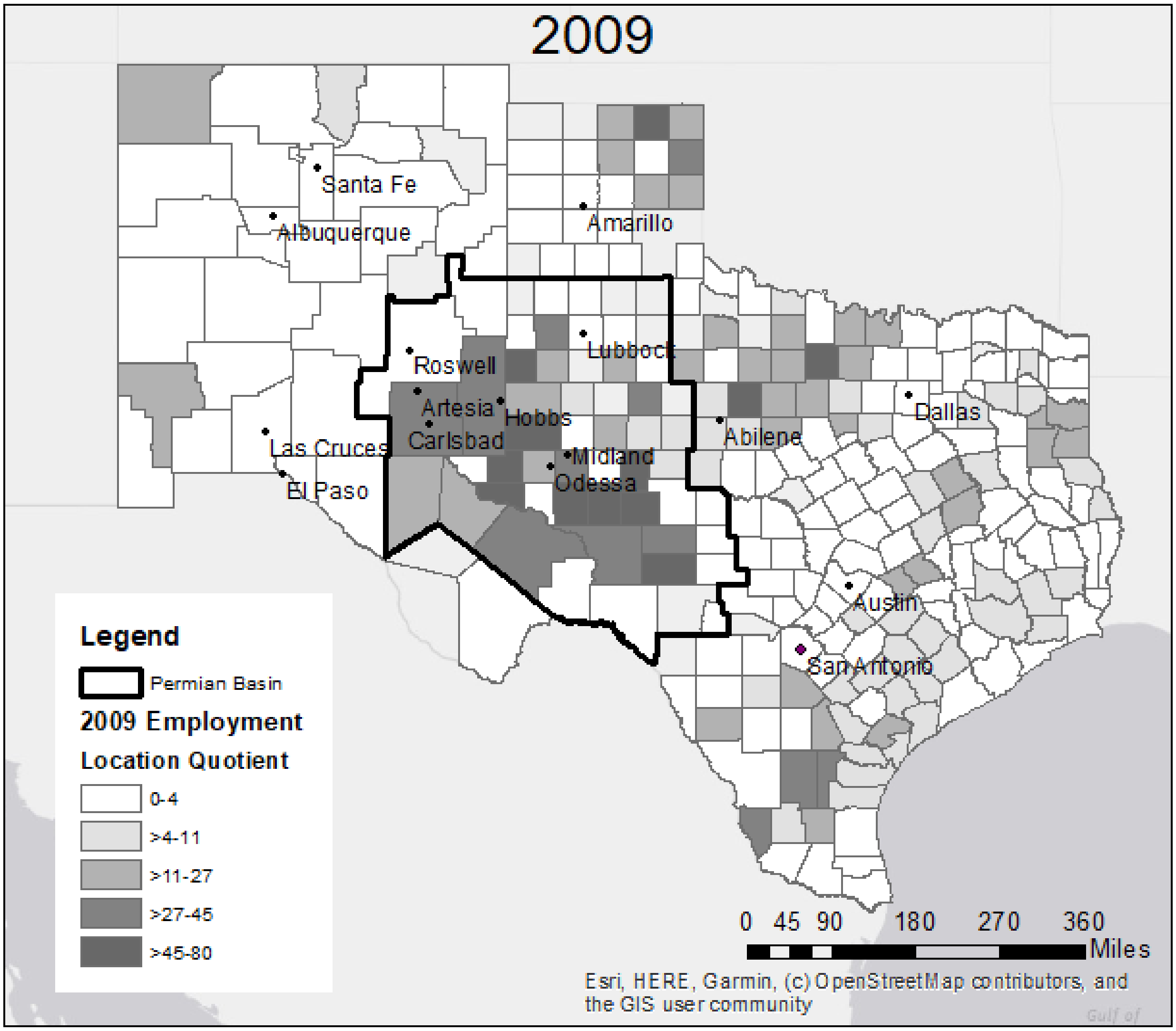


Figure 4: Distribution of average annual employment level location quotient of NAICS 21 (mining, quarrying, and oil and gas extraction) in NM and TX for 2009 (pre-boom). Notes: The location quotient measures the concentration of employees in NAICS 21 relative to the concentration of employees nationwide employed in NAICS 21. A value equal to 1 indicates the same number of employees per sector as the U.S; values >1 indicate more employees are in the sector than the rest of the U.S. Counties without borders are missing data. Sources: U.S. BLS (2023), Census TIGER files, ArcMap, and authors' calculations.

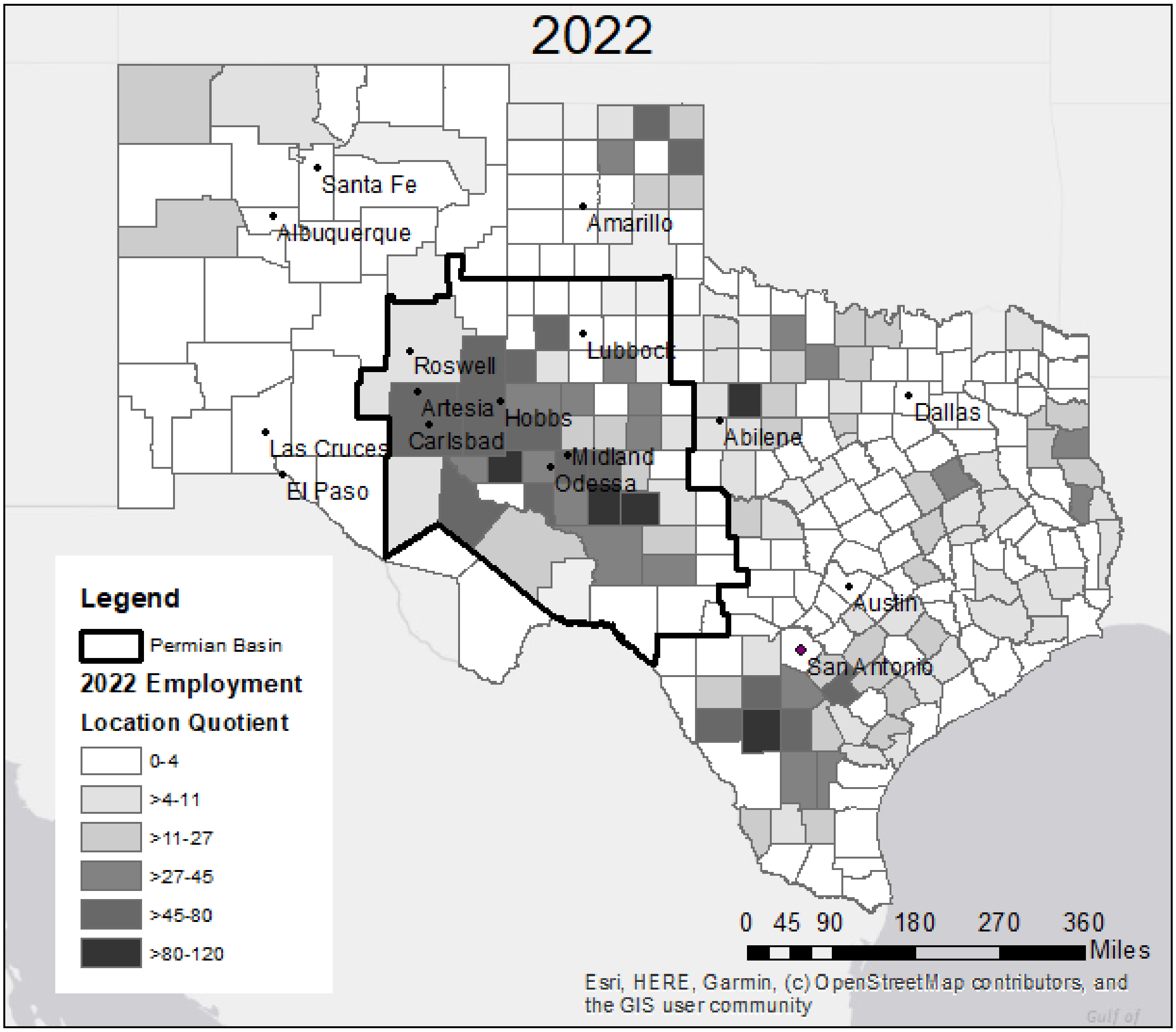


Figure 5: Distribution of average annual employment level location quotient of NAICS 21 (mining, quarrying, and oil and gas extraction) in NM and TX for 2022 (during-boom). Notes: The location quotient measures the concentration of employees in NAICS 21 relative to the concentration of employees nationwide employed in NAICS 21. A value equal to 1 indicates the same number of employees per sector as the U.S; values >1 indicate more employees are in the sector than the rest of the U.S. Counties without borders are missing data. Sources: U.S. BLS (2023), Census TIGER files, ArcMap, and authors' calculations.

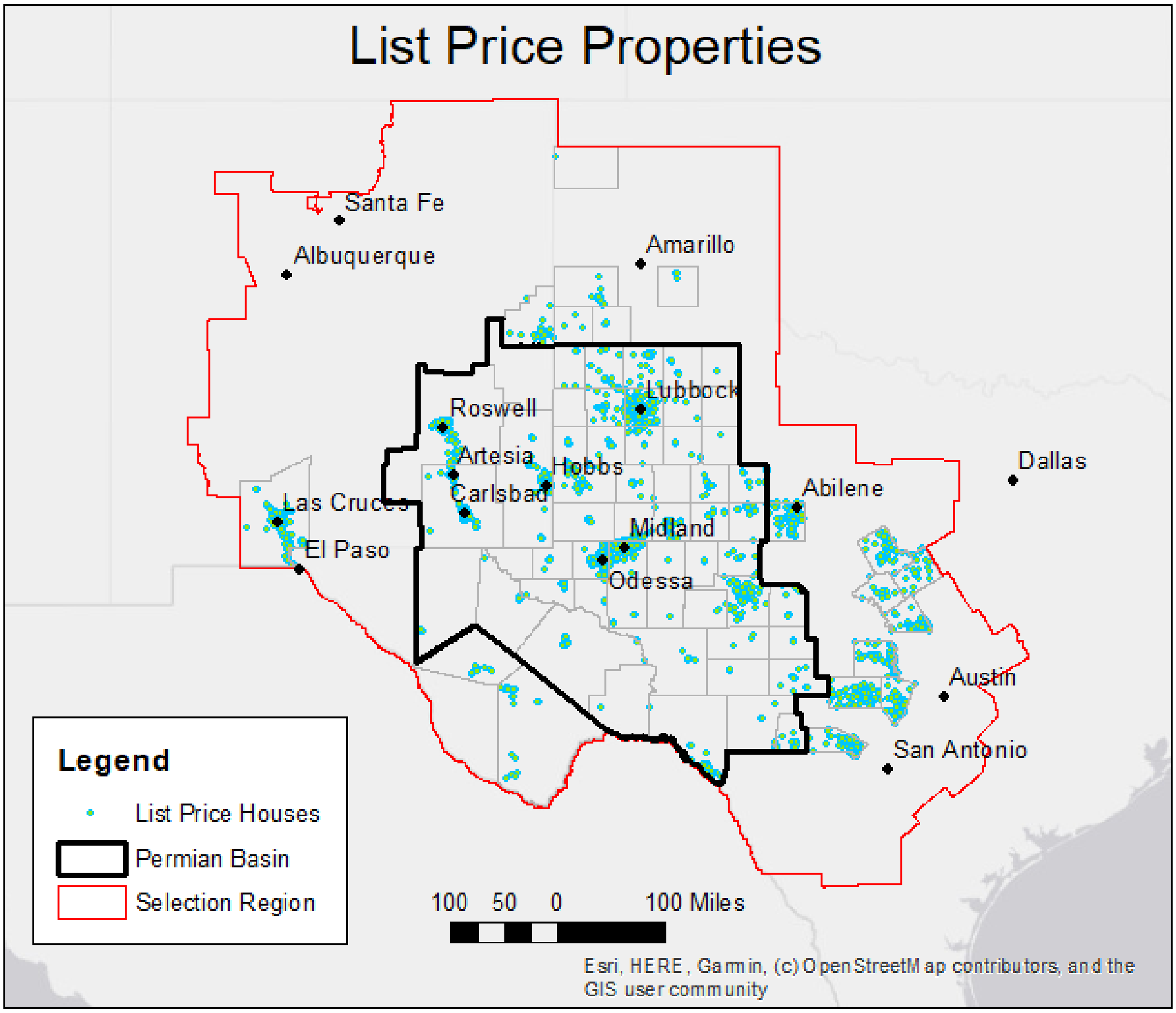


Figure 6: Distribution of the sample housing units with a LISTPRICE geolocated in the selection region. Notes: The geolocation for the 6,808 houses is done with ArcMap. Sources: Zillow, ArcMap.

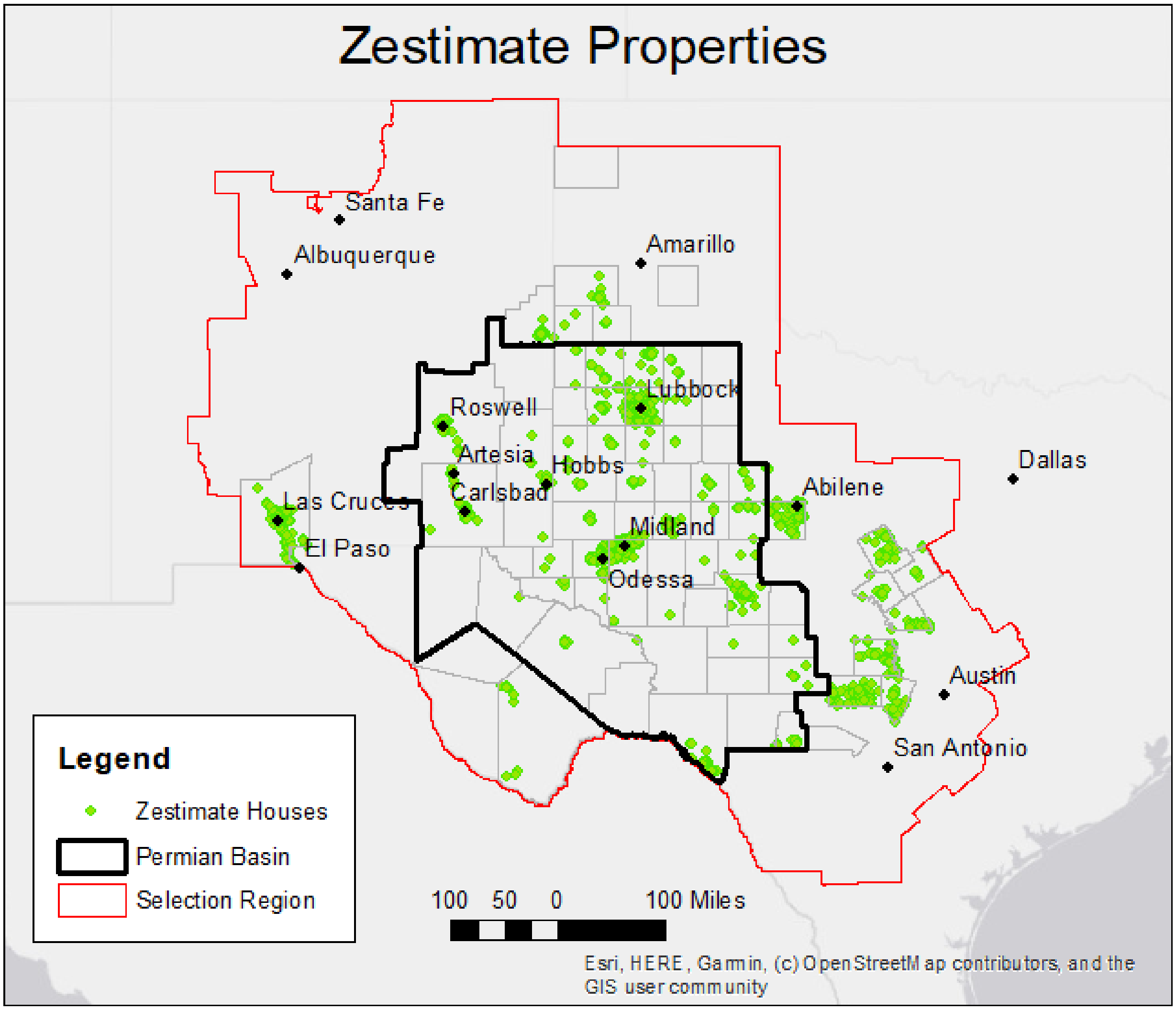


Figure 7: Distribution of sample housing units with a ZESTIMATE geolocated in the selection region. Notes: The geolocation for the 2,956 houses is done with ArcMap. Sources: Zillow, ArcMap**.**

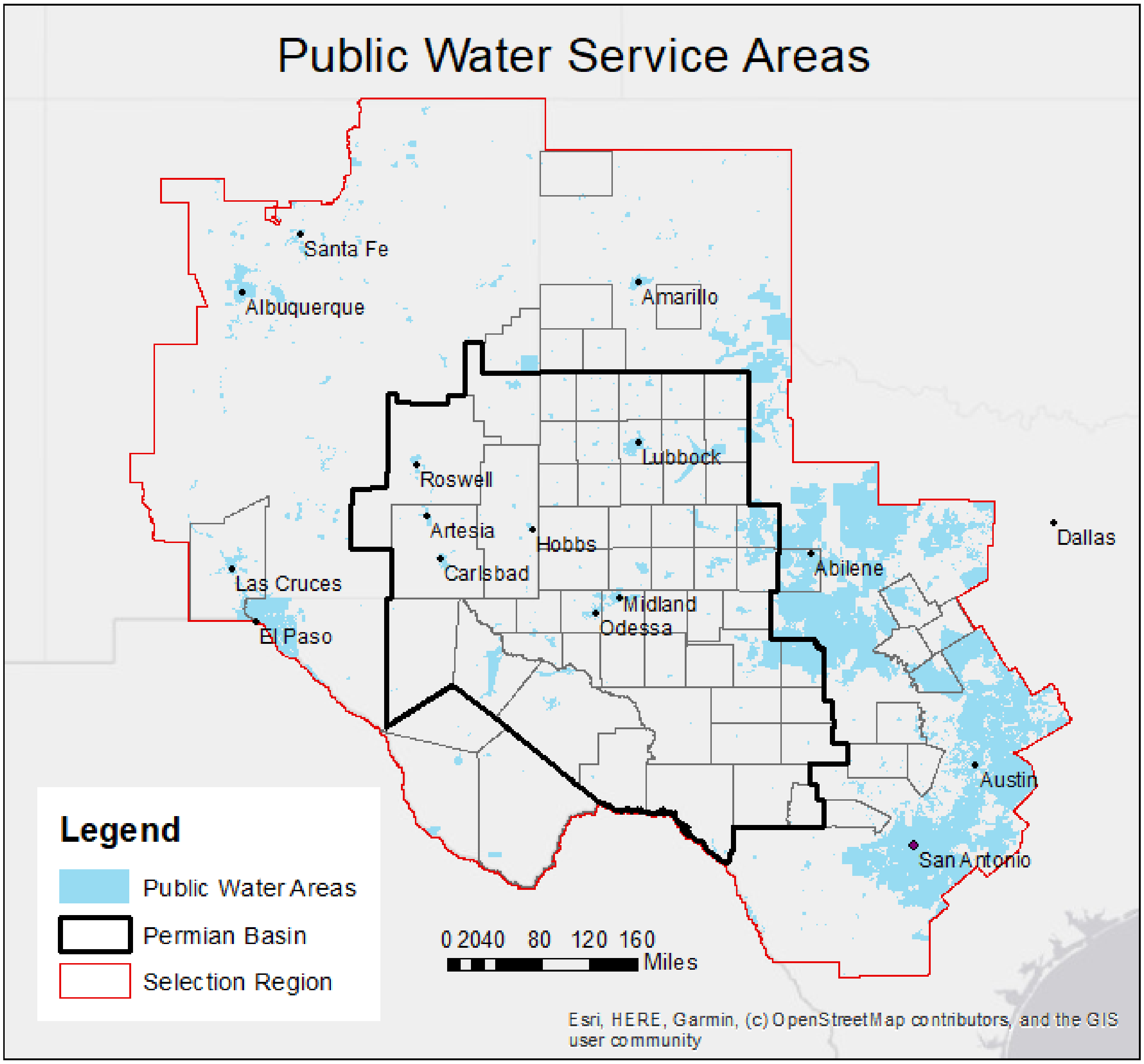
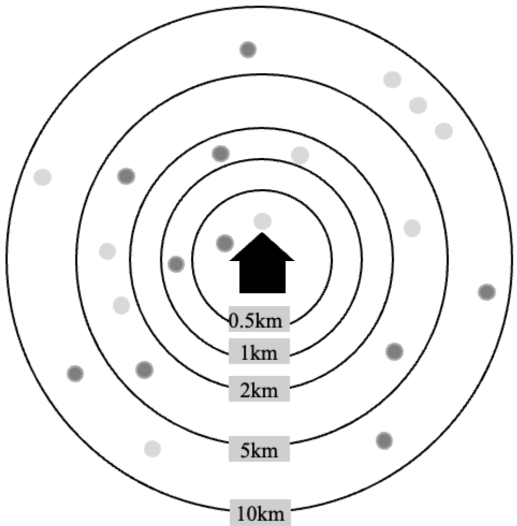


Figure 8: Delineation of public water service areas for NM and TX. Sources: Texas Water Development Board, the Office of the State Engineer, and ArcMap.

Well Count Diagram



Distance	INJ&DISP	OIL&GAS	ALLWELLS
0.5km	1	1	2
1km	2	1	3
2km	3	2	5
5km	6	5	11
10km	10	10	20

Figure 9: Construction of well count densities from various distances from a house. Note: While 5 rings are shown our models focus on the 1 km and 2 km rings.

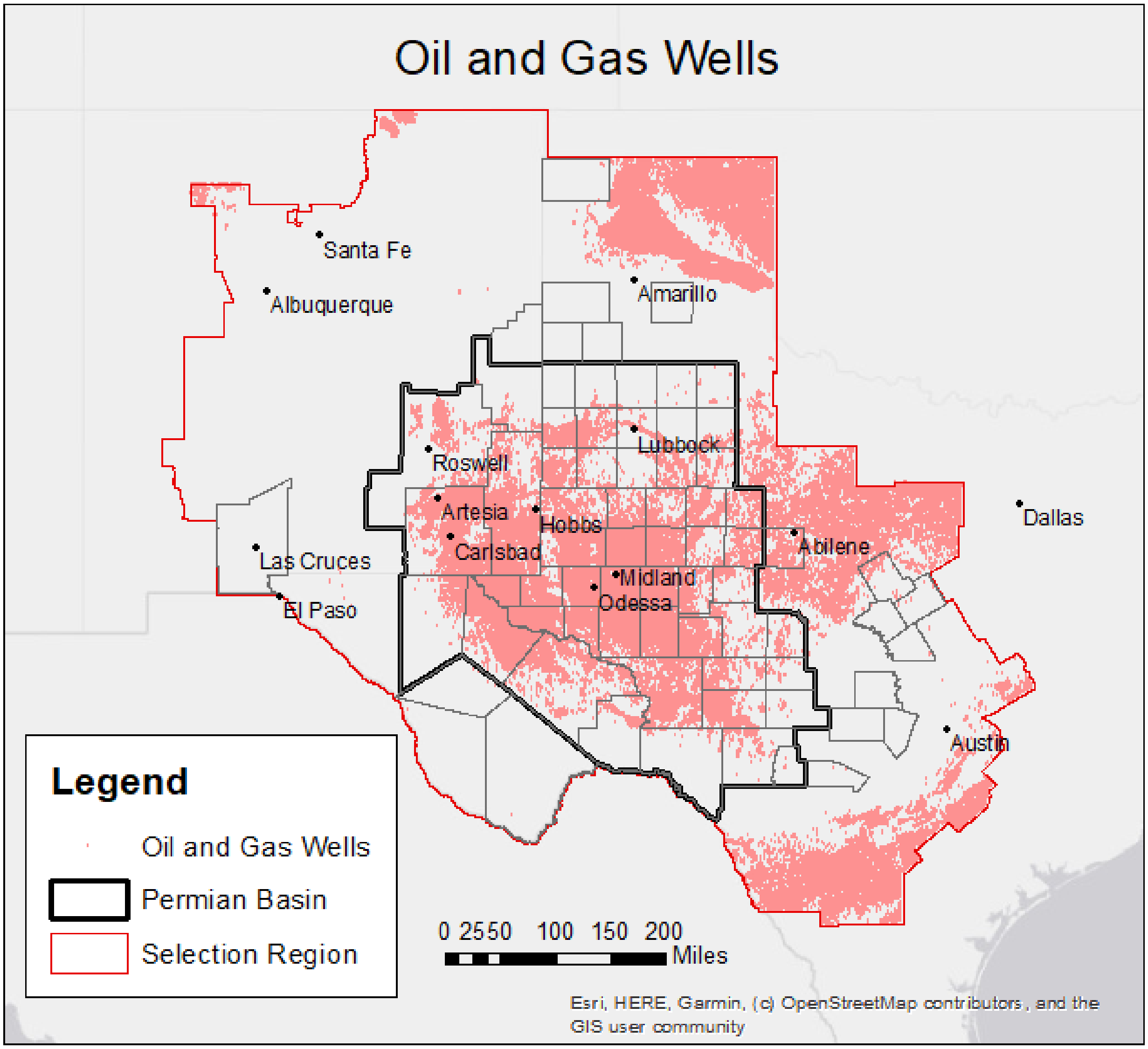


Figure 10: Oil and gas wells in the Permian basin and surrounding region. Sources: ArcMap, Railroad Commission of Texas, NM Oil and Gas Conservation Division.

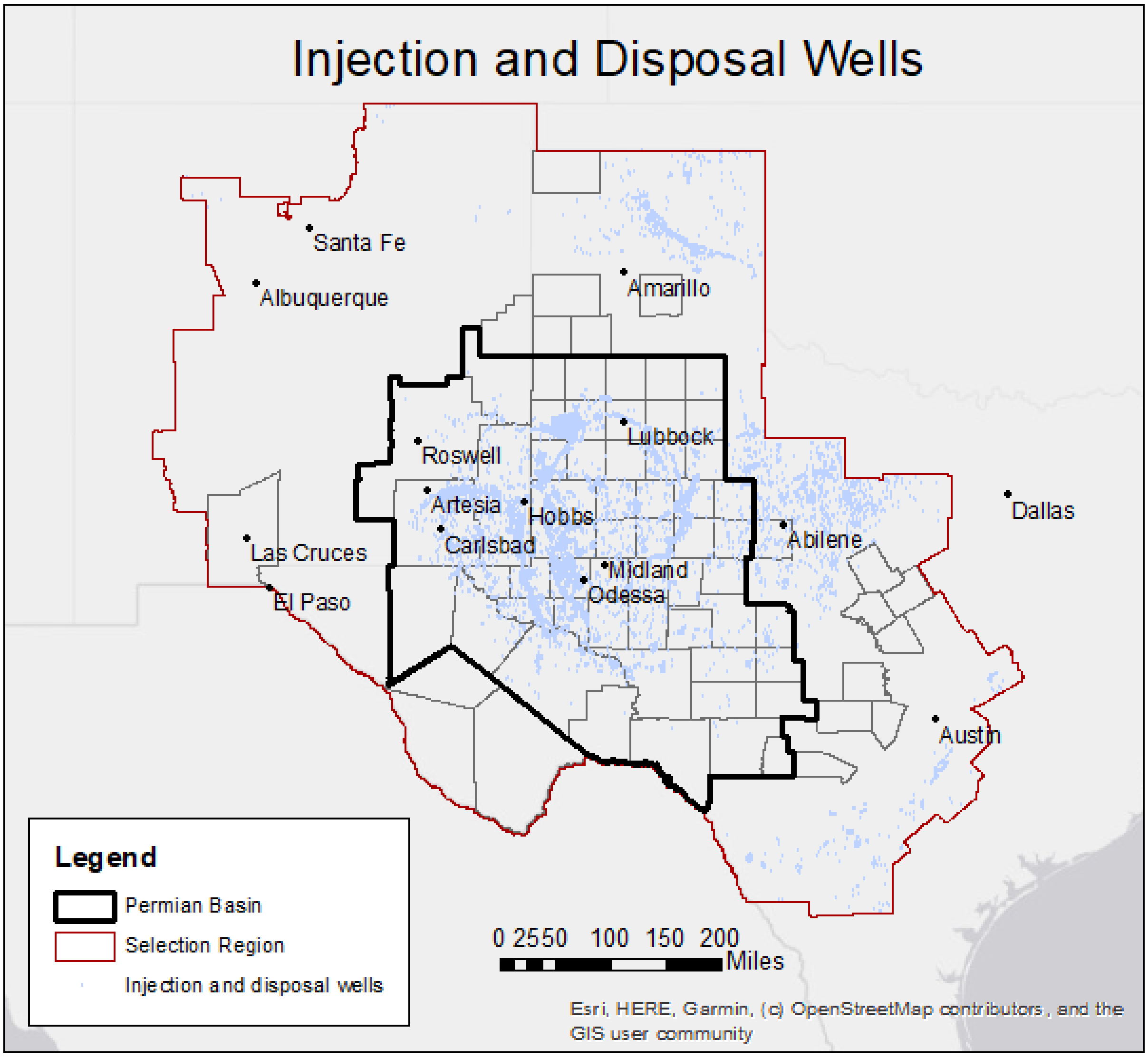


Figure 11: Injection and disposal wells distribution in the Permian Basin and surrounding region. Sources: ArcMap, Railroad Commission of Texas, NM Oil and Gas Conservation Division.

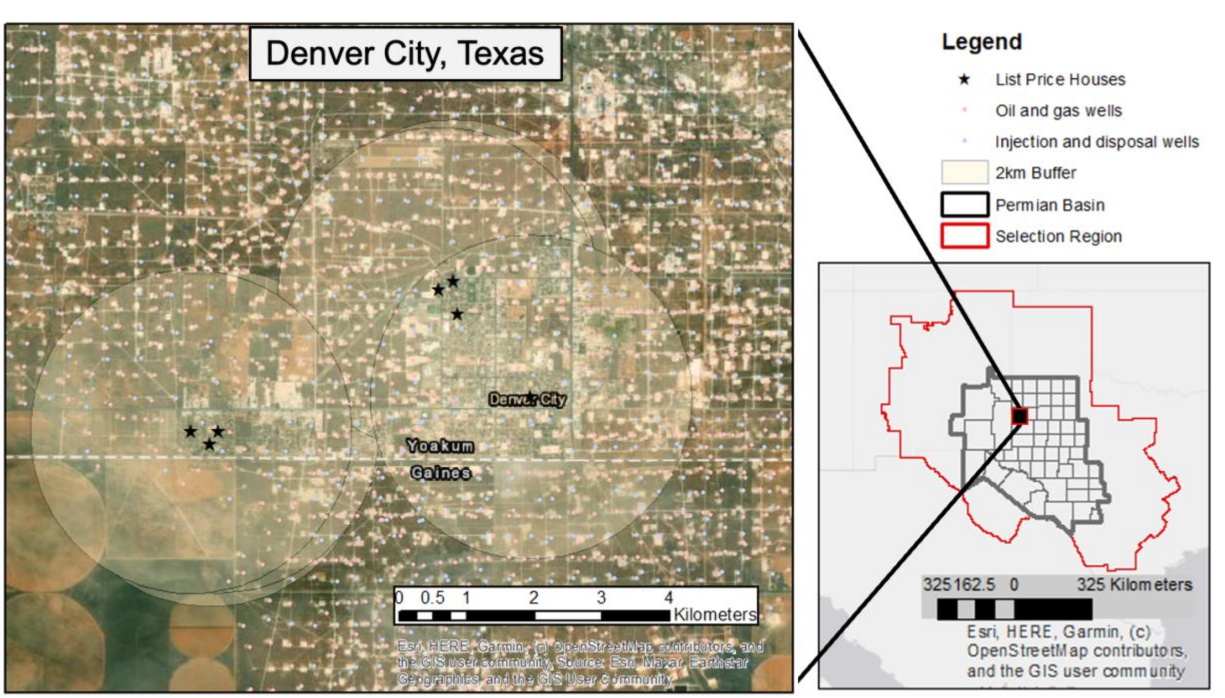


Figure 12: Distribution of both oil and gas, and injection and disposal wells in Denver City TX, with representative 2 km buffer around geolocated houses. Sources: ArcMap, Railroad Commission of Texas, NM Oil and Gas Conservation Division, Zillow.

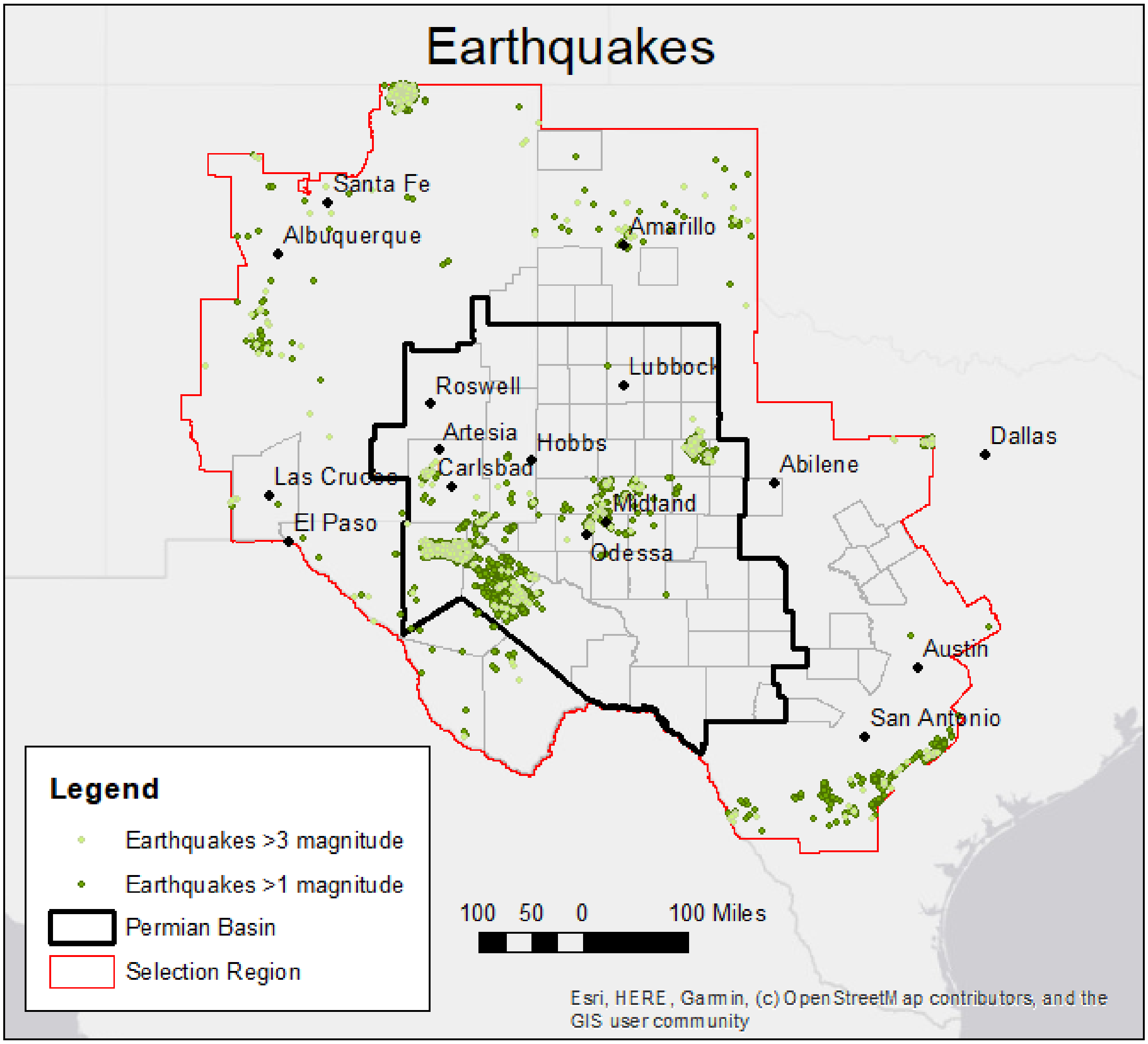


Figure 13: Distribution of earthquakes greater than magnitude 1 and 3 on the Richter scale from 1/1/2010-4/4/2023. Sources: U.S. Geological Survey and ArcMap.

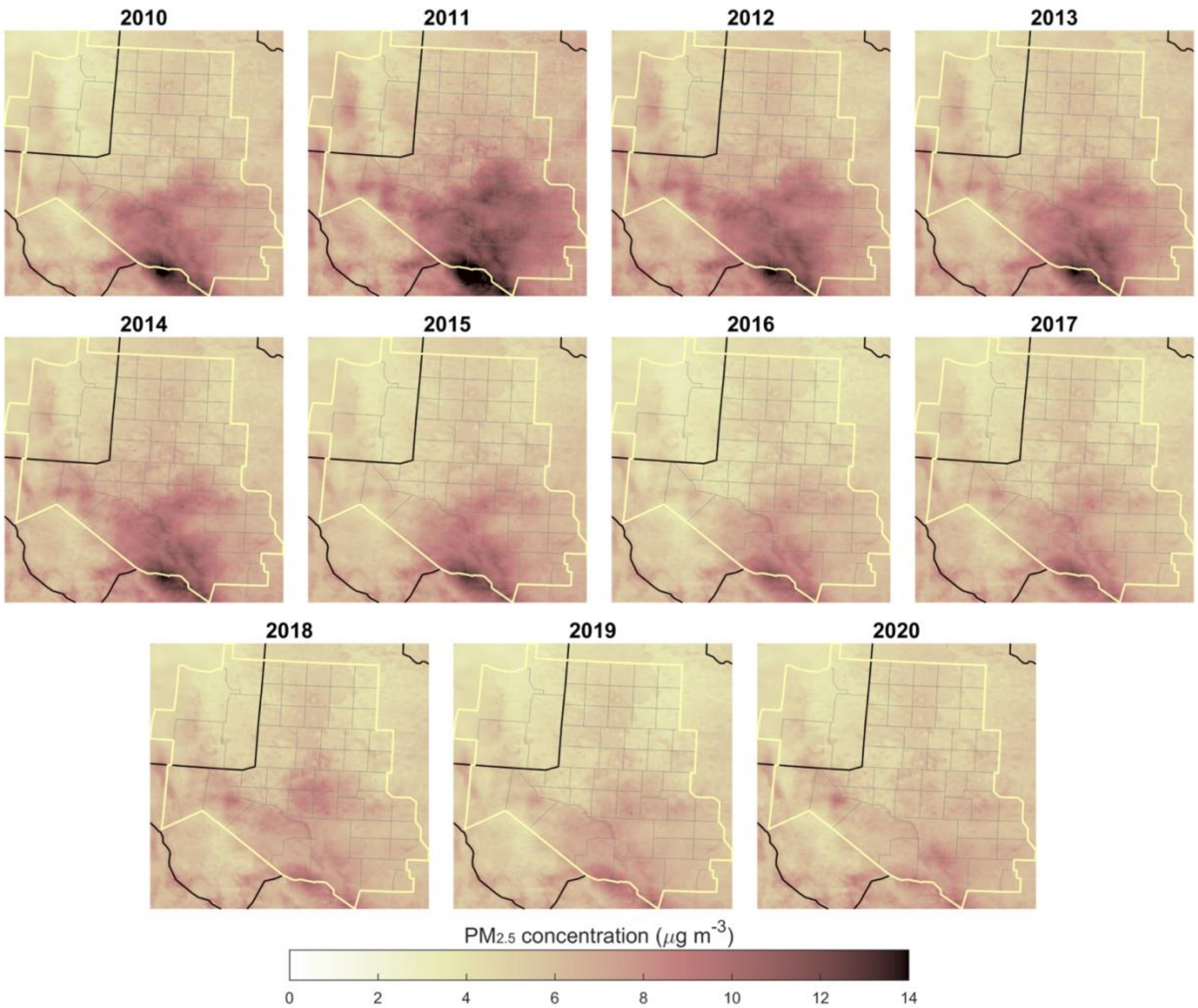


Figure 14: PM2.5 concentrations by year from 2010-2020 in the Permian Basin. Notes: 2017 is used in the analysis (PM2.5) because it is the same year as the National Emissions Inventory used to calculate **ΔPM2.5**. Data is calculated at a 5×5 km grid with the Permian Basin outlined in yellow. Sources: van Donkelaar et al. (2021) and Goodkind et al. (2023).

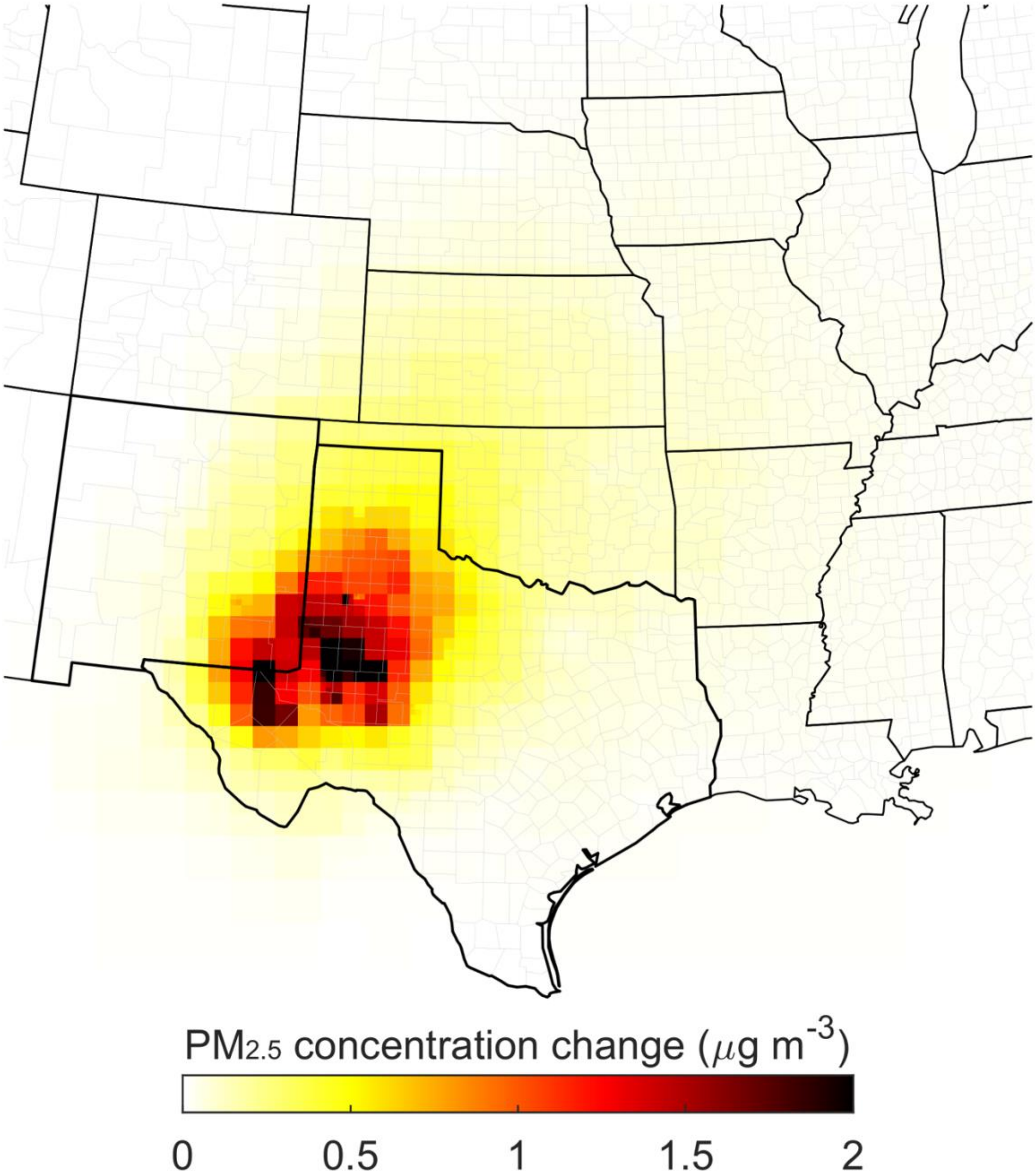


Figure 15: Change in $PM_{2.5}$ concentrations for 2017 due to oil and gas emissions originating in the Permian Basin (ΔPM2.5). Notes: Values include primary $PM_{2.5}$ and precursor emissions of $PM_{2.5}$. Values are attributed to census block groups and matched with geocoded addresses. Sources: Goodkind et al. (2023).

10. Tables

Table 1: Employment Metrics

Panel A: Average Location Quotients for NAICS 21			
	2009	2022	Change
Permian	19.77	26.48	+6.71
Non-Permian	5.80	8.15	+2.35
Panel B: All Industry Annual Wage			
	2009	2022	Change
Permian	$47,204.66	$58,002.89	$10,798.23
Non-Permian	$43,992.93	$51,129.65	$7,136.72
Panel C: NAICS 21 Annual Wage			
	2009	2022	Change
Permian	$59,832.04	$73,345.69	$13,513.64
Non-Permian	$58,533.44	$67,729.21	$9,195.77

Notes: 2009 values have been adjusted to $2022. Notes: Panel A and C are missing 25 counties in 2009 and 22 in 2022; Panel B is missing 2 counties for both years. Zero values were left as zeroes. Sources: U.S. BLS, 2009; U.S. BLS, 2022; author's calculations.

Table 2: Select Price or Value Information Used in Hedonic Pricing Housing Studies

Price or Value Variable	Notation	Variable Description and Discussion
SALEPRICE	P_h	A publicly available, observed sales price (P) for an individual residence or housing (h) unit. In disclosure states, this information is public (e.g., available in a county office), and would typically come with a parcel identifier, and address. In non-disclosure states, this information is publicly available. When available it often comes with detailed information on housing characteristics (lot size, sq feet of house, number of bedrooms etc.). Matching an address with geo-coordinates allow it to be matched to a wide variety of geospatial information, at the smallest available scale.
LISTPRICE	P_h^{LIST}	A posted or listed (LIST) sales price (P) for an individual residential housing unit (h), as provided by a variety of real estate advertising forums. When available it often comes with information on the detailed housing characteristics (lot size, sq feet of house, number of bedrooms and bathrooms etc.). This variable is like P_h in matching to geospatial information.
ZESTIMATE	P_h^Z	An *estimated* market price (P) for an individual residence or housing (h) unit, as provided by a private real estate corporation, such as the Zillow "Zestimate" (Z). It will typically come with information on individual house characteristics, which might have to be scraped, cleaned, and standardized. The available address allows this information to be geo-located and matched with a wide variety of geospatial information. These price estimates are based on propriety algorithms or formulas, typically expected to include available information on prior or neighboring sales, assessments, mortgages, listing information etc.
ASSESSED-VALUE	V_h^A	The publicly available assessed (A) value (V) for an individual residence or housing (h) unit. As used in ad valorem property value tax assessments, this information will commonly be available at county assessor websites or offices. Note that the assessed value is not necessarily the same as the taxable assessed value assigned (e.g., which might only be, say, 1/3 of assessed value in some states, like NM). There may be a variety of reasons why this measure is not closely correlated with market prices (e.g., lag in assessments, tax increase rate restrictions under state law, etc.). If an address exists, then it would be like P_h in matching to geospatial information.
SAMPLED-VALUE	V_h^S	A survey sample (S) of residents of their *perceived* market value (V) for their individual residence or housing (h) unit, as based on the individual responses. This may or may not be a US Census Bureau based product but would typically not be attached to geo-coordinates. For the example of the American Housing Survey (AHS), these responses do include detailed information on individual housing unit and property characteristics, and then some broad geographic location (e.g., the metropolitan statistical area, MSA). Geospatial matching can only happen at the level of the smallest available geographic location information (e.g., county or MSA). This data be available over time in standardized waves (e.g., AHS)
MED-SAMPLE-VALUE	$medV_g^S$	The statistical mean or median (med) for a survey sample (S) of residents of their perceived market value (V) for their individual residential housing unit, based on a particular geographic unit (g). This estimate could be a US Census Bureau product, such as the American Community Survey (ACS), or some other standardized national or sub-national survey. The available information on geographic unit may vary (e.g, median values of houses at the County, census tract and census block group levels). It may be available over time in standardized waves (e.g, ACS).

Table 3: Description of the Structural Variables and Housing Characteristics

Variable	Notation	Description
BEDROOMS	S_h^{BED}	Number of bedrooms in housing unit as taken from Zillow listing
BATHROOMS	S_h^{BATH}	Number of bathrooms in housing unit as taken from Zillow listing
SQFT	S_h^{SQFT}	Listed square feet of housing unit as taken from Zillow listing
MANU	S_h^{MANU}	Whether or not the housing unit is a manufactured home, as taken from Zillow listing: 1 = yes, 0 = otherwise
AGE	S_h^{AGE}	Age of housing unit in years as taken from Zillow listing. Variable determined as 2023 minus the date built (house in 2023 is 0). Houses categorized with a range are given oldest age in the range (i.e. 40-60 years is set to 60)
ACCENTRAL	S_h^{AC}	Whether or not housing unit includes air conditioning description, as taken from Zillow, using word “central”; 1 = yes, 0 otherwise
MULTI-GARAGE	$S_h^{MULTI-GAR}$	Whether or not housing unit, as taken from Zillow, is described as having a two-car garage or larger: 1= yes, 0=otherwise
LOTACRES	S_h^{LOT}	Lot size of the housing unit in acres, as taken from Zillow, Descriptions given in square feet have been converted to acres based on 43,560 square feet =1 acre

Table 4: Description of Location Variables

Variable	Notation	Description
URBAN	L_h^{URBAN}	Whether or not the address for a housing unit is located in an area defined by the 2020 US Census Bureau definition of Urban or Rural: 1 = yes, 0 = otherwise. Census defines an urban city as one with >5,000 people or 2,000 household units (US Census Bureau, 2023).
PERMIAN	$L_c^{PERMIAN}$	Whether or not the address for housing unit is located in county within Permian Basin. 1= in Permian, 0= in control group. Permian Basin counties defined usin Federal Reserve Bank of Dallas' map (*Energy in the Eleventh District*, n.d.). There are 55 Permian counties, and 18 control group counties, from eastern NM and western TX. For full list of counties, and the control group selection process, see Appendix A.
STATE	L^{STATE}	Whether the housing unit is in TX or NM: 1=NM, 0=TX
DIST	L_h^{DIST}	Distance of housing unit to nearest principial road or interstate in km. Roads in U.S. have three major categories: local, collectors, and arterials (Federal Highway Administration, 2016). Within arterials there are interstates, other principal arterials, and other freeway/expressways. Distance from house calculated to either an interstate or a road considered "other principal arterial".
MED-HINC	$L_b^{MED-HINC}$	Median annual household income (in thousands) for the block group where housing unit is located, as determined from 2019 American Community Survey (ACS); data and corresponding shapefiles accessed using IPUMS (Mason et al., 2022).
PCT-WHITE	$L_b^{PCT-WHITE}$	The percentage of the population of the block group who are white, as determined from 2019 ACS; data and corresponding shapefiles accessed using IPUMS (Mason et al., 2022).
PC-INC	L_b^{PC-INC}	Per capita annual income for the block group where a housing unit is located, as determined from 2019 ACS; data and corresponding shapefiles accessed using IPUMS (Mason et al., 2022).
POP-DENS	$L_b^{POP-DENS}$	Population density for block group where housing unit is located scaled by 100. Density calculated using 2019 ACS population value divided by land area of block group in square kilometers; data and corresponding shapefiles accessed using IPUMS (Mason et al., 2022).
AVG-UE	L_c^{AVG-UE}	Average unemployment rate, March 2022-February 2023, in the county of a housing unit. NM data collected from Local Area Unemployment Statistics (LAUS) website (New Mexico Workforce Connection, 2023). TX data collected from LAUS section of Texas Labor Market Information website (Texas Laborforce Commission, 2023).
PUBWATER	L_h^{PW}	Whether or not a housing unit is located within area with a public water supply system: 1= yes, 0 otherwise. Houses are joined to state public water shapefiles, as provided by: Office of the NM State Engineer (Office of the State Engineer, 2022) and Water Service Boundary Viewer from Texas Water Development Board (Texas Water Development Board, 2023).

Table 5: Description of Environmental Quality Variables

Variable	Notation	Description
EQS-MAG3	Q_h^{EQ3}	Number of earthquakes measured above magnitude 3.0 on Richter scale, from 1/1/2010-4/4/2023, and within 10 km of housing unit (U.S. Geological Survey, 2023).
SEIS-ACT-MAG3	Q_h^{SA3}	Indicator variable of whether at least one earthquake measured over magnitude 3.0 on Richter scale occurred within 10 km of housing unit: 1= yes, 0 otherwise
EQS-MAG1	Q_h^{EQ1}	Number of earthquakes measured above magnitude 1.0 on Richter scale, from 1/1/2010-4/4/2023, and within 10 km of housing unit (U.S. Geological Survey, 2023).
SEIS-ACT-MAG1	Q_h^{SA1}	Indicator variable of whether at least one earthquake measured over magnitude 3.0 on Richter scale occurred within 10 km of housing unit: 1= yes, 0 otherwise
ΔPM2.5	$Q_b^{\Delta PM}$	Block group level $PM_{2.5}$ concentration change attributable to oil and gas production in Permian Basin based on 2017 National Emissions Inventory (NEI). $PM_{2.5}$ is particulate matter in air with diameter less than 2.5 micrometers, measured as micrograms per cubic meter of air ($\mu g/m^3$) (New York Department of Health, 2018; US EPA, 2016). Goodkind et al. (2023) provided values from their attribution analysis of emissions in Permian Basin. $PM_{2.5}$ Precursor emissions are emissions that through chemical reactions become $PM_{2.5}$ (Indiana Department of Environmental Management, 2021). Goodkind et al. (2023) use four precursor emissions (primary $PM_{2.5}$, NO_x, VOCs, and SO_2) from 2017 NEI combined with InMAP Source-Receptor Matrix air quality model to measure downwind changes in PM2.5 concentrations due to emissions originating in Permian Basin. Resulting changes are measured at block group level and paired with each housing unit.
PM2.5	Q_b^{PM}	Average $PM_{2.5}$ value for block group the housing unit is in. $PM_{2.5}$ is particulate matter in air with a diameter less than 2.5 micrometers, measured as micrograms per cubic meter of air ($\mu g/m^3$) (New York Department of Health, 2018; US EPA, 2016). Value was calculated using satellite data from van Donkelaar et al. (2022) processed by Goodkind et al. (2023) then paired with the block group of a housing unit. Value is overall $PM_{2.5}$ value of block group for a housing unit.

Table 6: Description of Well Variables

Variable	Notation	Description
INJ&DISP-10KM	W_h^{INJ10}	Number of injection and disposal wells within 10 km of house
INJ&DISP-5KM	W_h^{INJ5}	Number of injection and disposal wells within 5 km of house
INJ&DISP-2KM	W_h^{INJ2}	Number of injection and disposal wells within 2 km of house
INJ&DISP-1KM	W_h^{INJ1}	Number of injection and disposal wells within 1 km of house
INJ&DISP-0.5KM	$W_h^{INJ0.5}$	Number of injection and disposal wells within 0.5 km of house
O&G-10KM	W_h^{OG10}	Number of oil and gas wells within 10 km of house
O&G-5KM	W_h^{OG5}	Number of oil and gas wells within 5 km of house
O&G-2KM	W_h^{OG2}	Number of oil and gas wells within 2 km of house
O&G-1KM	W_h^{OG1}	Number of oil and gas wells within 1 km of house
O&G-0.5KM	$W_h^{OG0.5}$	Number of oil and gas wells within 0.5 km of house
ALLWELLS-10KM	W_h^{WELL10}	Number of all four types of wells within 10 km of house
ALLWELLS-5KM	W_h^{WELL5}	Number of all four types of wells within 5 km of house
ALLWELLS-2KM	W_h^{WELL2}	Number of all four types of wells within 2 km of house
ALLWELLS-1KM	W_h^{WELL1}	Number of all four types of wells within 1 km of house
ALLWELLS-0.5KM	$W_h^{WELL0.5}$	Number of all four types of wells within 0.5 km of house

Notes: Wells in NM determined using NM Oil and Gas Division's Geospatial Hub map of all well locations (Livengood, 2023). NM has seven types: oil, gas, injection, saltwater disposal, CO_2, miscellaneous, and water. INJ&DISP layer combines injection and saltwater disposal wells. O&G layers combine oil and gas wells. ALLWELLS layer combines INJ&DISP layer with O&G layer. TX data is obtained from Railroad Commission of Texas. SYMNUM is the type of well from the code description provided in the Digital Map Information User Guide (Railroad Commission of Texas, 2021). We combine wells from all counties of interest and then keep the wells with a SYMNUM of 21- 23, 104-107, 124-127, and 144-147 to capture the INJ&DISP wells. O&G wells fall under SYMNUM 4 and 5. ALLWELL layer contains both INJ&DISP layer and O&G layer. The wells included in this study are considered active in the NM database and we exclude SYMNUM's of plugged or shut-in wells in TX. Layers for both states combined for three resulting production layers: INJ&DISP, O&G, and ALLWELLS. Buffers created around each housing unit using radii of 0.5 km, 1 km, 2 km, 5 km, and 10 km. Number of wells from any respective layer (INJ&DISP, O&G, and ALLWELLS) within each ring around a housing unit are counted to create the variable.

Table 7: Select Past Research Using HPM with Oil and Gas Development

Paper	Price or Value Measure	Location	Key Topics	Findings
Balthrop & Hawley (2017)	P_h	Fort Worth, TX (Tarrant CO)	Well proximity	Within 3,500 feet of a well lowered home values 1.5-3.5% on average
He et al. (2017)	P_h	Weld County, CO	Well permit proximity, water type, distance to road	Inconclusive
Lee & Whitacre (2021)	P_h	Oklahoma	Well proximity, water type, distance to road	Inconclusive
Gopalakrishnan & Klaiber (2013)	P_h	Washington County, PA	Well proximity, water type, distance to road	Homes on well water within 0.75mi of an active well worth 21.7% less, effect is less as distance increases
Muehlenbachs et al. (2015)	P_h	Pennsylvania	Well proximity, water type	Within 1-1.5 km of well piped water benefits $6,339 annually. Non-piped losing $39,820 annually
Ferreira et al. (2018)	P_h	Oklahoma	Earthquakes	Injection well within 2 km and additional earthquake over 3.0M decreases value by $571.
Gibbons (2021)	P_h	United Kingdom	Earthquakes	Willingness to pay to avoid earthquakes between $577 and $696 annually
Metz et al. (2017)	P_h	Oklahoma	Earthquakes	3.15%-4.71% decrease in home values (~$8,458) after earthquakes started
Boxall et al. (2005)	P_h	Central Alberta, Canada	Air quality	Increased H_2S emissions lead to 4.3% decrease in price, on average
Bennett & Loomis (2015)	P_h	Weld County, CO	Well proximity, well density	In 7 of 12 models, an additional well within 0.5 miles decreases home values 1% in non-rural areas
Weber et al. (2016)	$medV_{ZIP}^{S}$	Dallas/Ft. Worth, Texas	Well density	Using ZHVI, a $1.27 per student increase in O&G property tax base led to $0.19 increase in home value

Note: all values are converted into $2022.

Table 8: Description of Alternative Dependent Variables

Variable	Notation	Description
lnLISTPRICE	$ln\ P_h^{LIST}$	Natural log of the listing price of a housing unit and connected property, as taken from Zillow listing
lnZESTIMATE	$ln\ P_h^{Z}$	Natural log of the Zestimate, the Zillow estimated value of a housing unit and connected property, as taken from Zillow listing. Zestimate based on a proprietary model that accounts for public data, multiple listing service (MLS) data, user-submitted data, location information, and market trends (Zillow, 2023).

Table 9: Price Variables Summary Statistics

	Permian		Control		Total	
Variable	N	Mean [Median] (Std. Dev.)	N	Mean [Median] (Std. Dev.)	N	Mean [Median] (Std. Dev.)
P_h^{LIST}	4,353	326,115 [244,900] (392,095)	2,455	600,425 [359,900] (937,383)	6,808	425,032 [275,000] (657,586)
P_h^{Z}	1,638	287,687 [232,197] (244,577)	1,318	525,816 [363,050] (573,038)	2,956	393,862 [277,029] (439,890)

Table 10: Structural Variables Summary Statistics

	Permian		Control		Total	
Variable	N	Mean [Median] (Std. Dev.)	N	Mean [Median] (Std. Dev.)	N	Mean [Median] (Std. Dev.)
S_h^{BED}	4,353	3.2977 [3] (0.8112)	2,455	3.2420 [3] (0.8744)	6,808	3.2776 [3] (0.8349)
S_h^{BATH}	4,353	2.2885 [1] (0.9674)	2,455	2.4301 [2] (1.0004)	6,808	2.3396 [2] (0.9817)
S_h^{SQFT}	4,353	2,109.66 [1,893] (1,111.11)	2,455	2,145.12 [1,914] (1,056.98)	6,808	2,122.45 [1,900] (1,091.96)
S_h^{AGE}	4,034	41.4955 [43] (26.9682)	2,367	35.161 [28] (28.6482)	6,401	39.1531 [39] (27.7681)
S_h^{LOT}	4,046	8.6793 [0.2222] (216.989)	2,292	13.1488 [0.32] (230.64)	6,338	10.2956 [0.2410] (222.015)
S_h^{MANU}	4,353	0.0542 [0] (0.2265)	2,455	0.0562 [0] (0.2304)	6,808	0.0549 [0] (0.2279)
S_h^{AC}	4,343	0.7840 [1] (0.4115)	2,423	0.7924 [1] (0.4057)	6,766	0.7870 [1] (0.4094)
$S_h^{MULTI-GAR}$	4,341	0.4879 [0] (0.4999)	2,433	0.5113 [1] (0.5000)	6,774	0.4963 [0] (0.5000)

Table 11: Location Variables Summary Statistics

	Permian		**Control**		**Total**	
Variable	N	Mean [Median] (Std. Dev)	N	Mean [Median] (Std. Dev)	N	Mean [Median] (Std. Dev)
L_h^{URBAN}	4,353	0.8707 [1] (0.3356)	2,455	0.6705 [1] (0.4701)	6,808	0.7985 [1] (0.4012)
$L_c^{PERMIAN}$	4,353	1 [1] (0)	2,455	0 [0] (0)	6,808	0.6394 [1] (0.48020
L^{STATE}	4,353	0.1907 [0] (0.3929)	2,455	0.3198 [0] (0.4665)	6,808	0.2372 [0] (0.4254)
L_h^{DIST}	4,353	2.6335 [0.7597] (6.7886)	2,455	4.7970 [1.2600] (9.4439)	6,808	3.4137 [0.8942] (7.9181)
$L_b^{MED-HINC}$	4,201	71.0922 [65.655] (33.1169)	2,418	63.2143 [57.75] (23.504)	6,619	68.2143 [62.333] (30.2022)
L_b^{PC-INC}	4,353	32,192.7 [28,991] (16,267.3)	2,455	33,945.3 [29,761] (17,741)	6,808	32,824.7 [29,379] (16,219.9)
$L_b^{POP-DENS}$	4,353	8.2622 [5.1621] (8.7650)	2,455	4.5531 [1.3455] (6.3160)	6,808	6.9247 [3.4271] (8.1652)
L_c^{AVG-UE}	4,353	4.6119 [4.5171] (1.4310)	2,455	5.2182 [5.0848] (1.8781)	6,808	4.8306 [4.5171] (1.6327)
L_h^{PW}	4,353	0.8390 [1] (0.3676)	2,455	0.8692 [1] (0.3372)	6,808	0.8499 [1] (0.3572)

Table 12: Well Variable Summary Statistics

Variable	**Permian** N	**Permian** Mean [Median] (Std. Dev.)	**Control** N	**Control** Mean [Median] (Std. Dev.)	**Total** N	**Total** Mean [Median] (Std. Dev.)
W_h^{INJ2}	4,353	1.7138 [0] (7.5841)	2,455	0.0489 [0] (0.2555)	6,808	1.1134 [0] (6.1185)
W_h^{INJ1}	4,353	0.3701 [0] (2.0469)	2,455	0.0118 [0] (0.1222)	6,808	0.2409 [0] (1.6474)
W_h^{OG2}	4,353	12.9412 [0] (26.0561)	2,455	0.8778 [0] (3.6525)	6,808	8.5911 [0] (21.7354)
W_h^{OG1}	4,353	2.5449 [0] (6.7528)	2,455	0.1735 [0] (1.1276)	6,808	1.6898 [0] (5.5596)
W_h^{WELL2}	4,353	14.655 [0] (30.5479)	2,455	0.9267 [0] (3.7652)	6,808	9.7045 [0] (25.4006)
W_h^{WELL1}	4,353	2.915 [0] (7.9406)	2,455	0.1853 [0] (1.1640)	6,808	1.9307 [0] (6.5207)

Table 13: Environmental Quality Summary Statistics

Variable	Permian N	Permian Mean [Median] (Std. Dev.)	Control N	Control Mean [Median] (Std. Dev.)	Total N	Total Mean [Median] (Std. Dev.)
Q_h^{EQ3}	4,353	1.4154 [0] (3.6731)	2,455	0.0016 [0] (0.0807)	6,808	0.9056 [0] (3.0148)
Q_h^{SA3}	4,353	0.1895 [0] (0.3920)	2,455	0.0004 [0] (0.0202)	6,808	0.1213 [0] (0.3265)
Q_h^{EQ1}	4,353	13.2826 [0] (31.5354)	2,455	0.0293 [0] (0.2058)	6,808	8.5034 [0] (26.0064)
Q_h^{SA1}	4,353	0.1264 [0] (0.3323)	2,455	0 [0] (0)	6,808	0.0809 [0] (2.7874)
$Q_b^{\Delta PM}$	4,353	2.2135 [1.3098] (3.2748)	2,455	0.2429 [0.1043] (0.2213)	6,808	1.5029 [0.8806] (2.7874)
Q_b^{PM}	4,353	6.0082 [5.9] (1.0426)	2,455	5.8231 [5.9] (0.5970)	6,808	5.9414 [5.9] (0.9118)

Table 14: Base Models, and Well Density (N=5,767)

Dependent Variable: lnLISTPRICE				
Variables	Model 1	Model 2	Model 3	Model 4
SQFT	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MANU	-0.3410***	-0.3169***	-0.3461***	-0.3434***
	(0.0581)	(0.0600)	(0.0581)	(0.0581)
AGE	-0.0062***	-0.0059***	-0.0062***	-0.0062***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
LOTACRES	0.0002	0.0002	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
BEDROOMS	0.0437**	0.0491***	0.0460***	0.0452***
	(0.0175)	(0.0169)	(0.0172)	(0.0173)
MULTI-GARAGE	0.0875***	0.0774***	0.0825***	0.0859***
	(0.0222)	(0.0214)	(0.0217)	(0.0219)
ACCENTRAL	0.1469***	0.1205***	0.1460***	0.1467***
	(0.0251)	(0.0258)	(0.0247)	(0.0249)
AVG-UE	-0.0873***	-0.0976***	-0.1013***	-0.0945***
	(0.0282)	(0.0265)	(0.0275)	(0.0279)
DIST	0.0062**	0.0061***	0.0060**	0.0060**
	(0.0024)	(0.0023)	(0.0024)	(0.0024)
MED-HINC	0.0008	0.0015***	0.0011**	0.0009*
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
POP-DENS	-0.0078***	-0.0057***	-0.0087***	-0.0084***
	(0.0013)	(0.0012)	(0.0013)	(0.0013)
PCT-WHITE	0.0062***	0.0069***	0.0059***	0.0061***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
PUBWATER	0.0478***	0.0496***	0.0461**	0.0462**
	(0.0183)	(0.0178)	(0.0181)	(0.0182)
PERMIAN		-0.2727***		
		(0.0299)		
ALLWELLS-2KM			-0.0024***	
			(0.0004)	
ALLWELLS-1KM				-0.0053***
				(0.0013)
Constant	11.581***	11.63***	11.6487***	11.6138***
	(0.1428)	(0.1377)	(0.1382)	(0.1403)
R^2	0.6426	0.6621	0.6470	0.6442
VIF>10	No	No	No	No

Notes: All models include month fixed effects, and robust standard errors clustered by block group. Significance denoted by: *** p<0.01, ** p<0.05, *p<0.1

Table 15: Extended Models (N=5,767)

Dependent Variable: lnLISTPRICE						
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
SQFT	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MANU	-0.3330***	-0.3233***	-0.3461***	-0.3246***	-0.3425***	-0.3176***
	(0.0572)	(0.0582)	(0.0581)	(0.0598)	(0.0578)	(0.0600)
AGE	-0.0061***	-0.0052***	-0.0062***	-0.0059***	-0.0063***	-0.0059***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
LOTACRES	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
BEDROOMS	0.0453***	0.0568***	0.0460***	0.0509***	0.0439**	0.0492***
	(0.0174)	(0.0165)	(0.0172)	(0.0168)	(0.0174)	(0.0169)
MULTI-GARAGE	0.0915***	0.1062***	0.0825***	0.0750***	0.0894***	0.0783***
	(0.0217)	(0.0206)	(0.0217)	(0.0211)	(0.0219)	(0.0213)
ACCENTRAL	0.1447***	0.1050***	0.1460***	0.1199***	0.1466***	0.1205***
	(0.0252)	(0.0256)	(0.0247)	(0.0256)	(0.0250)	(0.0258)
AVG-UE	-0.1061***	-0.1669***	-0.1013***	-0.1067***	-0.0932***	-0.0993***
	(0.0299)	(0.0291)	(0.0275)	(0.0266)	(0.0276)	(0.0265)
DIST	0.0060**	0.0059**	0.0060**	0.0059**	0.0061**	0.0061**
	(0.0024)	(0.0024)	(0.0024)	(0.0023)	(0.0024)	(0.0024)
MED-HINC	0.0017***	0.0020***	0.0011**	0.0016***	0.0010*	0.0015***
	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0006)	(0.0005)
POP-DENS	-0.0060***	-0.0051***	-0.0087***	-0.0064***	-0.0075***	-0.0056***
	(0.0013)	(0.0012)	(0.0013)	(0.0013)	(0.0013)	(0.0012)
PCT-WHITE	0.0059***	0.0053***	0.0059***	0.0068***	0.0060***	0.0068***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
PUBWATER	0.0532***	0.0475***	0.0461**	0.0482***	0.0483***	0.0497***
	(0.0182)	(0.0173)	(0.0181)	(0.0177)	(0.0183)	(0.0178)
PERMIAN		-1.7834***		-0.2671***		-0.2702***
		(0.3970)		(0.0301)		(0.0300)
PM2.5	-0.0077	-0.1998***				
	(0.0119)	(0.0570)				
ΔPM2.5	-0.0205***	-1.3593***				
	(0.0038)	(0.1917)				
PERMIAN*PM2.5		0.1976***				
		(0.0585)				
PERMIAN*ΔPM2.5		1.3529***				
		(0.1920)				
ALLWELLS-2KM			-0.0024***	-0.0082**		
			(0.0004)	(0.0040)		
PERMIAN* ALLWELLS-2KM				0.0070*		
				(0.0040)		
EQ-MAG1					-0.0010*	0.0335
					(0.0005)	(0.0885)
PERMIAN* EQ-MAG1						-0.0337
						(0.0885)
Constant	11.6515***	13.4346***	11.6487***	11.6684***	11.6001***	11.6351***
	(0.1435)	(0.4177)	(0.1382)	(0.1366)	(0.1400)	(0.1378)
R^2	0.6466	0.6831	0.6470	0.6637	0.6433	0.6621
VIF>10	No	Yes	No	Yes	No	Yes

Notes: All models include month fixed effects, and robust standard errors clustered by block group. Significance denoted by: *** p<0.01, ** p<0.05, *p<0.1

Table 16: Permian Counties Sample Only (N=3,602)

Dependent Variable: lnLISTPRICE				
Variables	Model 1	Model 2	Model 3	Model 4
HOUSESQFT	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MANU	-0.2243***	-0.2230***	-0.2268***	-0.2221***
	(0.0759)	(0.0762)	(0.0760)	(0.0760)
AGE	-0.0055***	-0.0057***	-0.0056***	-0.0055***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
LOTACRES	0.0002	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
BEDROOMS	0.0608***	0.0616***	0.0612***	0.0609***
	(0.0178)	(0.0177)	(0.0178)	(0.0178)
MULTI-GARAGE	0.1726***	0.1704***	0.1712***	0.1716***
	(0.0241)	(0.0239)	(0.0241)	(0.0240)
ACCENTRAL	0.1700***	0.1751***	0.1700***	0.1701***
	(0.0262)	(0.0265)	(0.0261)	(0.0263)
AVG-UE	-0.0605***	-0.0526**	-0.0633***	-0.0585**
	(0.0226)	(0.0242)	(0.0228)	(0.0230)
DIST	0.0039	0.0037	0.0039	0.0040
	(0.0041)	(0.0041)	(0.0040)	(0.0041)
MED-HINC	0.0018***	0.0018***	0.0019***	0.0018***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
POP-DENS	-0.0028**	-0.0028**	-0.0031**	-0.0029**
	(0.0012)	(0.0012)	(0.0012)	(0.0012)
PCT-WHITE	0.0036***	0.0033***	0.0035***	0.0036***
	(0.0009)	(0.0009)	(0.0009)	(0.0010)
PUBWATER	0.0355*	0.0355*	0.0350*	0.0352*
	(0.0198)	(0.0199)	(0.0199)	(0.0198)
PM2.5		-0.0230**		
		(0.0115)		
ΔPM2.5		0.0013		
		(0.0024)		
ALLWELLS-2KM			-0.0004	
			(0.0004)	
EQ-MAG1				0.0003
				(0.0004)
Constant	11.4832***	11.6139***	11.5016***	11.4738***
	(0.1160)	(0.1202)	(0.1160)	(0.1176)
R^2	0.6797	0.6805	0.6800	0.6799
VIF>10	No	No	No	No

Notes: All models include month fixed effects, and robust standard errors clustered by block group. Significance denoted by: *** p<0.01, ** p<0.05, *p<0.1

Table 17: Control Counties Sample Only (N=2,165)

Dependent Variable: lnLISTPRICE				
Variables	Model 1	Model 2	Model 3	Model 4
HOUSESQFT	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MANU	-0.4541***	-0.4474***	-0.4594***	-0.4543***
	(0.0852)	(0.0855)	(0.0850)	(0.0851)
AGE	-0.0060***	-0.0047***	-0.0060***	-0.0060***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
LOTACRES	0.0002	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
BEDROOMS	0.0547*	0.0567*	0.0556*	0.0549*
	(0.0313)	(0.0297)	(0.0313)	(0.0313)
MULTI-GARAGE	0.0105	0.0778**	0.0074	0.0118
	(0.0338)	(0.0357)	(0.0339)	(0.0335)
ACCENTRAL	0.0953**	0.0750*	0.0941**	0.0950**
	(0.0454)	(0.0424)	(0.0453)	(0.0453)
AVG-UE	-0.2100***	-0.4511***	-0.2131***	-0.2118***
	(0.0609)	(0.0788)	(0.0611)	(0.0609)
DIST	0.0065**	0.0110***	0.0066***	0.0067**
	(0.0025)	(0.0031)	(0.0025)	(0.0027)
MED-HINC	0.0031***	0.0026***	0.0031***	0.0030***
	(0.0010)	(0.0008)	(0.0009)	(0.0010)
POP-DENS	-0.0092***	-0.0088***	-0.0097***	-0.0091***
	(0.0032)	(0.0026)	(0.0033)	(0.0033)
PCT-WHITE	0.0095***	0.0062***	0.0098***	0.0095***
	(0.0021)	(0.0017)	(0.0021)	(0.0021)
PUBWATER	0.0635**	0.0706**	0.0653**	0.0634**
	(0.0318)	(0.0298)	(0.0316)	(0.0318)
PM2.5		-0.0730		
		(0.0473)		
ΔPM2.5		-1.5395***		
		(0.1977)		
ALLWELLS-2KM			-0.0073*	
			(0.0038)	
EQ-MAG1				0.0496
				(0.0970)
Constant	11.6599***	13.5675***	11.6574***	11.6653***
	(0.2412)	(0.4268)	(0.2407)	(0.2417)
R^2	0.6346	0.6799	0.6356	0.6347
VIF>10	No	No	No	No

Notes: All models include month fixed effects, and robust standard errors clustered by block group. Significance denoted by: *** p<0.01, ** p<0.05, *p<0.1

Table 18: Base Models and Well Density with lnZESTIMATE (N=2,601)

Dependent Variable: lnZESTIMATE				
Variables	Model 1	Model 2	Model 3	Model 4
HOUSESQFT	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MANU	-0.2652***	-0.2275***	-0.2676***	-0.2659***
	(0.0882)	(0.0831)	(0.0883)	(0.0881)
AGE	-0.0059***	-0.0058***	-0.0059***	-0.0059***
	(0.0006)	(0.0005)	(0.0006)	(0.0006)
LOTACRES	4.78e-05	6.59e-05	6.26e-05	5.99e-05
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
BEDROOMS	0.0263	0.0318	0.0271	0.0268
	(0.0270)	(0.0264)	(0.0267)	(0.0269)
MULTI-GARAGE	0.1159***	0.0948***	0.1090***	0.1137***
	(0.0284)	(0.0272)	(0.0280)	(0.0281)
ACCENTRAL	0.1663***	0.1473***	0.1680***	0.1689***
	(0.0358)	(0.0352)	(0.0351)	(0.0354)
AVG-UE	-0.0983***	-0.1057***	-0.1177***	-0.1090***
	(0.0334)	(0.0307)	(0.0329)	(0.0331)
DIST	0.0048	0.0049	0.0049	0.0048
	(0.0030)	(0.0031)	(0.0030)	(0.0030)
MED-HINC	0.0011**	0.0014***	0.0012**	0.0011**
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
POP-DENS	-0.0057***	-0.0030**	-0.0065***	-0.0063***
	(0.0015)	(0.0014)	(0.0015)	(0.0015)
PCT-WHITE	0.0050***	0.0055***	0.0048***	0.0049***
	(0.0011)	(0.0010)	(0.0011)	(0.0011)
PUBWATER	0.0322	0.0427*	0.0345	0.0328
	(0.0228)	(0.0221)	(0.0226)	(0.0227)
PERMIAN		-0.2643***		
		(0.0298)		
ALLWELLS-2KM			-0.0028***	
			(0.0005)	
ALLWELLS-1KM				-0.0067***
				(0.0016)
Constant	11.8360***	11.7819***	11.9158***	11.8775***
	(0.2033)	(0.1892)	(0.2011)	(0.2019)
R^2	0.7038	0.7239	0.7086	0.7060
VIF>10	No	No	No	No

Notes: All models include month fixed effects, and robust standard errors clustered by block group.
Significance denoted by: *** p<0.01, ** p<0.05, *p<0.1

Table 19: Extended Models with lnZESTIMATE (N=2,601)

Dependent Variable: lnZESTIMATE						
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
HOUSESQFT	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MANU	-0.2509***	-0.2235***	-0.2676***	-0.2325***	-0.2648***	-0.2299***
	(0.0874)	(0.0783)	(0.0883)	(0.0832)	(0.0881)	(0.0832)
AGE	-0.0057***	-0.0051***	-0.0059***	-0.0059***	-0.0059***	-0.0058***
	(0.0006)	(0.0005)	(0.0006)	(0.0005)	(0.0006)	(0.0005)
LOTACRES	5.15e-05	5.42e-05	6.26e-05	7.28e-05	4.78e-05	6.57e-05
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
BEDROOMS	0.0284	0.0395	0.0271	0.0323	0.0263	0.0319
	(0.0271)	(0.0262)	(0.0267)	(0.0263)	(0.0270)	(0.0265)
MULTI-GARAGE	0.1190***	0.1208***	0.1090***	0.0917***	0.1171***	0.0957***
	(0.0276)	(0.0263)	(0.0280)	(0.0271)	(0.0282)	(0.0271)
ACCENTRAL	0.1612***	0.1311***	0.1680***	0.1489***	0.1663***	0.1458***
	(0.0358)	(0.0338)	(0.0351)	(0.0349)	(0.0357)	(0.0352)
AVG-UE	-0.1296***	-0.1822***	-0.1177***	-0.1177***	-0.1029***	-0.1061***
	(0.0372)	(0.0352)	(0.0329)	(0.0308)	(0.0333)	(0.0310)
DIST	0.0049	0.0055*	0.0049	0.0050	0.0048	0.0052*
	(0.0030)	(0.0033)	(0.0030)	(0.0031)	(0.0030)	(0.0031)
MED-HINC	0.0018***	0.0020***	0.0012**	0.0015***	0.0012**	0.0014***
	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0005)
POP-DENS	-0.0040***	-0.0027**	-0.0065***	-0.0036**	-0.0055***	-0.0030**
	(0.0015)	(0.0013)	(0.0015)	(0.0014)	(0.0015)	(0.0014)
PCT-WHITE	0.0047***	0.0050***	0.0048***	0.0054***	0.0049***	0.0055***
	(0.0011)	(0.0009)	(0.0011)	(0.0010)	(0.0011)	(0.0010)
PUBWATER	0.0398*	0.0398*	0.0345	0.0437**	0.0325	0.0434**
	(0.0225)	(0.0211)	(0.0226)	(0.0219)	(0.0228)	(0.0221)
PM2.5	0.0010	-0.1357***				
	(0.0134)	(0.0509)				
ΔPM2.5	-0.0270***	-1.2118***				
	(0.0047)	(0.1870)				
PERMIAN		-1.5373***		-0.2532***		-0.2646***
		(0.3579)		(0.0294)		(0.0298)
PERMIAN*PM2.5		0.1603***				
		(0.0524)				
PERMIAN*ΔPM2.5		1.2041***				
		(0.1871)				
ALLWELLS-2KM			-0.0028***	-0.0043		
			(0.0005)	(0.0045)		
PERMIAN*				0.0027		
ALLWELLS-2KM				(0.0044)		
EQ-MAG1					-0.0007	0.1293
					(0.0005)	(0.0895)
PERMIAN*						-0.1292
EQ-MAG1						(0.0894)
Constant	11.9068***	12.9995***	11.9158***	11.8317***	11.8532***	11.7769***
	(0.1928)	(0.3911)	(0.2011)	(0.1893)	(0.2030)	(0.1905)
R^2	0.7090	0.7413	0.7086	0.7256	0.7041	0.7242
VIF>10	No	Yes	No	Yes	No	Yes

Notes: All models include month fixed effects, and robust standard errors clustered by block group. Significance denoted by: *** p<0.01, ** p<0.05, *p<0.1

Table 20: Base Models and Well Density with Conley Standard Errors (N=5,767)

Dependent Variable: lnLISTPRICE				
VARIABLES	Model 1	Model 2	Model 3	Model 4
SQFT	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MANU	-0.344***	-0.325***	-0.350***	-0.347***
	(0.0632)	(0.0681)	(0.0632)	(0.0633)
AGE	-0.0062***	-0.0059***	-0.0062***	-0.0062***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
LOTACRES	0.0002	0.0002	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
BEDROOMS	0.0444**	0.0515***	0.0470**	0.0461**
	(0.0184)	(0.0190)	(0.0188)	(0.0187)
MULTI-GARAGE	0.0919***	0.0886***	0.0875***	0.0906***
	(0.0264)	(0.0244)	(0.0256)	(0.0261)
ACCENTRAL	0.141***	0.104**	0.140***	0.141***
	(0.0389)	(0.0429)	(0.0385)	(0.0387)
AVG-UE	-0.0815	-0.0826*	-0.0947*	-0.0884*
	(0.0528)	(0.0467)	(0.0521)	(0.0526)
DIST	0.0060*	0.0056*	0.0058*	0.0058*
	(0.0033)	(0.0030)	(0.0032)	(0.0033)
MED-HINC	0.0001	0.0014***	0.0011**	0.0009
	(0.0006)	(0.0004)	(0.0005)	(0.0006)
POP-DENS	-0.0078***	-0.0055***	-0.0087***	-0.0084***
	(0.0022)	(0.0017)	(0.0023)	(0.0023)
PCT-WHITE	0.0061***	0.0067***	0.0058***	0.0060***
	(0.0013)	(0.0013)	(0.0012)	(0.0012)
PUBWATER	0.0472**	0.0479***	0.0453**	0.0455**
	(0.0189)	(0.0178)	(0.0180)	(0.0180)
PERMIAN		-0.290***		
		(0.0626)		
ALLWELLS-2KM			-0.0024***	
			(0.0009)	
ALLWELLS-1KM				-0.0054**
				(0.0024)
R^2	0.5655	0.5913	0.5710	0.5675
Distance	50 km	50 km	50 km	50 km
Panel Var	State	State	State	State

Notes: All models include month fixed effects, and Conley standard errors. Significance denoted by: *** p<0.01, ** p<0.05, *p<0.1

Table 21: Extended Models with Conley Standard Errors (N=5,767)

Dependent Variable: lnLISTPRICE						
VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
SQFT	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MANU	-0.337***	-0.331***	-0.350***	-0.333***	-0.347***	-0.326***
	(0.0622)	(0.0670)	(0.0632)	(0.0677)	(0.0633)	(0.0682)
AGE	-0.0062***	-0.0053***	-0.0062***	-0.0059***	-0.0063***	-0.0059***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
LOTACRES	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
BEDROOMS	0.0468**	0.0602***	0.0470**	0.0534***	0.0448**	0.0516***
	(0.0190)	(0.0192)	(0.0188)	(0.0194)	(0.0186)	(0.0191)
MULTI-GARAGE	0.0984***	0.119***	0.0875***	0.0864***	0.0946***	0.0900***
	(0.0257)	(0.0220)	(0.0256)	(0.0241)	(0.0263)	(0.0244)
ACCENTRAL	0.137***	0.0875**	0.140***	0.103**	0.140***	0.104**
	(0.0388)	(0.0418)	(0.0385)	(0.0426)	(0.0389)	(0.0428)
AVG-UE	-0.0946*	-0.147***	-0.0947*	-0.0917*	-0.0870*	-0.0849*
	(0.0558)	(0.0446)	(0.0521)	(0.0473)	(0.0528)	(0.0470)
DIST	0.00563*	0.00520*	0.00577*	0.00546*	0.00585*	0.00563*
	(0.0031)	(0.0030)	(0.0032)	(0.0030)	(0.0033)	(0.0031)
MED-HINC	0.0016***	0.002***	0.0011**	0.0016***	0.001**	0.0015***
	(0.0004)	(0.0003)	(0.0005)	(0.0004)	(0.0005)	(0.0004)
POP-DENS	-0.0058***	-0.0048***	-0.0087***	-0.0062***	-0.0075***	-0.0054***
	(0.0017)	(0.0013)	(0.0023)	(0.0018)	(0.0021)	(0.0017)
PCT-WHITE	0.0057***	0.0049***	0.0058***	0.0066***	0.0059***	0.0066***
	(0.0012)	(0.0010)	(0.0012)	(0.0012)	(0.0012)	(0.0013)
PUBWATER	0.0524***	0.0459***	0.0453**	0.0465***	0.0476**	0.0481***
	(0.0194)	(0.0170)	(0.0180)	(0.0174)	(0.0188)	(0.0178)
PERMIAN		-1.737***		-0.286***		-0.287***
		(0.4150)		(0.0617)		(0.0612)
ALLWELLS-2KM			-0.00239***	-0.00896		
			(0.0009)	(0.0057)		
PM2.5	-0.0159	-0.206***				
	(0.0235)	(0.0564)				
ΔPM2.5	-0.0216*	-1.364***				
	(0.0119)	(0.2397)				
PERMIAN*PM		0.187***				
		(0.0585)				
PERMIAN* ΔPM2.5		1.357***				
		(0.2394)				
PERMIAN* ALLWELLS-2KM				0.00777		
				(0.0056)		
EQ-MAG1					-0.00104	0.0416
					(0.0008)	(0.0922)
PERMIAN* EQ-MAG1						-0.0420
						(0.0921)
R^2	0.5710	0.6178	0.5710	0.5934	0.5665	0.5915
Distance	50 km	50 km	50 km	50 km	50 km	50 km
Panel Var	State	State	State	State	State	State

Notes: All models include month fixed effects, and Conley standard errors. Significance denoted by: *** p<0.01, ** p<0.05, *p<0.1

Table 22: Water Source and Injection/Disposal Wells

VARIABLES	Model 1	Model 2	Model 3	Model 4
SQFT	0.0003***	0.0003***	0.0003***	0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
MANU	-0.318***	-0.3175***	-0.4558***	-0.2254***
	(0.0600)	(0.0600)	(0.0852)	(0.0759)
AGE	-0.0059***	-0.0059***	-0.0060***	-0.0055***
	(0.0005)	(0.0005)	(0.0008)	(0.0005)
LOTACRES	0.0002	0.0002	0.0002	0.0002
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
BEDROOMS	0.0493***	0.0492***	0.0553*	0.0610***
	(0.0169)	(0.0169)	(0.0313)	(0.0179)
MULTI-GARAGE	0.0766***	0.0765***	0.0099	0.1713***
	(0.0213)	(0.0213)	(0.0339)	(0.0241)
ACCENTRAL	0.121***	0.1210***	0.0933**	0.1709***
	(0.0258)	(0.0258)	(0.0454)	(0.0261)
AVG-UE	-0.0966***	-0.0966***	-0.2110***	-0.0592***
	(0.0265)	(0.0265)	(0.0610)	(0.0226)
DIST	0.0061***	0.0061***	0.0065**	0.0039
	(0.0023)	(0.0023)	(0.0025)	(0.0041)
MED-HINC	0.0014***	0.0015***	0.0031***	0.0018***
	(0.0005)	(0.0005)	(0.0009)	(0.0004)
POP-DENS	-0.0058***	-0.0058***	-0.0091***	-0.0029**
	(0.0012)	(0.0012)	(0.0033)	(0.0012)
PCT-WHITE	0.0069***	0.0069***	0.0096***	0.0036***
	(0.0010)	(0.0010)	(0.0021)	(0.0010)
PUBWATER	0.0484***	0.0507***	0.0562*	0.0364*
	(0.0178)	(0.0182)	(0.0323)	(0.0204)
PERMIAN	-0.270***	-0.2696***		
	(0.0301)	(0.0301)		
INJ&DISP-2KM	-0.0027***	-0.0013	-0.2103*	-0.0016
		(0.0017)	(0.1229)	(0.0017)
	(0.0010)			
PUBWATER * INJ&DISP-2KM		-0.0020	0.1785	-0.0017
		(0.0020)	(0.1271)	(0.0021)
Constant	11.63***	11.6262***	11.6668***	11.4813***
	(0.1377)	(0.1377)	(0.2414)	(0.1158)
Observations	5,767	5,767	2,165	3,602
Subset	All	All	Controls	Permian
R-squared	0.6623	0.6624	0.6352	0.6804
VIF>10	No	No	Yes	No

Notes: All include month fixed effects, and robust standard errors clustered by block group.
Significance denoted by: *** p<0.01, ** p<0.05, *p<0.1

11. Appendices

Appendix A: Control Counties Group Selection Process

This appendix describes the selection process for choosing the set of counties as a control group, relative to those counties in the Permian Basin. Geographic location and the presence of oil and gas production activity define the Permian Basin. To account for areas not as exposed to production growth at the same magnitude as the basin, but sharing a similar socio-demographic profile, counties outside the Permian Basin are included to provide a pseudo-control category. The term pseudo-control is used because revenues from oil and gas benefit the whole state, so no county is immune to the effects of industry growth.

Note that the hedonic pricing data is collected during 2022-2023; this data is web-scraped via a time-consuming process, and the control group had to be chosen ahead of time. So, broadly the objective was to pick a set of control counties that were not within the Permian boundaries, but still within the general region (i.e., roughly eastern NM and western TX), and were not exposed to O&G production at any comparable scale (i.e., an order of magnitude less), but were statistically similar over the prior decade on a set of five Census-based socio-economic/demographic variables. In an iterative process all possible counties in the broader region were compared, and then from this selected the control group (i.e., similar on five socio-economic demographic variables and dis-similar on exposure to O&G production).

Counties within the Permian Basin are defined by the Federal Reserve Bank of Dallas' map of the region (*Energy in the Eleventh District*, n.d.). There are 55 Permian Basin counties. The 51 TX counties in the basin are: Andrews, Bailey, Borden, Cochran, Coke, Concho, Crane, Crockett, Crosby, Culberson, Dawson, Dickens, Ector, Edwards, Fisher, Floyd, Gaines, Garza, Motley, Schleicher, Scurry, Sterling, Sutton, Terrell, Terry, Tom Green, Upton, Val Verde, Ward, Winkler, Yoakum, Glasscock, Hale, Hockley, Howard, Irion, Kent, Kimble, Lamb, Loving, Lubbock, Lynn, Martin, Menard, Midland, Mitchell, Nolan, Pecos, Reagan, Real, and Reeves. The four NM counties in the basin are: Chaves, Eddy, Lea, and Roosevelt.

The geographic region control counties were selected from is limited to those in Eastern NM which we defined as east of and including counties crossed by Interstate 25. In TX, the counties were limited to those in specific production districts as defined by the Texas Railroad Commission (RRC) to limit the region to what is roughly the western part of Texas (RRC, 2020). The districts included for selection are 1, 7B, 7C, 8, 8A, and 10[25]. The selection region covering NM and TX is outlined in red in the map in Figure 1a.

The control counties were selected from the red outlined area to create a control group statistically similar to the Permian Basin counties on five variables: unemployment rate, per capita income, median household income, population density, and the percentage of the population that is white. The American Community Survey (ACS) for 2009 and 2019 synthesized by IPUMS at the county level was used to collect each of the five variables (Mason et al., 2022).

[25] https://www.rrc.texas.gov/media/3bkhbut0/districts_color_8x11.pdf

As shown in Table A1 panel A, for 2009, the data are statistically similar on four of the five variables. UE–2009 is statistically different between the Permian and control counties (6.8% versus 5.3%). As shown in Table A1 panel B, for 2019, the data matches on three of five demographic variables. PER–CAP–INC–2019 ($25.4K versus $27.9K) and PCT–WHITE–2019 (83% versus 89%) are statistically different between the two regions based on *t*-tests of the difference in the group means. So, even where there are differences, they were of similar magnitude relative to alternatives (e.g., the much more urban areas).

Comparison of the production levels is based on production amounts from November of 2022 as the data could be obtained at the county level for both states. As shown in Table A1, panel C, both raw production numbers and the percentile of the production are compared. Using a *t*-test allowing for unequal variances, we reject the null hypothesis that the production means are the same. For these variables statistical difference is a positive outcome as the control group represents counties that are not nearly as exposed to oil and gas production to the extent of Permian Basin counties. For each measure, we observe at least an order of magnitude difference between the Permian Basin and the control group counties.

In combination, based on the statistical comparisons of 2009 and 2019 socio-economic/demographic data and 2022 production data, the 16 TX control counties are Armstrong, Bandera, Blanco, Brewster, Castro, Comanche, Dallam, Deaf Smith, Gillespie, Hamilton, Jeff Davis, Lampasas, Llano, Mills, Parmer, and Taylor. The two New Mexico control counties are Doña Ana and Curry counties. The counties are shown in the map below in blue. Note that the selection generally leaves out counties that would be part of large metropolitan areas: i.e., Albuquerque, NM, Amarillo, TX, Austin, TX, El Paso, TX, and San Antonio TX.

Figure A1: Map of Selection Region, Permian Basin, and Control Counties

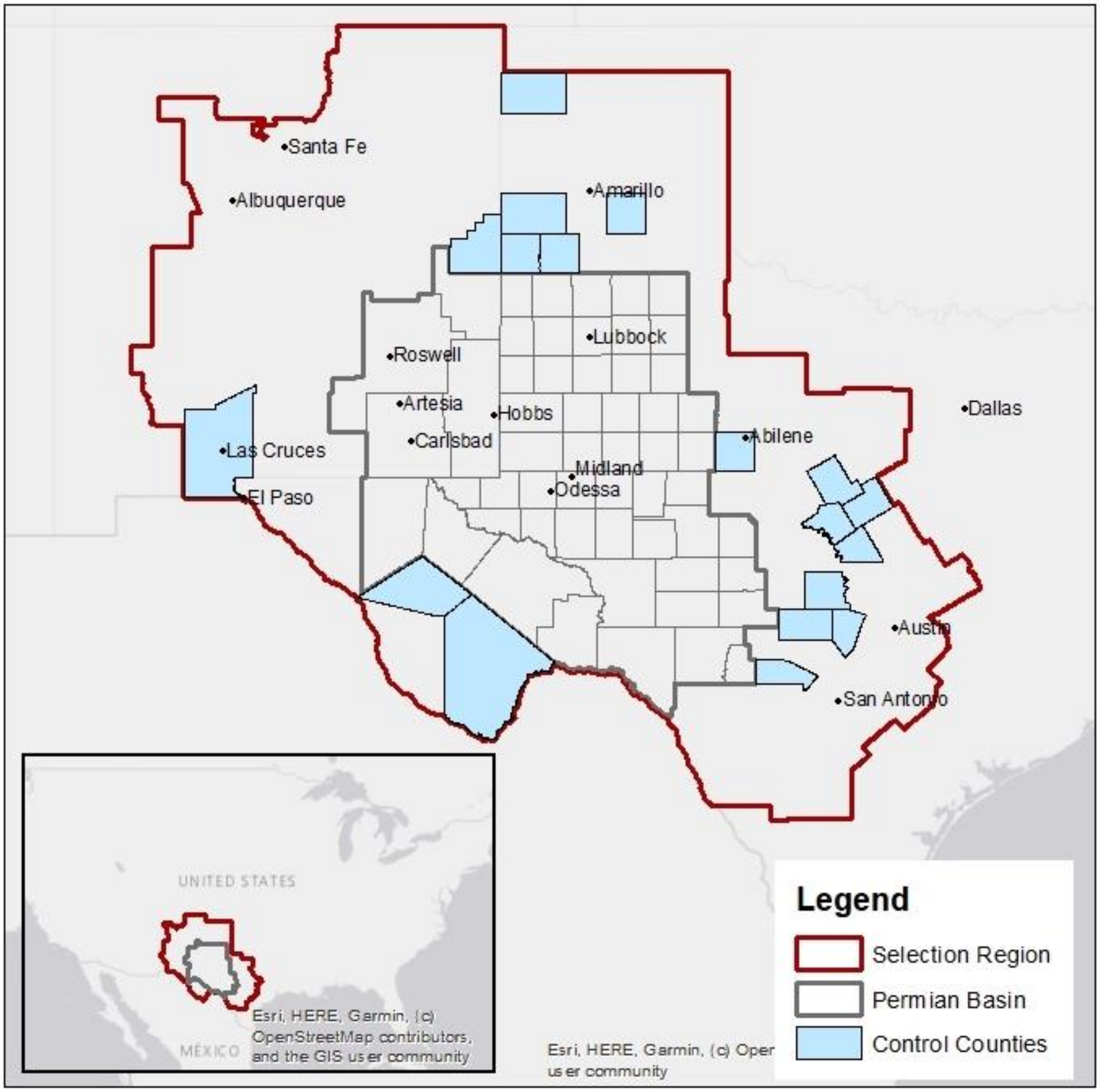


Table A1: Summary Statistics and *t*-Test Results

	Permian			Control			
Panel A: 2009 Demographic Data							
Variable	N	Mean	SD	N	Mean	SD	*t*-test
UE–2009	55	0.068	0.016	18	0.053	0.009	4.9754*
PER–CAP–INC–2009	55	20,960.04	5,095.75	18	20,974.33	3,801.38	-0.0109
MED–HH–INC–2009	55	40,704.82	8,793.05	18	40,876.72	6,881.34	-0.0756
POP–DENSITY–2009	55	24.786	51.454	18	26.555	43.338	-0.1312
PCT–WHITE–2009	55	0.841	0.075	18	0.866	0.089	-1.1961
Panel B: 2019 Demographic Data							
Variable	N	Mean	SD	N	Mean	SD	*t*-test
UE–2019	55	0.032	0.008	18	0.031	0.009	0.337
PER–CAP–INC–2019	55	25,366.91	4,458.78	18	27,972.89	4,842.53	-2.1075*
MED–HH–INC–2019	55	53,115.15	11,797.78	18	54,329.17	7,583.00	-0.5074
POP–DENSITY–2019	55	28.074	60.072	18	28.822	47.142	-0.0481
PCT–WHITE–2019	55	0.828	0.132	18	0.891	0.074	-2.5665*
Panel C: 2022 Production Data							
Variable	N	Mean	SD	N	Mean	SD	*t*-test
Raw Production	55	2,319,000	5,231,000	18	1,072.11	4,493.57	3.29*
Percentile Production	55	0.653	0.279	18	0.061	0.133	12.07*

Notes: * indicates statistical difference in the means at the 0.005 level. All comparisons were first tested for statistical differences in the standard deviations. Where applicable, the *t*-test adjusts for unequal variances.

Appendix References

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