Building with Externalities: Local Governments and Wind Farms

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Abstract

Does local government regulation of new infrastructure with local externalities result in efficiency? Although local governments' choices can internalize local costs, political or contracting frictions may cause actual outcomes to deviate from the idealized benchmark of Coase (1960). I study this problem in the context of wind farms. I develop a model of interaction between wind developers and local governments where wind farms are built only if they are both profitable *and* allowed by local governments, who weigh local costs against payments from developers. I estimate that the average household's cost of living three miles from a wind farm is around 7.5% of its home's value. I find that built wind farms trade off more than $7 of engineering profit for each $1 of cost to households. This arises in part because local governments must be paid roughly $3 for every $1 of externality to approve projects. Moreover, I find that state regulations limiting payments to local governments further depress wind-farm construction. I compare the performance of alternative developer-government contracting rules in reaching the United States' net-zero carbon goals. I find that requiring wind developers to pay local governments 20% of nearby homes' value raises social welfare by about $220 billion relative to when developers cannot pay local governments.

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1 Introduction

> "While policymakers may set lofty goals, the future of the American power grid is in fact being determined in town halls, county courthouses and community buildings across the country."
>
> David Gelles, *New York Times* (2022)

Plans to decarbonize the U.S. energy sector require developing approximately 250 million acres of land—roughly two and a half times the size of California—for wind farms (Merrill, 2021). A typical wind farm comprises about 80 turbines, each over 500 feet tall (DOE, 2024). Building a wind farm typically requires local government approval, and one in four planned projects is canceled due to local regulation (Nilson et al., 2024). Consequently, community opposition is often cited as a major obstacle to new wind development.[1] While local governments may be representing their constituents' preferences when they block wind farms, the magnitude of households' welfare costs remains contested (Roth, 2021).

The challenge of developing projects that generate local negative externalities is not unique to wind farms and has drawn sustained attention from journalists and policymakers (Klein and Thompson, 2025). Other "locally undesirable land uses" (Been, 1994) include housing developments, factories, nuclear plants, and data centers. An efficient spatial allocation of infrastructure must trade off private returns with externalities. Under the Coase (1960) theorem, if bargaining is frictionless and property rights are complete, outcomes will be efficient. Local governments hold broad authority to determine what new infrastructure is built and to regulate construction that may impose externalities on their constituents. Realized development is thus a product of both political economy and contracting frictions. Constraints—such as limits on negotiating payments to local governments for fear of bribery, and asymmetric information—may preclude efficiency (Myerson and Satterthwaite, 1983).

In this paper, I propose and estimate a model of wind farm development. In my model, local governments trade off payments from developers against the externalities borne by their constituents, and may decide to block projects. Developers build any profitable project, but must make costly investments in planning before the local government decides whether to block it. This model suggests three potential frictions. First, local governments may over- or under-weight the externalities suffered by their constituents. Second, developer investment before negotiation may expose them to hold-up. Finally, regulations that restrict how developers can contract over payments to local governments may prevent socially efficient projects from being built. This can occur either because local governments obstruct development when they are inadequately compensated for local costs, or because developers do not earn sufficient profit.

I use the estimated model to study counterfactual regulations and market designs that determine how developers contract with local governments. I evaluate scenarios in which the federal government subsidizes

[1] As noted by Demsas (2023); Nilson et al. (2024); Plumer and Popovich (2024); and others.

the wind industry to levels consistent with net-zero goals, to isolate how different rules affect efficiency and incidence. This allows me to abstract away from the optimal quantity of wind production. I consider alternative regulations, including (i) property taxes that scale with the value of nearby homes—including both a Pigouvian tax and payments greater than the expected externality, and (ii) up-front negotiations.

The paper proceeds in two parts. First, I measure the private profits and household costs of wind farm development to test whether the observed allocation is consistent with a Coasian benchmark. Second, I exploit state-level regulatory variation to estimate a model of households, local governments, and wind developers to explain the observed allocation and assess counterfactual market designs.

I first show that the value of nearby homes strongly predicts whether a wind farm is constructed. Locations with \$100 million in home value within five miles are only one-third as likely to have a wind farm developed as locations with $\$100,000$ in nearby home value, controlling for engineering profit. Moreover, wind farms built in these higher home-value locations are about \$40 million more profitable, based on observable characteristics, than those built in low-value areas.

I seek to explain this wedge in the profitability of wind farms built in high and low home value areas. Such a wedge could arise in a Coasian benchmark if households experience large costs from nearby wind farms; in that case, projects must still be profitable after compensating households. However, the wedge could also reflect frictions. First, if local governments' approval decisions are relatively inelastic, they may require payments exceeding externality costs to allow construction. Second, if developers are restricted from paying governments, they may be unable to build in many profitable, high-externality locations.

To assess the Coasian explanation, I estimate household-specific costs of living near wind farms using a revealed-preference approach. I show that wind farm construction reduces nearby home prices. A key empirical challenge is selection: places that allow wind farms may differ systematically from those that do not. To address this, I estimate event studies comparing homes at similar distances from a wind farm built five to ten years later.[2] I find an immediate and stable reduction of about twelve percentage points in home transaction prices within three miles of a wind farm, with effects that diminish at greater distances.

I estimate households' costs from wind farms to match treatment effects of wind farm entry on home prices and migration patterns. In my model, households have preferences over wind farms and the non-wind characteristics of census tracts. I estimate the model in two steps. First, I estimate the non-wind determinants of demand using annual tract-to-tract migration flows and a novel price instrument: exposure to nearby deaths. I then use pre-period demand curves for each treated location to study how the elasticity of demand influences market equilibrium after a wind farm is built. In "thin" markets with few potential in-migrants, home prices drop substantially and households engage in minimal re-sorting. In "thick" markets with many

[2] My research design leverages quasi-exogenous variation in timing. As discussed in Gentzkow et al. (2011), the assumptions required to identify this effect are consistent with idiosyncratic variation in exactly *when* a successful wind farm is built, given the multi-year gap between initiation and completion of a project.

potential in-migrants, home prices decline modestly and re-sorting is substantial. Using a deconvolution technique, I exploit variation in re-sorting in response to different price changes to recover the full distribution of costs. I find that on average, households are willing to pay around 7.5% of their home's value to avoid a wind farm within three miles. There is substantial heterogeneity: about 13% of households would pay more than 25% of their home's value to avoid a nearby wind farm.

Using the estimated distribution of household costs, I test whether the observed allocation of wind farms satisfies Coasian efficiency. Following Coase (1960), deviations from a dollar-for-dollar trade-off between profit and externalities indicate market failures. Using engineering profitability measures and imposing a free entry condition, I find that what is built trades off more than \$7 of profit for every \$1 of cost to households within five miles. I consider proximate costs and do not account for diffuse externalities.[3]

In the second part of the paper, I develop and estimate a model of households, local governments, and developers to account for the observed deviation from the Coasian benchmark. I specify a two-period dynamic model of developer-government interaction. This captures how hold-up risk in negotiation and the threat of local governments' rejection shape developers' investment decisions. The estimates from this model allow me to quantify the market failures arising from political and contracting frictions separately and evaluate alternative contracting rules and market designs.

Wind developers' ability to contract over transfers affects construction. Leveraging variation in state regulations governing property tax payments to local governments, I estimate a spatial regression discontinuity at state borders where tax treatment of wind farms differs. I find that projects are more likely to be built on the side of the border where wind farms do pay taxes than when they either are exempt or may negotiate payment. In empty locations, where local approval may be less binding, this pattern reverses: fewer projects are built when developers must pay taxes. This suggests that when externalities are small, exempting developers from taxes leads to more wind farms being built. In the full sample, however, the inability to compensate local governments dominates this exemption effect.

I subsequently examine which sites are built as a function of their expected externality and the developers' property tax rules. I find that when developers cannot negotiate payments, there is a threshold level of externality beyond which wind farms become infeasible to build. This threshold is higher when developers pay taxes than when they do not, suggesting that local governments trade off tax revenue against externalities. No such threshold arises when developers are allowed to negotiate transfers. Despite the risk of hold-up, this flexibility allows some high-profit, high-externality sites to be developed.

To estimate the developer-government model I match which locations are planned and which are ul-

[3]This test assumes that the costs to households are realized by homes within five miles of the site. This test does not identify whether the aggregate level of wind construction is efficient. If developer profits are socially insufficiently given their carbon externalities, this test will not capture that margin. A back-of-the-envelope calculation suggests that the average wind farm abates roughly \$56 million in social cost of carbon annually relative to \$11 million in yearly production tax credits (EPA, 2015; USGS, 2018; EELP, 2025).

timately constructed. I find that communities' implied cost of wind exposure is about three times higher than my preference estimates, suggesting that the political economy frictions in representation are substantial. Investment costs are large and much of the negotiated surplus accrues to the local government, making hold-up risk important empirically.

Finally, I use these estimates to evaluate a projected wind generation expansion consistent with a net-zero carbon energy sector (Larson et al., 2020) under alternative market designs. Engineering forecasts suggest that planned wind farms would impose around $50 billion in costs on local communities. Many of these projected locations, however, may not be feasible, given community resistance. I analyze how different market designs affect the spatial allocation of wind farms. I first compare three existing tax treatments governing developers' payments to local governments. I find that social welfare is about $220 billion lower under exemption and $125 billion lower under negotiation, relative to developers paying fixed taxes.

I then evaluate more complex alternative market designs. I consider posted prices tied to the average externality cost of a site and find that this approach generates a social cost $5 billion higher than the current uniform tax. This reflects the fact that local governments' preferences deviate from a utilitarian money-metric benchmark. I then consider up-front negotiations, which reduce social costs by $10 billion relative to the uniform tax. This is undermined, however, by the high take-it-or-leave-it transfers demanded by local governments. The first-best allocation, which is infeasible given private information about profits and local costs, improves social welfare by $100 billion relative to the uniform tax. I find that a simple policy of paying 20% of the value of nearby homes captures $75 billion of these potential gains. This policy is straightforward to administer, as it relies only on information already collected by tax assessors.

I contribute to the literature on local regulation of new infrastructure with local costs, focusing on wind farms.[4] I develop and estimate a model of developer-government interaction to explain why development deviates from a Coasian benchmark. In doing so, I contribute to the literature estimating the effect of wind development on nearby home prices.[5] I measure these price effects using a comprehensive sample of U.S. properties and a control group that addresses selection into permitting wind farms. I find larger price effects than earlier work, consistent with recent evidence from the U.K. and Germany (Jarvis, 2024; Quentel, 2025). This is likely attributable to two factors. First, prices fall even at moderate distances from wind farms, so common ring-based designs compare different treatment intensities rather than treated versus untreated homes. Second, I study wind farms rather than single turbines.

This paper connects to a long literature on the costs and benefits of decentralized governance, specifically federalist systems (Oates, 1972).[6] I find that local governments make choices that trade off heterogeneous

[4]Stokes et al. (2023) and Jarvis (2024) also study local resistance to wind development. Glaeser and Gyourko (2018) study this in the context of housing supply and zoning.

[5]See Hoen et al. (2011); Heintzelman and Tuttle (2012); Lang et al. (2014); Gibbons (2015); Jensen et al. (2018); Sampson et al. (2020); Droes and Koster (2021); Guo et al. (2024); Jarvis (2024); Quentel (2025).

[6]See Inman and Rubinfeld (1997); Hoxby (2000); Lockwood (2002); Turner et al. (2014); Bordeu (2024).

costs, both observable and unobservable, to their constituents with payments. Relative to a utilitarian social planner, however, local governments also over-weigh the local externalities relative to payments. A related literature studies how local governments compete for firms with tax subsidies.[7] This paper highlights how this process is different when firms impose negative externalities, and may instead wish to compensate local governments for them. I highlight the role of local taxation as facilitating Coasian transfers in these settings, connecting to a literature on state and local taxation and place-based policies.[8]

I also contribute to the literature on non-market valuation using revealed preferences from the housing market.[9] I use discrete choice models of demand to estimate preferences when prices are endogenously determined in market equilibrium, as in Bayer et al. (2007), Diamond (2016), and others. More broadly, I make two methodological contributions to the literature on flexibly estimating substitution patterns from revealed choices.[10] I incorporate state dependence in discrete choice demand by allowing for heterogeneity across consumer types and realistic substitution patterns by conditioning on past-year choices (Hendel and Nevo, 2006; Handel, 2013). Second, I introduce a new instrument—deaths in nearby tracts—that affects prices by increasing the supply of homes for sale in closely competing areas.

I develop a method for estimating a nonparametric distribution of preferences from revealed choices. My approach requires estimates of pre-treatment demand curves that predict differential incidence of an identical treatment on prices and re-sorting responses. I construct a measure of market "thickness" in the pre-period, which is analogous to a participation shifter in the empirical auctions literature (Athey and Haile, 2002; Athey et al., 2011; Krasnokutskaya and Seim, 2011). I identify and estimate preferences nonparametrically, leveraging a revealed preference condition and proof technique similar to Agarwal et al. (2023).

I contribute to the literature on the determinants of firm entry in empirical industrial organization. In particular, I model the regulator as a strategic player and estimate their preferences. I model this as a two-period game with a Markov-Perfect equilibrium concept, following Ericson and Pakes (1995). I recover parameters to rationalize decisions, as in the second step of Bajari et al. (2007). This work also relates to the literature on geographic determinants of entry.[11] More specifically, it connects to Ryan (2012) and Ryan (2021), who study the role of environmental regulation in entry decisions.

Finally, I estimate how developers and local governments negotiate over transfers. My model allows for two-sided private information, which may preclude some efficient trades, as in Myerson and Satterthwaite (1983). My method relates to empirical work measuring the value of information in negotiation (Backus

[7] See Black and Hoyt (1989); Glaeser (2001); Mast (2020); Slattery and Zidar (2020); Slattery (2025).

[8] See Glaeser and Gottlieb (2008); Busso et al. (2013); Kline and Moretti (2014); Suarez Serrato and Zidar (2016); Gaubert et al. (2021).

[9] See Black (1999); Davis (2004); Chay and Greenstone (2005); Greenstone and Gallagher (2008); Linden and Rockoff (2008); Cellini et al. (2010); Davis (2011); Muehlenbachs et al. (2015); Keiser and Shapiro (2019).

[10] See McFadden (1973); Ben-Akiva (1973); Berry et al. (1995, 2004).

[11] See Bresnahan and Reiss (1990, 1991); Berry (1992); Holmes (1998); Jia (2008); Holmes (2011); Houde (2012).

et al., 2020; Grennan and Swanson, 2020; Larsen, 2021), and to work estimating the division of surplus in negotiation (Crawford and Yurukoglu, 2012; Grennan, 2013; Collard-Wexler et al., 2019).

The remainder of the paper is organized as follows. Section 2 describes the data, legal framework, and setting. Section 3 relates the value of nearby homes to construction decisions. Section 4 introduces and estimates a residential choice model to identify the cost of living near wind farms. Section 5 develops a model of the interaction between households, local governments, and developers, presents motivating facts, and then solves and estimates the model. Section 6 uses these estimates to compare existing market designs to potential alternatives, and Section 7 concludes.

2 Data and setting

This section describes the data, the construction of project profitability measures by location, and the institutional framework governing local approval of wind development.

2.1 Data

Wind turbines. I use data from the Federal Aviation Administration (FAA), available through the U.S. Fish and Wildlife Service, on the universe of planned projects (Dick, n.d.). These data include detailed information on project timing as well as supplementary information on planned but unbuilt sites. I use data from the Lawrence Berkeley National Lab (LBNL) (Hoen et al., 2018) to identify the location and project name of all built wind turbines. The LBNL data are validated with satellite imagery.

Home prices. I obtain home sales data from CoreLogic, which cover nearly the full universe of property tax filings. Specifically, I use the 'Deeds' data, which records property transactions. These data span transactions from before 1900 until 2019. For nearly all transactions I observe the date and price. In most instances I also observe the acreage, building size, and number of bedrooms and bathrooms. I obtain the exact location of the homes from Geocodio. I record key summary statistics for this sample in Appendix Table A2. I use these data to measure home values near each point in the U.S., including properties that have not transacted recently. I describe this process in Appendix B.1.

Residency decisions. I use data from Infutor to record U.S. households' full address histories from 2000 to 2017.[12] This dataset links individuals to their names, gender, age, address, and dates of residence. I use these address histories to construct census tract to census tract yearly migration flows, using the 2010 census tract borders. For discussion on data representativeness see Section A of Diamond et al. (2019).

Location characteristics. I use data from the 2000 Census and the 2010 American Communities Survey (ACS) on census tract racial demographics, employment by sector, income, and more.

[12] Other papers that use this data include Diamond et al. (2019); Diamond et al. (2020); Van Nieuwerburgh (2022); Mast (2023); Asquith et al. (2023).

Deaths. I obtain data on local mortality from two sources. First, I use a link from the Social Security Death Master File (SSDMF) to Infutor as in Bernstein et al. (2022) to observe individuals' addresses at their time of death.[13] From the SSDMF-Infutor data, I observe the name, age, and location of death of individuals who are reported deceased through 2013. Second, I use the Centers for Disease Control and Prevention's (CDC) Multiple Cause of Death data. I observe left-censored counts of deaths by each year by county and ten-year age bins.[14]

School finances. I obtain annual data on school district finances and expenditures from the National Center for Education Statistics' (NCES) Common Core of Data.

Wind resources. I use data from the National Renewable Energy Lab (NREL) on the hourly wind speeds, wind directions, and atmospheric pressure at a 100-meter height for all points in the continental United States (Draxl et al., 2015). NREL collected wind data for a full calendar year at over 126,000 locations in the United States. For locations between measurement areas, they approximate appropriately based on nearby measurements and detailed models of the geography and meteorology.

Transmission grid. I use data from LBNL on each location's distance to transmission interconnection for each point in the continental United States (Hoen et al., 2018).[15]

Road network. I use OpenStreetMap to measure each point's distance, as the crow flies, from a non-residential road using OSMnx (Boeing, 2017). I use distance to non-residential roads, to ensure that the roads are large enough to transport wind turbine components.[16]

Electricity prices. I obtain data on current hourly locational marginal prices (LMP), as well as projected future LMPs, for each of 134 balancing areas in the continental U.S. from Cambium, an NREL project. To a first approximation, LMPs are set to clear the market at nodal balancing areas, so producers in these zones tend to face identical prices when they sell their electricity.

Power purchase agreements. I obtain data on Power Purchase Agreements from the American Clean Energy Association.[17] Nearly every wind farm signs a long-term contract—typically about 25 years, the useful life of these facilities—that codifies the prices they will receive for the electricity they produce. I observe the agreed-upon price for many of these contracts for successful projects.

Renewable portfolio standards. I use data from the Rocky Mountain Institute's Utility Transition Hub to measure state-level renewable portfolio standards (RPS) and the statutory renewable share they require. These policies mandate the fraction of electricity production that must come from renewable sources.

Agricultural productivity. I obtain data on agricultural productivity, specifically average per-acre profit, from the USDA's 2017 Census of Agriculture, measured at the congressional district level.

[13] I access a public use copy of Social Security Death Master File from SSDMF.INFO as in Bernstein et al. (2022).

[14] I use both death measures as instruments for home prices, as I discuss further in Section 4.3.1.

[15] If a point is not available, I impute distance to transmission as the average of the nearest four points.

[16] More specifically, I only considering roads that are of tertiary size or greater as defined here.

[17] Many thanks to Luming Chen for sharing these data.

2.2 Engineering profitability

Wind farms' profits can be summarized succinctly. Fixed costs primarily reflect procuring turbines and constructing access roads and electrical lines to interconnect to the electricity grid. There are a variety of other costs, such as land lease costs and land preparation costs.[18] Once operational, wind farms incur variable operation and maintenance costs that depend on power generation. The revenues can also be described concisely. Nearly every wind farm signs a long-term Power Purchase Agreement (PPA) that specifies the price received for generated power for the useful life of the project.[19] Power generation is a nonlinear function of hourly wind speeds and atmospheric conditions, as determined by engineering models.

These components can be combined into a net present value of development for a standard-size wind farm at any U.S. location. I use siting tools built for developers by NREL that calculate net present values, accounting for the cost of capital and typical corporate taxes.[20] Further detail is provided in Appendix B.2. Appendix Figure A1 maps estimated profitability across U.S. locations, as well as the likelihood of construction as implied by engineering profit. I restrict the sample to sites where the number of houses within one and two miles is below the 99th percentile of existing wind farms, ensuring that the analytical sample focuses on realistically buildable locations.

2.3 Timeline of development

In Figure 7, I present a stylized timeline of wind development, based on developer interviews and existing documentation (LBNL, 2021; ABO, 2024). Developers first survey potential sites to assess their profitability and likelihood of successful approval. Once they identify a promising site, developers often contact local officials to gauge the likelihood that the project will be blocked. If local politics appear favorable, developers will proceed with the costly up-front investment, such as signing land leases, engineering the site, and securing PPAs. Once the site is fully planned, the final step is for the local government to allow construction.

2.4 Legal status

Local governments have wide discretion in determining land use, so long as the decisions are welfare-relevant and not arbitrary (Taft, 1926). As of 2025, there were over 450 documented wind rejections in the U.S. (Bryce, 2025). Further, as of 2019, there were over 275 documented ordinances regulating wind farms (Lopez et al., 2019). Additionally, both governments and individuals may sue to block wind farms' entry.

[18] Typically, wind farms intermingle with other land uses. For instance, in the Midwest, 94% of wind farms are built on cropland that remained in agricultural use after wind entry (Maguire et al., 2024). The footprints of each turbine are quite small, and the land lease costs are primarily driven by the disruption to the harvest when these generators are installed.

[19] In other work, such as Chen (2024), these PPA prices are endogenized from a Nash bargaining framework. I assume that the developers take PPA prices as given, as a function of the market price, forecast market price, and the state RPS existence.

[20] I primarily use the *System Advisory Model*, which is designed for use by developers, which I access through an API, PySAM. I additionally use *LandBOSSE* to estimate different construction costs on observable characteristics.

Wind developers generally have limited ability to contract over zoning approval. In many states, conditioning payment on approval is considered "illegal contract zoning" and is not permitted (Trager, 1963; Fraietta, 2012). Courts have typically have held this to be illegal due to "fears of corruption or political favoritism" (Trager, 1963). It must be explicitly legislated for developers and communities to be permitted to contract or negotiate "fees in lieu of taxes" to avoid the risk of being considered illegal.

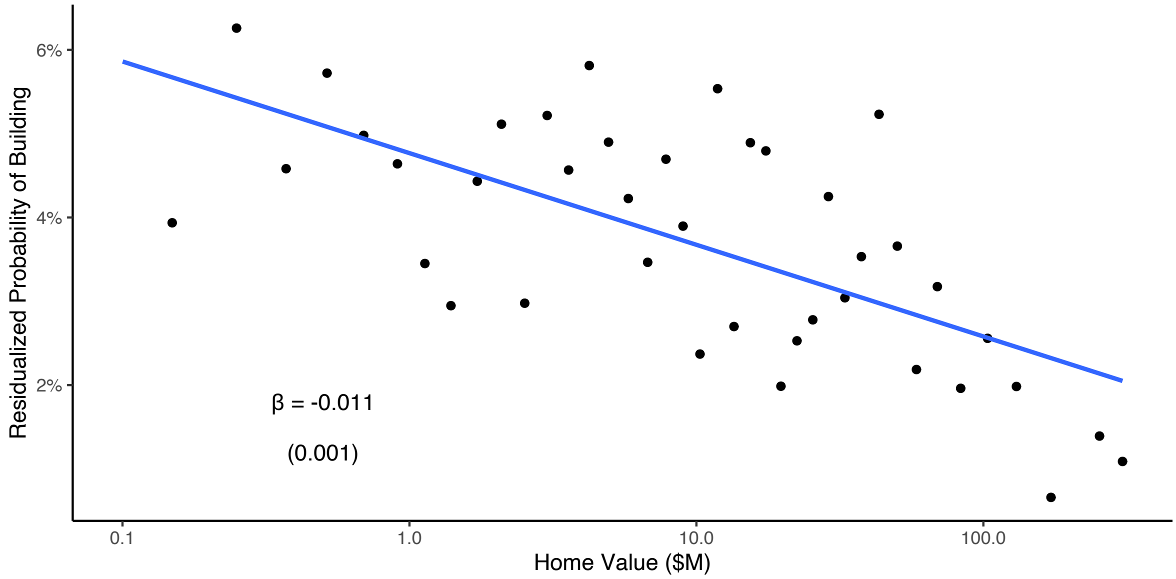
2.5 Role of taxes

Developers claim to "like paying taxes" because doing so allows them to pay the community, which increases the likelihood of project approval. This trade-off has been highlighted in the press (AP, 2024) and in local news coverage about permitting decisions (Robledo, 2018; Draper, 2019; Gerber, 2020; Fey, 2023; Harward, 2023; Wildeman, 2024). In one district, the superintendent stated: "If we didn't have the wind farms we probably would not have built a new high school" (Robledo, 2018). Elsewhere, it was determined that although the "most significant benefit is ... property tax revenue", the fact that they could not "mitigate 600 feet of tower" led the county planning commission to reject a planned wind farm (Benda, 2021).

3 Relationship between construction and home values

Places with higher potential costs to households have fewer wind farms built. Specifically, the value of homes within five miles is negatively associated with the likelihood of development. Figure 1 shows a binscatter of construction rates by levels of nearby home value, residualizing for engineering profit and state fixed effects. Locations with less than $\$100,000$ in nearby home value are nearly three times as likely to have a wind farm as those with \$100 million in nearby home value. In Appendix Table A1, I show this relationship is robust to alternative geographic fixed effects.

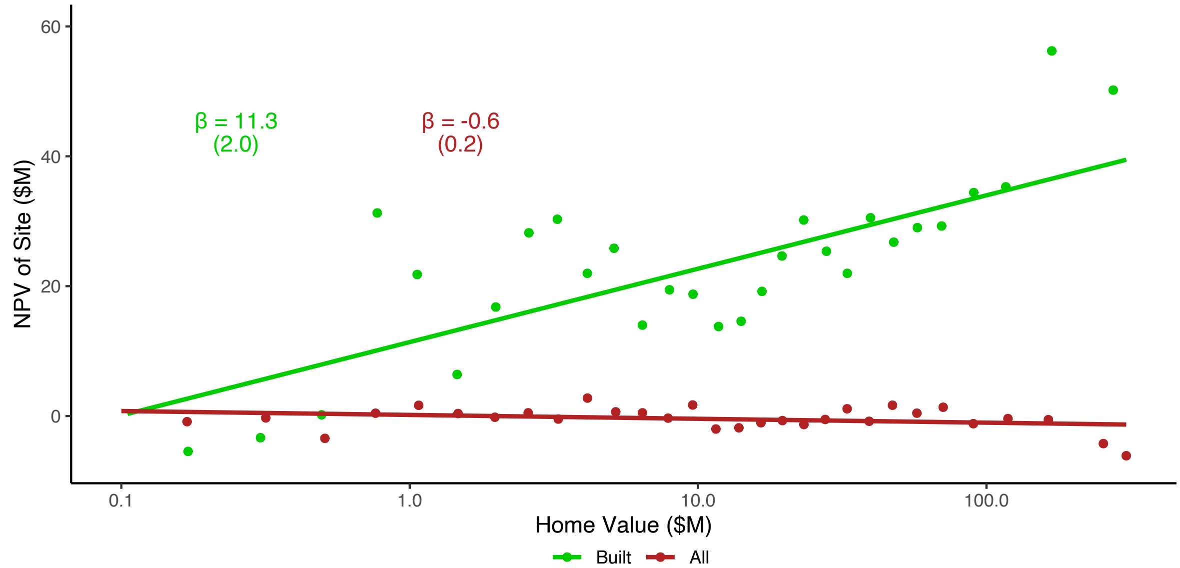
Figure 1: Probability of construction and home values



Note: The value of homes within five miles is calculated from a hedonic price index using CoreLogic data. The probability of construction is residualized by profit and state from a probit, selecting only locations with profit over 10th percentile of profit of wind farms built in the state. Presented as a bin-scatter with 40 bins. The baseline rate of construction in this sample is 4.1%.

In locations with high externalities, only very profitable projects are built. The value of nearby homes is strongly associated with built projects being observably more profitable. Figure 2 presents this fact as a bin-scatter, residualized by state. In locations near $100,000 of home value, the chosen projects' observable profitability is statistically indistinguishable from the population average. The built locations with $100 million in nearby home value are roughly $40 million more observably profitable than the average site. This occurs even though the average profitability of all possible sites is slightly lower in high-home value areas. In Appendix Figure A2, I present similar patterns using alternative geographic residualization.

Figure 2: Profitability of selected sites and home values



Note: The value of homes within five miles is calculated from a hedonic price index using CoreLogic data. The profitability of a site is calculated using NREL's *System Advisory Model*, residualized by state. Presented as a bin-scatter with 30 bins. The baseline rate of construction is 2.0%.

Discussion. Several factors may explain why wind farms that are built in areas with higher nearby home values are more profitable. One possibility, consistent with the Coase (1960) theorem, is that households experience large disutility from living near wind farms. Such disutility would tend to scale with the value of homes within five miles. If developers internalized their local externalities, then only more productive potential projects would be built. In Section 4, I quantify households' costs to assess how closely the green line in Figure 2 aligns with a Coasian benchmark.

Several potential market failures may also shape which projects are ultimately built. The first, political frictions, arrives if local governments' decisions are less responsive to compensation than a utilitarian money-metric benchmark would suggest. In this case, developers must pay more than the value of their local externality to secure approval. To assess this channel, I estimate the preferences of local governments in Section 5. A second source of inefficiency, contracting frictions, arises when developers have difficulties in negotiating payments at all. When payments are inflexible, developers may be unable to make Coasian transfers, preventing high-externality projects from being built. In Section 5, I document the legal rules that constrain these transfers and analyze their effects on construction.

4 Costs of living near turbines

I estimate event studies measuring the effects of wind entry on home prices. I then introduce and estimate a model of residential demand to disentangle changes in home prices from re-sorting to measure households' costs of living near turbines. In the model, households make static discrete choices over where to live and have preferences over wind and non-wind location characteristics.[21] The model is identified and estimated in two steps. First, I recover demand for the non-wind characteristics of each treated location using pre-treatment data. Second, I estimate wind preferences to rationalize a range of observed price and re-sorting effects of wind entry.

4.1 Effects on home prices

I investigate how wind farm construction affects home transaction prices. Wind farms can be highly visible for over ten miles Sullivan et al. (2012), and heard over two miles away Hansen et al. (2019). Existing work has shown that their effects on long-run job creation are minimal (Fabra et al., 2024). I estimate an event study following the application of an eventually built wind farm.[22] The control group is homes that are eventually at the same distance from a wind turbine, five to ten years later. This estimation strategy assumes that the *timing* of wind farms' entry is quasi-exogenous, conditional on eventual construction.[23]

Properties are treated upon the first application for an eventually built wind farm, which I define to be ten or more turbines, within twenty miles.[24] I observe 803 such events. It is possible that in subsequent years, additional closer turbines are built near these properties. Since I only observe a home's price if it is sold, I estimate the dynamic treatment effect as a repeated cross-section.[25] I use a stacked controls estimator, where I create a control group of houses that are treated between five and ten years after the treated group:[26]

$$\log(p_{i,t}) = \sum_{k\neq-1} \tau_k^d B_{i,t-a}^d + \beta X_i + \nu_{c(i)} + \phi_t + \mu_{C(i),\, g(t)} + \varepsilon_{i,t}. \tag{1}$$

[21] This allows for wind farms to affect the utility of living in a location in ways not solely attenuated by distance. This does not require continuous choice sets, as required by Bajari and Benkard (2005). A discrete choice framework allows me to measure infra-marginal households' welfare changes, which hedonic frameworks do not accommodate (Banzhaf, 2021).

[22] Application is typically less than a year prior to planned construction, as presented in Appendix Figure A31.

[23] Anecdotally, wind developers are building over time in places that were previously less profitable. This is consistent with evidence that exogenous characteristics can predict the timing of wind construction in Quentel (2025).

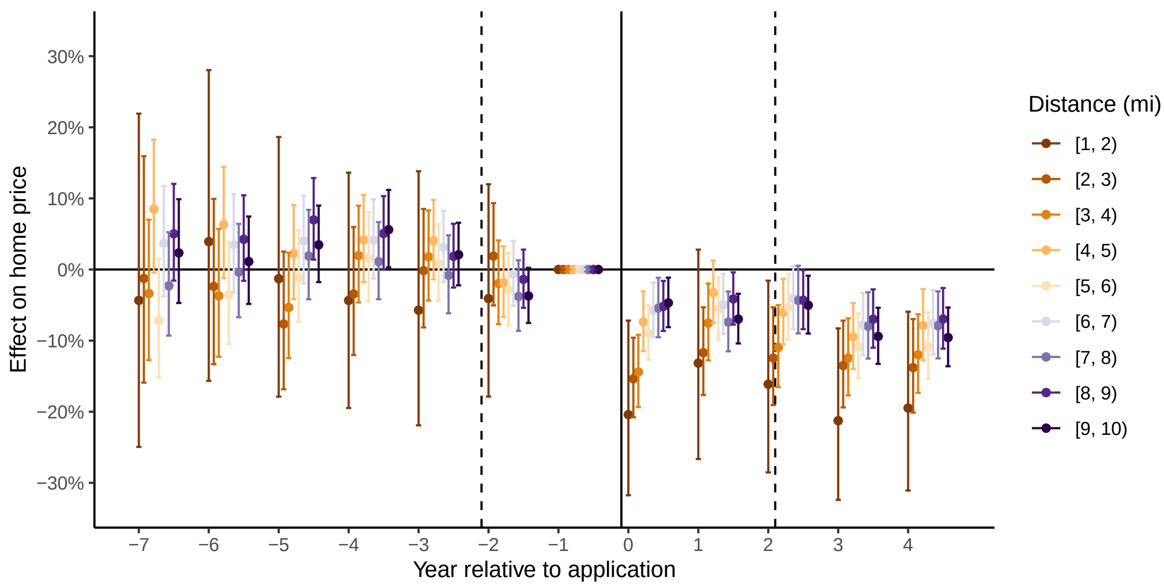
[24] In Appendix B.5 I discuss the relationship between applications and eventual construction.

[25] This treatment effect on home transaction price could, in principle, capture both a change in the value of homes as well as selection in the unobservable quality of which homes transact. A common signal of luxury in real estate is the ratio of bathrooms per bedroom (Beale, 2012). In Appendix Figure A4, I find this ratio is unchanged after wind entry and the acreage of transacted properties are largely unchanged.

[26] My preferred interpretation is that, prior to the wind farm's eventually successful application, households perceived the likelihood of a wind farm entry as close to zero. Three things support this. First, by the end of my sample period only 0.54% of all households in the U.S. are within three miles of a wind farm. This is approximately 2% of rural homes (FHFA, 2024). Second, over 75% of my treated group, that have later-treated controls, are treated in 2009 or earlier, prior to a large wind energy expansion. Finally, the flat pre-trends between the control and treatment groups up to seven years prior does not suggest that there were large changes in the perceived probability of a wind farm being built amongst the treated group.

For some property i, $p_{i,t}$ is the price at which it is transacted at time t. $B_{i,t-g}$ is an indicator for the years from application time g. $X_{i,t}$ are logged home characteristics: acres, bedrooms, bathrooms, and age. I include census tract, $c(i)$, year t, and three-year bin × county fixed effects as $\nu_{c(i)}$, ϕ_t, and $\mu_{C(i),\ g(y)}$.

Figure 3: Effects of wind farm entry on property values within 10 miles



Note: Control group is homes near turbines that are treated five to ten years later at the same distance. Control for: census tract, year, and county × three-year bin FE, log of acreage, bedrooms, bathrooms, and age. Distance is from *first* built turbine. SE clustered by stack × tract × treatment × distance bin.

I find large and stable decreases in home prices immediately upon application. Figure 3 presents the results for homes by the distance from the initial closest turbine. I find the price decreases are largest for the closest homes and diminish smoothly with distance. I present the pooled difference-in-difference effects by distance in Appendix Figure A3. I find that there are few homes transacted within one mile. Those that do have a much smaller and statistically insignificant price drop, consistent with anecdotal evidence that some of these households are either leasing their land to wind developers or receive “good neighbor” payments tied to their deeds. I show that wind farm entry leads to an increase in the number of homes that are transacted in Appendix Figure A5.

4.2 Model of residential choice

4.2.1 Demand specification

Setup. I model households’ static choice of where to live within a given state. In each period t, there exists a set of homes $\mathcal{J}_t$, a subset of which sold in that period $\mathcal{J}_t^s \subseteq \mathcal{J}_t$. $\mathcal{J}_t$ is partitionable into census tracts $\mathcal{D}$. Options outside the state are represented as a single outside option with utility normalized to zero. Each household $i \in \mathcal{I}$ is characterized by the tract and home they lived in the previous period: $o(i,t) \in \mathcal{D}$ and $j(i,t) \in \mathcal{J}_{t-1}$ respectively. In period t, i may choose to remain in their prior home or move to any home in $\mathcal{J}_t^s$. Households take the set of available homes, $\mathcal{J}_t^s \backslash j(i,t)$, as given. I partition $\mathcal{J}_t^s \backslash j(i,t)$ into a choice set of destination-wind-status pairs:

$$C_t = (d, w)\{d \in \{-1, 0\} \cup \mathcal{D},\ w \in \{0, 1\}\}, \tag{2}$$

where $d = -1$ is the endowed option, $d = 0$ is the outside option, and w indicates whether the home is within three miles of a wind farm in period t. Each household must choose exactly one housing option each period.

Utility. Household i in state s receives the following indirect utility from $(d, w) \in C$:

$$u^o_{i,d,w,t} = \underbrace{\omega_i' w}_{\text{wind prefs}} \underbrace{-\alpha_i \log(p_{d,w,t})}_{\text{price}} + \underbrace{\gamma^o_d}_{\text{tract prefs.}} + \underbrace{\beta X_{d,w,t}}_{\text{chars.}} + \underbrace{\phi_{m,s,t} + \mu^o_t}_{\text{FE}} + \underbrace{\xi^o_{d,t}}_{\text{unobs.}} + \underbrace{\log(\lambda_t(d,w))}_{\text{scaling factor}} + \underbrace{\varepsilon_{i,d,w,t}}_{\text{T1EV}}, \tag{3}$$

where $\omega_i \sim W$ is a heterogeneous value for living near wind turbines, and $\omega_i' = \omega_i \cdot \alpha_i$. $\gamma^o_d$are fixed effects for the average preferences for living destination d for households coming from $o = o(i,t)$, and m is an indicator for whether the choice involves moving, or $d \neq -1$. Distaste for the log of the average home sale price, $\log(p_{d,w,t})$, is moderated by $\alpha_i = \alpha_0 + \alpha_I I_{o(i,t)}$, which is a function of origin tract o's income in 2000, I_o. $\xi^o_{d,t}$ is a time-variant unobserved amenity of d to residents from o. $\log(\lambda_t(d,w))$ scales the mean utility by what fraction of the homes in destination, d, have wind farm exposure, w, at time t.[27] $\varepsilon_{i,d,w,t}$ are idiosyncratic errors distributed as Type I Extreme Values. $X_{d,w,t}$ contains home characteristics, including acreage, bedrooms, square-feet, and number of units, and location characteristics, including the number of deaths in the tract and an exposure measure to elderly individuals.[28]

This model builds on Bayer et al. (2007). I assume that households from a common origin tract share a mean utility from the non-wind amenities of staying in their endowed home or moving to any other tract in a given year. This amenity consists of: (i) a time-invariant component, γ^o_d; (ii) time-varying observables, $\beta X_{d,w,t}$; and (iii) fixed effects, $\phi_{m,s,t}$, μ^o_t, that capture yearly variation in moving costs by state and the utility level of all options for households from o.[29] This structure captures household inertia, be it persistence

[27] When wind farms enter, they create new elements of C_t. I scale the mean utility so that at baseline this new option, if $\omega_i = 0$ and price was unchanged, would face $\lambda_t(d,w)$ of the total demand for d. I additionally re-scale $\mu^o_t$to ensure that $\pi^o_{oo,t}$ is unchanged.

[28] This controls for the non-random component of exposure to nearby deaths, which I use as a price instrument in Section 4.3.1, as described by Borusyak and Hull (2023).

[29] Origin-destination fixed effects are one of many ways to use consumer panel data to learn about substitution patterns. Other examples of this sort of data include yearly health insurance choices, car purchases, weekly grocery trips, and more. As Berry and Haile (2021) discuss, the practical concerns with directly using the simulated log-likelihood of choices with households' full choice histories become quite large given that with J choices and N periods there are $(J+1)^N$ possible choice combina-

preference heterogeneity or moving costs, as in Handel (2013). Furthermore, it allows households with similar revealed choices to share similar average preferences over observable and unobservable characteristics of destinations.[30]

4.3 Identification

4.3.1 Identification of non-wind preferences

I begin by estimating all components of utility in Equation 3 other than ω_i by only considering destinations with no homes near wind farms in that period. I use the observed choices in this sample to recover all non ω_i parameters. For any individual i at time t, the likelihood of choosing a $(d, 0)$ is given by

$$\pi^o_{i,d,0,t} = \frac{\exp\left(\delta^o_{d,0,t}\right)}{\int_{\omega_i'} 1 + \sum_{(d,w)\in C_t} \exp\left(\omega_i' w - \delta^o_{d,w,t} + \log\left(\lambda_t\left(d,w\right)\right)\right) d\omega_i}, \tag{4}$$

where, $\delta^o_{d,w,t} = -\alpha_i \log\left(p_{d,w,t}\right) + \gamma^o_d + \beta X_{d,w,t} + \phi_{m,s,t} + \mu^o_t + \xi^o_{d,t}$, and the denominator, Θ^o_t.

The observed shares, $s^o_{d,w,t}$, reflect both the true choice probabilities and finite-sample noise.[31] I construct moment inequalities that bound the true choice probabilities $\pi^o_{i,d,0,t}$ as a function of the observed shares. The two moment inequalities on average serve as conservative upper and lower bounds for $\pi^o_{i,d,0,t}$, following Gandhi et al. (2023).[32] The moment conditions require instruments that must be uncorrelated with violations of these bounds. From Gandhi et al. (2023), the parameters of this model, particularly α_0 and α_I, are point identified due to the existence of a few dominant options with predictably large shares $s^o_{d,t}$ for which these bounds are close, and asymptotically converge to hold as equalities.[33]

Instrumenting for $\log\left(p_{d,t}\right)$. With no nearby wind farm, $\log\left(\pi^o_{i,d,0,t}\right) = \delta^o_{d,0,t} - \log\left(\Theta^o_t\right)$. Since $\log\left(\pi^o_{oo,t}\right) = -\log\left(\Theta^o_t\right)$, $\log\left(\pi^o_{i,d,0,t}\right) - \log\left(\pi^o_{oo,t}\right) = \delta^o_{d,0,t}$, for all products without individual heterogeneity in their mean utility Berry (1994). Still, the price level, $\log\left(p_{d,0,t}\right)$, is potentially endogenous as it may be correlated with unobservable demand shocks $\xi^o_{d,t}$. To identify the disutility from price, α_i, I require an instrument for home prices.[34] I construct a new instrument, which is a census tract d's exposure to deaths in nearby

tions. I coarsen this by only considering the most recent choice and avoid inferring households' preferences over observed and unobserved characteristics by pooling the total non-idiosyncratic components of the non-wind mean utilities within each group.

[30] I further explore the properties of this utility specification in Appendix C. In Appendix C.2, I compare the shares implied by fixed effects to specifications with location observables. In Appendix C.3, I show via Monte Carlo simulations that this estimator performs well at recovering price elasticities in settings where the true data generating process includes persistent preferences over unobservables. Lastly, I show empirically in Appendix C.4 that, conditioning on prior residence choice, the relationship between the observable similarity of two locations and their cross-price elasticity is both economically and statistically small. This supports the assumption in Equation 3 of within-group logit substitution patterns.

[31] In my setting, each tract contains between 1,200 and 8,000 people and states contain on average more than 1,400 tracts.

[32] In Appendix C.6, I provide more detail on the formulation of these moment conditions.

[33] One such choice is the option to remain in the same home as the year before, which 95.4% of households in my sample choose.

[34] Since the sole endogenous variable in this specification is $\log\left(p_{d,t}\right)$ and I estimate α_0 and α_I using a set of two demeaned and excluded instruments and their interactions with I_o, I achieve the "strong exclusion" property of Andrews et al. (2025). Causal

tracts in year t. The instrument is relevant if nearby deaths increase the number of homes that are for sale. This instrument isolates shifts in the supply of homes for sale in tracts that are likely close substitutes. These shifts in supply in turn affect prices in the focal tract through competitive pressures in equilibrium. The moment inequality estimator requires at least two instruments, so I construct these using disparate data sources and formulations to ensure they are not collinear.

First, I use the Social Security Death Master File (SSDMF) to count the number of individuals who die in a given census tract, as measured by matching the SSDMF to Infutor using the procedure in Bernstein et al. (2022). I construct the first instrument as a gravity measure of exposure to deaths of residents in the two nearest census tracts,

$$Z^1_{d,t} = \sum_{d' \in \{d_1, d_2\}} \tilde{x}^{SS}_{d',t} / \delta\left(d, d'\right)^2, \tag{5}$$

where d_1 and d_2 are the two closest census tracts, $\tilde{x}^{SS}_{d',t}$ is the count of deaths in year t and tract d' from the SSDMF multiplied by the year prior's share of households from d moving to d',[35] and $\delta\left(d, d'\right)$ is the distance between the population centroid of d and d'. The distance weighting and the interaction with the prior period's share allow for the impact of deaths in adjacent tracts to be mediated by two measures of substitutability, both of which are considered to be exogenous at the time of the choices at time t.

Second, I use county-level counts of deaths of individuals 75 or older from the CDC. I consider older residents, whose deaths are more likely both to trigger a home sale. I use these to construct a shift-share instrument (Bartik, 1991; Goldsmith-Pinkham et al., 2020). The count of deaths of older individuals in the county is a "shift", and the "shares" are a distance-weighted measure of the year prior's exposure to older people within the county. This exposure is measured as

$$C_{d,t} = \sum_{d' \in c, d' \neq d} e_{d',c} / \delta\left(d, d'\right) \tag{6}$$

where $e_{d',c}$ is the share of the county's elderly, as measured in Infutor, in tract d' within county c. I then construct a second instrument as

$$Z^2_{d,t} = C_{d,t} \cdot \tilde{x}^{CDC}_{c,t}, \tag{7}$$

where $\tilde{x}^{CDC}_{c,t}$ is the CDC's left-censored count of individuals above 75 who died in county c in year t. To maximize first-stage power, the instruments have different rates of spatial decay, underlying data sources, and interaction with observables from the year prior.[36]

summaries, such as the own-price elasticity, will thus be approximately correct given the strong identification shown by Gandhi et al. (2023) of my estimator via Proposition 3 of Andrews et al. (2025).

[35] This is a measure of prior substitutability that is expected to mediate how shocks to the supply of homes for sale in d' affect prices in d. This specification uses the historical shares of d moving to d' to estimate how deaths in d' influence prices in d, and subsequently affect household moves from o to d.

[36] The estimator proposed by Gandhi et al. (2023) requires the discretization of at least two non-collinear instruments, motivating

To satisfy exclusion, it must be the case that the unobservable demand shocks $\xi^o_{d,t}$ are uncorrelated with both $Z^1_{d,t}$ and $Z^2_{d,t}$. In Equation 3, I control directly for the observed deaths in tract d at time t as well as the potentially endogenous component of $Z^2_{d,t}$, the exposure to the county's elderly $C_{d,t}$, as well a generalization of tract fixed effects, γ^o_d. I recenter the instruments with regard to the fixed effects, γ^o_d, μ^o_t, and $\phi_{m,s,t}$. Thus, $\mathbb{E}\left[Z^1_{d,t}|d,(o,t),(m,s,t)\right] = \mathbb{E}\left[Z^2_{d,t}|d,(o,t),(m,s,t)\right] = 0$. These controls isolate the effects of time-series variation in $Z^1_{d,t}$ and $Z^2_{d,t}$ that is unrelated to both deaths in the focal tract and the age mix of nearby areas.[37]

4.3.2 *Identification of wind preferences*

I identify households' preferences for living near wind farms, ω_i, to rationalize their migration choices in response to wind farm entry. For each treated location, I use estimated demand curves, consisting of the full vector of non-wind amenities, to study how non-wind demand shapes market equilibrium after entry. With heterogeneous preferences, theory predicts that in "thin" markets with few potential in-migrants, wind entry should cause a large decrease in home prices and a small amount of re-sorting. Conversely, in "thick" markets, wind entry should cause smaller price decreases and greater re-sorting.[38]

After a wind farm is built, households choose to live near it if doing so maximizes their utility. For ease of exposition, I define an intermediate distribution which is a transformation of the vector of non-wind preferences and data. A household i's marginality, $v_{i,d,w,t} \sim V^o_{d,w,t}$, to living in (d,w), the homes in d near a wind farm, is the change in price in (d,w) at which i is exactly indifferent to living there. If $v_{i,d,w,t} = 0.05$, then i would be indifferent to living in (d,w), and their favorite non-(d,w) option, if prices in (d,w) increased by 5%. An individual's non-wind marginality can be written as

$$v_{i,d,w,t} = \left[\left(\delta^o_{d,w,t} + \varepsilon_{i,d,w,t} + \log\left(\lambda_t\left(d,w\right)\right)\right) - \max_{(d',w')\neq(d,w)}\left(\omega_i' w + \delta^o_{d,w,t} + \varepsilon_{i,d,w,t} + \log\left(\lambda_t\left(d,w\right)\right)\right)\right]/\alpha_i. \tag{8}$$

For periods t' after wind entry, I define $\tilde{V}^{o,w}_{d,w,t'}$ to be as in Equation 8 where $\delta^o_{d,w,t}$ is replaced by $\tilde{\delta}^o_{d,w,t}$ which is the counterfactual mean utility of the homes in (d,w) had a wind farm not been built.

When a wind farm is built, the market re-equilibriates in each treated tract. This involves a treatment effect on price and the in- and out-migration rates of, $\tau^p_{d,w}$, $\tau^{q,\text{ in}}_{d,w}$, $\tau^{q,\text{ out}}_{d,w}$, unrelated to any changes in $\xi^o_{d,t}$.[39]

two independent sources of this death shock instrument. I provide more details on the discretization procedure in Section C.6.

[37] In both instruments, the plausibly exogenous component, $\tilde{x}$, enters the instrument formulation linearly. Per Borusyak and Hull (2023), recentering and controlling for potentially endogenous determinants of Z is sufficient to remove the bias from non-random exposure to the expected level of treatment.

[38] In Appendix C.1, I provide a proof and graphical illustration of this theory.

[39] Since Equation 3 contains preferences for living near wind farms, these would be unobservable demand shocks unrelated to a wind farm.

By revealed preference, household i chooses to live near a wind farm in d if and only if

$$\underbrace{\omega_i}_{\text{wind pref.}} + \underbrace{\tau^p_{d,w}}_{\text{price }\Delta} + \underbrace{\tilde{v}^{o,w}_{i,d,w,t'}}_{\text{c.f. marginality}} \geq 0, \tag{9}$$

where $\tilde{v}^{o,w}_{i,d,w,t'} \sim \tilde{V}^{o,w}_{d,w,t'}$.

Households who lived near wind farms the year before will move out if their Equation 9 does not hold. This likelihood must equal the incumbent move-out rate, yielding the following relationship to the out-migration rate:

$$\tau^{q,\text{ out}}_{d,w} = \mathbb{P}\left(\omega_i + \tau^p_{d,w} + \tilde{v}^{d,w}_{i,d,w,t'} < 0\right). \tag{10}$$

There are also N^{out}_o households who may move in to the treated area from other locations, o. Their average rate of in-migration is:

$$\tau^{q,\text{ in}}_{d,w} = \sum_{(d',w')\neq(d,w)} N^{out}_o \mathbb{P}\left(\omega_i + \tau^p_{d,w} + \tilde{v}^{d',w'}_{i,d,w,t'} \geq 0\right). \tag{11}$$

The full distribution of ω_i is identified using the revealed preference conditions in Equations 10 and 11, along with the corresponding treatment effects on price and migration and the distributions of marginality, $\tilde{V}$. The proof of identification, provided in Appendix C.1, relies only on mild regularity conditions. Intuitively, identification comes from comparing how households re-sort in response to wind farm entry under varying magnitudes of price changes. When prices fall sharply after a wind farm is built, the number of households that move out identifies the share with very negative ω_i. Conversely, when prices decline only slightly, the extent of re-sorting identifies the share with moderately negative ω_i.

4.4 Estimation and results

4.4.1 Estimating non-wind preferences

Sample. I estimate the model using data on yearly flows of households between Census tracts, and between homes, from Infutor. I restrict the sample to the 26 states in the U.S. that have more than one in ten thousand homes that are near a wind turbine as of 2020. I further subset to origin tracts where there is ever a household from that tract that moves to a tract that ever has a wind farm. I study the period between 2000 and 2013. I measure average prices and characteristics of homes from transacted properties in CoreLogic within each tract during each year. I measure choice shares $s^o_{d,w,t}$ to be the fraction of households, whose addresses I observe in t, who lived in origin tract o in year $t-1$ who chose d in year t. My sample consists of 300, 485, 874 flows, where there was at least one home for sale in that destination in that year, subsetting to only origin-destination flows that are *ever* non-zero.[40]

First stage. I present the linear version of the first stage in Appendix Table A3.[41] The first column shows a "zeroth" stage in which both instruments increase the number of homes sold in the two nearest tracts. This is consistent with deaths increasing the supply of homes for sale in closely competing areas. The second column shows that both instruments decrease the transaction prices of homes in the focal tract, as expected. The ratios of the coefficients of the effects on supply of close competitors and the eventual transaction prices are similar, supporting the exclusion argument.

Estimation. I estimate the vector of non-wind preferences, $\hat{\theta}$, to minimize violations of the moment inequalities described in Section 4.3.1. The nonlinearity of these moment inequalities makes it impossible to use standard estimators for linear high-dimensional fixed effect instrumental variable estimators. I instead solve for $\hat{\theta}$ via gradient descent, making use of the analytical gradient.[42]

Parameter estimates. I find the mean own-price elasticity to be -0.311 $[-0.321,\ -0.282]$.[43] Further, I find that households from higher-income origin tracts are less price sensitive. A 1 standard deviation increase in household income is associated with an estimated 22.6% [20.3%, 26.8%] decrease in their disutility from price, α_i. I present the estimated parameters, excluding fixed effects, in Appendix Table A5.

Discussion. I find substantial heterogeneity in tracts' own-price elasticities. The inter-quartile range of estimated own-price elasticities is 0.204 [0.186, 0.210], as shown in Appendix Figure A10. This heterogeneity arises from two sources. First, tracts have different mean utilities to households from other origin tracts, due to heterogeneity in estimated $\hat{\delta}$. Some areas attract many households who do not currently live there with high mean utilities from living there, while others attract few. Although within-group own-price elasticities are homogeneous in this specification, differences in $\hat{\delta}$ imply differences in baseline demand levels, and thus heterogeneous aggregate elasticities. Second, locations differ in the incomes of the households who most value living there, and generating further variation in the price elasticities.

In Appendix Table A4 I provide several robustness exercises. First, I emphasize the importance of the moment inequality estimator by noting how sensitive estimated price elasticities are to the choice of smoothing parameters that ensure shares are positive and thus estimable by way of a Berry (1994) inver-

[40] If in all periods $s^o_{d,t} = 0$ then γ^o_d will not be identified. For this reason, I exclude origin tracts where no one from that tract ever moves to a tract that ever has a wind farm, because their γ^o_d will be unidentified. In these cases, I set γ^o_d to an arbitrarily low value. If there were no transactions, I conclude that this option was not available to any households not already living there.

[41] The estimator uses a whitened and discretized version of the instruments, as described in Appendix C.6.

[42] I begin by searching over 500 perturbations of a vector of the non-fixed effect parameters from a guess, using the Frisch-Waugh-Lovell theorem (Frisch and Waugh, 1933; Lovell, 1963) to target the average of the bounds to solve for an intermediate guess of the fixed effects, and then converging to the full vector of $\hat{\theta}$ by way of gradient descent. This method ensures that the numerical optimizer does not become stuck at a local optimum. The specification in Equation 3 adds computational tractability since it ensures that the moments have a closed-form, and thus an analytical gradient, as opposed to common alternatives such as a mixed logit utility function.

[43] I validate this estimate in Appendix C.8, where I estimate the price coefficient α_0 using *only* the endowed options and find a similar preference parameter, which is consistent with the utility specification in Equation 3.

sion.[44] Second, I illustrate the importance of instruments by targeting the average of the Gandhi et al. (2023) bounds with and without instruments, since the moment inequality estimator does not allow for straightforward comparisons to OLS. In this specification, the OLS price elasticity is around 120 times smaller than the IV estimate, underscoring the importance of instruments for price.

4.4.2 *Estimating wind preferences*

Treatment effects on price and in- and out-migration. I require treatment effects for each treated location (d, w). I assume that in the short-run supply is inelastic and the market clears. I can then relate the rate of in-migration to the rate of out-migration as $\tau_{d,w}^{q,\text{ out}} = \left(1 - \tau_{d,w}^{q,\text{ in}}\right) N^{\text{in}} / \left(\sum_o N_o^{\text{out}}\right)$.[45] I use a one-dimensional summary of the pre-period demand curves to estimate heterogeneous treatment effects. I assume that treatment effects can be parameterized as a function of a characteristic of non-wind demand. I use the following pre-period measure, outside demand, which is the model-implied percentage increase in population of (d, w) from in-migrants if prices dropped 5%:[46]

$$\iota_{d,w,t} = \sum_o \hat{D}_{d,w,t}^o(-0.05) \Big/ \left(\hat{D}_{-1,w,t}^d(0) + \sum_o \hat{D}_{d,w,t}^o(0)\right), \tag{12}$$

where $\hat{D}_{d,w,t}^o$ is the estimated demand from households from origin o. I define the heterogeneous treatment effects as $\tau_{d,w,t}^p = \tau^p(\bar{\iota}_{d,w})$ and $\tau_{d,w,t}^{q,\text{ out}} = \tau^{q,\text{ out}}(\bar{\iota}_{d,w})$, where $\bar{\iota}_{d,w}$ is the average of $\iota_{d,w,t}$ in the three years prior to wind entry. I estimate the functions $\hat{\tau}^p(\iota)$ and $\hat{\tau}^{q,\text{ out}}(\iota)$ by first recovering the treatment effects on price and out-migration, $\hat{\tau}_O^p$ and $\hat{\tau}_O^{q,\text{ out}}$, for each octile of the distribution of $\bar{\iota}_{d,w}$. I create the functions $\hat{\tau}^p$ and $\hat{\tau}^{q,\text{ out}}$ by linearly interpolating between the estimates for each of these quantiles.

I estimate the treatment effects on price and out-migration at different quantiles of model-implied in-migration rates, $\bar{\iota}_{d,w}$, by estimating heterogeneous difference-in-difference effects on the price of homes and volume of home sales. This specification is closely related to Equation 1 in Section 4.1. I estimate a difference-in-difference with treatment heterogeneity by $\bar{\iota}_{d,w}$, comparing to homes that have a wind farm

[44] This is consistent with the results in Dingel and Tintelnot (2025).

[45] Since homes are durable, it is unlikely that homes are destroyed in the short run. Further, since this is a negative demand shock, it is unlikely that new homes will be built in the area. This appears to hold, given no evidence of population changes in Infutor.

[46] This is closely related to the own-price elasticity with the main difference being that it is the change in demand from non-residents normalized by total demand. For the purposes of estimation, I associate each home with the average of $\iota_{d_w,t}$ for the three years just prior to a wind farm being built. In areas where the treated zone d_w is a fraction b of the total tract, I calibrate the demand for d_w to be equal to the demand for d multiplied by b.

built five to ten years later with the same set of controls. I estimate the following specifications:

$$\log\left(p_{i,t}\right) = \sum_{O\in\{1,\ldots,8\}} \left(\tau_O^p \cdot B_{i,t} + \chi_O^p \cdot T_{i,t} + \rho_O^p\right) \cdot \mathbb{I}\left\{O_i = O\right\} + \beta X_i + \nu_{c(i)}^p + \phi_t^p + \mu_{C(i),\ g(t)}^p + \varepsilon_{i,t}^p, \quad (13)$$

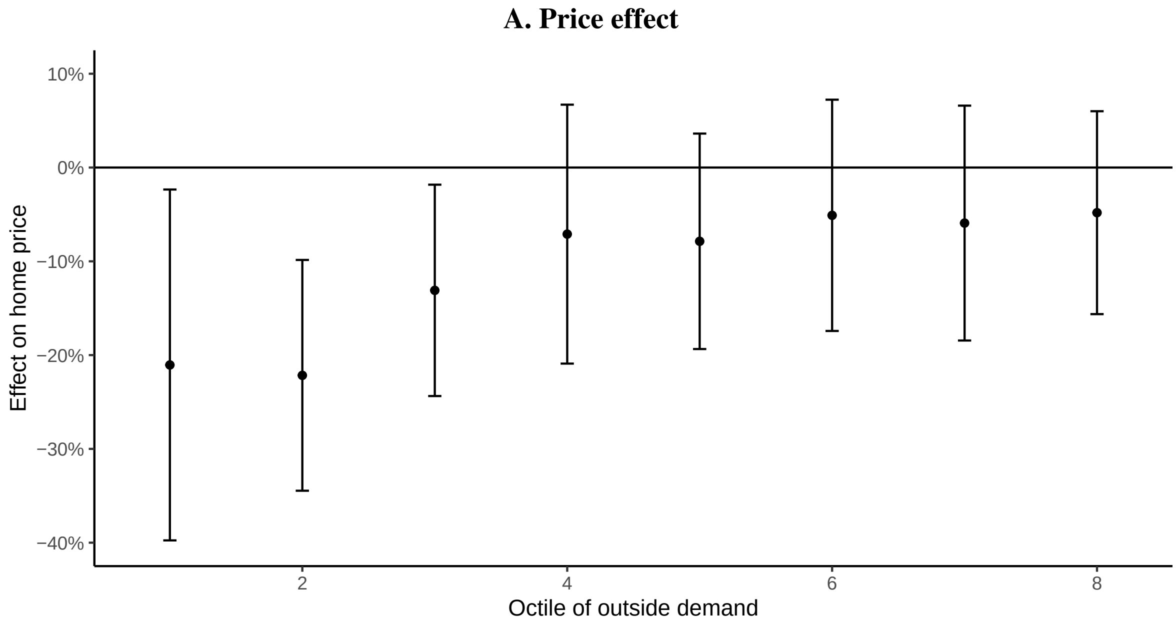
$$s_{i,t} = \sum_{O\in\{1,\ldots,8\}} \left(\tau_O^{q,\text{ out}} \cdot B_{i,t} + \chi_O^q \cdot T_{i,t} + \rho_O^q\right) \cdot \mathbb{I}\left\{O_i = O\right\} + \nu_{c(i)}^q + \phi_t^q + \mu_{C(i),\ g(t)}^q + \varepsilon_{i,t}^q. \quad (14)$$

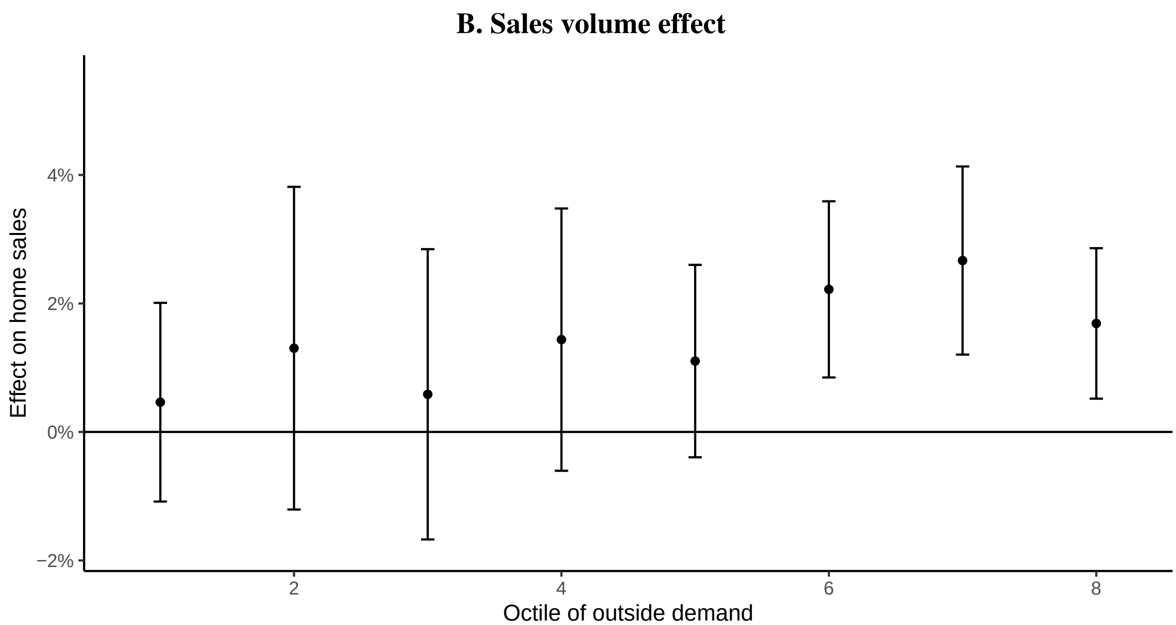
For some property i, $s_{i,t}$ is an indicator whether it was transacted at t, and $p_{i,t}$ is its transaction price if $s_{i,t} = 1$. $B_{i,t}$ is an indicator for whether t is after wind farm entry for i, $T_{i,t}$ is an indicator for whether i is treated in this stack, and O_i is i's octile of ι. In Equation 13 I also control for $X_{i,t}$, which are logged home characteristics: acres, bedrooms, bathrooms, and age. I include census tract, $c(i)$, year t, and three-year bin $\times$ county fixed effects as $\nu_{c(i)}$, ϕ_t, and $\mu_{C(i),\ g(y)}$ in both specifications.

I present the estimated $\hat{\tau}_O^p$ and $\hat{\tau}_O^{q,\text{ out}}$ in Figure 4, both of which vary substantially by ι. Panel A shows that in areas with little outside demand, wind farm entry leads to large decreases in home prices. In contrast, in areas with high outside demand, the estimated price effects are small and statistically insignificant. Panel B shows that in areas with little outside demand, out-migration changes very little, while in areas with lots of outside demand it increases sharply. These results are consistent with a model in which households have heterogeneous costs of living near a wind farm and choose to move out if price declines are insufficient to offset their disutility, as in Equation 10. The identifying assumption is that, among places that eventually allow a wind farm to be built, the exact timing of entry is plausibly exogenous. This is supported by no observed pre-trends in event studies using this control group, most specifically the event study effects on price by octile of $\bar{\iota}_{d,w}$ (Appendix Figure A13). Additionally, Figure 3 presents the effects on price by distance and Appendix Figure A5 shows the effects on home sales volumes, using the same control group.

The range of these estimated price effects, from around −0.20 to 0, provides sufficient support to identify the distribution of wind preferences, as proven in Appendix A.2. The measure of outside demand, $\bar{\iota}_{d,w}$, is most strongly related to the fraction of residents who had not lived there the year before, as shown in Appendix Figure A11 and Table A6. I find similar heterogeneity in price effects by this observable characteristic, presented in Appendix Figure A14.

Figure 4: Effect of wind farms on price and sales volume by outside demand





Note: Both effects are estimated by comparing homes near turbines to homes near turbines that are treated between five and ten years after, but have not been treated yet. Home price effect is estimated controlling for age, acreage, bedrooms, baths, census tract, county × three-year bin, and year. Sales effect is estimated controlling for census tract, county × three-year bin, and year. Both sets of effects are estimated as a stacked difference-in-differences estimator jointly.

Counterfactual marginality distributions $\tilde{V}$. In order to appropriately account for individuals' $\tilde{v}_i$ in the in- and out-migration moments, presented in Equations 10 and 11, I require the counterfactual distribution of marginality, constructed from non-wind preferences. I assume that for the five years after wind entry, the relevant $\tilde{V}_{d,w}$ is equal to the average of the measured $\tilde{V}_{d,w,t}$ for the three years prior to wind entry.[47]

I assume stationarity of the average distribution of non-wind marginality over a short time horizon. This could be achieved if, for each origin group, the total utility of all non-(d, w) options, or $\Theta_t^o - u_{i,d,w,t}$, was constant in the short run. This assumption requires wind farm entry to solely affect the utility of living in the treated area. This may be feasible, given the small number of homes that are treated in a given area.[48]

Estimation of $\omega_i \sim W$. I estimate the distribution W as a grid of mass points. Given the relative sparsity of wind farms in my sample period, I assume that preferences for wind are independent and identically distributed in the population, or that households are not sorted according to their wind preferences in the pre-period.[49] Each location (d, w) with average outside demand $\bar{\iota}_{d,w}$ has an associated treatment effect on price and effect on in- and out-migration from my estimates of $\hat{\tau}^p(\iota)$, $\hat{\tau}^{q,\text{ out}}(\iota)$, and $\hat{\tau}^{q,\text{ in}}(\iota)$. To solve for $\hat{W}$ I consider a candidate, W_g. For each location, given their relevant $\tilde{V}_{d,w}$ and $\hat{\tau}^p\left(\bar{\iota}_{d,w}\right)$, I find their model-implied in- and out-migration from W_g consistent with Equations 10 and 11. I use both in- and out-migration moments for additional statistical power, although one series would be sufficient for identification as shown in Proposition 1. Intuitively, how many households move out is directly related to the left tail of ω_i. How many households move in is directly related to the right tail of ω_i.

I solve for $\hat{W}$ as a constrained regression to find the distribution of mass points that minimizes the deviations between the model-implied migration moments and the associated treatment effects, $\hat{\tau}^{q,\text{ out}}\left(\bar{\iota}_{d,w}\right)$ and $\hat{\tau}^{q,\text{ in}}\left(\bar{\iota}_{d,w}\right)$ with an additional penalization term to enforce regularity of the tails. I provide more details on the exact estimation procedure in Appendix C.9.

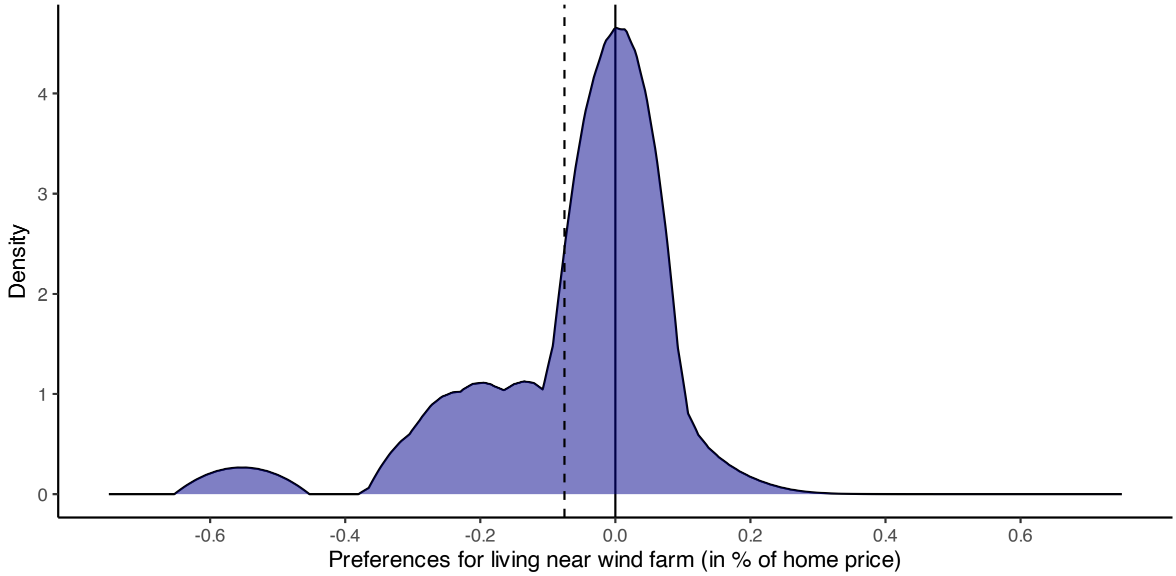
Results and discussion. I present the preference estimates, smoothed using an Epanechnikov kernel, in Figure 5. The mean of this distribution is -7.54%. There is considerable heterogeneity. I find a substantial mass of households to be close to indifferent. At the same time, around 13% of households are willing to pay 25% or more of their homes' value to avoid having a wind farm built nearby. The distribution of these preferences is qualitatively similar to, although somewhat more negative than, poll responses of households who live near wind farms, measured after any potential re-sorting (Hoen et al., 2019).

[47] This assumption, given the demand curve smoothness from the logit errors, and the fact that year-to-year populations and out-migration rates are typically relatively constant is similar to an assumption that the own-price elasticity of demand for d_w from incumbents and non-incumbents would have been constant, but for the wind farm.

[48] This shuts down broader equilibrium effects. I motivate the lack of a need to do so with two facts related to my empirical setting. First, typically very few homes are affected at one time. The median fraction of the tract that is within three miles of a wind farm is 4.2%. Second, the price effects estimated in Appendix Figure A3 decay quickly in space, even though distance is to the *first* wind farm and additional ones may be built. The treated census tracts are quite large, on average roughly 180 square miles, and the wind farms tend to be in remote parts of the tract, implying close to no change in price for the remaining untreated portion of the tract, and likely small effects on neighboring tracts.

[49] There appears to be an empirically quite small amount of pre-sorting in my setting. In Appendix B.8, I estimate the effects of wind entry on the rate at which in- and out-migrants had previously lived near wind farms. I find a precise, but quite small, 2.5% increase in the chance that in-migrants were previously living near a wind farm, as presented in Appendix Figure A34.

Figure 5: Estimated distribution of W



Note: These preferences are in units of equivalent log change in property values. For instance, if $\omega = -0.1$ that would be equivalent to a 10% increase in price. After transforming each point to an equivalent percentage change the mean is -0.0754. The untransformed mean, not accounting for the log approximation, is -0.0511.

4.5 Test of Coase (1960)

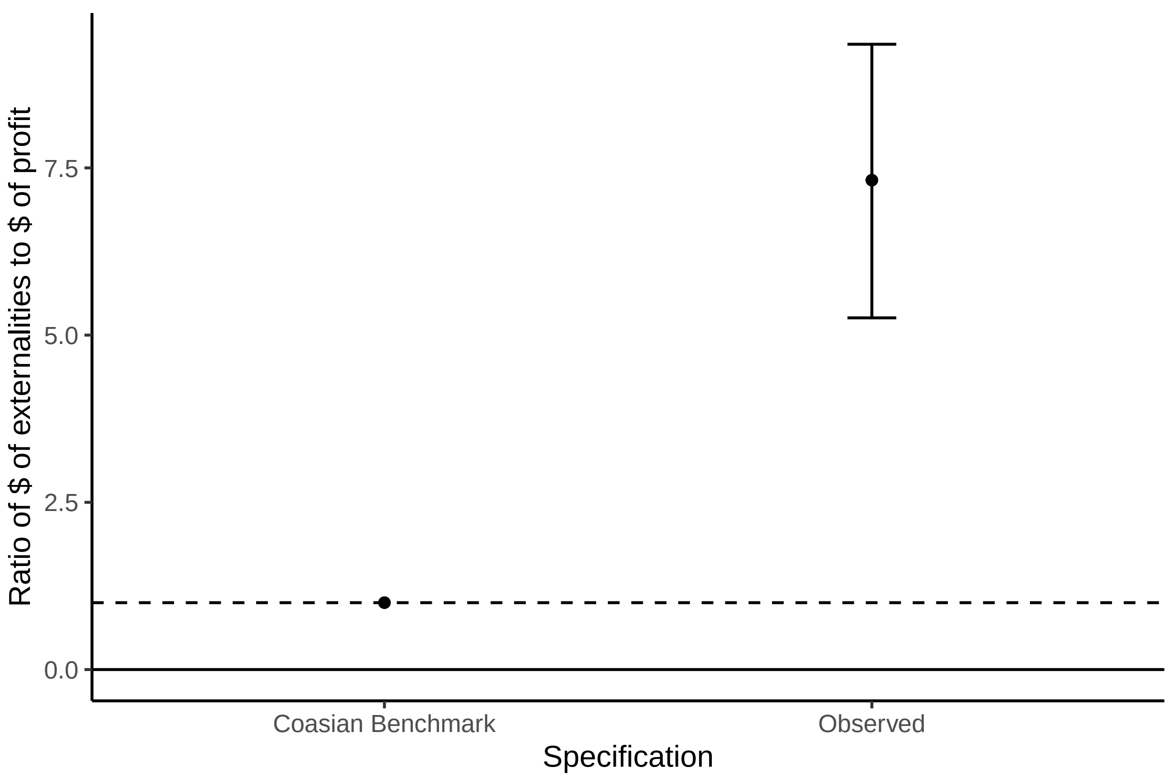
I test whether the aggregate distribution of wind farms efficiently trades off developer profitability with the costs borne by nearby households. In the Coasian benchmark with frictionless bargaining and fully delineated property rights, developers could contract directly with affected households and fully internalize the social costs of their project. For each location l, the total net social value of building a wind farm in that location is $\hat{\Pi}_l + \mathbb{E}[C_l]$. When ω_i are households' preferences for living near turbines and P_l is the total value of homes within five miles of site l, then $\mathbb{E}[C_l] = \mathbb{E}[\omega_i] \cdot P_l$ is an upper bound estimate of the true welfare cost to the incumbents, in a logic similar to Diamond and McQuade (2019). Some households may choose to move if doing so is preferable to their change in indirect utility had they stayed. By the envelope theorem, households' change in utility is greater than or equal to $\omega_i - \tau^p_{d_w,t}$, where both ω_i and $\tau^p_{d_w,t}$ are in percentage changes of home price. Multiplying by home price, $(\omega_i - \tau^p_{d_w,t})p_i$ transforms this into money-metric units. Price changes, $\tau^p_{d_w,t}p_i$, are permanent wealth changes to homeowners that are exactly offset as transfers to renters. Summing across incumbent households and homeowners, the total welfare change, not considering potential entrants, is bounded from below by $(\sum_i \omega_i p_i) = \mathbb{E}[\omega_i] \cdot P_l$. Appendix Figure A15 maps these estimated social values across all potential sites.

I test the Coasian benchmark by estimating the following probit regression,

$$\text{Built}_l = \beta_p \underbrace{\hat{\Pi}_l + \beta A_l^{\text{ag}} + \gamma_{s(l)}}_{\text{profit}} + \beta_e \underbrace{\mathbb{E}\left[C_l\right]}_{\text{externality}} + \varepsilon_l \geq 0 \tag{15}$$

where $\gamma_{s(l)}$ is a state fixed effect, A_l^{ag} is agricultural productivity, and $\varepsilon_l \sim N(0,1)$. This is a reduced-form test of the trade-off between profit and externality. I test the Coasian benchmark by assessing whether $\hat{\beta}_e/\hat{\beta}_p = 1$ in Figure 6. In Section 5, I develop and estimate a structural model of developers-government interaction. In Appendix B.9, I implement a structural test of the model of Coase (1960) and find an aggregate trade-off consistent with the reduced-form evidence.

Figure 6: Estimated developer sensitivity to nearby homes' values



Note: The value of homes within five miles is from a hedonic price index from CoreLogic which is scaled by the mean preference of −7.54%. Confidence intervals calculated from 200 iterations of a Bayesian bootstrap.

I find that what is built is substantially too sensitive to the value of homes nearby. This is consistent with a model where developers paid 55% of the total price of homes in a five mile radius. This is roughly seven times as much as the preference estimates, suggesting that there may be some failures of efficient Coasian bargaining. These market failures lead to an aggregate avoidance of areas with many nearby properties. I assess the cause of these failures in Section 5, which could be due to frictions in preference aggregation, regulated prices, or hold-up risk. In Appendix Figure A7 I present a heat-map of data underlying this specification comparing the Coasian benchmark with the observed trade-offs. In Appendix Figure A6 I present the same bin-scatter as in Figure 2.

5 Developer-government interaction

5.1 Model

5.1.1 Developer-government interaction

There is a set of locations $\mathcal{L}$. Each location l has an exogenous profitability if developed, Π_l. There exists a mapping $\mathcal{I} : \mathcal{L} \to \mathcal{P}(\mathcal{H})$ where $\mathcal{I}(l)$ is the set of households impacted by construction of a wind farm l. The affected households' set of costs is $\mathbf{d} = \left\{\omega_i' \text{ for } i \in \mathcal{I}(l)\right\}$. The game is between a homogeneous developer, D, and the associated local government $G = \mathcal{G}(l)$. The game proceeds as follows, with the timing shown graphically in Figure 7.

If the project is built, the developer receives a payoff of $\Pi_l = \Pi_{l,0} + \Pi_{l,1} - T_l$, where $\Pi_{l,0}$ is the site's expected profitability, $\Pi_{l,1}$ is the final-period profit shock, and T_l is a transfer paid to the local government. Similarly, if the project is built the local government receives a net benefit of $\zeta_l \mathbb{E}[C_l] + V_l \cdot T_l$ where ζ_l is the government's political friction, $\mathbb{E}[C_l]$ is the government's aggregation of its constituents' costs, and V_l is the government's idiosyncratic value for money. This model focuses on the dynamic strategic interaction between developers and local governments, abstracting away from the precise timing of actions. I measure the total welfare cost to incumbent households from the model in Section 4, which spans many periods. Section 4.5, shows how to relate the total costs to incumbents to ω_i.[50]

Period 1: Initial investment The developer can choose to contact the government G for a cost e. If contacted, the local government may block them from continuing for a cost B_1.[51] The site's expected profitability, $\Pi_{l,0}$, is common knowledge. If the developer is not blocked, they must pay an investment cost E to design the site and learn their final private profit shock $\Pi_{l,1}$. At this point, the local government aggregates its constituents' costs as $\zeta_l \cdot \mathbb{E}[C_l]$ where $C_l = \sum \mathbf{d}$. The government's private political friction ζ_l and its value for money V_l, are both random variables drawn from a known distribution, where V_l has a mean of 1. The ratio ζ_l / V_l is how many additional dollars of revenue the local government requires to be indifferent to a \$1 increase in the size of the total household costs.

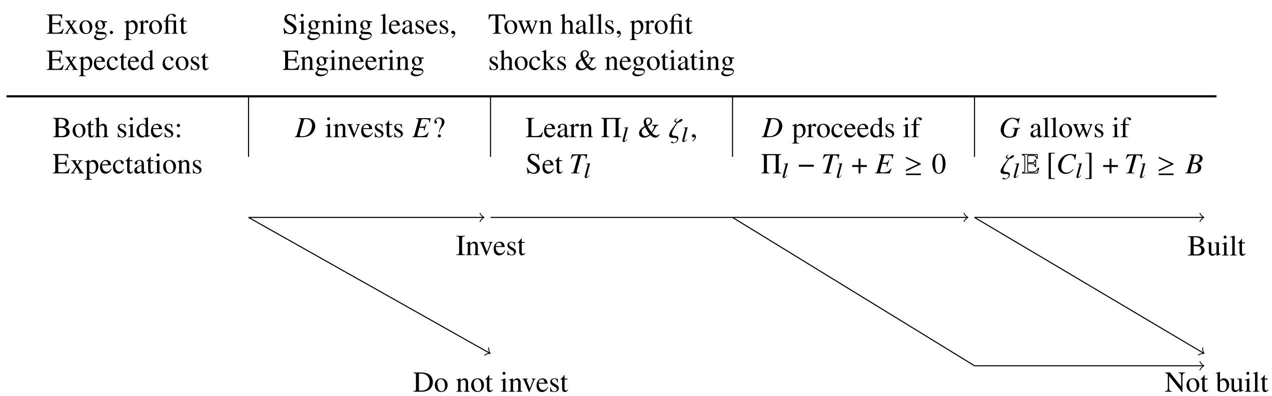
[50] The multiple periods of the model in Section 4 allow me to use yearly out-migration effects to estimate the full distribution of ω_i, which I express as percentage differences of households' willingness-to-pay for home prices.

[51] Common methods for blocking projects include voting on and passing new county laws imposing moratoria on wind farms or filing for conservation easements to block the interconnection of potential wind farms from the electrical grid, as documented in Fowlie and Taylor (2025). The costs may also include a hassle-cost component to the local government. As I discuss in Section 2.4, local governments have wide leeway in determining land use, but may not make clearly arbitrary or unreasonable rules (Taft, 1926).

Period 2: Potential negotiation If regulated, the developer may be required to pay an exogenous transfer T_l to the local government. If negotiation is allowed, the local government and developer will bargain over a transfer payment T_l at this point. Both sides receive a signal about the other side's private information, ζ_l / V_l or $\Pi_{l,1}$. With probability ρ, the government may make a take-it-or-leave-it offer T_l with the ability to commit to blocking if the developer rejects it. Otherwise, the developer makes a take-it-or-leave-it offer T_l.

Period 3: Final determination The developer may decide whether she wants to construct the project after considering her final-period profit shock $\Pi_{l,1}$ and T_l. The developer will construct if $\Pi_l + E - T_l > 0$, or if the continuation value of doing so is positive. Subsequently, the local government may decide whether they wish to block the project for some cost $B_2 > B_1$. They will do so if $V_l \cdot T_l + \zeta_l \mathbb{E}\left[C_l\right] < -B_2$.

Figure 7: Simple timeline of wind development



Note: I present, above the line, the description of wind development from industry documents and conversations with wind developers. I present, below the line, the model analog action space and information structure. The flow chart demonstrates the game tree. As the econometrician, I observe the decisions to invest and whether a wind farm is built.

5.2 Potential market failures

This model allows for three potential market failures, which I discuss in more detail below. These market failures are in comparison to the benchmark suggested by Coase (1960), in which I assume that each household has a property right to not allow a wind farm to be built and bilateral bargaining is frictionless.[52] For each household $i \in \mathcal{I}(l)$ there is an associated transfer from the developer to the household, $t_i^* \in \mathbb{R}$. In this case, the wind farm will be built if and only if $t_i^* \geq \omega_i'$ for all i and $\Pi_l - \sum_{i \in \mathcal{I}(l)} t_i^* \geq 0$. There exists such a series of transfers $\left\{t_i^*\right\}$ such that a wind farm is built if and only if $\Pi_l - \sum_{i \in \mathcal{I}(l)} \omega_i' \geq 0$, which is equivalent to all projects with positive social value being built.

[52]In this model, who holds the property right has no effect on the outcome, but does affect the direction of the transfer.

5.2.1 *Political frictions*

The local government trades off costs to households with transfers. If $\zeta_l/V_l \neq 1$, this trade-off is different from a money-metric utilitarian social planner's. The local government may overweight household costs ($\zeta_l/V_l > 1$) if, for example, the more acutely harmed households carry more weight in their decision-making process than those receiving diffuse benefits, or if the local government's marginal value of public funds is less than one.[53] Conversely, the local government may under-weigh household costs ($\zeta_l/V_l < 1$) if the opposite conditions hold, or if it seeks to maximize its own revenue.[54]

5.2.2 *Contracting frictions*

Regulated transfer amounts. In some states the transfer amounts, T_l, are regulated. If T_l is too high, some socially valuable projects may no longer be profitable to the developer, and will not be pursued. If T_l is too low, some socially valuable projects may be unacceptable to local governments, and will be blocked.

Hold-up. Where the transfer amount T_l can be negotiated, it is after the developer invests E. After sinking this cost, the developer would agree to some transfer, T^*, where

$$\Pi_l + E - T^* \geq 0, \text{ and}$$
$$\Pi_l - T^* < 0.$$

The developer anticipates this, and may not initially invest in some socially valuable locations depending on how the surplus from negotiation accrues to the local government.

5.3 Descriptive evidence: Effects of tax rules

I next describe how state rules governing developers' property tax payments to local governments affect construction. As classified by Uebelhor et al. (2021), there are three main categories of state laws, presented in Appendix Figure A16. The first is the default system, where developers pay property taxes on the wind farm's assessed value, consistent with a large exogenous T_l. The second exempts developers, fully or largely, from property taxes, consistent with an exogenous small or zero T_l. For example, Texas' 1978 Proposition 4 amended its state constitution to allow the legislature to exempt "solar and wind-powered energy devices" as "an effective method of encouraging private investment" (TLC, 1978). The third allows wind developers to negotiate payments to local governments in lieu of taxes. This tends to be legislated explicitly, as in

[53] For instance, harmed households may speak more in planning meetings, consistent with Einstein et al. (2019). Alternatively, much of the transfer revenue is used on educational expenditures, and school finance equalization may effectively tax away revenue gains to local governments. I find that this is the case in Appendix B.7, as do Brunner et al. (2022).

[54] There is some work that suggests a positive marginal value of public funds in school expenditures (Cellini et al., 2010; Biasi et al., 2025) and other work in support of the so-called "Leviathan hypothesis" (Brennan and Buchanan, 1980; Diamond, 2017).

Minnesota Statute 272.028 (Minnesota, 2001), and mimics host fees for toxic waste (Jenkins et al., 2004).

Through the lens of the model in Section 5.1, changing how developers may pay local governments consists of two forces. First, when developers pay taxes, this lowers the likelihood that a site is profitable. Second, tax payments increase the likelihood that a project is allowed by the local government. To isolate the first effect, I analyze empty locations, where there are no affected homes and local government opposition is assumed to be negligible.[55] I then consider the combined effect of these two forces in the full sample.

I estimate a spatial regression discontinuity at state borders where the tax policy faced by wind developers changes.[56] Unobservable determinants of wind construction are likely similar across borders. A potential confound is other state-level policies, most notably renewable portfolio standards (RPS), which govern the share of electricity consumption in a state that comes from renewable sources. Typically, generators can readily sell electricity across state borders. Since RPS rules regulate the generation mix of consumed electricity, not its origin, these policies are unlikely to differentially affect profitability across borders. This is not true of Texas, which I therefore exclude when estimating these border effects.[57]

I estimate the pooled effect along borders with a difference in tax treatment as a spatial regression discontinuity with multiple treatments for locations within 25 miles of relevant borders as

$$\text{Built}_l = \phi_{r(l)} + \gamma_{b(l)} + f_{r(l)}\left(d_l\right) + \varepsilon_l, \tag{16}$$

where Built_l indicates whether location l is built, $\phi_{r(l)}$ are fixed effects for the tax regime $r(l)$, $\gamma_{b(l)}$ are fixed effects for the border, $f_{r(l)}$ is a flexible spline function of distance from the border d_l, and there is an error term ε_l. Column 1 of Table 1 presents my main specification, with the corresponding sample of sites mapped in Appendix Figure A17. I find that, relative to states where developers pay property taxes, substantially fewer wind farms are built when developers are exempt from paying taxes. Allowing developers to negotiate payments results in fewer projects than under tax payment, but more than under full exemption.

Column 2 of Table 1 restricts the sample to areas with few or no nearby households. Community opposition should play a much smaller role in these areas, and so we expect the sign of the tax effect to reverse.[58] Indeed, in these areas, tax exemption leads to a large increase in wind farm construction relative to tax payment. In this sample, when developers may negotiate payments, more wind farms are built than when they must pay taxes, but fewer than when they may not pay taxes. This suggests that although negotiation may in expectation lead to lower tax payments than the inflexible amount, the way that surplus is

[55] Standard theories and empirical evidence about firms' location choices when facing heterogeneous tax rates suggest that firms would cluster on the side of the border where they pay *less* in taxes (Suarez Serrato and Zidar, 2016; Fajgelbaum et al., 2019).

[56] Some examples of this research design are Holmes (1998); Black (1999); Dell (2010); Turner et al. (2014).

[57] Texas is a so-called "energy island" with only four direct current connections to the rest of the U.S. (McGlinchy and Buchele, 2022). I find similar results exempting state borders that coincide with interconnection region borders (Appendix Table A9).

[58] I present the individual spatial RD plots for this subsample in Appendix Figure A18.

split makes it dispreferred relative to not paying taxes in locations with small to no externalities. Appendix Tables A7 and A8 report robustness checks using alternative controls and find similar results along a range of specifications. I find that the estimates in Table 1 are largely insensitive to excluding controls, the balance of which I present in Appendix Figures A19 and A20. Appendix Figure A22 examines how the number of affected households affects whether paying taxes is preferable to exemption. With as few as three to five homes, paying taxes leads to more wind farms being built than exemption.

Table 1: Border effects of tax rules on wind farm existence

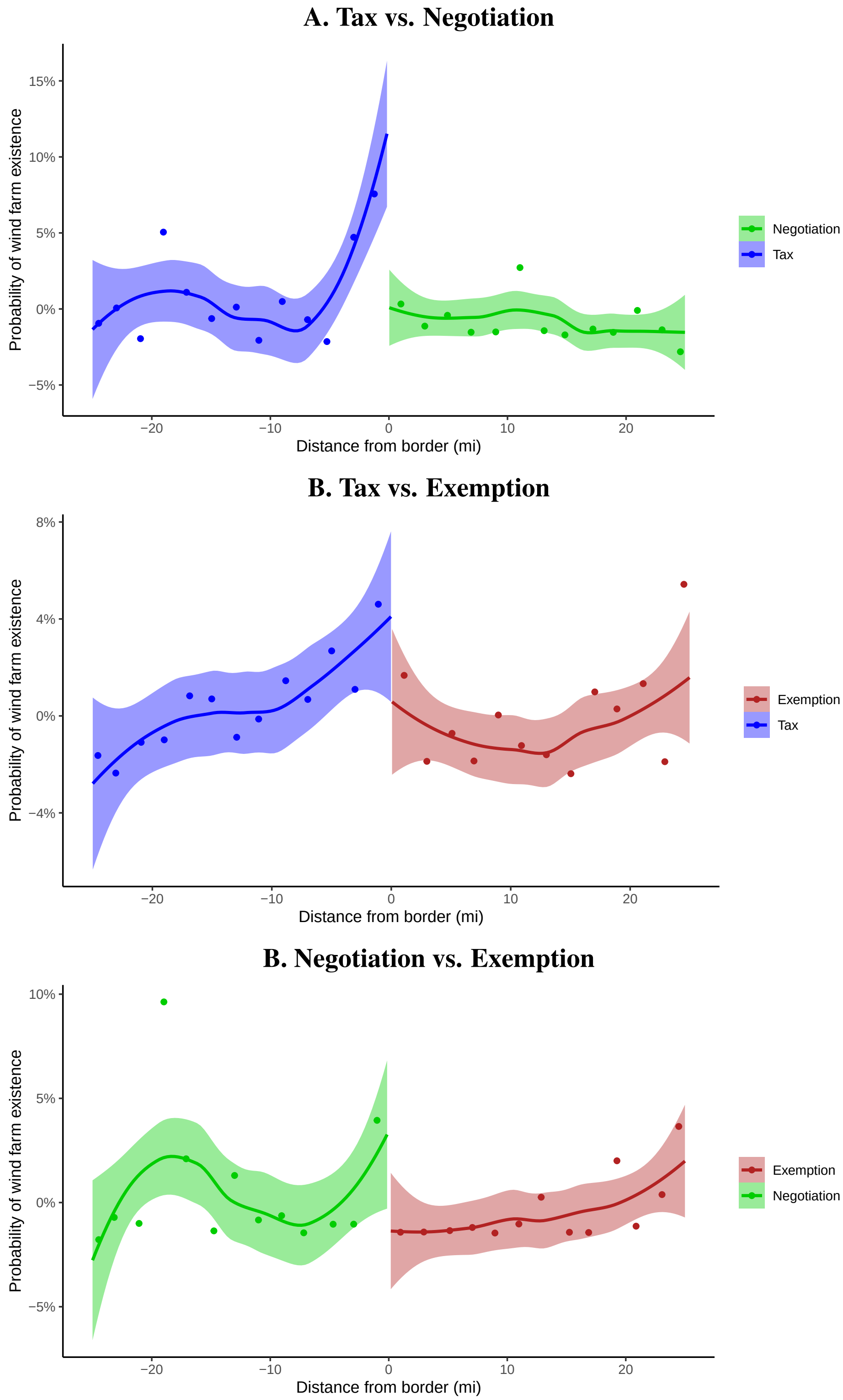
Dependent Variable:	Wind farm exists	
	Full Sample	No homes in 5 mi
Model:	(1)	(2)
Variables		
Negotiation relative to Tax	-2.4%	2.5%
	(0.9%)	(0.2%)
Exemption relative to Tax	-4.8%	3.8%
	(0.5%)	(0.2%)
Fixed-effects		
Border	Yes	Yes
Controls		
Engineering profitability	Yes	Yes
Distance from border by rule (5 d.f. spline)	Yes	Yes
Fit statistics		
Observations	7,310	1,955
R^2	0.03621	0.05204

Note: Standard errors allow for spatial correlation using Conley (1999). Tax rules from Uebelhor et al. (2021).

I decompose these pooled effects into the individual treatment thresholds following Calonico et al. (2014), I estimate robust regression discontinuities for the three transitions between tax laws, controlling for border fixed effects, engineering profitability, and the number of homes within five miles. Relative to paying property taxes, exemption and negotiation reduce construction likelihoods by 4.5% [1.8%, 10.7%] and 10.7% [1.7%, 27.2%] respectively. Negotiation lowers construction by 6.2% [−0.9%, 13.2%] relative to exemption. Figure 8 shows the Loess local polynomial and residualized bin-scatter underlying these RD estimates; Appendix Figure A18 presents the same for empty locations. Wind farms are more likely to be built near the border, suggesting that developers shift externalities to households who are not their constituents.[59]

[59] I find that wind farms are more likely to be built closer to a state border (Appendix Figure A21). This is consistent with minimizing constituents' costs, as found in other settings (Shoag and Veuger, 2018; Bordeu, 2024; Kashner and Ross, 2025).

Figure 8: Border RDD effects of tax rule on existence



Note: I present the Loess local polynomial at borders where the law changes as depicted. I residualize controlling for engineering profitability and include border FE. I exclude Texas since they constitute a distinct electricity market.

I then assess two additional channels. First, I examine whether tax rules influence how home prices respond to wind entry. Estimating event studies by tax regime (Appendix Figure A23),[60] I find large price decreases after wind entry in states with no tax payment, small decreases when developers may negotiate, and no changes when the developer pays property taxes. Higher local tax revenues appear to capitalize in home values, offsetting part of the household disamenity. Consistent with this, Appendix Figure A24 shows that in states where developers pay taxes, home prices five miles or further away may increase. This supports the view that increased tax revenues generate countywide benefits, while nearby households bear the brunt of the costs.

Second, I study local school districts' finances in Appendix B.7. Wind farms substantially raise expenditures when developers pay property taxes or negotiate payments. However, when developers pay taxes, part of this revenue is "taxed" away through reductions in state and federal transfers. This friction may influence how local governments weigh household costs against revenues, as described in Section 5.2.1.

5.4 Effects of tax rules by the size of the expected externality

I seek to characterize which potentially efficient sites are indeed constructed along two dimensions: the size of the expected externality and the tax rule. I consider only potential locations that, given the variance of unobservable profit shocks, have a substantial likelihood of being built.[61] I then estimate the following probit regression

$$Y_l = \hat{\Pi}_l + f_{r(l)}\left(P_l\right) + \gamma_{c(l)} + \varepsilon_l, \tag{17}$$

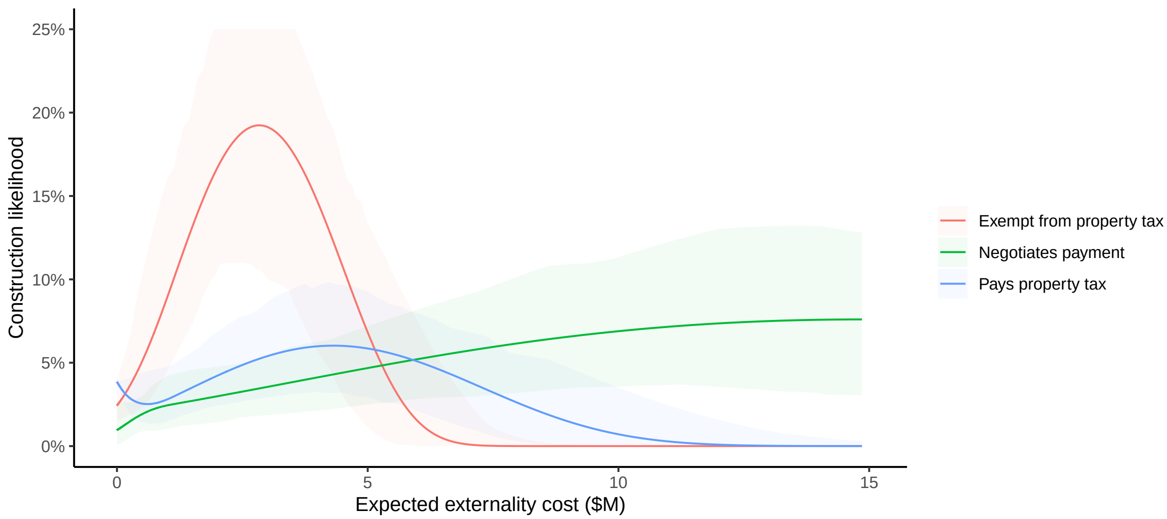
where a location l is built if and only if $Y_l \geq 0$, $\gamma_{c(l)}$ are fixed effects for the census region $c\left(l\right)$, and there is an error term $\varepsilon_l \sim N\left(0, \sigma_e^2\right)$. I estimate $f_{r(l)}$ separately for each tax regime separately as a Hermite spline with three degrees of freedom.

In Figure 9 I present the estimated curves $f_{r(l)}$. I find that for lower values of nearby homes, tax exemption is associated with the highest likelihood of construction, followed by paying a fixed tax rate, where negotiation is associated with the lowest likelihood. However, when developers are tax-exempt when $\mathbb{E}\left[C_l\right] \approx \$2.2$ million the likelihood of construction suddenly plummets to become vanishingly small. Similarly, when developers must pay taxes, at roughly $\mathbb{E}\left[C_l\right] \approx \$5$ million the likelihood of construction analogously plummets. This is in marked contrast to the locations where developers can negotiate. The likelihood of construction is relatively stable over the full sample, and it appears that the high social value locations where P_l is large are still able to be developed.

[60] I do so without fine geography-by-time fixed effects that may absorb the common gains to the county of increased tax revenue, in order to identify the bundled effects.

[61] I subset to locations where $\hat{\Pi}_l - 0.2 \times p_l \geq -15$M, which contains most but not all constructed locations.

Figure 9: Estimated effect of nearby homes' value on construction probability



Note: Fit of Hermite spline with three degrees of freedom relating the value of nearby homes to construction outcomes. Estimated as a probit controlling for engineering profit, FE for rule and census region. Sample includes only locations where engineering profit $-0.2 \times P_l > -15$M, or locations that are somewhat likely to be built. Pointwise confidence intervals from 200 Bayesian bootstrap draws.

5.5 Model parameterization

This game plays out in a tax regime $r(l) \in \{\mathrm{t},\ \mathrm{b},\ \mathrm{e}\}$ which correspond to exogenous tax, bargaining over payment, or exemption. The timing is shown graphically in Figure 7.

Profit. I model the site's ex ante expected profitability as

$$\Pi_{l,0} = \hat{\Pi}_l + \Pi_{l,\xi} + \beta X_l \tag{18}$$

where $\hat{\Pi}_l$ is the engineering profit, $\Pi_{l,\xi} \sim N\left(0, \sigma_\xi^2\right)$[62] is a persistent unobservable, and X are controls.[63] If the developer has approached the government in period 1 and was not blocked, she must pay an engineering cost E to design the site and learn her final private profit shock $\Pi_{l,1}$. I model the final true profit as

$$\Pi_l = \Pi_{l,0} + \Pi_{l,1}, \tag{19}$$

where $\Pi_{l,1} \sim N\left(0, \sigma_f^2\right)$.[64]

[62] I assume independence between first-period unobservable quality and final-period profit shocks. I show in Appendix D.5 that this nests a situation in which both $\Pi_{l,\xi}$ and $\Pi_{l,1}$ are drawn from a multivariate normal with arbitrary covariance so long as the developer correctly accounts for $\mathbb{E}\left[\Pi_{l,1}|\Pi_{l,\xi}\right]$ when making period 1 decisions.

[63] I include an intercept, an indicator for whether the state has a renewable portfolio standard, the level of the renewable portfolio standard, and the per-acre profit in the local agricultural area.

[64] This shock can be thought of as changing prices at which developers buy inputs or sell outputs, or as more intimate knowledge of the cost of development during engineering and surveying.

Government utility. The utility to the government of allowing a wind farm to be built is $\zeta_l \mathbb{E}[C_l] + V_l T_l$. The expectation of the sum of the money-metric costs to households of being exposed to a nearby wind farm is

$$\mathbb{E}[C_l] = \sum_{i \in \mathcal{I}(l)} \mathbb{E}[\omega_i \cdot p_i], \tag{20}$$

where ω_i is household i's preference for living near a wind farm, and p_i is their home's value. As discussed in Section 4.5, this provides an upper bound on the expected welfare cost to incumbents. If the game proceeds beyond period 1 the local government learns their private political friction $\zeta_l \sim N(\zeta_0, \mu^2)$. The local government also learns $V_l \sim \mathcal{N}(1, \nu^2)$. I assume on average they value a dollar of tax revenue as a dollar, so $\mathbb{E}[V_l] = 1$.

Potential negotiation. If the tax regime $r(l)$ allows bargaining, then the government and developer will bargain over a transfer payment T_l. The government observes a signal $\Pi_{l,1,g} \sim N(\Pi_{l,1}, \eta^2)$ centered around the true final period profit shock. Analogously, the developer observes a signal $\zeta_{l,d} \sim N(\zeta_l, \mu_c^2)$ centered around the true private cost. Each side forms posterior beliefs, over Π_l and ζ_l / V_l respectively, and make offers accordingly. Their beliefs are based on their common knowledge of $\Pi_{l,0}$ and $\mathbb{E}[C_l]$ and their knowledge of the distributions of $\Pi_{l,1,g}$, $\zeta_{l,d}$, $\Pi_{l,1}$ and ζ_l, as described in Appendix D.2.

5.6 Identification

I derive solutions for the developer and local governments' policy functions in Appendices D.1 and D.2. These have closed form solutions for the states where the transfers developers pay to local governments are exogenous. In states where developers and local governments may negotiate, no such closed forms exist. Instead, I numerically approximate continuation values via simulation. In all tax regimes, the determination in the final period—of whether to build and whether to allow construction—follows a cutoff rule. As such, all policy functions are solvable via backward induction.

5.6.1 Identification: no bargaining

There are seventeen parameters in θ to estimate. Here, I discuss the variation that is informative about four key parameters; the remaining thirteen are detailed in Appendix D.3. Although the parameters are jointly identified, I highlight the primary sources of variation that intuitively identify each parameter.

Taxes paid in tax regime: T_l. This is informed by the differences in the minimum pre-tax profitability, $\Pi_l + T_l$, at which projects are built between the exemption versus the property tax regimes. This corresponds to the gap between the red and blue curves in Figure 9 at low values of expected externality.

Blocking costs: B_l, B_2. B_2 is informed by the externality cost threshold at which projects begin to be blocked by the local government conditional on application in the exemption regime. This corresponds to the value of the expected externality at which the red curve in Figure 9 begins to sharply decline. The difference between B_1 and B_2 is inferred from the gap between the observed propensity of communities to block potential entrants and the threshold at which entry would be rational.

Political friction: ζ_0. This is informed by the difference in the blocking thresholds for blocking between the tax and exemption regimes. Empirically, this is closely related to the difference in the value of the externalities at which the red and blue curves begin to slope down rapidly in Figure 9, scaled by the estimated value of T_l.

5.6.2 *Identification: bargaining*

There are three additional parameters of θ which must be estimated, beyond those estimated in Section 5.7. I discuss the relevant informative variation. These parameters rationalize the observed lower likelihood of investment, conditional on externalities and profitability, by way of expectations of hold-up risk.

Probability of government offer: ρ. This parameter intuitively governs the way that the surplus is split between the government and the developer. The rate of investment is particularly informative. Lower values of ρ would correspond with more entry.

Noise around final-period profit shock: η. This parameterizes how private the developer's final cost shock is. If η is very small, the government can extract nearly all of the surplus. The failure rate conditional on application, and how it varies at different levels of $\Pi - \Pi_{l,1}$, informs this.

Noise around community cost shock: μ_c. This parameterizes how private the government's cost shock ζ_l is. Similarly, the rate of failure as a function of $\mathbb{E}[C_l]$ is informative about this parameter, corresponding to the shape of the green curve in Figure 9.

5.7 Estimation

I estimate the model using non-linear least squares with simulated unobservable characteristics. The two-step selection process allows me to separate persistent unobserved profit differences from final-period profit shocks and other forces. Similar to the second step of Bajari et al. (2007), I minimize the deviation between predicted and observed outcomes for planning and for construction conditional on planning. Estimation is subject to the constraint that the predicted fraction of locations receiving applications equals the observed fraction.[65]

To allow for selection on the persistent component of profit that is unobserved to the econometrician, I simulate 150 draws of $\Pi_{l,\xi}$, $\Pi_{l,1}$, ζ_l, and V_l for each location to form an estimation set of locations $\mathcal{L}$.[66] For

[65] In practice, without this constraint the estimator may converge to corner solutions that lead to only one site being applied for, where this site's construction status is correctly classified.

[66] In the estimation of negotiation, I also simulate $\zeta_{l,d}$ and $\Pi_{l,1,g}$

each $l \in \mathcal{L}$ I denote the model prediction of selection into planning and construction as a function of the parameters θ to be $e_l(\theta)$ and $c_l(\theta)$ respectively. I compare this to the observed decisions $\mathbf{e}_l$ and $\mathbf{c}_l$.

I then calculate the following mean squared errors

$$S_e(\theta) = \frac{\sum_{l \in \mathcal{L}} (\mathbf{e}_l - e_l(\theta))^2}{\sum_{l \in \mathcal{L}} 1}, \tag{21}$$

$$S_c(\theta) = \frac{\sum_{l \in \{l' \in \mathcal{L}: e_{l'}(\theta)\}} (\mathbf{c}_l - c_l(\theta))^2}{\sum_{l \in \{l' \in \mathcal{L}: e_{l'}(\theta)\}} 1}. \tag{22}$$

I also calculate the fraction of locations that are applied for as $F_e(\theta) = \frac{\sum_{l \in \mathcal{L}} e_l(\theta)}{\sum_{l \in \mathcal{L}} 1}$,which I can compare to $\mathbf{F}_e = \frac{\sum_{l \in \mathcal{L}} \mathbf{e}_l}{\sum_{l \in \mathcal{L}} 1}$. I estimate θ as

$$\begin{aligned} \hat{\theta} &= \arg\min_{\theta} S_e(\theta) + S_c(\theta) \\ \text{s.t. } & F_e(\theta) = \mathbf{F}_e. \end{aligned} \tag{23}$$

To estimate the remaining parameters governing the negotiation process, I take $\hat{\theta}$ as given and estimate $\hat{\rho}$, $\hat{\eta}$, and $\hat{\mu}_c$, which represent the probability of each group making the take-it-or-leave-it offer, and the standard deviations of the signal about the final-period profit shock and cost shock that the other party observes.[67] I use simulation-based methods to approximate $\mathbb{E}\left[\mathbb{V}_d | \mathbb{E}[C_l], \Pi_{l,0}\right]$ and $\mathbb{E}\left[\mathbb{V}_c | \mathbb{E}[C_l], \Pi_{l,0}\right]$. As before, I estimate the model via non-linear least squares. I conduct inference via a Bayesian bootstrap. I draw weights for each location l from a standard Dirichlet distribution and then re-draw the replicate simulated values of $\Pi_{l,\xi}$, $\Pi_{l,1}$, ζ_l, and V_l. This accounts for both uncertainty from the underlying data and simulation error.

5.8 Results and discussion

I present the most important parameter estimates below in Table 2, with the additional parameters presented in Appendix Table A10. The estimated parameters shed light on the sources of market failure that lead to inefficient allocation. Below, I discuss and interpret the key estimates.

[67] Estimating all parameters jointly is possible, however, this approach has two benefits. The first is that model misspecification, as it pertains to bargaining, does not bias parameter estimates from the first step. The second is that when tax rates are exogenous, policy functions are solvable in closed form, which allows for more efficient numerical optimization.

Table 2: Key parameter estimates

A. Estimates from Exogenous T_l

Parameter	Description	Value
ζ_0	Externality: linear multiplier on cost	2.98 [2.98, −3.45]
T_l	Tax paid in tax regime	\$10.7M [10.4, 11.6]
B_2	Cost of blocking in last period	\$24.8M [20.9, 28.1]
E	Cost of planning and engineering	\$10.2M [10.0, 10.4]

B. Estimates from Endogenous T_l

Parameter	Description	Value
ρ	Probability government offers	0.47
$\sqrt{(\eta^2\sigma^2)/(\eta^2+\sigma^2)}$	SD of posterior of profit shock ($\Pi_{1,l}$)	\$22.7M

Note: Estimated to match observed decisions to invest and eventually construct, as described in Section 5.7. Each observation is one of 82,563 locations in the continental U.S., with 150 simulated draws each. Confidence intervals are calculated from 42 Bayesian bootstrap iterations re-simulating and re-weighting each location. Posterior beliefs are described in Appendix D.2.

Political friction $\zeta_0 = 2.98$. I find that local governments trade off roughly one dollar of utility cost to households for about three dollars in tax revenue. This suggests that preference aggregation frictions in government decision-making are quantitatively meaningful. Local governments may place excess weight on the losses of directly affected households. This pattern is plausible if affected households exert greater political influence, for example by attending public hearings or meetings.

Engineering cost E = \$10.2 million. The sunk cost is key for understanding how ignoring dynamics would bias parameter estimates in a static framework. Uncertainty about whether a local government will approve wind construction affects equilibrium entry decisions: developers invest less if they expect it to be more likely that they forfeit a large sunk cost. Without accounting for this channel, such strategic behavior would be misattributed to local governments' preferences. The estimates also help to quantify hold-up risk in negotiation regimes, clarifying how expectations about the division of final-period surplus may reduce investment. The magnitude of the estimate is consistent with industry evidence. Firms report, in the popular press, that they spend around \$7 − 12 million on engineering and planning (Goldstein, 2019). Likewise, a survey of utility-scale wind developers found average sunk costs of \$7.5 million (95% confidence interval of [\$4, \$11]) when projects were cancelled, based on 14 responding firms (Nilson et al., 2024).

Tax cost T_l = \$10.7 million. In states without exemptions, property tax payments serve as the incentive that facilitates local government approval of wind projects with costlier local externalities. Based on estimates from the *System Advisory Model*, the total tax cost without depreciation would be between \$12 and \$18 million, assuming property tax rates of 1 to 1.5%, which are typical. Accounting for depreciation, the estimated amount is broadly consistent with expected tax costs. Moreover, this estimate is within the range of reported tax payments in local newspapers (Robledo, 2018; Benda, 2021).

Probability government offers $\rho = 0.47$. In roughly half of negotiations, the local government makes the take-it-or-leave-it offer. When the government makes the offer, developers anticipate greater hold-up risk, leading to more hesitation to incur the planning cost in the first place. This parameter governs the split of the surplus, net of sunk costs, between the government and the developer.

SD of government knowledge of shock \$22.7 million. The government's signal represents around 44% of the total variance of the developer's final-period profit shock. This estimate suggests two key features of government offers. First, the developer receives less information rent, so more of the surplus accrues to the government. Second, government knowledge allows offers to be better targeted, reducing negotiation failures relative to a benchmark where the government has no information about the final period profit shock.

Do local governments' choices reflect information about heterogeneous costs to their residents? In my model, governments allow wind farms to be built if and only if $\zeta_l \mathbb{E}[C_l] + V_l T_l \geq -B_2$. The coefficient ζ_l can be systematically too large, but can also vary across localities. This local variation may represent idiosyncratic noise, which can be statistical error or genuine heterogeneity in government preferences. Alternatively, it may represent government information about heterogeneous household costs; a low draw of ζ_l could indicate that the local government expects $\mathbb{E}[C_l]$ to be smaller than the population mean. In Appendix D.7, I test whether ζ_l is correlated with *actual* changes in home prices. For each eventually constructed location, I recover the posterior expectation of ζ_l and estimate a heterogeneous difference-in-differences effect on home prices as a function of this posterior. I find that when ζ_l is smaller, home prices decrease by a smaller amount, consistent with ζ_l containing information about heterogeneous costs.

Do developers negotiate with local governments or individuals? Following Coase (1960), the canonical theory posits that developers could, in principle, negotiate a transfer individually with all affected households.[68] In this paper, I model the developers as purchasing from an intermediary, the local government. This is supported by both anecdotal evidence and two reduced form patterns. In Appendix Figure A3 I find that the households within one mile of a wind farm experience much smaller price declines than those one to two miles away, likely because only those closest households receive direct payments through land leases or other compensation. In Appendix Figure A22, I re-estimate the effect of tax vs. exemption border effects by the number of homes. I find that the estimated benefits of tax exemption, as in Column 2 of Table 1, are only positive for one and two homes, turning negative once three or more homes are nearby, as in Column 1

[68] Haghpanah et al. (2024) show that when buying a single item, in this case permission to build a wind farm, from multiple sellers, the optimal mechanism reflects a weighted average of the sellers' virtual valuations. Given the estimated variance of household preferences in Figure 5, these virtual values may be substantially greater than the mean preference.

of Table 1. Suggestively, when as few as three households are involved, it becomes preferable for developers to pay property taxes to the local government, rather than negotiate individually with residents.

6 Alternative market designs

In this section, I compare existing markets and alternative market designs in reaching the state-specific wind capacity goals outlined in the net-zero America plans of Larson et al. (2020), shown in Appendix Figure A26. For each market, I calibrate a state-specific subsidy for wind farms to ensure that aggregate capacity meets the targeted quantities.[69]

6.1 Alternative markets

Benchmark (net-zero plan). The proposed wind farm sites in Larson et al. (2020) may not be fully achievable given local governments' decisions. If built as planned, however, residents would face a cost of around \$50 billion.

First best spatial allocation. I consider a first best allocation, which is infeasible given private information. This allocation features efficient engineering and investment incentives and construction that only occurs when doing so is socially optimal. It could be implemented if each location reported, and was paid, its exact willingness to accept a wind farm. The resulting posted prices would guide investment decisions.

Existing tax rules. I compare the three status quo tax rules, which are the existing market designs.

Expected externality taxes. I consider a posted price, or tax, equal to the expected cost to households. In this setting, I set $T_l = \bar{\bar{\omega}} \cdot P_l$. I maintain political-economy aggregation frictions.

Overpayment of expected externality. Due to the aggregation frictions (wherein $\zeta_0 > 1$) it may be preferable from a social welfare perspective to have developers over-pay the expected externality to ensure that the local governments allow construction. I multiply the expected externality by around 2.5 such that $T_l = \frac{1}{5} P_l$.

Up-front negotiation. Hold-up risk in negotiation occurs due to the timing of contracting after the investment cost is sunk. This timing also has some efficiency benefits because it is after the realization of the final-period profit shock. I consider a mechanism where the developer buys a permit before realizing their final-period profit shocks. In this, negotiation occurs after the local government learns its idiosyncratic cost from wind farm entry. The government may commit to blocking wind farms if there is no contract, which leads wind developers to only proceed if bargaining succeeds. I derive the updated policy functions in Section D.4.

[69] This allows me to compare the efficiency of siting under these rules without taking a stance on the social value of carbon emissions abatement or the general equilibrium effects of decarbonizing the energy sector, both of which are outside of my model.

6.2 Social welfare

To calculate the total social welfare I consider the following groups.

Developers. The net value to a developer of a market is their realized profits net of the forfeited sunk costs which can be described as

$$SV_m^D = \sum_{l \in B_m} \Pi_l - T_{l,m} + S_{s(l),m} - \sum_{l \in E_m \setminus B_m} E, \tag{24}$$

where B_m and E_m are the sets of locations that are constructed and engineered in market m, $T_{l,m}$ is the transfer in location l in this market, and $S_{s(l).m}$ is the subsidy from the federal government.

Local communities. The total value to local communities is the cost to affected households plus the value of the tax revenue, net of any blocking costs,

$$SV_m^C = \sum_{l \in B_m} \left(V_l T_{l.m} + \sum_{i \in \mathcal{I}(l)} \omega_i P_l \right) - \sum_{l \in E_m \setminus B_m} B_2. \tag{25}$$

I allow for the governments' ζ_l to partially represent heterogeneity in household costs, consistent my findings find in Appendix D.7.[70]

Government. The cost to the government is the total paid out subsidy times the marginal cost of public funds. In the baseline setup I choose a conservative MCPF of $\mu = 10\%$, however the differences between markets become more stark with higher values of MCPF. The cost can be represented as

$$SV_m^g = -(1+\mu) \sum_{l \in B_m} S_{s(l),m} \tag{26}$$

6.3 Results

I compare the net social values of alternative market designs to that under the status quo property tax regime. In this regime, successful construction yields approximately \$1.4T in profit to developers. However, achieving the net-zero plan's roughly tenfold expansion of U.S. wind capacity would require \$3.6T in subsidies. In this case, the total cost of visual disamenities to households is around \$52B. Panel A of Figure 10 presents the total value of each market, net of the profits and subsidy cost from the tax regime, and Panel B decomposes these values by channel. Moving all states to this simple flat tax payment increases social welfare by \$125B relative to the existing payment rules.

When developers pay the existing flat taxes, local governments receive roughly \$210B in tax revenue.

[70] I set $\sum_{i \in \mathcal{I}(l)} \omega_i P_l = (\mathbb{E}[\omega_i] + 0.761(\zeta_l - \zeta_0)) \cdot \sum_{i \in \mathcal{I}(l)} P_l$. This rescales the difference between the idiosyncratic value ζ_l and the actual household cost to be centered around the true distribution of ω_i from Section 4.4.2, where the deviation from this corresponds to the relationship between the posteriors of ζ_l and home price changes estimated in Appendix D.7.

Although nearby households may be worse off, this appears to benefit the local communities overall. This is consistent with the findings in Appendix Figure A24, which shows that beyond approximately five miles from the nearest turbine, wind farm entry leads to increased home prices. The costs of blocking are small, only around \$4B, because both taxes are high and developers generally avoid entering locations that are likely to block them.

I next compare the property tax regime to the two existing tax regimes: exemption and negotiation. I find that exemption, though benefiting from some Harberger-style efficiency by not taxing developers, yields a net social value around \$220B lower than the property tax regime. The profitability of selected sites, net of subsidies, is around \$1.25T lower, suggesting that when developers cannot pay taxes they are forced to select less productive sites. In this setting, households are subject to around \$13B less in visual disamenity, but receive no offsetting value from tax revenue. Consistent with this, home prices decline by more when wind farms are built in the exemption states, as shown in Appendix Figures A24 and A23.

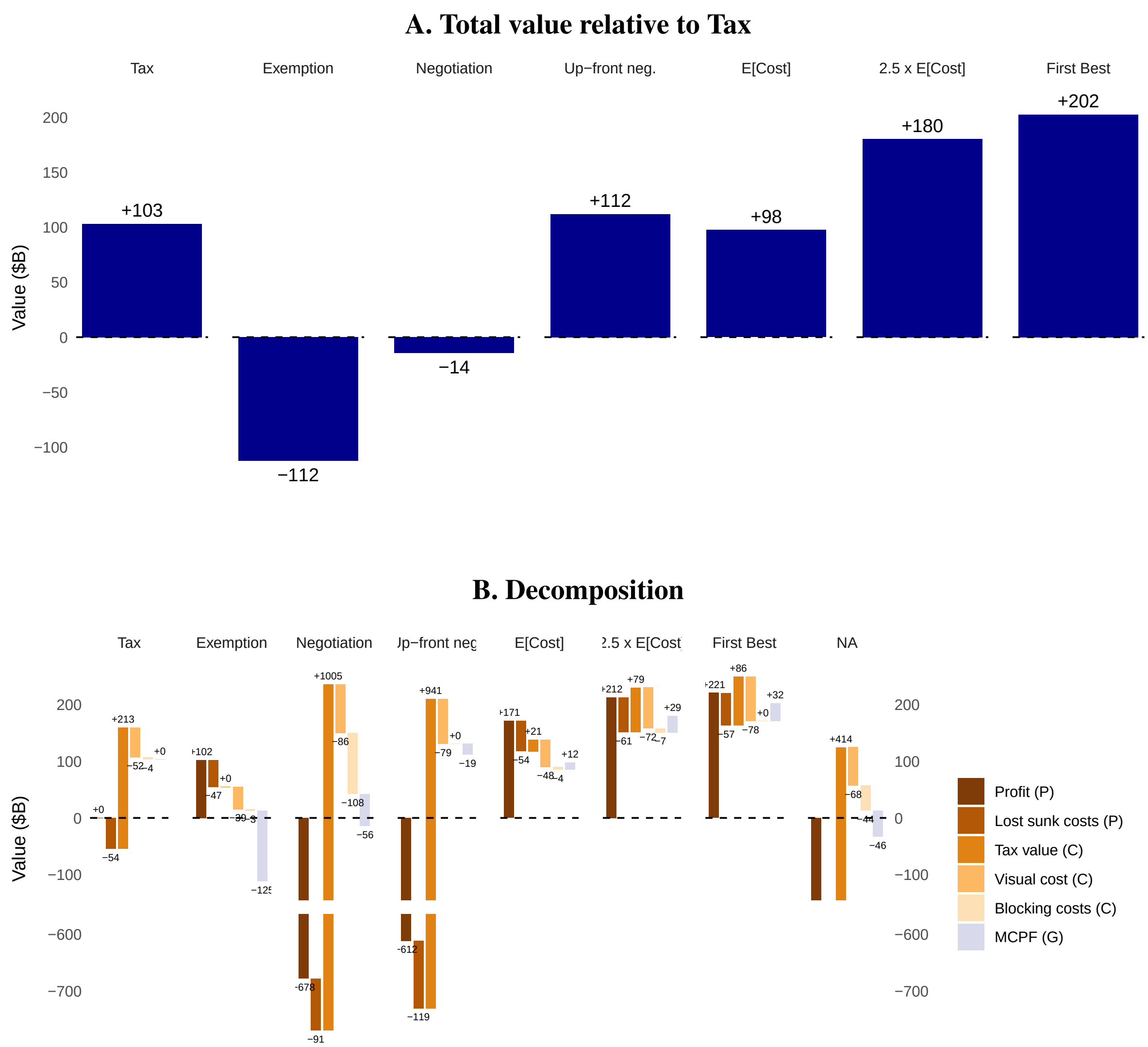
When developers can negotiate, they anticipate hold-up risk from local communities. As a result, they require much larger subsidies before they are willing to enter. Despite these higher subsidies, the realized profits are about \$675B lower, because local governments capture much of the surplus when they make a "take-it-or-leave-it" offer. This generates substantial revenues for local communities. This represents a costly form of intra-governmental redistribution, however, effectively transferring money to local governments through an inefficient channel of developers' payments. On net, social welfare under negotiation is roughly \$120B lower than paying flat property taxes.

Up-front negotiation can mitigate the existing hold-up risk. Currently, payments are negotiated only after the wind developer has invested around \$10 million in planning and engineering. I consider a regime in which payments are negotiated after local governments learn their idiosyncratic costs but before developers plan. This results in a social value roughly \$10 billion greater than the status quo fixed taxes. Substantial information rents on both sides continue to distort the spatial allocation of wind farms, however, leading to only a modest welfare improvement relative to the status quo property tax regime.

A Pigouvian-style solution would require developers to pay the expected cost to households from the wind farm in a given location. This approach targets observable differences in the value of exposed homes. Due to the political economy frictions, however, this policy yields a social value around \$5 billion lower than the status quo tax regime. This is because local governments trade off around \$3 of tax revenue with \$1 of externalities. An alternative payment scheme—paying 20% of the value of nearby homes, or about 2.5 times the expected externality—leaves the local governments close to indifferent to wind farm entry. On net, this design yields a social value roughly \$75B higher than under status quo fixed taxes.

I compare all regimes to an infeasible first-best without private information, where developers can perfectly observe and contract on payments equal to the exact costs to local communities prior to deciding whether to invest. This unattainable benchmark yields a social value roughly \$100B higher than the simple property tax regime. Still, much of this improvement can be achieved by allowing developers to pay 20% of the value of nearby homes. This captures about 75% of the gains of moving from a lump-sum property tax to the first best, and roughly 90% of the gains relative to current laws.

Figure 10: Social welfare under alternative market designs



Note: Profits and cost of public funds are relative to the tax regime, which are \$1.39T and −\$3.55T respectively. Calculated with government subsidy to producers to match state-by-state generation targets. Marginal cost of public funds is 10%.

7 Conclusion

The success of the U.S. green transition depends on the country's ability to build renewable energy. Wind development is a classic locally undesirable land use where the emissions benefits are global, but the local costs are borne by nearby households. I show that despite large local disamenities, the current pattern of wind farm development deviates from a Coasian benchmark, trading off over seven dollars of profit for each dollar of externality. Using variation in state rules governing developers' tax payments to local governments, I find that much of this inefficiency stems from incomplete contracting opportunities created by regulation.

I model the "not in my backyard" or NIMBY problem by considering local governments as strategic actors deciding which projects to approve. I develop a nonparametric discrete choice approach to measure households' costs from living near wind farms. The observed distribution of wind farms is socially inefficient, with too *few* built near households. I find that local governments trade off around three dollars of revenue for each one dollar of cost to their constituents. In many cases wind farms are not built due to lack of incentives to allow them. Without compensation, communities have little reason to permit wind development, and developers are often constrained from offering such payments.

I then compare existing and alternative policy regimes governing how developers compensate local governments. Two policies intended to encourage wind development—tax exemption and the ability to negotiate payment—both inadvertently reduced the number of built projects. When developers are exempted from local taxes, local governments lack incentive to allow them to build. When developers may negotiate payments, hold-up risk leads to decreased investment. A simple alternative, linking developer payments to the value of nearby homes, better aligns incentives and increases social welfare.

Overall, I show that local governments respond to fiscal incentives and that inefficient siting reflects contractual constraints in addition to preference aggregation frictions. Policies that permit well-targeted payments to local governments can expand renewable energy at no additional subsidy cost by alleviating these contracting frictions.

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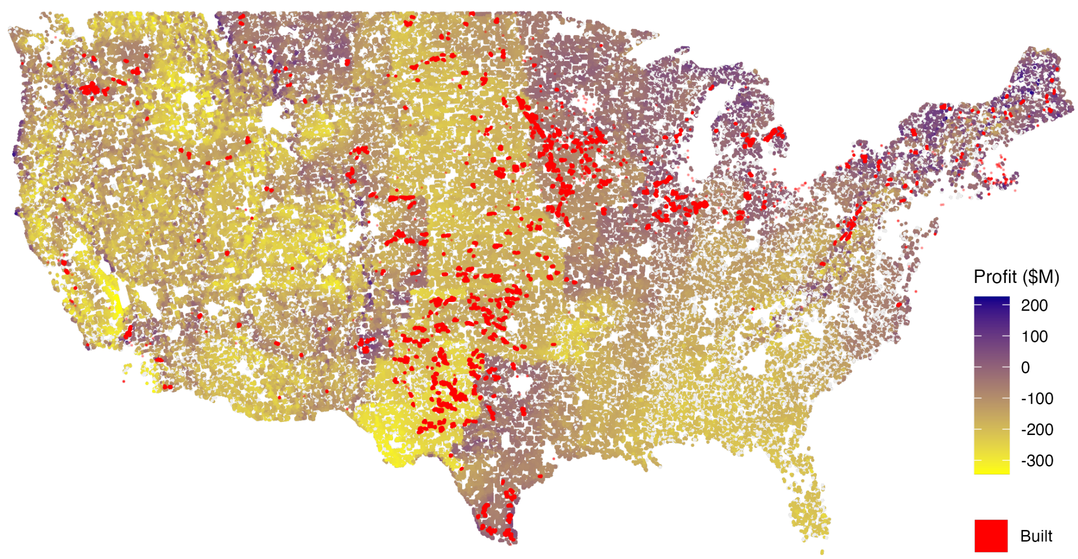
A Appendix

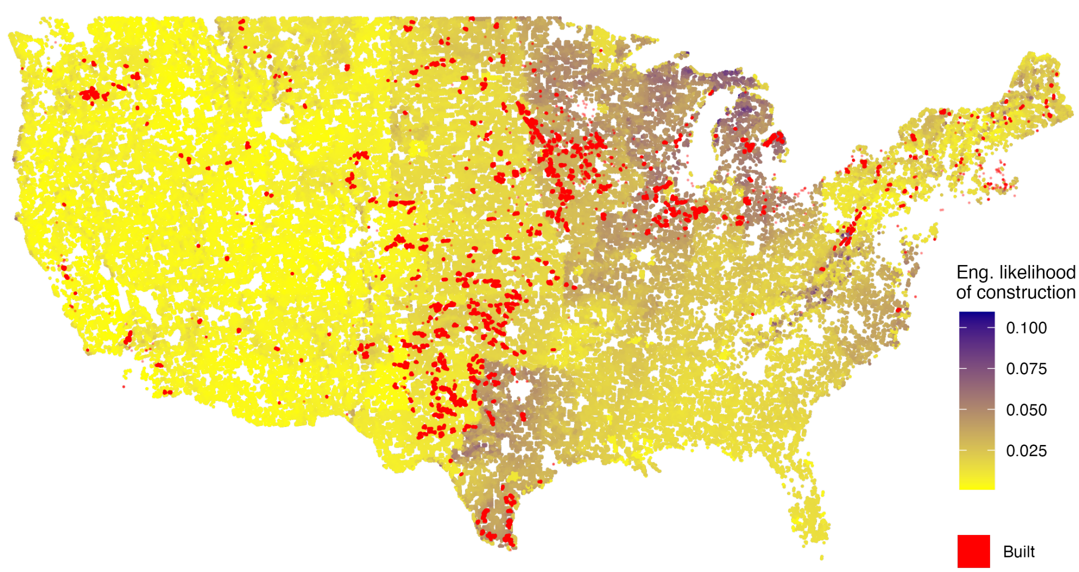
A.1 Appendix Figures and Tables

Figure A1: Engineering profits and constructed wind farms

A. Engineering profit



B. Likelihood of construction



Note: Red dots are built windmills. Present discounted profit calculated using NREL *SAM* using inferred PPA prices, inclusive of PTC. Likelihood of construction estimated using a probit including only engineering profitability and Census region fixed effects.

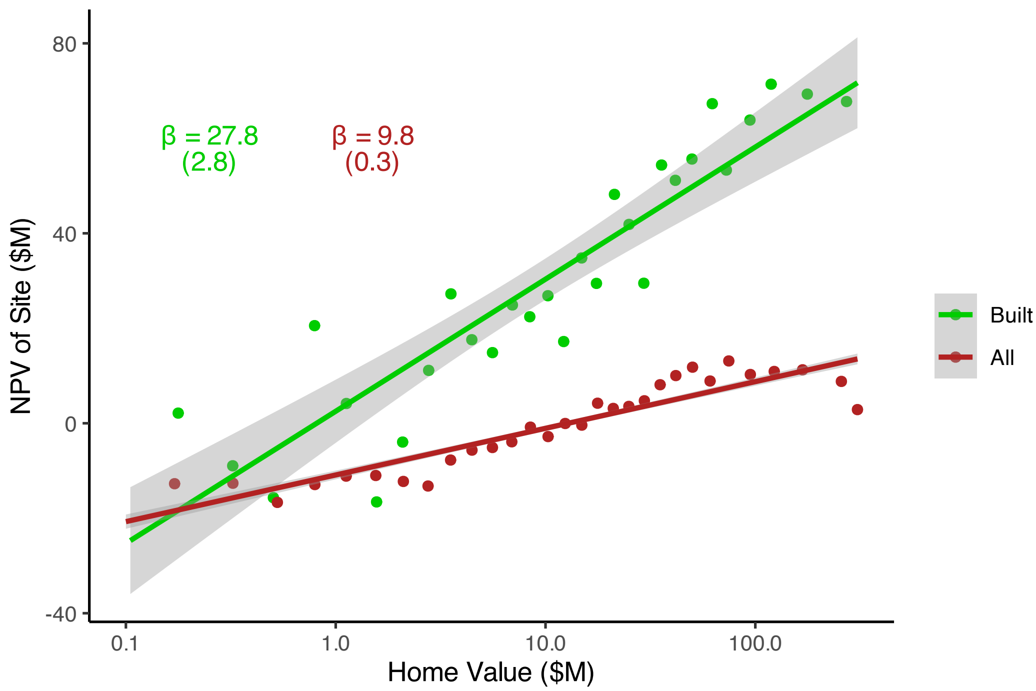
Table A1: Home values and construction likelihood

Dependent Variable:	Built		
Model:	(1)	(2)	(3)
Variables			
Home Value ($B)	−1.51	−2.43	−1.52
	(0.544)	(0.698)	(0.707)
Fixed-effects			
State	Yes		
County		Yes	
Census Region			Yes
Fit statistics			
Observations	71,651	15,942	82,563
Pseudo R^2	0.09602	0.20128	0.03405

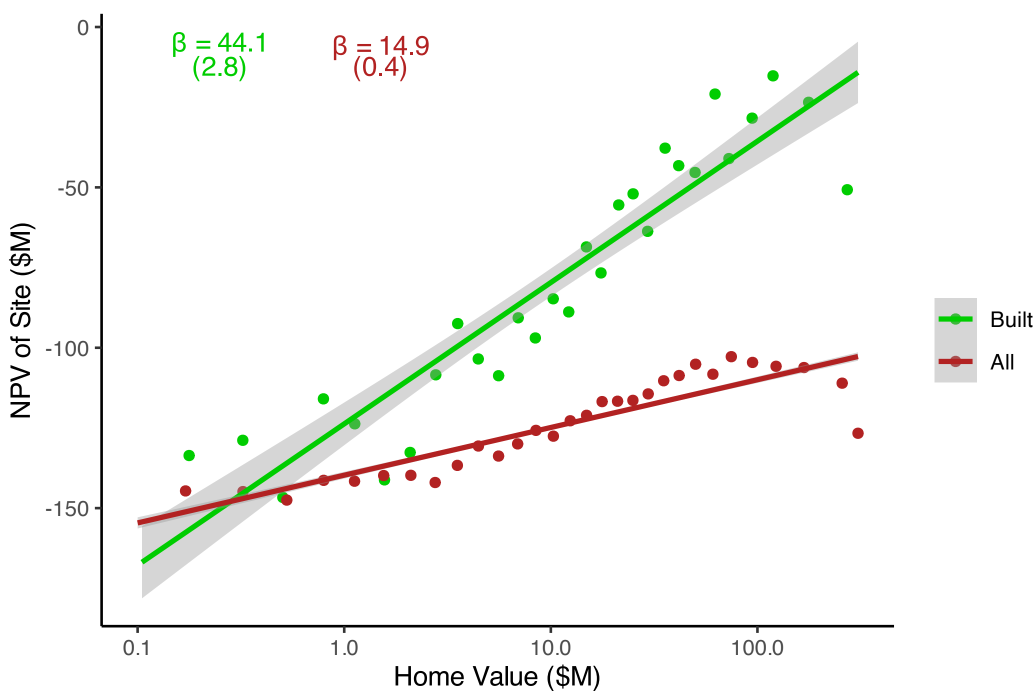
Note: These are estimated as a probit. The value of homes within five miles is from a hedonic price index calculated from CoreLogic data.

Figure A2: Profitability of selected sites and home values: Different residualizations

A. Census Region



B. Full U.S.



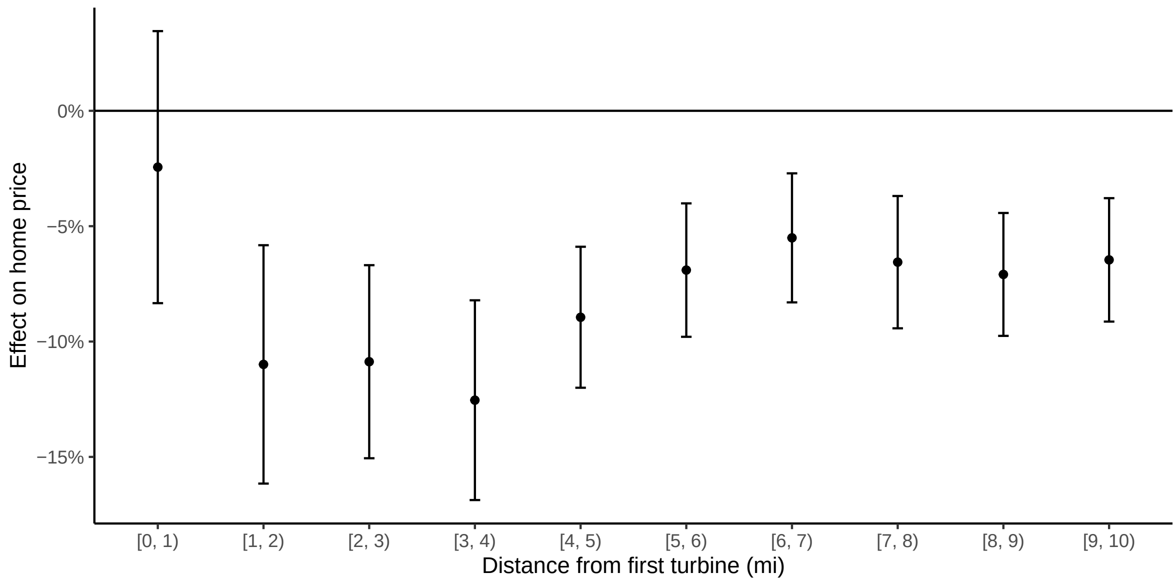
Note: The value of homes within five miles is calculated from a hedonic price index using CoreLogic data. The profitability of a site is calculated using NREL's *System Advisory Model*, residualized by Census Region or un-residualized in Panels (A) and (B) respectively. Presented as a bin-scatter with 30 bins. Baseline rate of construction is 2.0%.

Table A2: Characteristics of homes transacted within 10 miles of a built wind farm

Variable	Mean	St. Dev.	Min	Max	N
Sale Price ($)	175,024	176,245	15,000	3,000,000	300,570
Distance from first turbine (mi)	6.819	2.369	0.026	10.000	300,570
Wind farm application year	2009.644	2.519	2004	2015	300,570
Sale year	2008.012	4.789	2000	2019	300,570
Age (years)	42.887	32.248	0	100	293,090
Bedrooms	3.183	1.017	1	50	300,570
Bathrooms	2.087	1.073	1	136	293,090
Acres	1.540	6.388	0.001	99.910	300,570
Square-feet	1,809.461	1,301.186	1	526,968	300,570

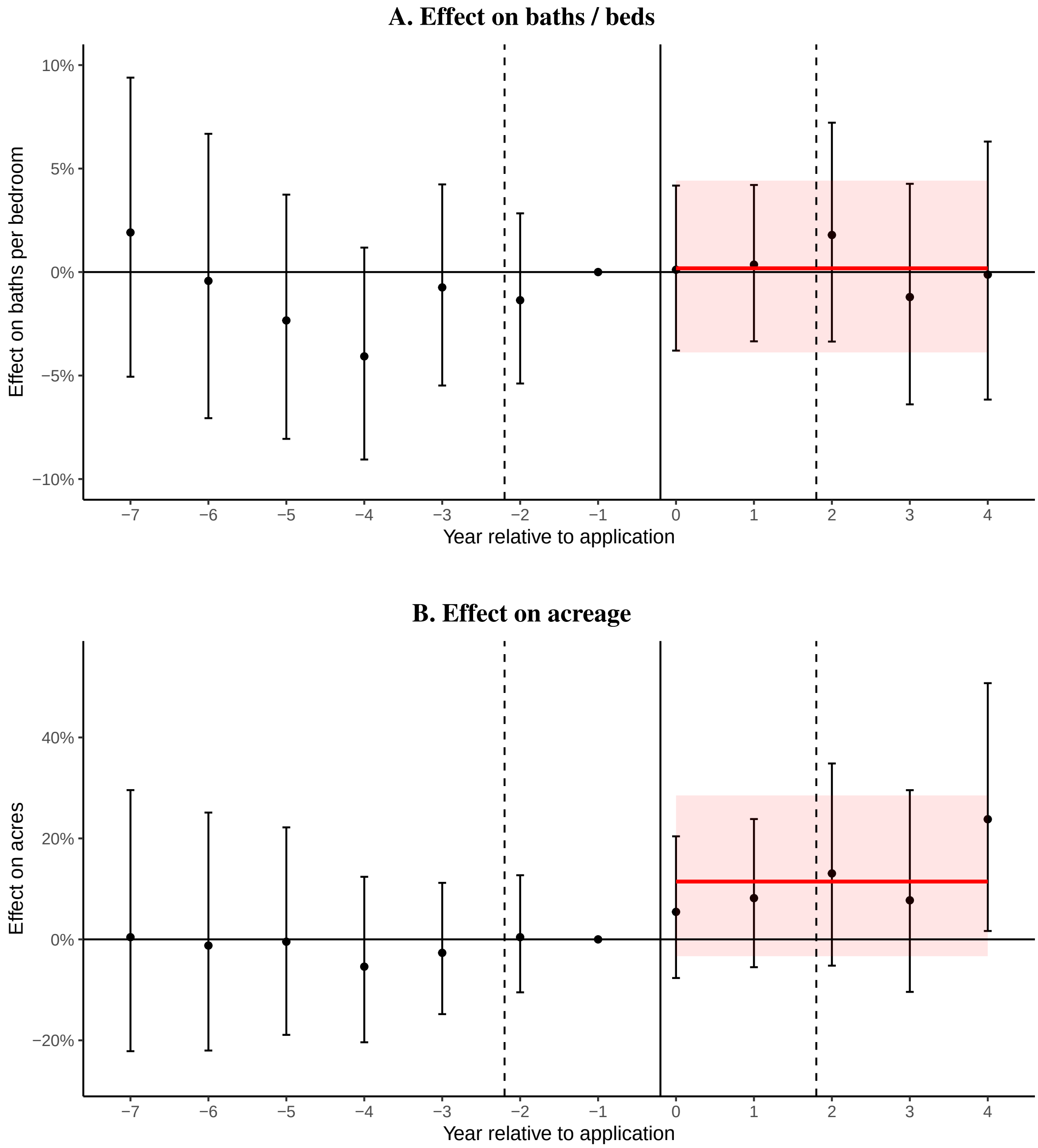
Note: Data from CoreLogic. Due to potential data entry issues regarding of price, bedrooms, bathrooms, acres, and square-feet I winsorize at 2.5% and 97.5% for all price effect estimation.

Figure A3: Price effects by distance from turbine



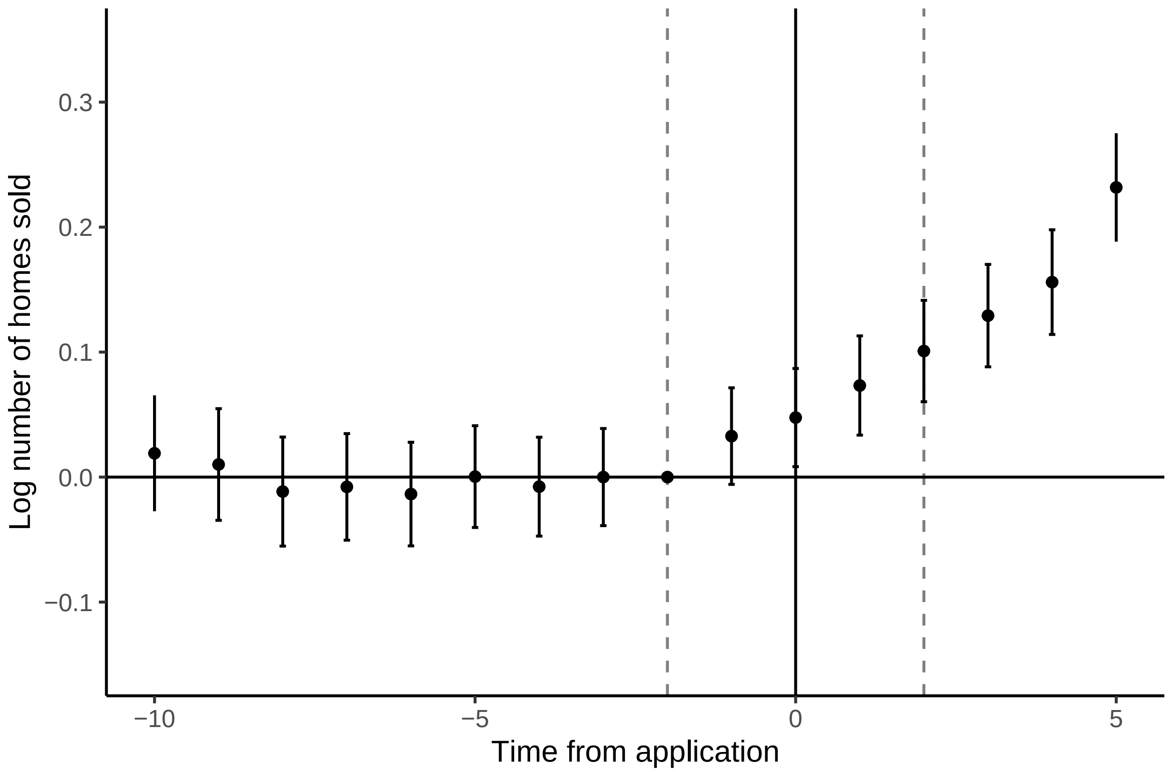
Note: Home price effect is estimated by comparing homes near turbines to homes near turbines that are treated later. Using matched controls of homes who will have a nearby farm built five to ten years after. As an institutional detail, many of the homes within one mile are receiving either lease or "good neighbor" payments from wind developers that are tied to the deed of the home.

Figure A4: Effects of wind farm entry on transacted home characteristics within 5 miles



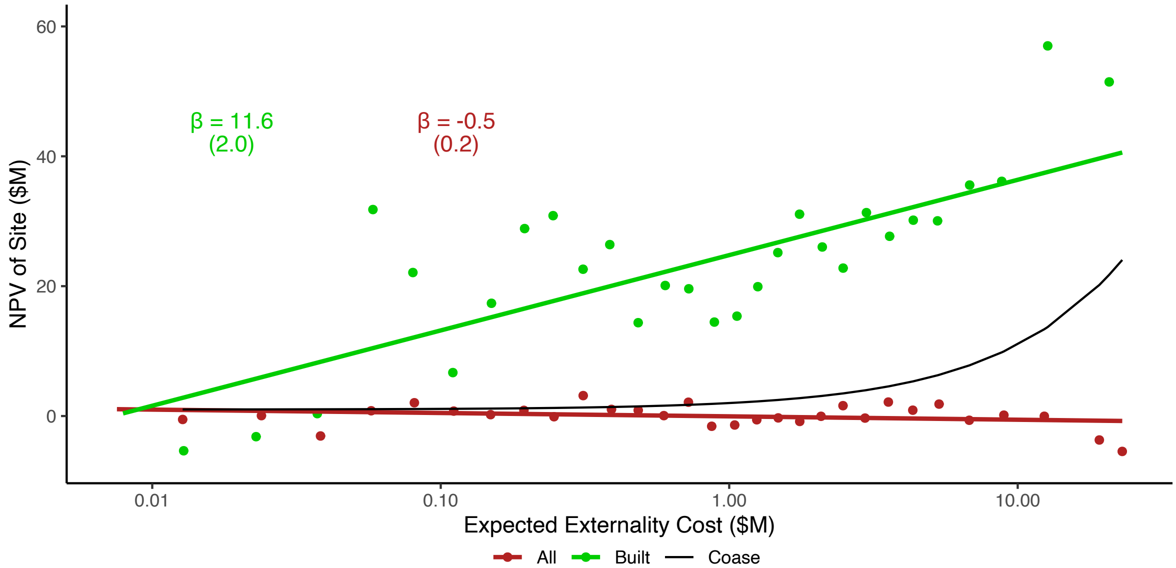
Note: Effect is estimated by comparing homes near turbines to homes near turbines that are treated later. Using matched controls of homes who will have a nearby farm built five to ten years after. Estimated as in Equation 1, pooling effects across distances and excluding the relevant characteristic from X_i. SE by stack × tract × treatment bin. Bathrooms per bedroom is a common signal of luxury in the real estate business (Beale, 2012).

Figure A5: Effects of wind farm entry on home sales



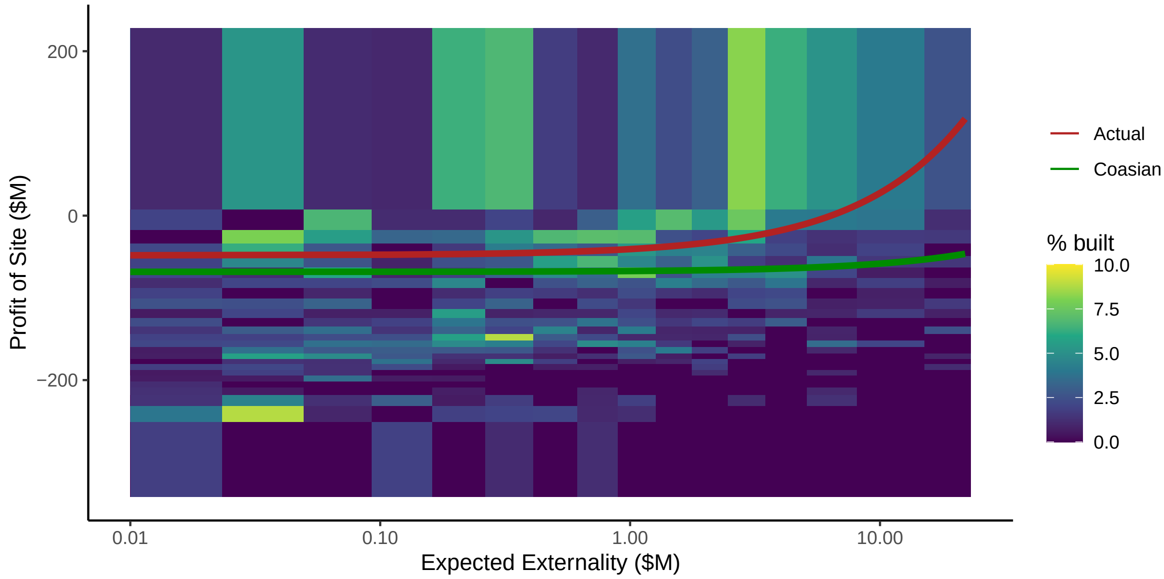
Note: Left dashed line is approximate timing of signing leases with landowners. Right dashed line is approximate timing of construction. Sample are all locations that ever had a wind farm proposed. Sun and Abraham (2021) difference-in-differences specification with year-county and event fixed effects.

Figure A6: Profitability of selected sites and expected externality



Note: The value of homes within five miles is calculated from a hedonic price index using CoreLogic data and multiplied by $\mathbb{E}[\omega_i]$ from Section 4. The profitability of a site is calculated using NREL's *System Advisory Model*, residualized by state. Presented as a bin-scatter with 30 bins. The baseline rate of construction is 2.0%.

Figure A7: Heat map of probability of construction by profit and externality



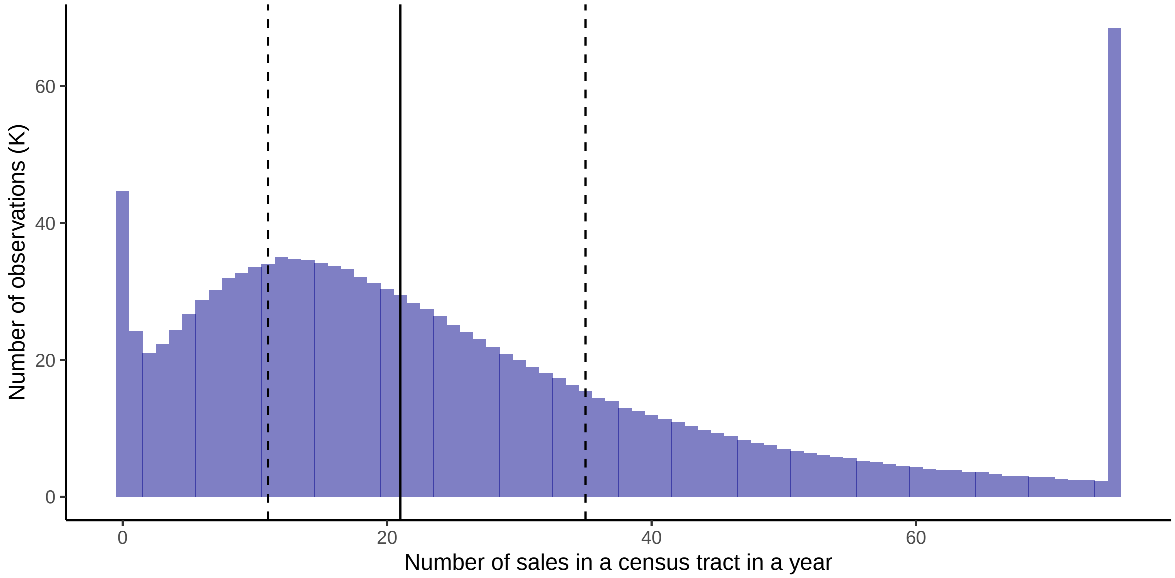
Note: Green and red lines represent the threshold at which the likelihood of construction is 5%. The green line is a Coasian benchmark, fitting the size of the unobservable component of profit in locations with externalities equal to zero by a probit and mapping that threshold under a Coasian benchmark. The red line is the actual threshold fitting a probit in the full sample controlling for profit and expected externality separately.

Table A3: Price instruments first stage

Dependent Variables:	Count of homes sold in 2 nearest tracts	$\log(p_{d,t})$
Model:	(1)	(2)
Variables		
$Z^1_{d,t}$	0.5436	-0.0047
(SSDMF 2 nearest deaths)	(0.0421)	(0.0012)
$Z^2_{d,t}$	0.3907	-0.0023
(CDC 75+ death shift-share)	(0.0784)	(0.0018)
$\tilde{x}^{SS}_{d,t}$	-0.0144	0.0007
(SSDMF own-tract deaths)	(0.0061)	(0.0001)
$C_{d,t}$	319.1609	4.0182
(Tract elderly exposure)	(86.5410)	(1.9089)
Fixed-effects		
Tract	Yes	Yes
Year × state	Yes	Yes
Fit statistics		
Observations	573,436	573,421
R^2	0.744	0.807
First stage F-statistic (KP)		48.6

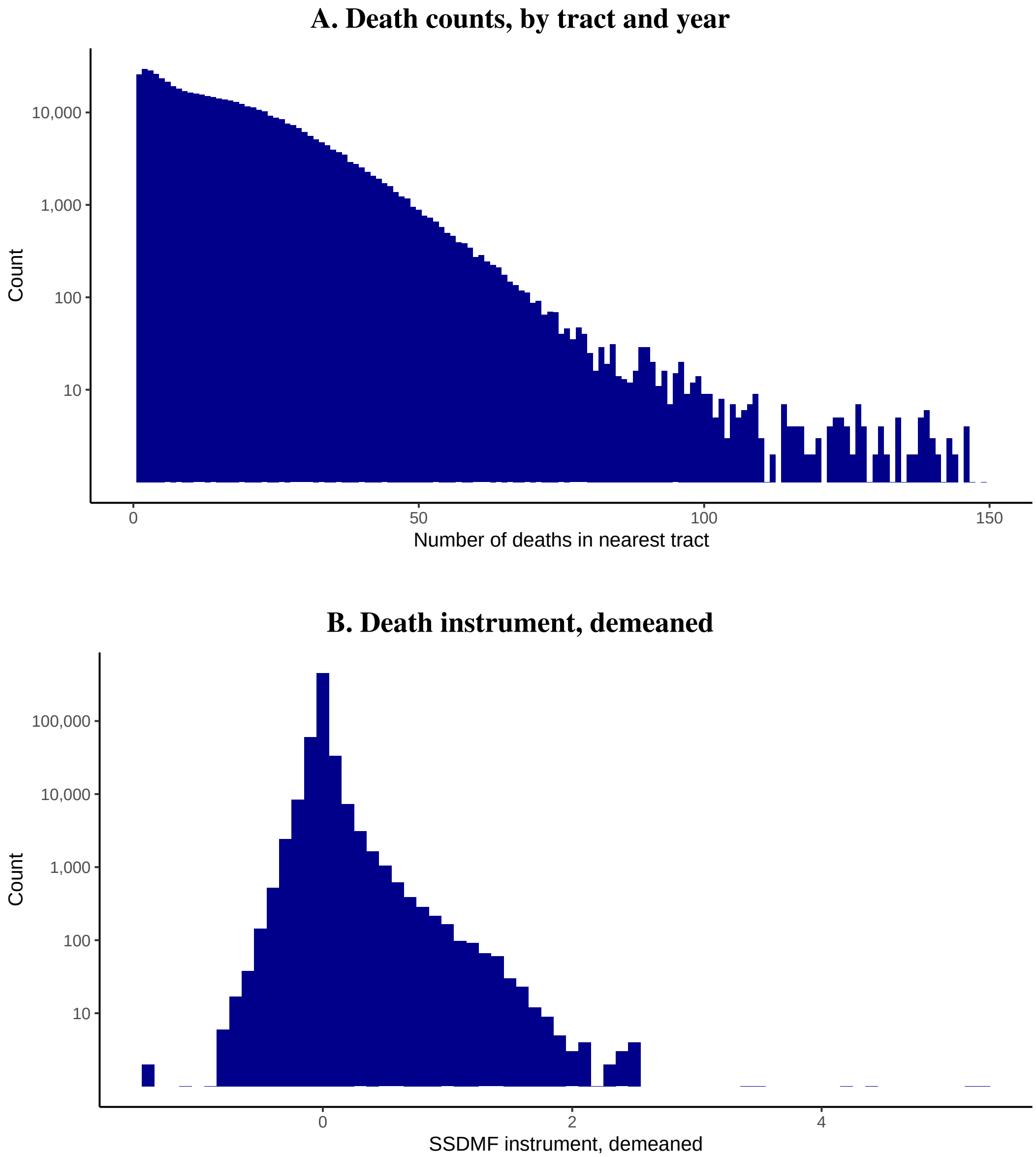
Note: Exact formulations for all included and excluded instruments in 4.3.1. Standard errors are clustered at the Census tract level. First stage Kleinberg-Paap F-statistic is for 1 block-bootstrap sample ($2,500$ origin tracts), clustered at the origin-destination level. Column (2) additionally contains controls for average home characteristics. With no repeated observations, as in the above regression, the first stage F-statistic is 15.7.

Figure A8: Distribution of number of homes sold in each census tract per year



Note: I present the histogram, pooling all counts of 75 or more. The vertical dashed lines represent the inter-quartile range, and the solid vertical line represents the median. For the median tract, 1 additional home sale would represent a 4.8% increase in supply.

Figure A9: Histogram of death instrument values



Note: Panel A presents a histogram of the count of deaths in each tract. Panel B presents $\tilde{x}^{SS}_{d,t}$ as described in Section 4.3.1, interacting the number of deaths in Panel A with the pre-period share.

Table A5: Demand parameter estimates

Parameter	Value
Central estimate of price sensitivity (α_0)	-3.329 $[-3.435,\ -3.024]$
Effect of 1SD income on price sensitivity (α_I)	0.749 [0.689, 0.818]
Valid own-tract deaths ($\tilde{x}^{SS}_{d,t}$)	0.0031 [0.0027, 0.0037]
Exposure to nearby older residents ($C_{d,t}$)	29.52 [28.37, 30.73]
Acres of transacted houses	0.0053 [0.0038, 0.0063]
Square-feet of transacted houses	0.0039 [0.0038, 0.0040]
Bedrooms of transacted houses	-0.0045 $[-0.0056,\ 0.0024]$
Number of units of transacted houses	0.97 [0.76, 1.04]

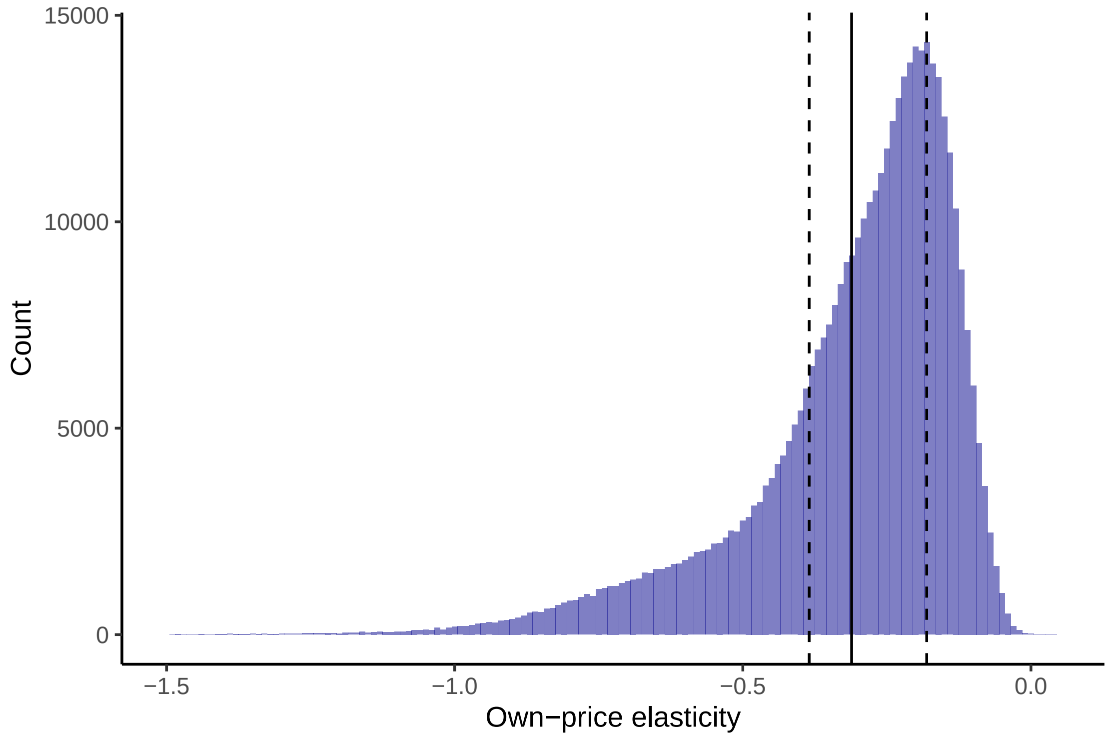
Note: Solved to minimize moment inequalities described in Appendix C.6. Inference conducted with 22 block-bootstrap iterations over 2, 500 origin tracts.

Table A4: Sensitivity of parameter estimates to smoothing parameters

Dependent Variables: $(All - \log(s^o_{oo,t}))$	$\left[\log\left(\frac{N^o_t s^o_{d,t}+\iota_l}{N^o_t}\right) + \log\left(\frac{N^o_t s^o_{d,t}+\iota_u}{N^o_t}\right)\right]/2$		$\log\left(s^o_{d,t}\right)$	$\log\left(s^o_{d,t} + 10^{-8}\right)$	$\log\left(s^o_{d,t} + 10^{-7}\right)$
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
$\log\left(p_{d,t}\right)$	-3.502	-0.027	-0.301	-2.339	-1.805
	(0.415)	(0.003)	(0.235)	(0.309)	(0.241)
$\log\left(p_{d,t}\right) \times I^o$	0.897	-0.004	0.099	0.678	0.528
	(0.426)	(0.003)	(0.308)	(0.324)	(0.252)
Deaths (SSDMF)	0.002	0.002	0.001	0.002	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$C_{d,t}$	15.898	0.659	3.320	10.212	7.721
	(3.477)	(2.556)	(2.105)	(2.566)	(1.993)
% old	5.008	0.889	0.711	3.435	2.662
	(0.515)	(0.122)	(0.171)	(0.384)	(0.299)
Acres	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Square-feet	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Bedrooms	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
# of units	0.838	0.010	0.079	0.560	0.433
	(0.101)	(0.006)	(0.060)	(0.075)	(0.059)
Fixed-effects					
Origin × destination tract	Yes	Yes	Yes	Yes	Yes
Origin × year	Yes	Yes	Yes	Yes	Yes
State × year × move	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	20,696,948	20,696,948	2,745,126	20,696,948	20,696,948
R^2	0.333	0.387	0.896	0.322	0.338
Within R^2	-0.087	0.000	-0.042	-0.080	-0.079

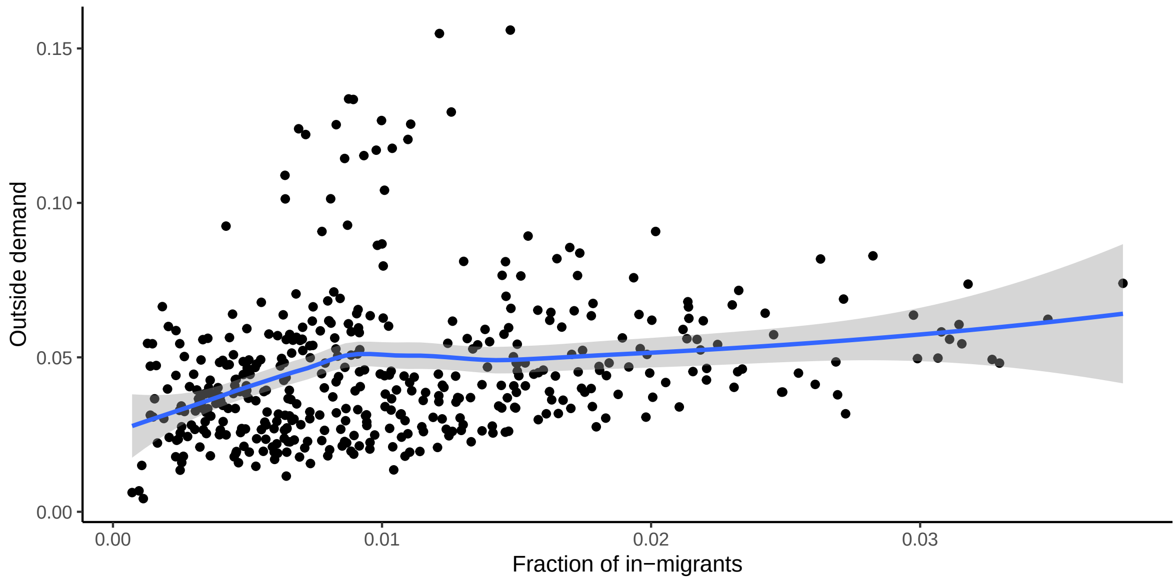
Note: I present a variety of linear specifications for the Berry (1994) inversion to estimate preferences–particularly as they relate to $\log\left(p_{d,t}\right)$. In Columns (1) and (2) I present a targeting of the average of the bounds as described in Section 4.4.1 from Gandhi et al. (2023). In Column (1) I instrument for $\log\left(p_{d,t}\right)$ and in Column (2) I present the OLS estimates. While linear IV differs from the discretization described in Section 4.4.1, however it demonstrates the overall importance of including instruments for price. In Columns (3), (4), and (5) I show how different smoothing of the shares affects elasticity estimates. Standard errors are clustered at the origin-destination level.

Figure A10: Histogram of estimated own-price elasticities of all census tracts



Note: Histogram of the own-price elasticity of all sample tracts, evaluated at the central estimates of $\hat{\alpha}_0$ and $\hat{\alpha}_I$.

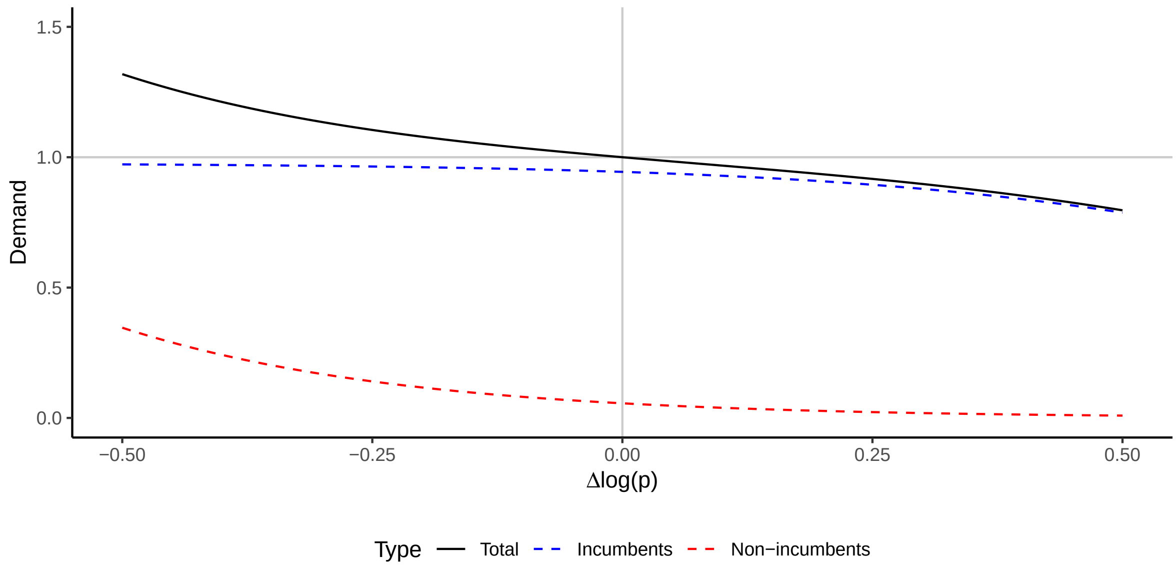
Figure A11: Relationship between outside demand and the ex-ante fraction of in-migrants



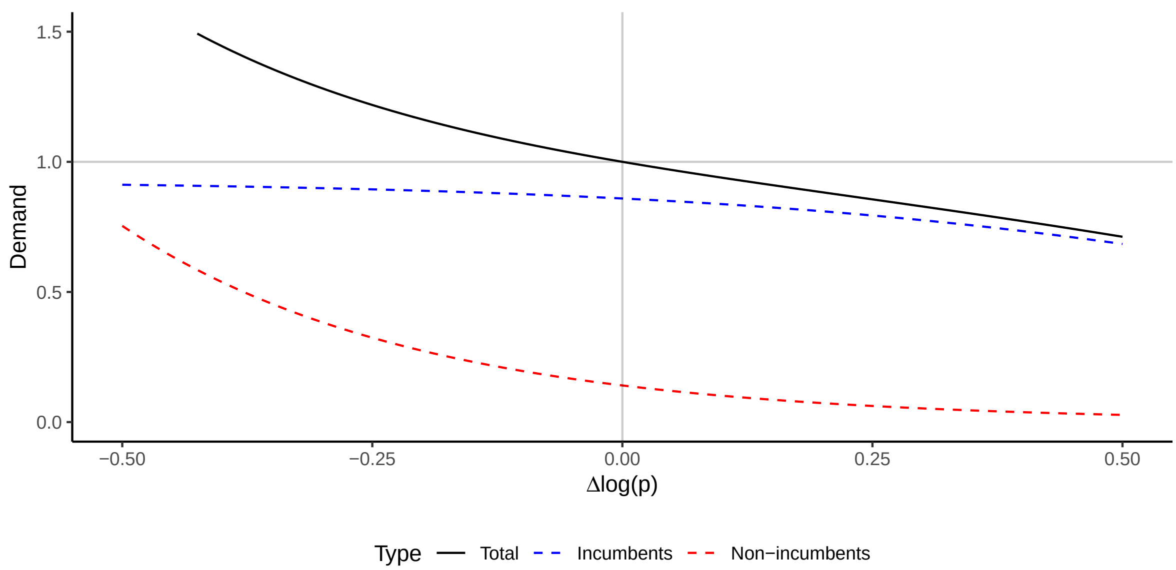
Note: Each point is an eventually treated census tract evaluated for the three years prior to wind farm entry. The R^2 of a rank-rank regression is 0.11.

Figure A12: Demand curves of eventually treated locations

A. 10**th percentile of outside demand**



B. 90**th percentile of outside demand**



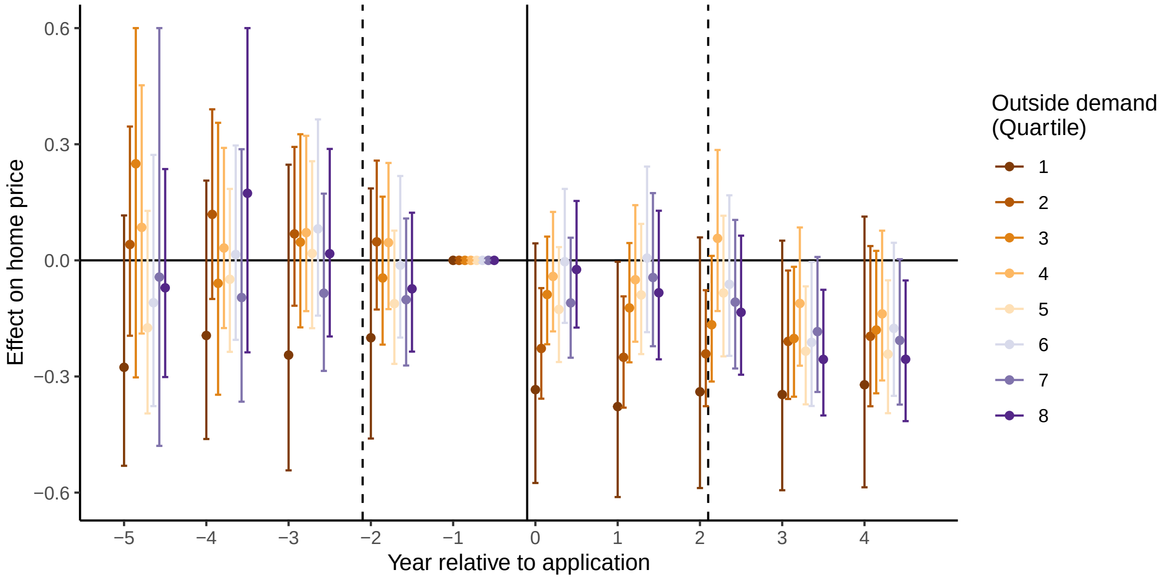
Note: In the solid black lines I present the total demand curves. The total demand can be decomposed as the demand from incumbents, in the blue dashed lines, and in-migrants, in the red dashed lines. The grey horizontal line represents the market-clearing quantity. These are the estimated demand curves for two eventually treated locations using the three years of demand data prior to wind farm entry.

Table A6: Factors related to higher outside demand

Dependent Variable:	Outside demand, ι		
Model:	(1)	(2)	(3)
Variables			
Travel time	0.010	0.005	0.005
	(0.001)	(0.002)	(0.002)
Fraction in-migrants	0.006	0.008	0.008
	(0.001)	(0.002)	(0.002)
% poverty	-0.003	-0.005	-0.004
	(0.001)	(0.001)	(0.001)
% professional	0.004	0.0009	-0.0006
	(0.001)	(0.001)	(0.001)
Median age	-0.005	-0.003	-0.002
	(0.001)	(0.002)	(0.002)
Fixed-effects			
State		Yes	
County			Yes
Fit statistics			
Observations	417	417	417
R^2	0.33673	0.65157	0.79123

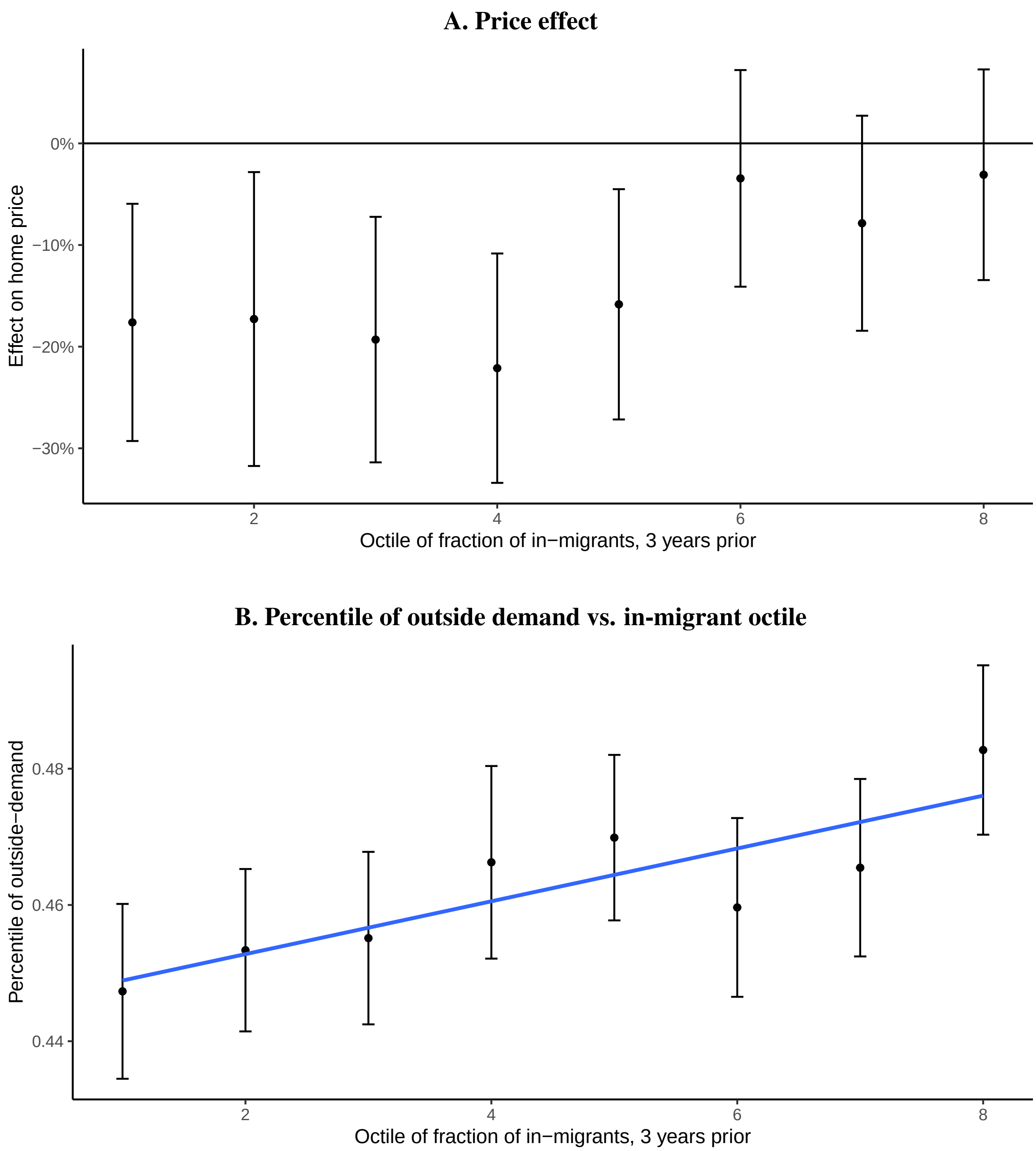
Note: OLS regressions relating variables from the 2010 ACS, other than the fraction of in-migrants from Infutor, to the model-implied measure of ι for each eventually treated location. X variables are all in z-scores within the eventually treated sample.

Figure A13: Effects of wind farm entry on home values by outside demand



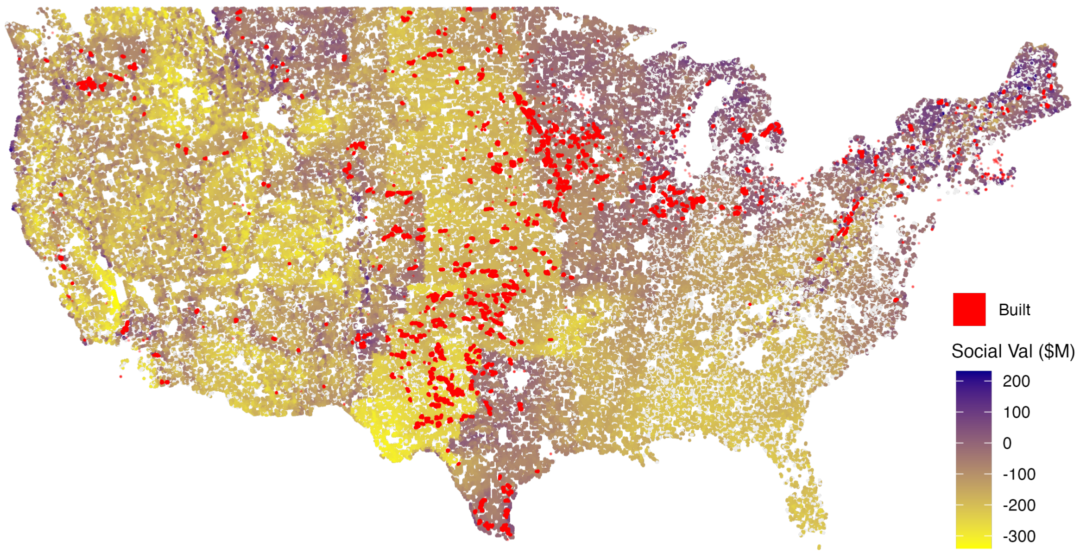
Note: Consider treated homes between one and four miles of the first wind farm. Control group is homes near turbines that are treated five to ten later at the same level of outside demand. Control for: census tract, year, and county × three-year bin FE, log of acreage, bedrooms, bathrooms, and age. SE clustered by stack × tract × treatment × demand bin. Upper SEs cropped at 0.6 for legibility. The results in Section 4 rely on difference-in-difference estimates, averaging across pre and post periods.

Figure A14: Effect of wind farms on price by pre-period in-migrants



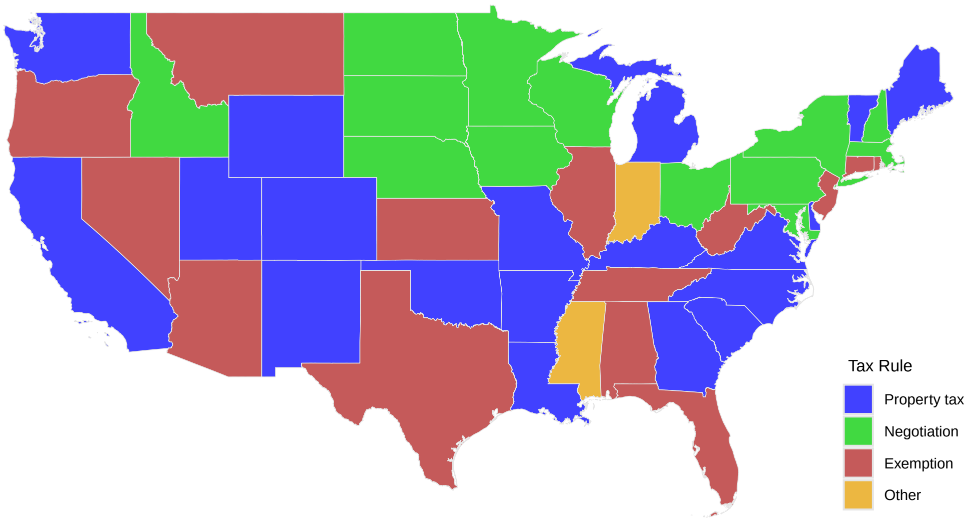
Note: Home price effects is estimated by comparing homes near turbines to homes near turbines that are treated between five and ten years after, but have not been treated yet, controlling for age, acreage, bedrooms, baths, census tract, county × three-year bin, and year. Estimated as a stacked difference-in-differences estimator jointly. Fraction of in-migrants is defined to be the population normalized share that were not living in that tract in the three years prior to wind entry.

Figure A15: Net social value and constructed wind farms



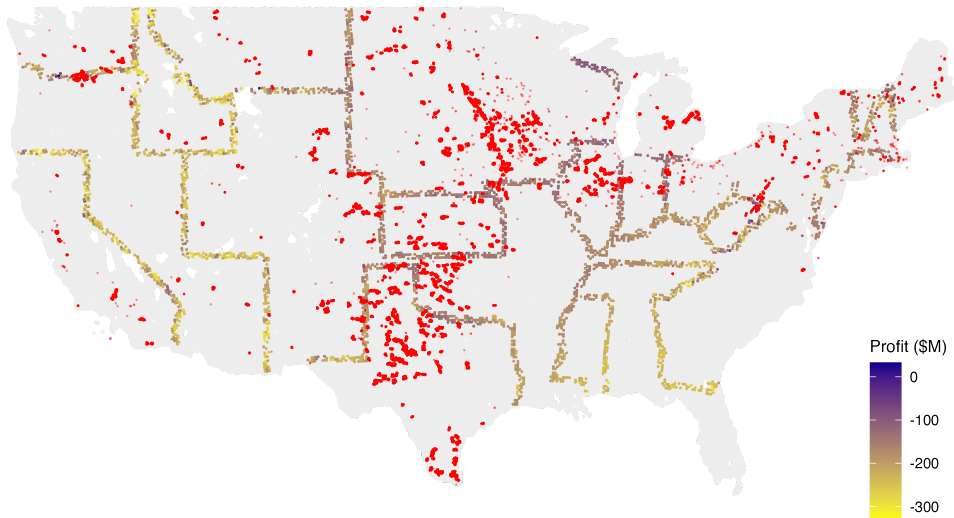
Note: Red dots are built windmills. Present discounted profit calculated using NREL *System Advisory Model* using inferred PPA prices, inclusive of PTC. Social value is profit net of $-0.0754 \times P_l$.

Figure A16: Map of local tax treatments



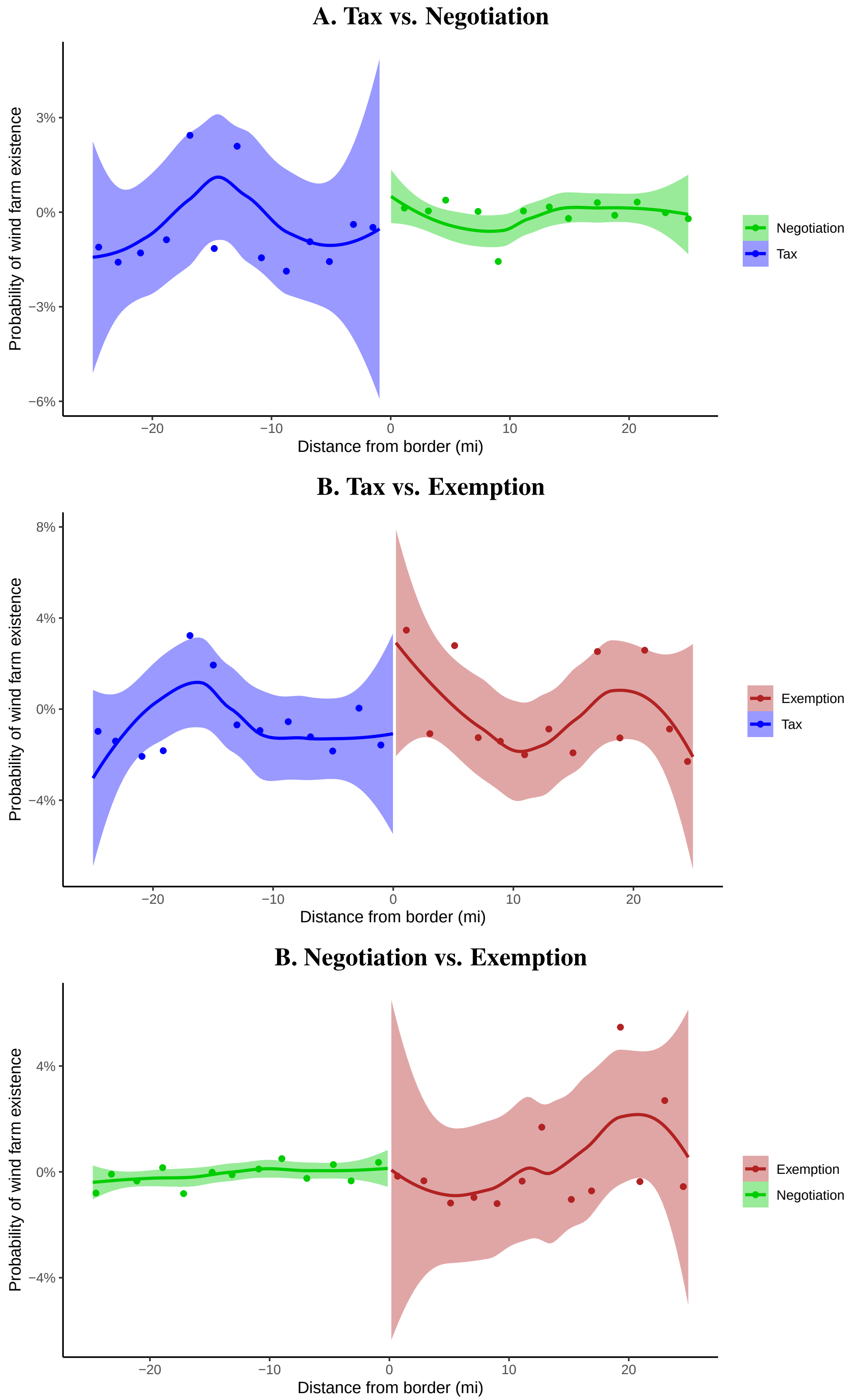
Note: Windmill location from *LBNL*. Red dots are windmills. Tax rules from Uebelhor et al. (2021). This is a simple bucketing abstracting away from substantial within-rule heterogeneity.

Figure A17: Sample of potential sites along borders



Note: Windmill location from *LBNL* Hoen et al. (2018). Profit using engineering estimates. Points shown are < 25 miles from a state border with another local tax regime.

Figure A18: Border RDD effects of tax rule on existence (≤ 1 house within 5 mi)



Note: I present the Loess local polynomial at borders where the law changes as depicted. I residualize controlling for engineering profitability and include border FE. I exclude Texas since Electricity Reliability Council of Texas constitutes a distinct electricity market. I subset to only locations with one or fewer homes within five miles.

Table A7: Border effects of tax rule on wind farm existence: Alternative specifications

Dependent Variable:	Wind farm exists							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Negotiation relative to Tax	-0.024	-0.025	-0.016	-0.029	-0.031	-0.025	-0.019	-0.024
	(0.009)	(0.010)	(0.004)	(0.005)	(0.007)	(0.006)	(0.005)	(0.010)
Exemption relative to Tax	-0.048	-0.048	-0.045	-0.051	-0.045	-0.033	-0.019	-0.048
	(0.005)	(0.005)	(0.008)	(0.003)	(0.005)	(0.007)	(0.007)	(0.005)
Fixed-effects								
Border	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls								
Engineering profitability	Yes		Yes	Yes	Yes	Yes	Yes	Yes
RPS & RPS amount			Yes					
Count Houses (5 mi)								Yes
Border dist. by rule (d.f. #)	5	5	5	3	4	6	7	5
Fit statistics								
Observations	7,310	7,310	7,310	7,310	7,310	7,310	7,310	7,310
R^2	0.03621	0.03421	0.03692	0.03483	0.03542	0.03723	0.03759	0.03680

Note: Standard errors allow for spatial correlation using Conley (1999). Tax rules from Uebelhor et al. (2021).

Table A8: Border effects of tax rule on wind farm existence: Alternative specifications (no homes)

Dependent Variable:	Wind farm exists						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Negotiation relative to Tax	0.025	0.029	0.032	0.018	0.021	0.029	0.028
	(0.002)	(0.003)	(0.002)	(0.0006)	(0.003)	(0.002)	(0.003)
Exemption relative to Tax	0.038	0.038	0.037	0.040	0.033	0.046	0.046
	(0.002)	(0.002)	(0.009)	(0.003)	(0.003)	(0.004)	(0.004)
Fixed-effects							
Border	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls							
Engineering profitability	Yes		Yes	Yes	Yes	Yes	Yes
RPS & RPS amount			Yes				
Border dist. by rule (d.f. #)	5	5	5	3	4	6	7
Fit statistics							
Observations	1,955	1,955	1,955	1,955	1,955	1,955	1,955
R^2	0.05204	0.05113	0.05472	0.05144	0.05208	0.05246	0.05268

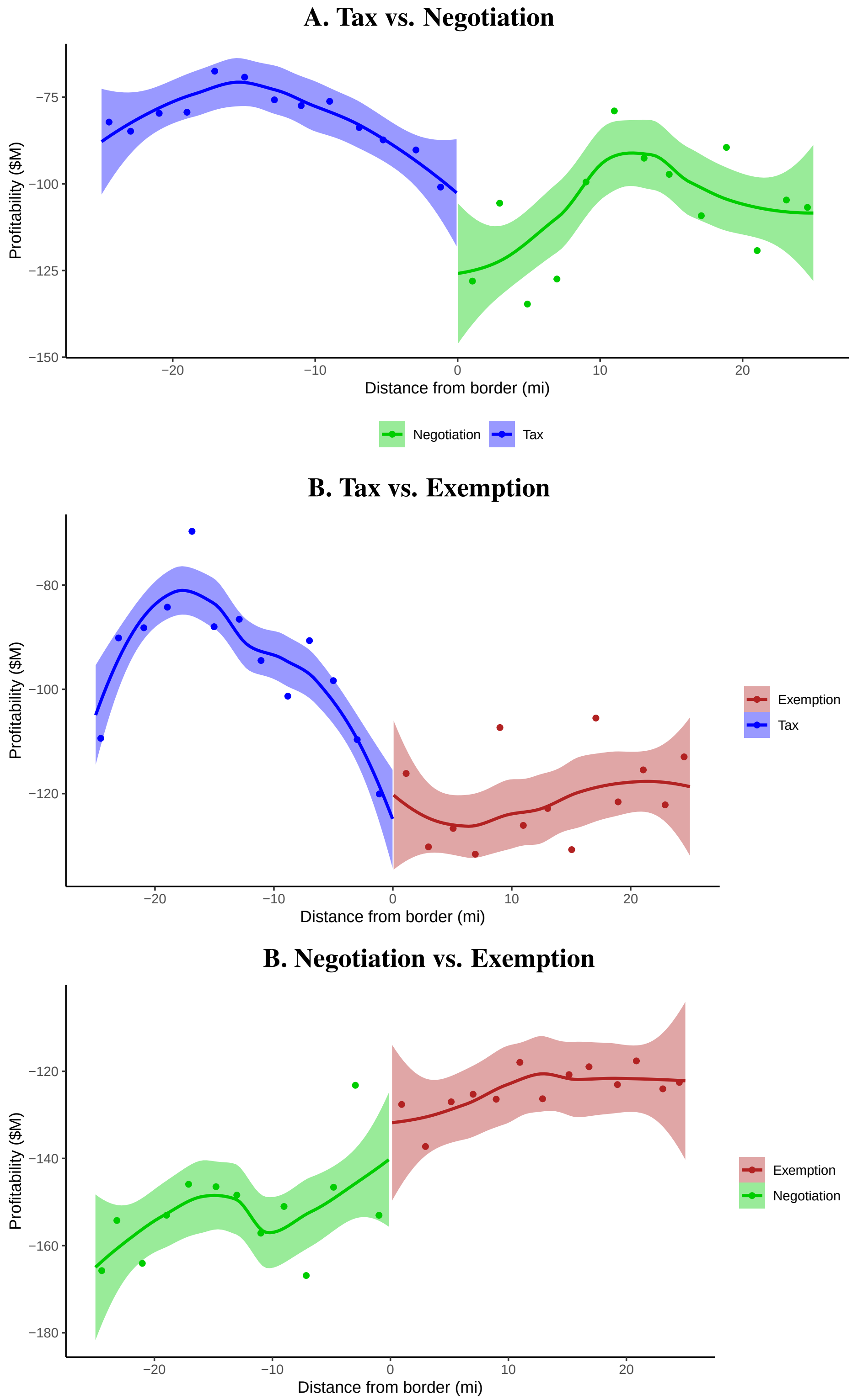
Note: Standard errors allow for spatial correlation using Conley (1999). Tax rules from Uebelhor et al. (2021).

Table A9: Border effects of tax rules on wind farm existence: Excluding interconnection region borders

Dependent Variable:	Wind farm exists	
	Full Sample	No homes in 5 mi
Model:	(1)	(2)
Variables		
Negotiation relative to Tax	-3.5%	2.8%
	(0.9%)	(0.2%)
Exemption relative to Tax	-6.2%	4.2%
	(0.7%)	(0.2%)
Fixed-effects		
Border	Yes	Yes
Controls		
Engineering profitability	Yes	Yes
Distance from border by rule (5 d.f. spline)	Yes	Yes
Fit statistics		
Observations	6,425	1,793
R^2	0.04021	0.05318
Within R^2	0.01107	0.00800

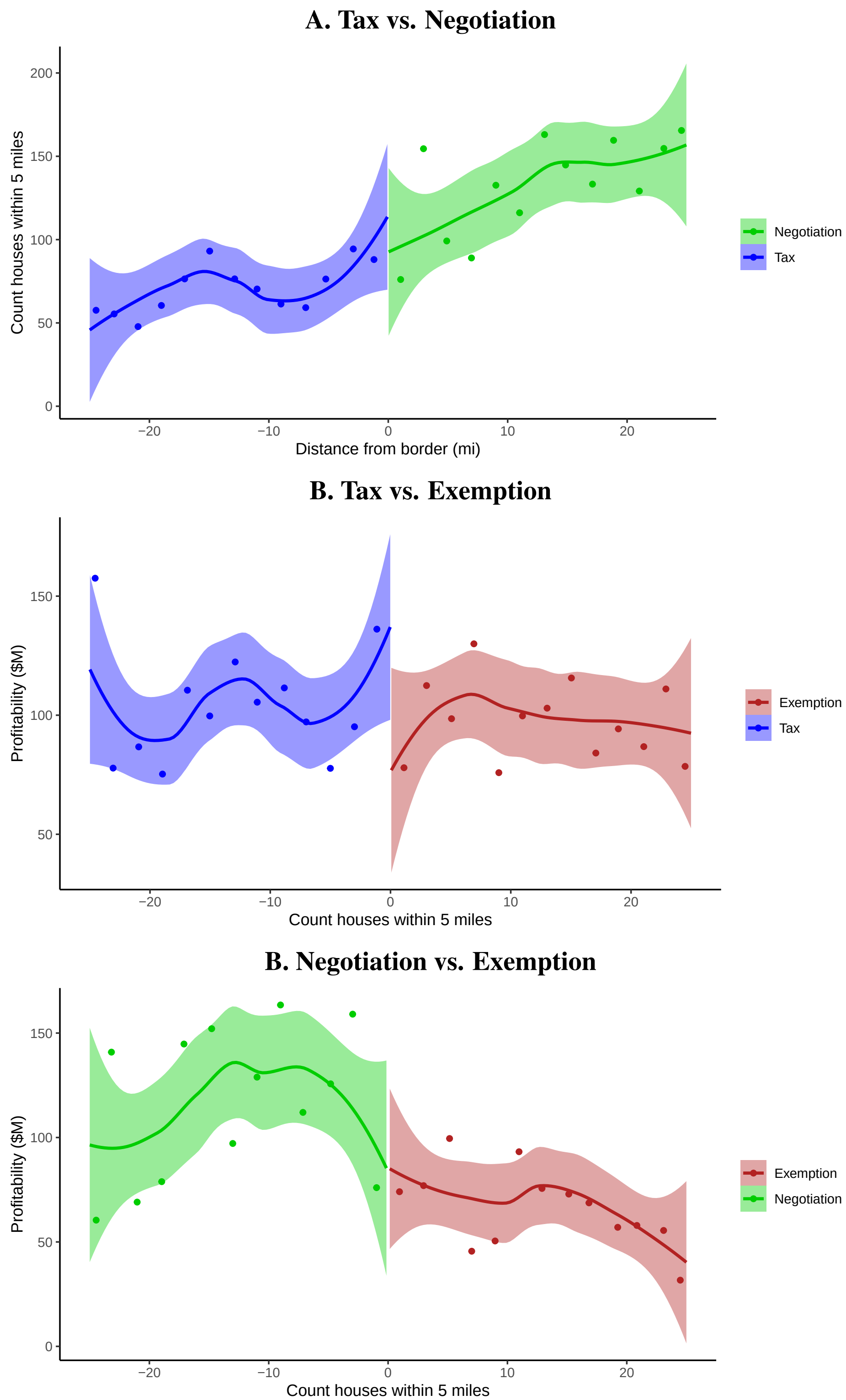
Note: Standard errors allow for spatial correlation using Conley (1999). Tax rules from Uebelhor et al. (2021). Excluding borders at which the interconnection region, as defined by the North American Electricity Reliability Commission here, changes.

Figure A19: Balance of profit at borders



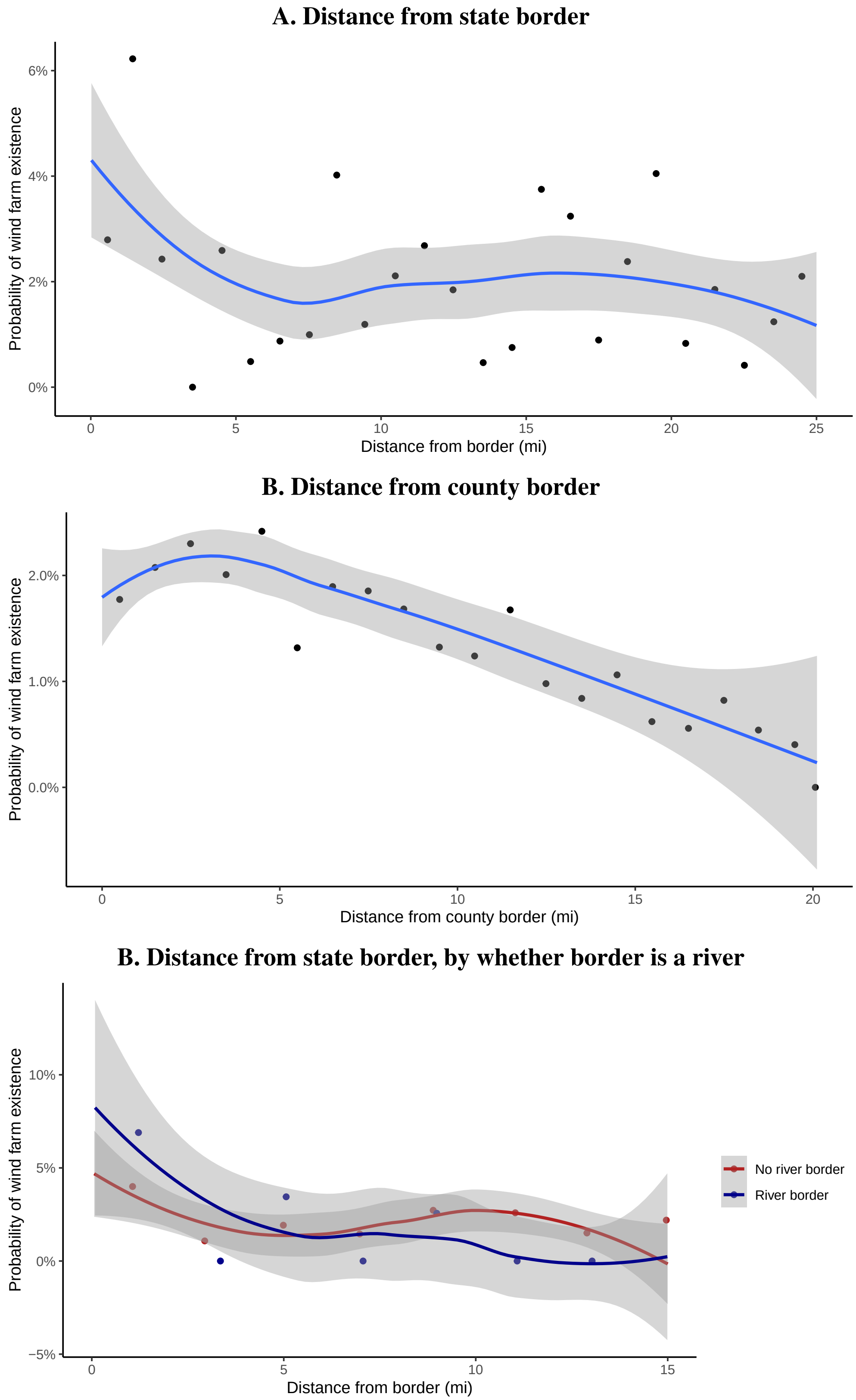
Note: I present the Loess local polynomial at borders where the law changes as depicted. I exclude Texas since Electricity Reliability Council of Texas constitutes a distinct electricity market.

Figure A20: Balance of the number of houses within 5 miles at borders



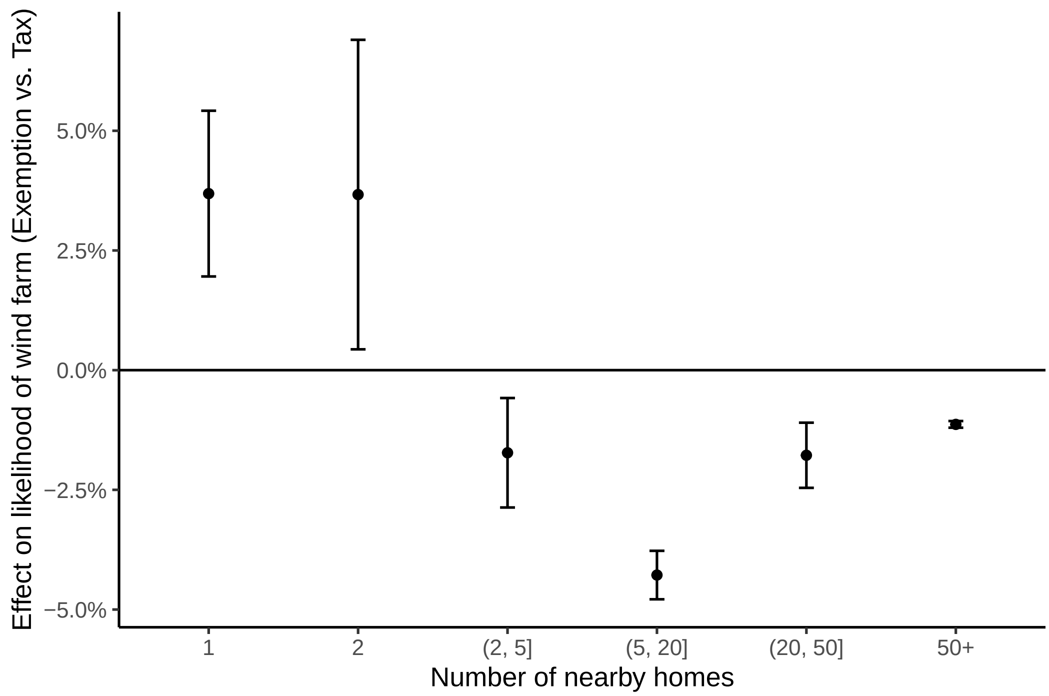
Note: I present the Loess local polynomial at borders where the law changes as depicted. I exclude Texas since the Electricity Reliability Council of Texas constitutes a distinct electricity market.

Figure A21: Relationship of likelihood of construction to distance from border



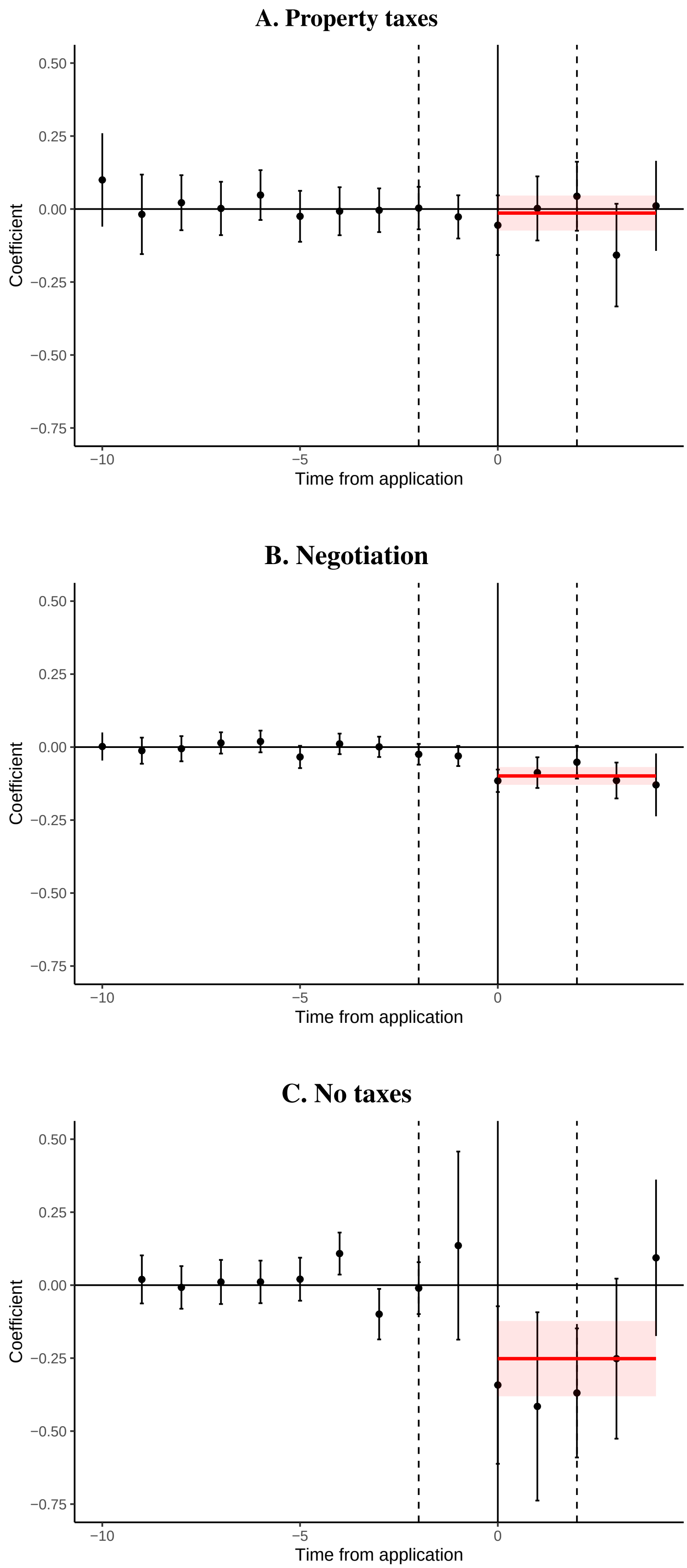
Note: Estimated likelihood of wind farm construction as a function of the distance from the border. Estimated as a Loess local polynomial. River border classification here.

Figure A22: Border effect of exemption vs. tax by number of nearby homes



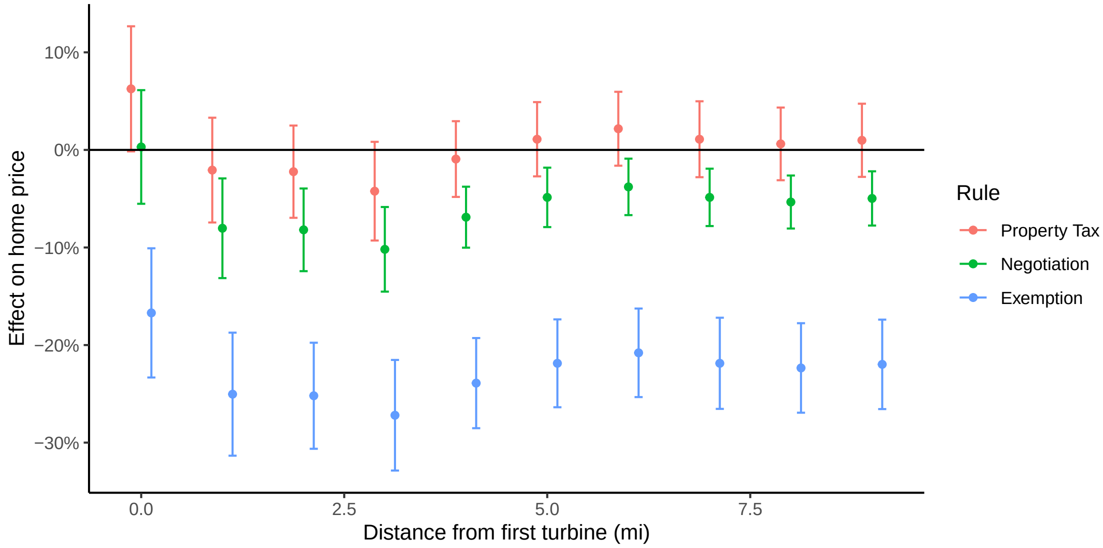
Note: Estimated differential likelihood of wind farm construction by bin of number of homes within five miles, controlling for engineering profitability, distance from border (with a 5 d.f. spline), and border FE. Sample includes only the borders from Figure A17 where one side is tax and the other exemption.

Figure A23: Price effects by tax regime



Note: Compares the total revenue on home transaction prices comparing to not-yet-treated homes in same tax regime using (Callaway and Sant'Anna, 2021) repeated cross-section estimator with census tract fixed effect considering homes within five miles of an eventual turbine. No additional controls.

Figure A24: Effects of wind farm entry on property values by distance and tax rule



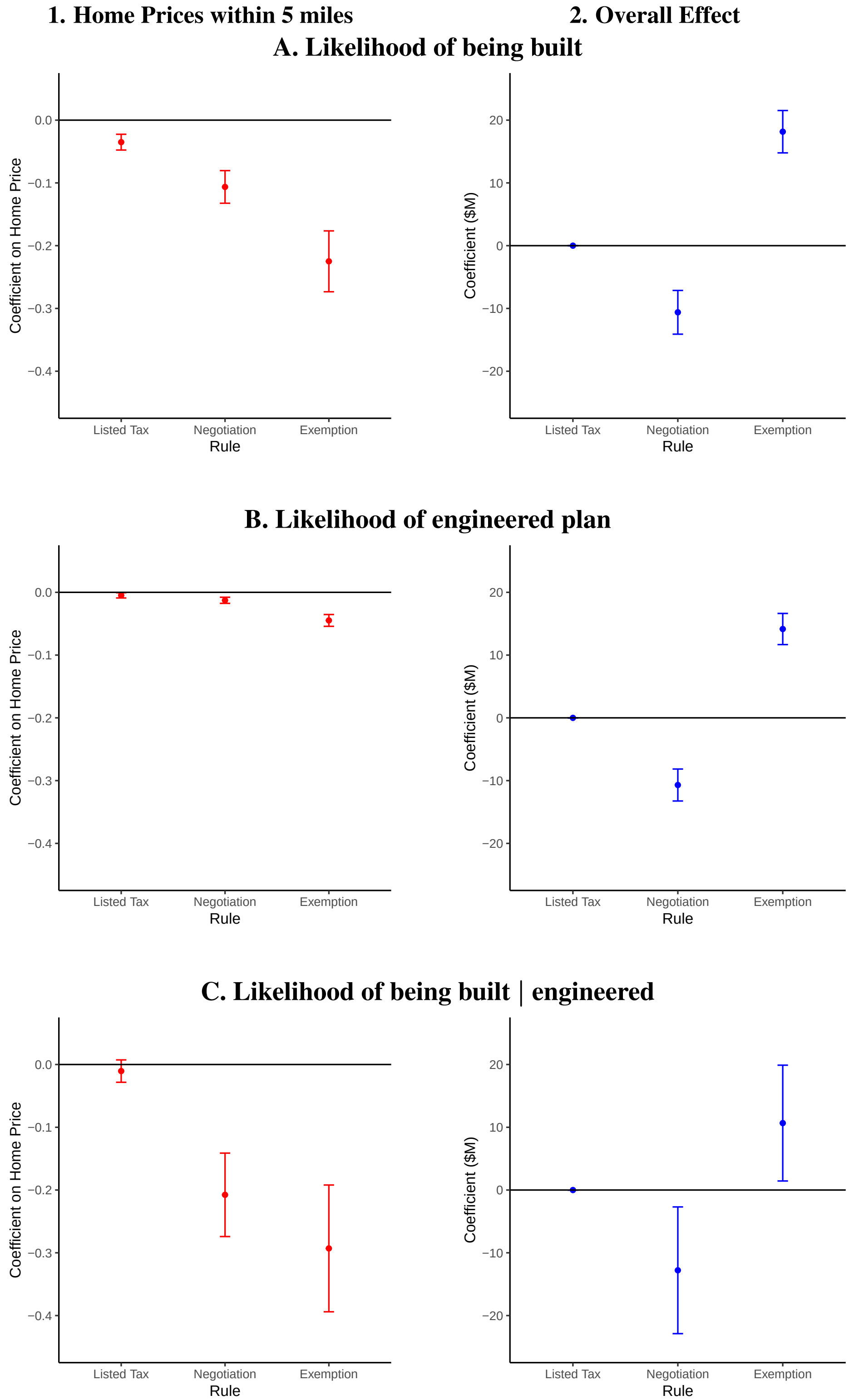
Note: Control group is homes near turbines that are treated five to ten years later than treatment. Estimated as $\log\left(p_{i,t}\right) = \sum_D \left(\tau_D \cdot B_{i,t} + \alpha_D \cdot T_{i,t} + \rho_D\right) \cdot \mathbb{I}\left\{D_i = D\right\} + \sum_R \left(\tau_R \cdot B_{i,t} + \alpha_R \cdot T_{i,t}\right) \cdot \mathbb{I}\left\{R_i = R\right\} + \beta X_i + \nu_{c(i)} + \phi_t + \mu_{C(i),\, g(t)} + \varepsilon_{i,t}$, where there is an additive shifter for the treatment effect by rule. Control for logged characteristics of the home, census tract FE, year FE, and three-year bin × county FE.

Table A10: Additional parameter estimates

Parameter	Description	Value
ν	Value of taxes SD	0.054 [0.049, 0.058]
μ	Cost of externality SD	1.922 [1.816, 2.108]
σ	Profit shock after approach SD	\$46.7M
σ_ε	Persistent unobserved profit shock SD	\$51.7M
B_1	Cost of blocking initially	\$16.5M [1.816, 2.108]
e	Cost of approaching	\$2.51M
β_{NE}	Northeast FE	\$37M
β_{MW}	Midwest FE	−\$16M
β_{S}	South FE	−\$20M
β_{W}	West FE	−\$94M
β_1	Slope of ag. profit / acre in profit	-2.27×10^5
β_2	FE of RPS in profit	\$3.7M
β_3	Slope of RPS × RPS amount in profit	4.8×10^5
η	SD of profit shock signal ($\Pi_{1,l}$)	\$25.3M
μ_c	SD of cost shock signal shock signal ($c_{1,l}$)	1.42

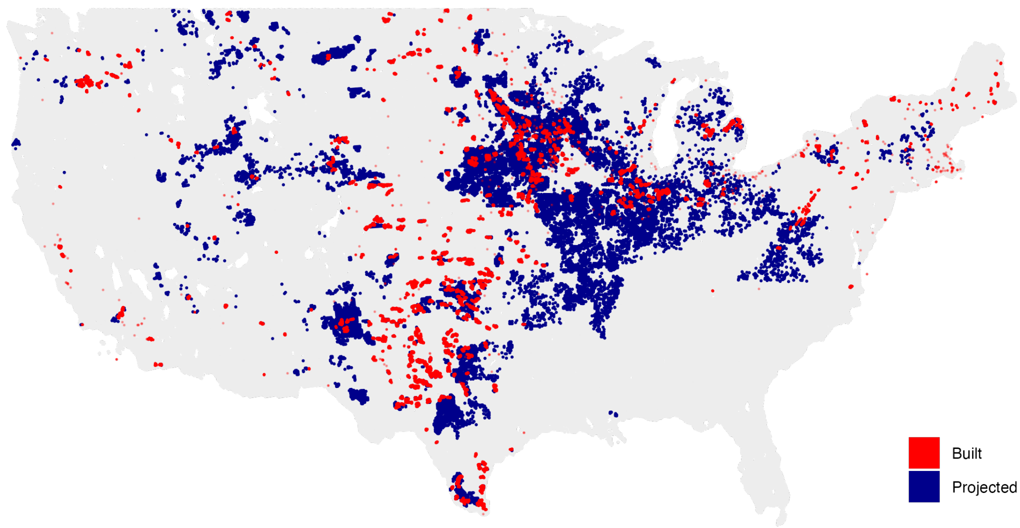
Note: Solved to rationalize dynamic discrete choices as a result of two threshold rules. Each observation is one of 82,563 locations in the continental U.S.—with 150 simulated draws each. Confidence intervals are calculated from 42 Bayesian bootstrap iterations re-weighting each location.

Figure A25: Relationship of entry margins & key covariates across regimes



Note: This figure plots three margins of entry. Panel (A) present probit coefficient estimates on a farm ever being built. Panel (B) presents probit coefficient estimates on a farm ever being applied for. Panel (C) presents probit coefficient estimates on a farm being built conditional on it being applied for. Excluded covariates here include the engineering measures of profitability, an indicator for whether the state has a renewable portfolio standard, as well as the stringency of that RPS, and the per acre profit in the relevant agricultural district. The blue "overall" coefficient is relative to the listed tax.

Figure A26: Planned wind farm sites from Net-Zero-America



Note: Blue dots are planned locations for wind farms from Princeton Net-Zero America Project (Larson et al., 2020). Windmill locations from *LBNL* (Hoen et al., 2018).

A.2 Proof of Proposition 1

Assumption 1. *For all households i, their value for some additive component W is independent and identically distributed.*

Assumption 2. *For the distribution W, the tails are regularly decaying (either polynomial, moderate exponential, or bounded at the tails)*

Proposition 1. *Suppose that for every household* $v^w_{i,g} = v_i + w_i$ *where* v_i *is drawn from some known distribution* $V_{i,g}$ *and w is drawn from some distribution W in a manner that Assumptions 1 and 2 are satisfied. Consider a series* $\left\{p_i, V_{i,1}, V_{i,2}, F_{V_{i,1}}(p_i), F_{V_{i,2}}(p_i)\right\}$ *where* p_i *is some real value within the supports of* $V_{i,g} + W$, $V_{i,1}$ *and* $V_{i,2}$ *are known smooth distributions with regularly decaying tails, and* $F_{V_{i,1}+W}(p_i)$ *and* $F_{V_{i,2}+W}(p_i)$ *are observations of the respective* $V_{i,g} + W$*'s cumulative density function at* p_i*. If* $\{p_i\}$ *spans some subspace of the relevant supports then the distribution W is uniquely identified.*

Proof. I can describe the CDFs as follows

$$F_{V_{i,1}+W}(p_i) = \int_{-\infty}^{p_i} F_{V_{i,1}}(p_i - w) f_W(w)\, dw, \tag{27}$$

$$F_{V_{i,2}+W}(p_i) = \int_{-\infty}^{p_i} F_{V_{i,2}}(p_i - w) f_W(w)\, dw. \tag{28}$$

I can thus differentiate both sides to get the PDFs

$$f_{V_{i,1}+W}(p_i) = \int_{-\infty}^{\infty} f_{V_{i,1}}(p_i - w) f_W(w)\, dw, \tag{29}$$

$$f_{V_{i,2}+W}(p_i) = \int_{-\infty}^{p_i} f_{V_{i,2}}(p_i - w) f_W(w)\, dw. \tag{30}$$

This is a convolution of $f_{V_{i,g}}$ and f_W, which can then be expressed as linear equations involving the convolution operator. Take the Fourier transform of both sides of the convolution equations, which will be the product of the individual Fourier transforms:

$$\mathcal{F}\left[V_{i,1}+W\right](\omega)=\mathcal{F}\left[f_{V_{i,1}}\right](w)\cdot\mathcal{F}\left[f_W\right](\omega), \tag{31}$$
$$\mathcal{F}\left[V_{i,1}+W\right](\omega)=\mathcal{F}\left[f_{V_{i,2}}\right](w)\cdot\mathcal{F}\left[f_W\right](\omega). \tag{32}$$

Since both $V_{i,1}$ and $V_{i,2}$ are smooth and regularly decaying it must be the case that both $\mathcal{F}\left[f_{V_{i,1}}\right](w)$ and $\mathcal{F}\left[f_{V_{i,2}}\right](w)$ are invertible. I find that

$$\mathcal{F}\left[f_W\right](\omega)=\frac{\mathcal{F}\left[V_{i,1}+W\right](\omega)}{\mathcal{F}\left[f_{V_{i,1}}\right](w)}=\frac{\mathcal{F}\left[V_{i,2}+W\right](\omega)}{\mathcal{F}\left[f_{V_{i,2}}\right](w)}. \tag{33}$$

Thus f_W is identified by taking the inverse Fourier transform of $\mathcal{F}\left[f_W\right](\omega)$ using either of the above ratios equivalently. The regularly decaying tails of W guarantee that the inversion is valid and unique. □

B Data construction and supplemental analyses

B.1 Inferring prices for untransacted homes

I need a measure of the price at which a home would transact, including for homes that do not sell in a given period, to measure the value of homes that would be exposed if a given location were developed. I estimate the following linear price model using over 80 million home sale observations:

$$\log\left(p_{i,t}\right)=\beta^{(1)}_{c(i)}X_i+\phi_{r(i)}+\nu_{c(i),t}+\beta^{(2)}_{s(i),t}X_i+\xi_i+\varepsilon_{i,t}. \tag{34}$$

I consider some property i at time t where X_i is a vector of logged characteristics of the property i (acres, bedrooms, bathrooms, square-feet, and the number of units). $\beta^{(1)}_{c(i)}$ and $\beta^{(2)}_{s(i),t}$ are county and state × year specific estimates of the relationship between these characteristics and price. $\phi_{r(i)}$ is a Census tract fixed effect and $\nu_{c(i),t}$ is a county × year fixed effect. ξ_i is an unobserved persistent quality component. This regression has an R^2 of around 0.69.

I fit a predicted price for each home in 2019 using this model. I recover, for all properties, where possible, the ξ_i of the most recent transaction as a residual and hold this fixed in the prediction.[71] If there are no prior transactions of i, I assume $\xi_i=0$.

B.2 Engineering profitability

Throughout, I consider a model wind farm that contains 80 1.5 MW turbines connecting to the grid at 130 kV in a standard design.

Wind production. I use a known engineering function that converts wind resources to output power given a farm's design and turbine characteristics. I use the standard, as of 2020, farm design and turbine characteristics, and use the functionality from NREL's *System Advisory Model* to convert the wind resource to hourly production, as in Freeman et al. (2014). This method accounts for heterogeneous wake effects given the direction of the wind, non-linearities in production at different wind speeds, and differential productivity given the wind's direction and atmospheric pressure. To my knowledge, this is the state of the art publicly available model of the production function of wind farms.

[71] This allows for houses to have persistent unobservable qualities. For houses that, conditional on observables, sold for 30% less than expected in 2005, I assume their value in 2019 would remain 30% less than predicted by Equation 34.

Contracted prices. I abstract away from the price-setting process, and model p_s^* to be determined as a function of current locational marginal prices, the curve of expected future locational marginal prices, and state policies. In Section B.3 I describe the estimation of p_s^* in more detail.
Costs. I use the average fixed cost of construction, excluding interconnection and road construction, as $\hat{C}$, from NREL reports using proprietary industry information. The engineers at NREL, as part of their LandBOSSE project in Eberle et al. (2019), propose a relationship between distance to interconnection and cost to be

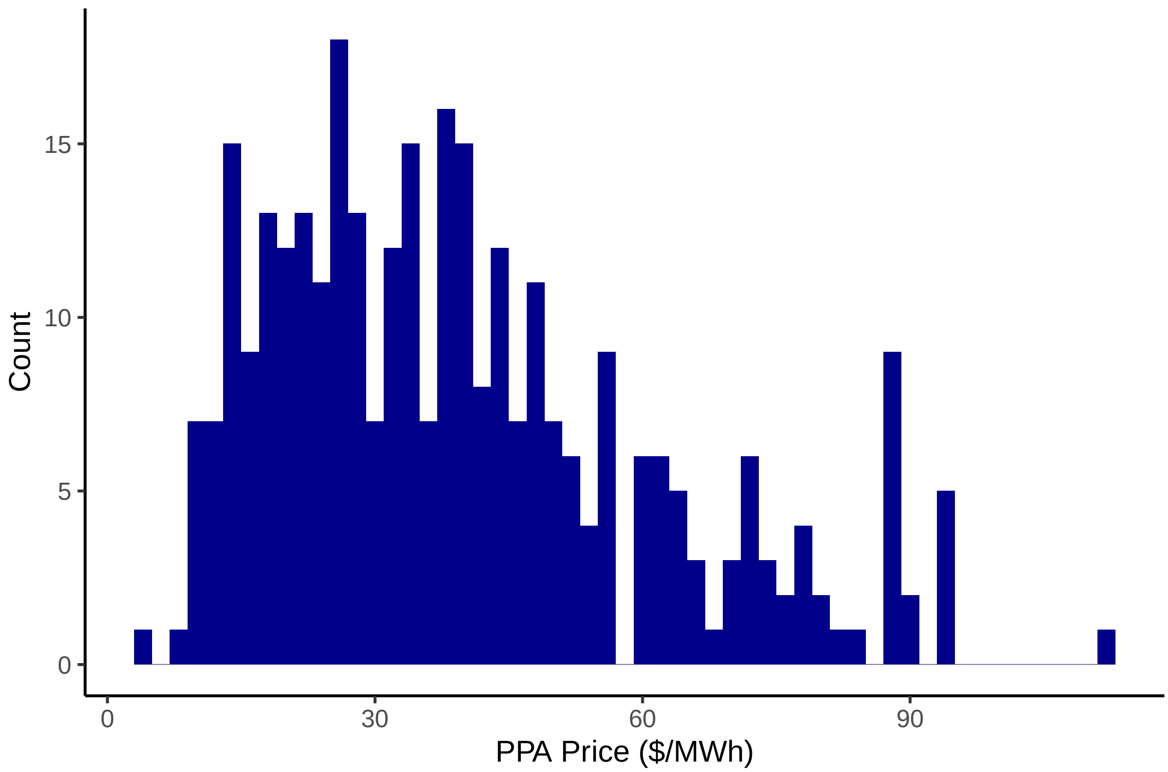
$$\hat{I}\left(\delta_{g,s}\right) = (1,176V + 218,257)\delta_{g,s}^{0.8937}, \tag{35}$$

where V is the voltage based on their independent analysis of industry data. The same project estimates the cost to build new roads, as $\hat{R}\left(\delta_{r,s}\right)$. These costs are not readily expressed in closed form but includes variable cost of stockpiling topsoil, compacting shoulders, acquiring materials, and laying new road as a function of the distance from existing roads. The yearly operation and expenditure cost is \$43 per kW per year as reported by Stehly et al. (2020), from a survey of wind industry experts from Wiser et al. (2019).
Combining. I use the industry standards costs of capital, as well as relevant payroll and corporate income tax rates, and the default NREL discount rate of $\delta = 0.94$. I use this to combine the costs and revenues into a net present value $\hat{\Pi}_s$.
Missing information. This method accounts for the exogenous engineering fundamentals that affect site-specific profitability. However, this does not account for the land lease costs, other unobservable determinants of profitability, or the costs of property taxes.

B.3 PPA prices

Typically, wind developers sign power purchase agreements (PPAs) with energy off-takers, most commonly utilities. These contracts are meant to last for the useful lifetime of the project. According to interviews with developers, the long-term nature of such contracts is essential to secure project financing. These contracts make the future cash flows to the developers largely predictable, with uncertainty arising mainly from maintenance costs or fluctuations in production over time. In Figure A27, I present the distribution of contracted PPA prices, using data collected by the American Clean Energy Association (ACEA).

Figure A27: Histogram of power purchase agreement prices



Note: Plotting inflation-adjusted power purchase agreements for each wind facility in the American Clean Energy Association (ACEA) data. For plants with more than one PPA, I presented the weighted mean by the capacity under contract.

For each project site s in the ACEA data I create the following production-weighted prices:

$$\bar{p}_s^{\text{myo}} = \frac{\vec{\rho}\,(\vec{w}_s) \cdot \vec{p}_s^{\,\text{myo}}}{\sum \vec{\rho}\,(\vec{w}_s)}, \quad \bar{p}_s^{\text{exp}} = \frac{\vec{\rho}\,(\vec{w}_s) \cdot \vec{p}_s^{\,\text{exp}}}{\sum \vec{\rho}\,(\vec{w}_s)} \tag{36}$$

where $\vec{\rho}$ is a function mapping hourly wind characteristics to hourly production, and $\vec{p}_s^{\,\text{myo}}$, $\vec{p}_s^{\,\text{exp}} \in \mathbb{R}^Y$ are the vector of hourly prices at s' node of the grid. These price vectors contain both current, myopic, and projected price path as published by NREL's Cambium project. I then relate these expected prices with actual contract prices as

$$p_s^* = \beta_0 + \beta_1 \bar{p}_s^{\text{myo}} + \beta_2 \bar{p}_s^{\text{exp}} + \beta_3 \text{RPS exists}_s + \varepsilon_s, \tag{37}$$

where RPS exists$_s$ is an indicator for whether the state that s is in has a renewable portfolio standard. I present the results of the regression in Equation 37 in Table A11.

B.4 Clarifying the existence and timing of construction

I combine information from the FAA and LBNL to clarify which locations were constructed as well as the exact timing of when. In Figure A28 I describe the number of turbines that are applied for and built in the FAA data that can be matched to LBNL data. As can be seen in Panel (A) nearly every turbine in the FAA

Table A11: Relationship of PPA contract prices with market prices

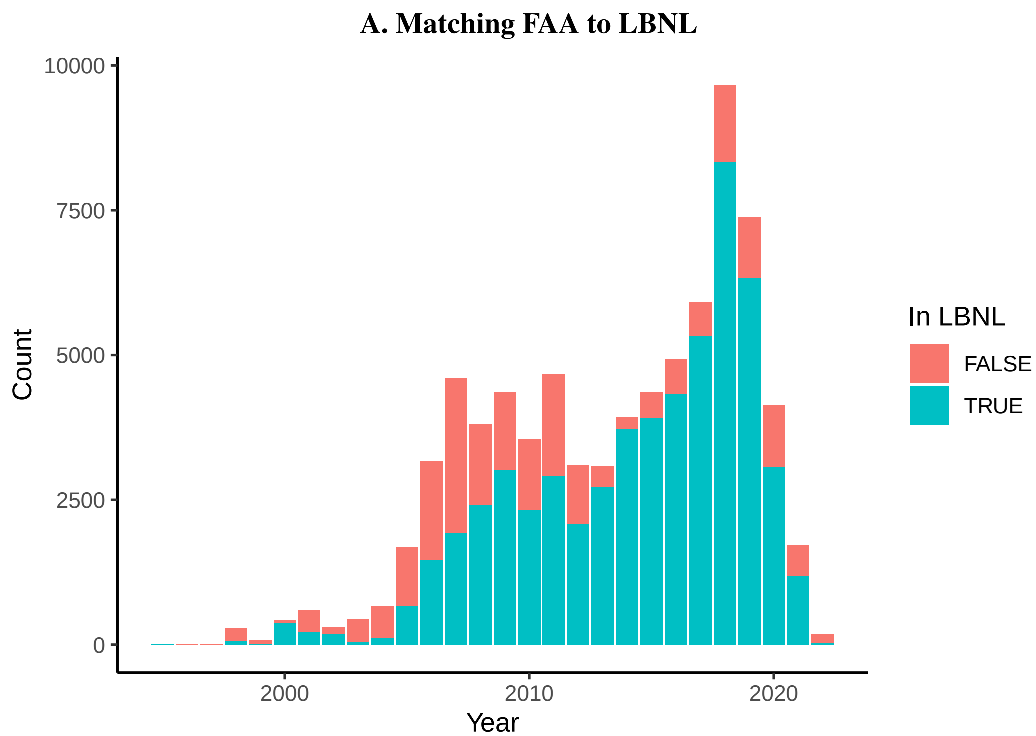
	PPA price ($)
Intercept	-38.67
	(9.793)
Myopic price	1.342
($/MWh)	(0.4006)
Projected price	1.081
($/MWH)	(0.9926)
RPS exists?	10.37
	(2.189)
Observations	320
R^2	0.46345

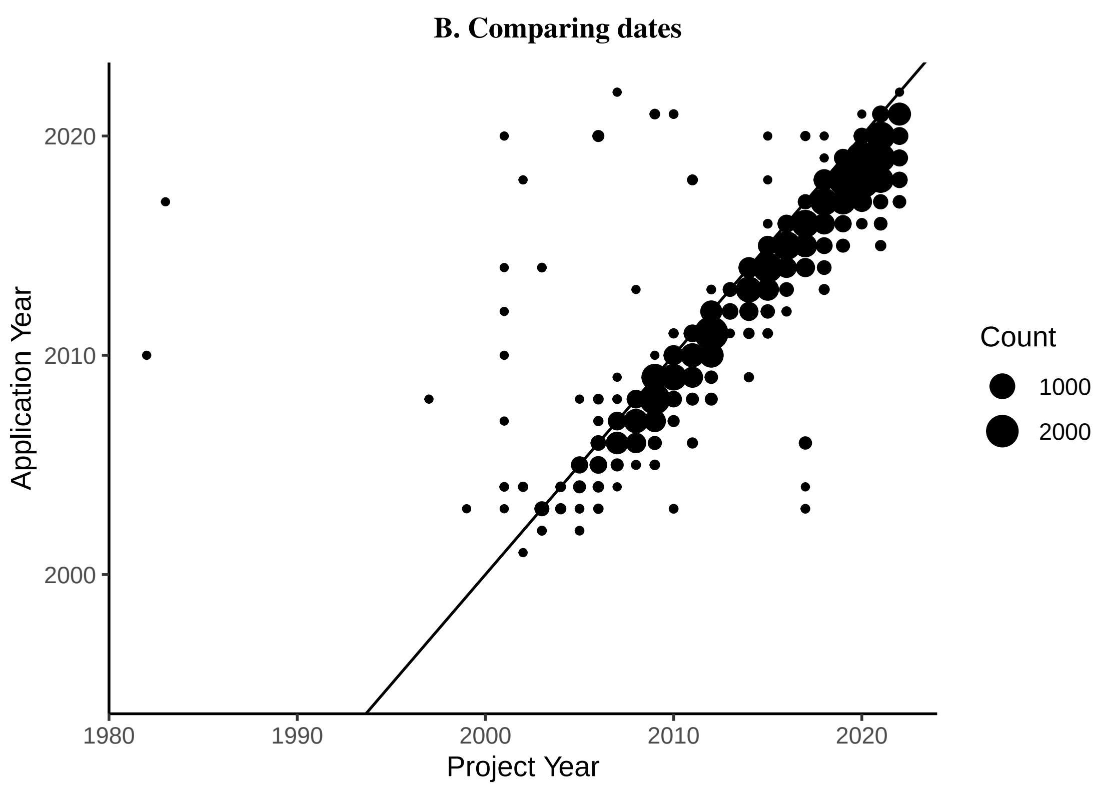
Note: Matching inflation-adjusted power purchase agreement contracts from the American Clean Energy Association (ACEA) with generation-weighted hourly prices from NREL *Cambium* as well as an indicator for if the state has a renewable portfolio standard (RPS) from *RMI*.

is verified to exist by LBNL, particularly for more recent construction. In Panel (B) I show that the project year from NREL appears to be on average around one year after the FAA application.

I take the set compliment of these turbines to form a full sample of built wind farms. If the application year is less than the project year, I set as the application date the project year since, as can be seen in Figure A29, follow-on applications tend to be for renovations or alterations of an existing wind farm.

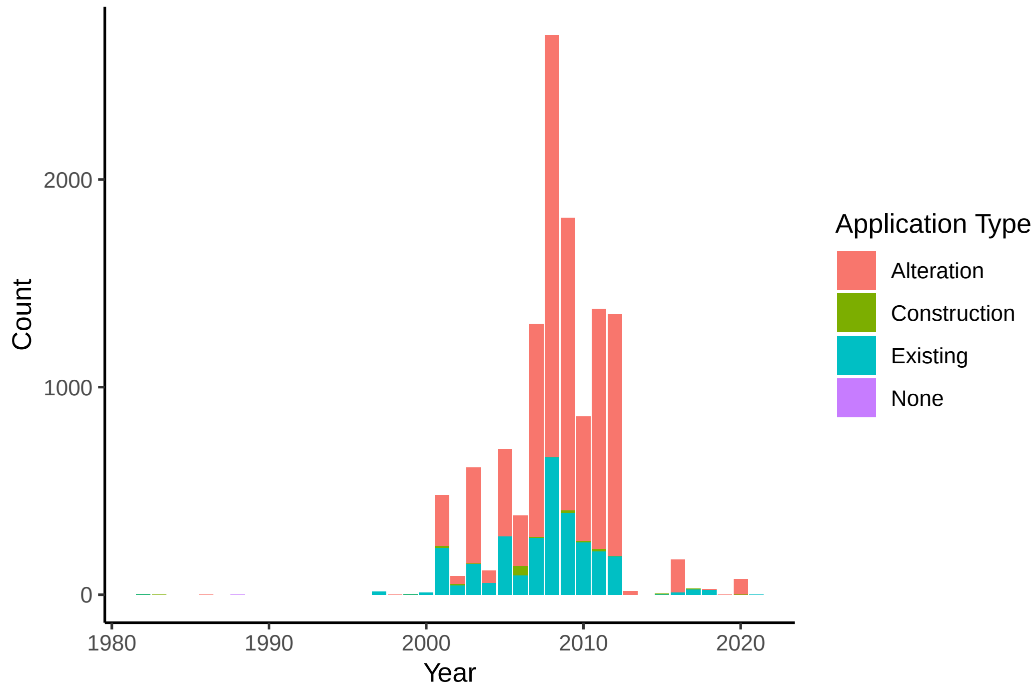
Figure A28: Built FAA turbines in LBNL data





Note: Matching exact turbine locations from FAA applications to the data from Lawrence Berkeley National Lab about which turbines exist in the United States as well as when they were built. In panel (B) I plot on the x-axis the project year from NREL vs. the application year from the FAA.

Figure A29: Stated reasons for applications after project year

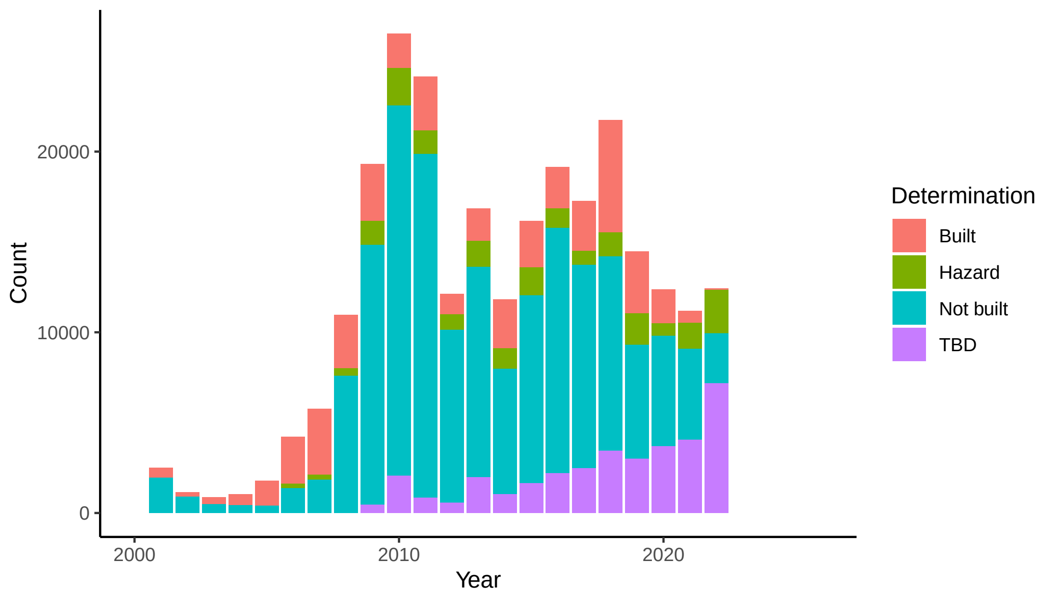


Note: Application type from FAA forms. Only considering FAA applications where the project date from LBNL is prior to the application.

B.5 Information on applications

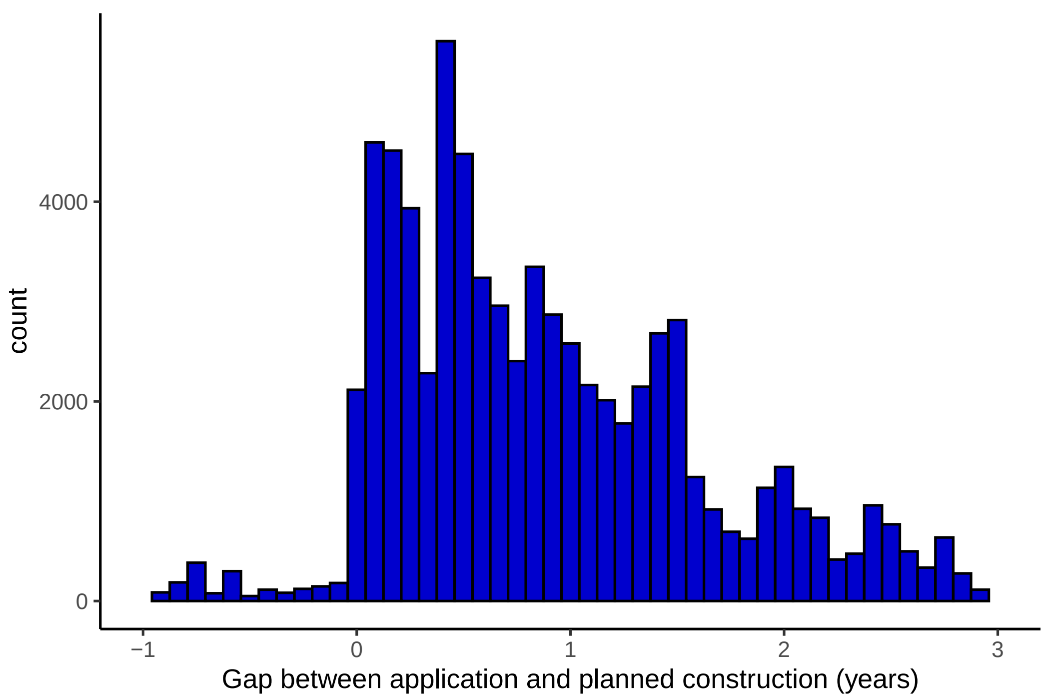
I use data from the Federal Aviation Administration (FAA) covering the universe of applications for wind turbines in the United States. All wind turbine constructed in the United States must be registered with the FAA at least 90-120 days before construction to ensure aviation safety and to verify that they do not infringe with other uses of the airspace. Additional details on this application process are available here and here. In Figure A30 I present the outcomes of these applications, with nearly all receiving approved. These data provide a comprehensive record of all fully planned wind farms. In Figure A31, I present the distribution of the time between application and the planned construction date. The figure shows that nearly all projects are planned for constructed within two years, with most scheduled within one year. An important limitation is that I observe only the stated planned construction date, not the actual completion date.

Figure A30: Outcomes of FAA applications over time



Note: Using reports of the determination from the FAA.

Figure A31: Time from FAA application to planned construction

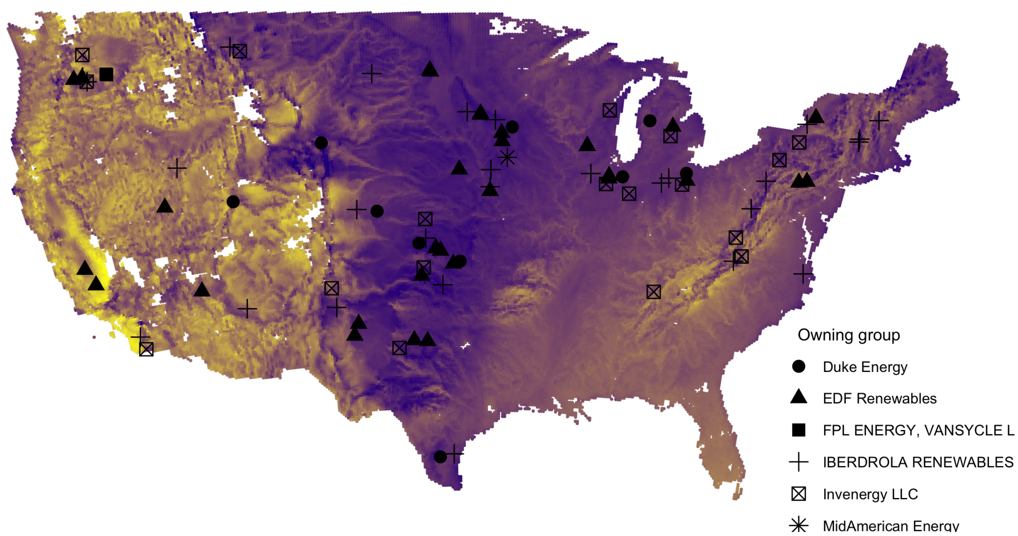


Note: Comparing FAA application dates to dates of planned construction.

B.6 Firm spatial concentration

The FAA applications identify the firm, and the individual, applying for each turbine. In Figure A32 I present the spatial distribution of wind farms built by the 6 largest wind developers. Qualitatively, the large developers build in geographically heterogeneous locations. Anecdotally, developers attest to having minimal geographic specialization.

Figure A32: Developer spatial distribution



Note: Plotting the farms built by the 6 largest developers.

B.7 Effects on local school finances

In Section 5.3 I present spatial border regression discontinuity estimates of the effects of different tax rules as outlined in Uebelhor et al. (2021) on wind construction. I supplement this by documenting the effects of wind farm construction on school district finances using detailed measures of revenue by source and expenditures from the National Center for Education Statistics' (NCES) Common Core of Data[72]. I provide two complementary analyses: (i) estimating the marginal effects of an additional wind turbine on school district revenues, and (ii) estimating event studies of how finances evolve after the entry of the first wind farm enters. In both analyses, I use the same control group as in Section 4.1, comparing school districts that receive wind farms earlier to those that have not yet—but will eventually—host a wind farm within their borders. I document novel evidence on the effects of wind farm entry on school district revenues and expenditures, and characterize heterogeneity that aligns with differences in tax regimes.

I first estimate marginal effect of the number of built turbines. Property taxes are assessed at the valuation of the project which approximately scales in the number of turbines. I control for both year and school district fixed effects, and estimate the following specification,

$$Y_{d,t} = \tau \cdot \#\,\text{Built}_{d,t} + \phi_d + \rho_t + \varepsilon_{d,t}. \tag{38}$$

[72] A similar analysis could be conducted in the Census of Governments, which would be noisier due to comprehensive data collection only every five years. However, school districts make up a majority of all spending from property taxes. School districts' received around \$343 billion of the full \$630 billion, or around 55%, in collected property tax revenue in 2021 (Tax Policy TPC, 2022; COE, 2024).

I present the full set of results in Table A12. I find that 100 built turbines in a district within a state where developers pay property taxes increases revenue from local sources by around 43%. This is crowded out, however, by decreases in both state and federal revenues. I observe modest revenue increases in the other two tax regimes. However, the total expenditure response to 100 built turbines is similar—about 3%—in both property-tax and negotiation states and nearly zero in states where the developers are exempt. I do not observe a meaningful effect on local tax revenue from wind construction in states where the developers can negotiate payments, possibly because "Fees in Lieu of Taxes" are recorded differently from standard local tax revenues.

Table A12: Effects of wind farm entry on school revenues

Dependent Variables:	log(Local rev.)	log(State rev.)	log(Federal rev.)	log(Total Exp.)
Model:	(1)	(2)	(3)	(4)
Built turbines (/100)	0.434	-0.137	-0.144	0.028
Pays property tax	(0.017)	(0.009)	(0.020)	(0.004)
Built turbines (/100)	0.051	0.041	-0.010	0.028
Negotiates payment	(0.021)	(0.015)	(0.024)	(0.006)
Built turbines (/100)	0.138	-0.009	-0.013	-0.004
Exempt from payment	(0.018)	(0.010)	(0.018)	(0.005)
FE: Year, District	✓	✓	✓	✓
Observations	9,242	9,238	9,219	9,245
R^2	0.98	0.98	0.97	1.00
Pre-wind mean	\$36.8M	\$29.5M	\$5.5M	\$60.3M

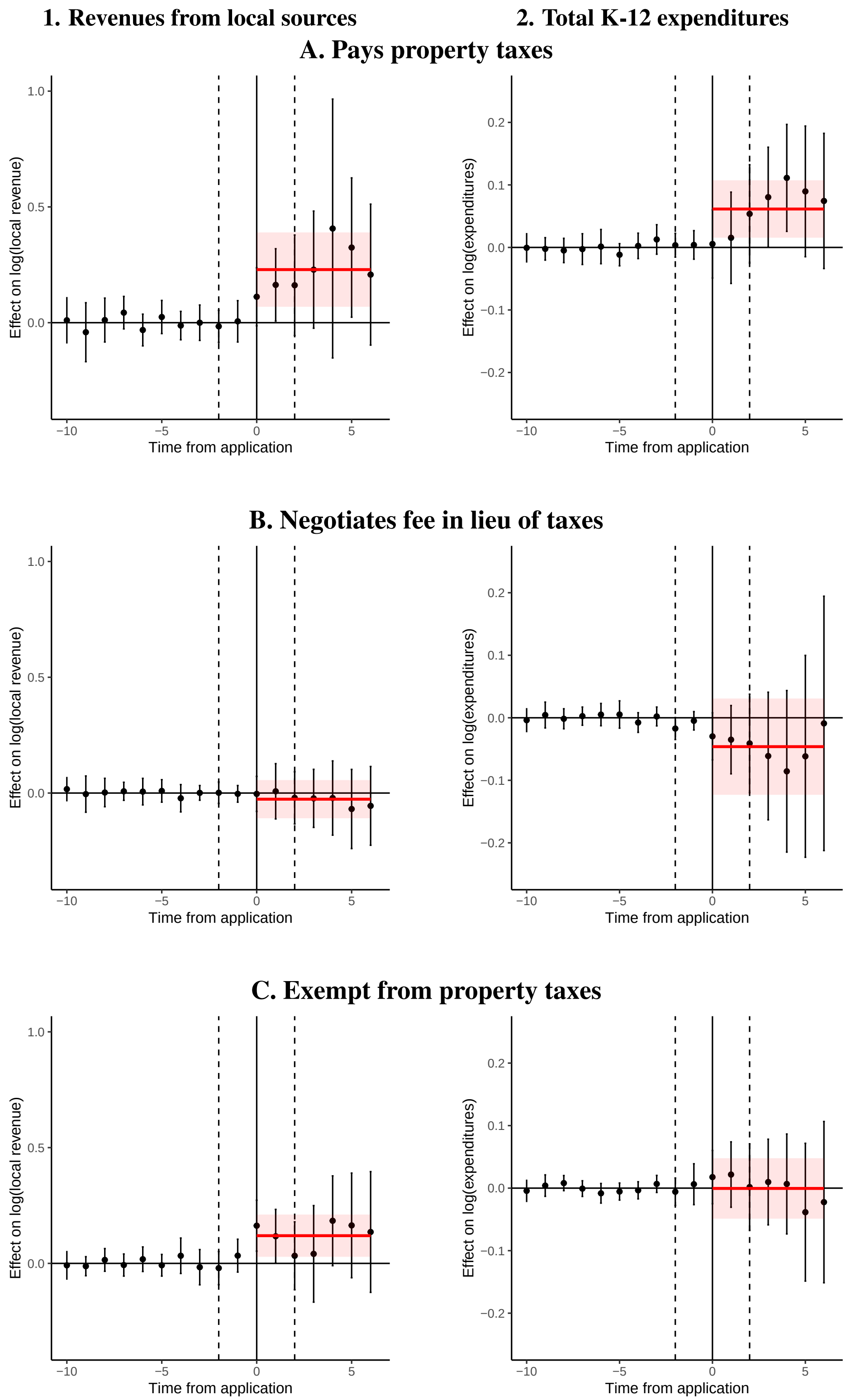
Note: Using data from the NCES' Common Core of Data. Standard errors clustered at rule level. Control group of not yet treated units. Pre-period of six years prior to first wind farm entry, post-period treatment is defined to be two to six years after first wind farm entry. Limited to 240 wind turbines (~ 3 wind farms) per district. Exemption can be full or partial.

I supplement this analysis with event study estimates where I define treatment to be application year of the first built wind farm. I estimate the following specification,

$$Y_{d,t} = \sum_{k \neq 1} \tau_k B_{d,t-g} + \phi_d + \rho_t + \varepsilon_{d,t}, \tag{39}$$

where the notation is as before wherein $B_{d,t-g}$ is an indicator how many years it is from treatment g. To account for staggered treatment timing, I estimate these event studies using the Callaway and Sant'Anna (2021) panel estimator, and present the results in Figure A33. I find broadly similar results to the linear estimates presented in Table A12, with one notable exception. Specifically, I observe a small and imprecisely estimated negative effect on expenditures under the negotiation regime. The effects on local revenues and total expenditures in Panel (A) increase over time, consistent with two empirical patterns in this setting. First, treatment is defined by the first wind farm's entry, although many school districts experience multiple projects over time. Second, as discussed in Section B.4, many projects are not constructed immediately after application and therefore do not generate tax revenue right away.

Figure A33: Relationship of wind farm entry & school district finances across regimes

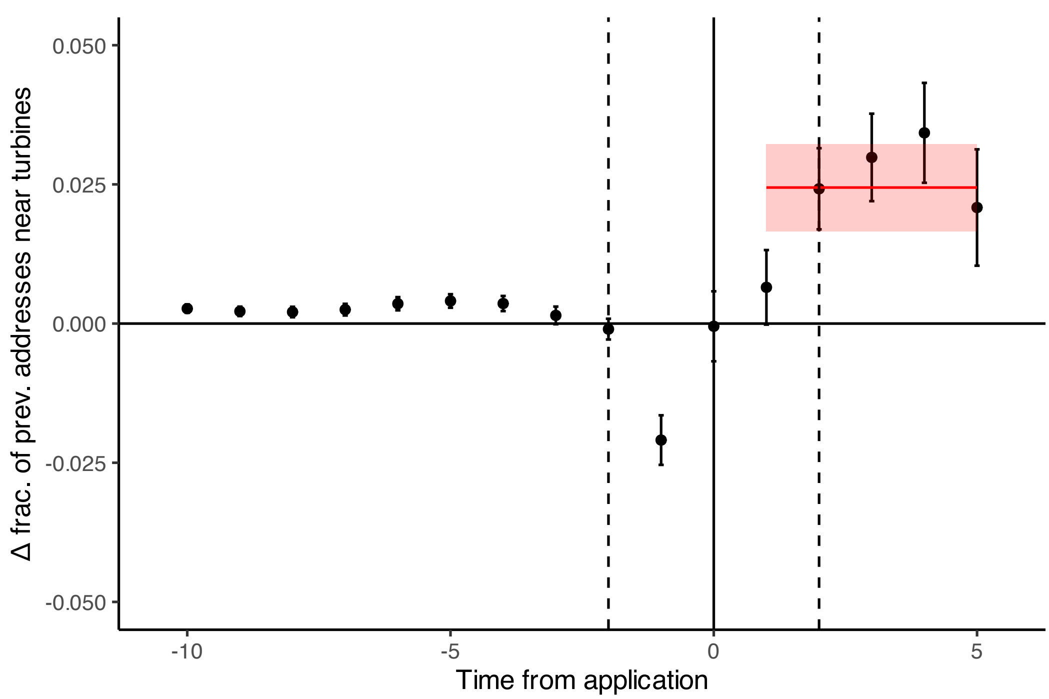


Note: Using data from the NCES' Common Core of Data. Standard errors clustered at rule level. Control group of not yet treated units. Limited to districts with final count of 25 – 240 wind turbines (∼ 0.5 – 3 wind farms). Estimated using Callaway and Sant'Anna (2021) panel estimator.

B.8 Effects on migration networks

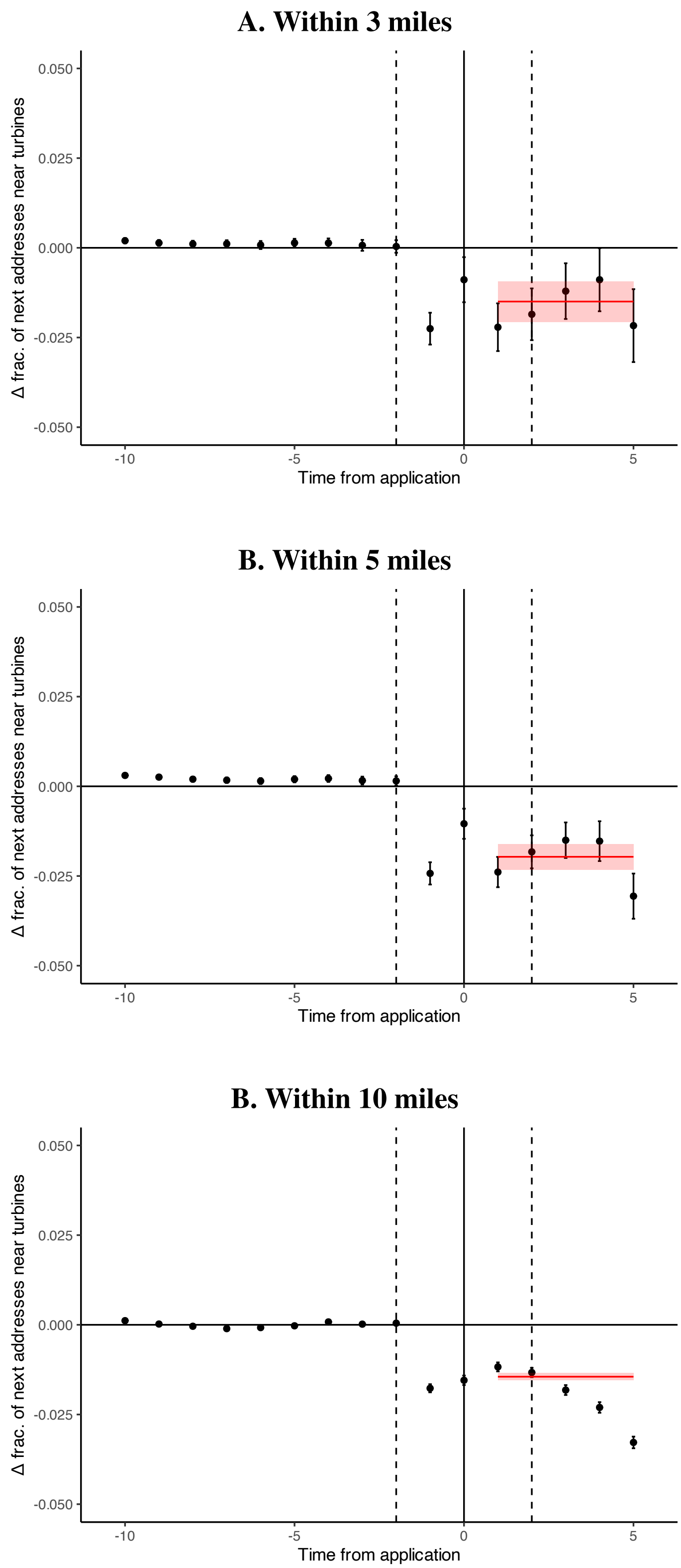
I test whether household migration patterns change in response to wind construction using data from Infutor. A key challenge is that exposure to wind farms increases discontinuously, since many areas that are common substitutes for movers are also treated around the same time. To address this, I compare migrants' realized exposure to wind farms to their predicted exposure had migration patterns remained unchanged. Formally, I compare the fraction of migrants who moved to or from areas with existing wind farm to their predicted exposure based on migration patterns during the pre-period from $t \in [-5, -2]$. In doing so, I consider $4,001,980$ subsequent addresses and $2,532,616$ previous addresses. In Figure A34 I show how the prior addresses of in-migrants within three miles of a farm change after construction. I find that after wind entry, the in-migrants are slightly more likely to have already lived near a wind farm. I conduct a parallel analysis on out-migrants in Figure A35. I find that out-migrants consistently choose destinations in a manner that leads to lower exposure to wind farms than had their pre-period migration patterns persisted. This suggests there may be some persistent heterogeneity in preferences for living near wind turbines. In Figure A36. I show that after wind farm entry, out-migrants had lived in the treated location for roughly 50 days longer, on average.

Figure A34: Effects on in-migrants' prior locations



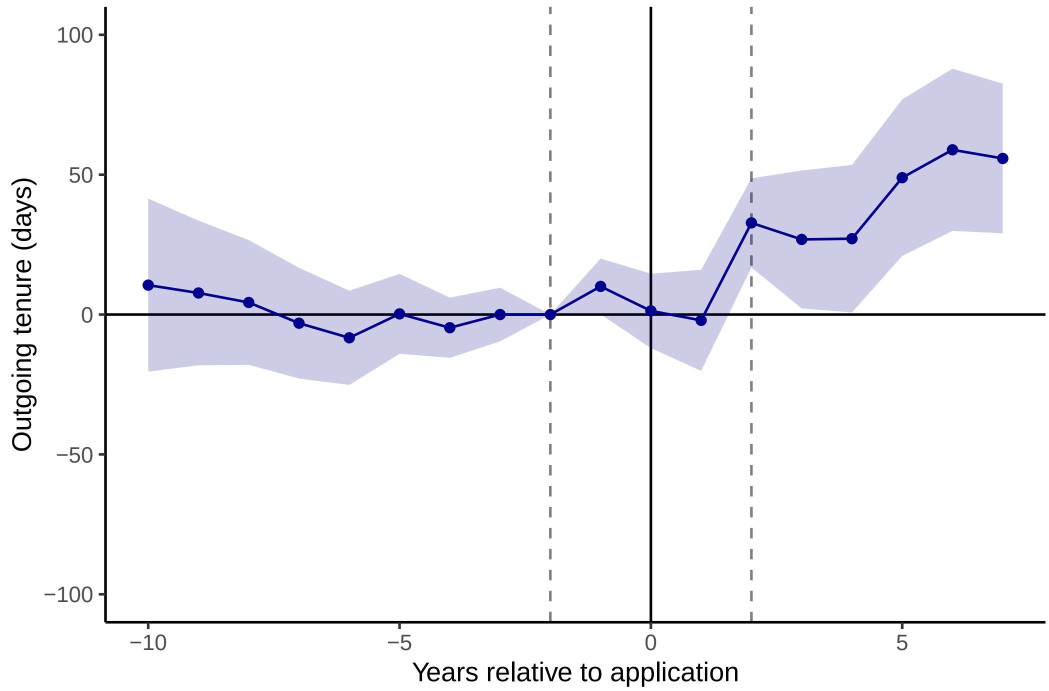
Note: Comparing the exposure to wind turbines of actual vs. simulated migration patterns had they moved from the same locations as from $t = -2$ to $t = -5$. Confidence intervals calculated using standard errors from the binomial distribution.

Figure A35: Effects on out-migration destinations



Note: Comparing the exposure to wind turbines of actual vs. simulated migration patterns had they moved to the same locations as from $t = -2$ to $t = -5$. Confidence intervals calculated using standard errors from the binomial distribution.

Figure A36: Effects on tenure of out-migrators



Note: Left dashed line is approximate timing of signing leases with landowners. Right dashed line is approximate timing of construction. Sample are all locations that ever had a wind farm proposed. Sun and Abraham (2021) difference-in-differences specification with year and event fixed effects. *Infutor* data from 2001-2016.

B.9 Robustness of the inefficiency of the aggregate distribution

B.9.1 Structural interpretation

In Section 4.5, I test whether development is efficiently trading off developer profit with household cost at a dollar-for-dollar rate. I do so by estimating the following probit regression,

$$\hat{\Pi}_l + \alpha \hat{E}_l + \gamma_{s(l)} + \varepsilon_l \geq 0, \tag{40}$$

where $\gamma_{s(l)}$ is a state fixed effect, $E_l = \bar{W} \cdot P_l$ where $\bar{W}$ is the mean preference for living near turbines from Section 4 and P_l is the value of homes within five miles of site l, and $\varepsilon_l \sim N(0, \mu)$.

I consider the following extension, which allows for more flexibility in the distribution of the unobservable. I posit the following decomposition where there is an unobservable component to profit as well as to the externality.

$$\begin{aligned} \Pi_l &= \hat{\Pi}_l + \gamma_{s(l)} + \varepsilon_{\Pi,l}, \\ E_l &= \hat{E}_l + \varepsilon_{E,l}. \end{aligned}$$

In this setting, I assume that the unobservable component of profitability is normally distributed and has a variance μ_Π. I also assume that the unobservable component of the externality has a variance following the central limit theorem given the estimated variance of the preference distribution in Section 4,$\varepsilon_{\Pi,l} \sim N(0, \mu_\Pi)$ and $\varepsilon_{E,l} \sim N\left(0, n_l \cdot \text{Var}(\omega) \cdot (P_l/n_l)^2\right)$. With an assumption that $\varepsilon_{\Pi,l}$ and $\varepsilon_{E,l}$ are independent, their sum becomes $\left(\varepsilon_{\Pi,l}+\varepsilon_{E,l}\right) \sim N\left(0, \mu_{\Pi}+n_l \cdot \operatorname{Var}(\omega) \cdot (P_l/n_l)^2\right)$. The analogous version of Equation 40 becomes

$$\frac{\hat{\Pi}_l + \alpha \hat{E}_l + \gamma_{s(l)}}{\sqrt{\mu_{\Pi} + n_l \cdot \operatorname{Var}(\omega) \cdot (P_l/n_l)^2}} + \varepsilon'_l \geq 0, \tag{41}$$

where $\varepsilon'_l \sim N(0,1)$. However, since μ_{Π} is unknown I must estimate it. When $n_l = 0$, Equation 41 collapses to become

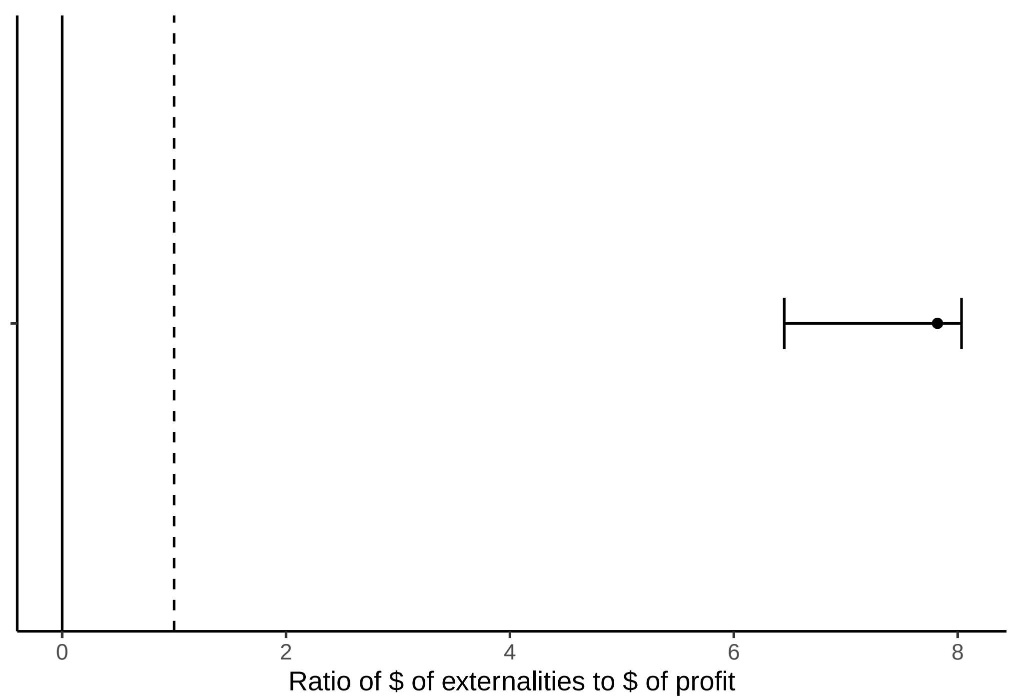
$$\frac{\hat{\Pi}_l + \gamma_{s(l)}}{\sqrt{\mu_{\Pi}}} + \varepsilon'_l \geq 0.$$

I then estimate, in a second step the equation

$$\frac{\hat{\mu}' \cdot \hat{\Pi}_l + \hat{\alpha} \hat{E}_l + \hat{\gamma}_{s(l)}}{\sqrt{\hat{\mu}_{\Pi} + n_l \cdot \operatorname{Var}(\omega) \cdot (P_l/n_l)^2}} + \varepsilon'_l \geq 0.$$

The ratio $\hat{\alpha}/\hat{\mu}'$ is the trade-off between a dollar of profit and a dollar of externality. I find this to be 7.82, which is quite similar to the estimate from Section 4.5. In Figure A37, I present the 95% confidence interval, calculated from a two-step Bayesian bootstrap.

Figure A37: Trade-off between profit and externality



Note: Using preference estimates from Section 4 and structure on the unobservable as above. 95% CI from 100 draws of a Bayesian bootstrap.

B.9.2 Data-driven robustness

I estimate a similar specification as before estimating the following probit regression,

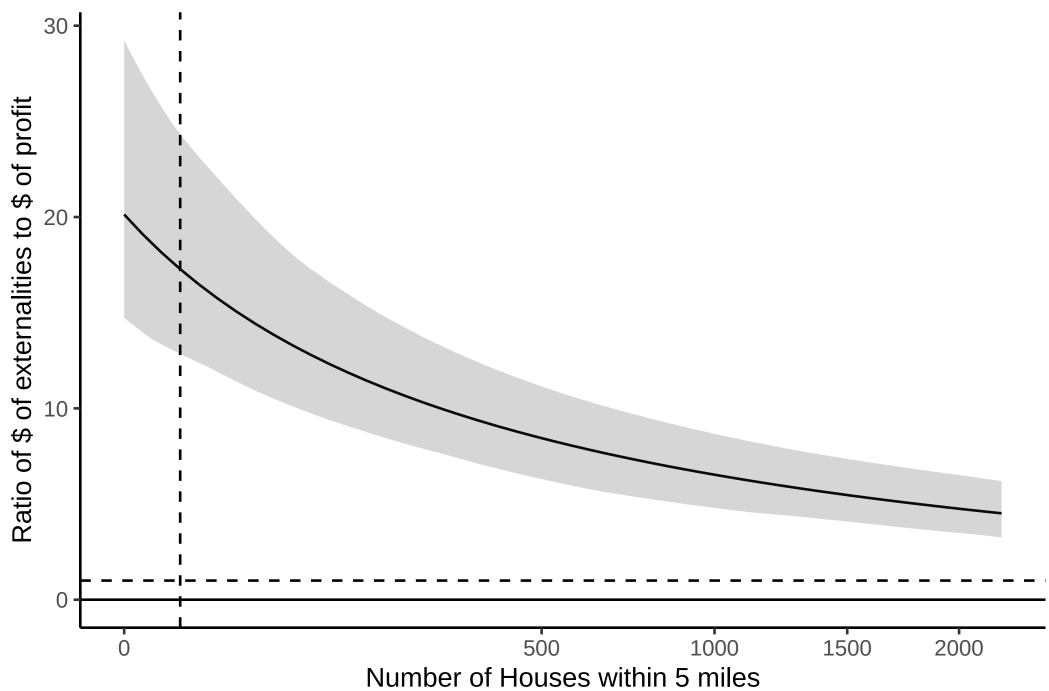
$$\hat{\Pi}_l + \alpha \hat{E}_l + \gamma_{s(l)} + \beta \sqrt{n_l} + \varepsilon_l \geq 0. \tag{42}$$

I consider the following extension, which allows for data-driven flexibility in the distribution of the unobservable. I maintain the following functional form decomposition where

$$\Pi_l = \hat{\Pi}_l + \gamma_{s(l)} + \varepsilon_{\Pi,l},$$
$$E_l = \hat{E}_l + \varepsilon_{E,l}.$$

To do so, I assume that the standard deviation of the unobservable is linear in the square-root of the number of homes, so $\varepsilon_{\Pi,l} \sim N\left(0, \left(\mu_\Pi^0 + \mu_\Pi^1 \sqrt{n_l}\right)^2\right)$ and $\varepsilon_{E,l} \sim N\left(0, \left(\vartheta^0 + \vartheta^1 \sqrt{n_l}\right)^2\right)$. I assume that $\varepsilon_{\Pi,l}$ and $\varepsilon_{E,l}$ are independent, as before. This allows me to measure the implied tradeoff between expected dollars of externality and expected dollars of profit at each value for the number of potentially exposed houses, n_l. I present the results in Figure A38, finding that the trade-off is particularly stark when there are very few homes, but remains substantially greater than one over the full support.

Figure A38: Trade-off between profit and externality: data-driven variance of the unobservable



Note: Using structure on the unobservable as above. 95% CI from 100 draws of a Bayesian bootstrap. The vertical dashed line represents the median number of exposed homes in the data.

C Demand estimation appendix

In this section I discuss the testable implications of my model of household demand census tracts described in Section 4.2. This model is central to identifying the full distribution of household preferences for living near wind turbines. It takes the form of a multinomial logit with observable preference heterogeneity based on each households' prior-year residential location. I estimate the model using a generalization of the change-of-variables from Berry (1994), rather than using the full choice likelihoods, which allows the cross-price elasticities to be used as un-targeted moments to validate the model.

In Section C.1 I provide a graphical illustration and proof of how the shape of demand may affect equilibrium price changes. In Section C.2, I show that observable characteristics explain little of the variation in choice shares relative to time-invariant fixed effects, suggesting the role of persistent unobserved heterogeneity. In Section C.3, I provide an illustrative Monte Carlo exercise showing that even when the true data-generating process is a random-coefficients logit, origin-destination fixed effects can closely approximate true price elasticities. In Section C.4, I document limited heterogeneity in cross-price elasticities by characteristic distance, within each origin-tract group, in contrast to the substitution patterns in Berry et al. (1995). In Section C.5 I describe the set of, potentially restrictive, assumptions under which this model nests dynamic discrete choice models. In Section C.6 I provide more detail on how I construct the moment inequalities described in Gandhi et al. (2023). In Section C.7, I compare my estimates of own-price elasticities to those implied by other estimated residential choice models. In Section C.8, I test whether the own-price elasticity of households' endowed options differs substantially from the own-price elasticities in the full sample. Finally, in Section C.9 I provide more detail on how I estimate the distribution of preferences for wind farms.

C.1 Relationship of demand curves with equilibrium price changes

I provide graphical intuition and a formal proof linking the demand for a given location to the equilibrium change in price and re-sorting. First, I show that in a discrete choice setting with heterogeneous preferences, using the change in price to infer the mean preference for a bundled characteristic introduces a bias whose sign cannot be determined without more information. As a corollary, I illustrate how variation in the shape of demand across locations generates systematic differences in equilibrium prices and re-sorting, which underpins the identification strategy in Section 4.3.2.

I define $v_{i,d}$ as the change in d's price at which i would be indifferent between living within the focal location and elsewhere, $v_{i,d} = u_{i,d} - \max_{d' \neq d} u_{i,d'}$ where $u_{i,l}$ is household i's indirect utility of living in l. I note for the CDF of $v_{i,d}$, V_d, demand for d is $1 - V_d\,(.)$. I consider additive preferences for some characteristic, such as living near wind farms, that are bundled with the location and are drawn from a distribution W.

Proposition 2. *The sign of $\Delta p - \mathbb{E}[W]$ is the same as the sign of $\int_{-\infty}^{0} v(x) \cdot [1 - W(-x + \mathbb{E}[W])]\, dx - \int_{0}^{\infty} v(x) \cdot W(-x + \mathbb{E}[W])\, dx$*

Proof. I begin by noting that for some Δp and some household i such that $v_{i,d}$, i will live in d if and only if $v_{i,d} + \omega_i - \Delta p \geq 0$ which has a probability of $1 - W\left(\Delta p - v_{i,d}\right)$. I note that the market clearing condition can be transformed into one in which the mass of in-migrants, households i where $v_{i,d} < 0$ and $v_{i,d} + \omega_i + \Delta p \geq 0$, is equal to the mass of out-migrants. This implies the following market clearing condition

$$\int_{-\infty}^{0} v(x) \cdot [1 - W(-x + \Delta p)]\, dx = \int_{0}^{\infty} v(x) \cdot W(-x + \Delta p)\, dx, \tag{43}$$

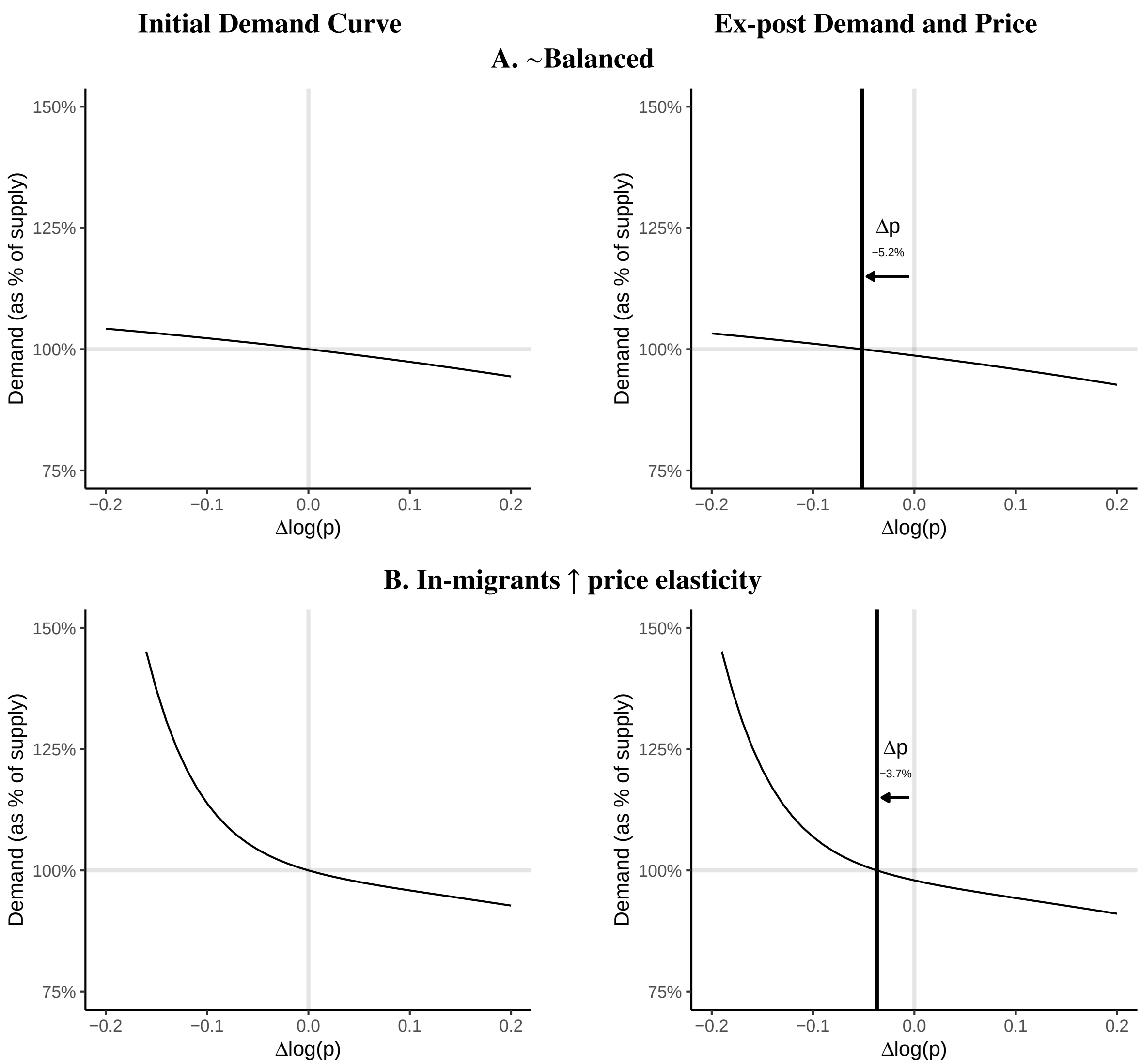
Consider the case where

$$\int_{-\infty}^{0} v(x) \cdot [1 - W(-x + \mathbb{E}[W])]\, dx > \int_{0}^{\infty} v(x) \cdot W(-x + \mathbb{E}[W])\, dx \tag{44}$$

Since W is a CDF, $W(-x + \Delta p)$ and $1 - W(-x + \Delta p)$ are monotonically increasing and decreasing in Δp respectively. If $v(x) > 0$ is non-zero everywhere and there is a Δp where then $\Delta p > \mathbb{E}[W]$. The opposite holds when the inequality is reversed, by symmetry. If the two are equal, $\Delta p = \mathbb{E}[W]$ mechanically. □

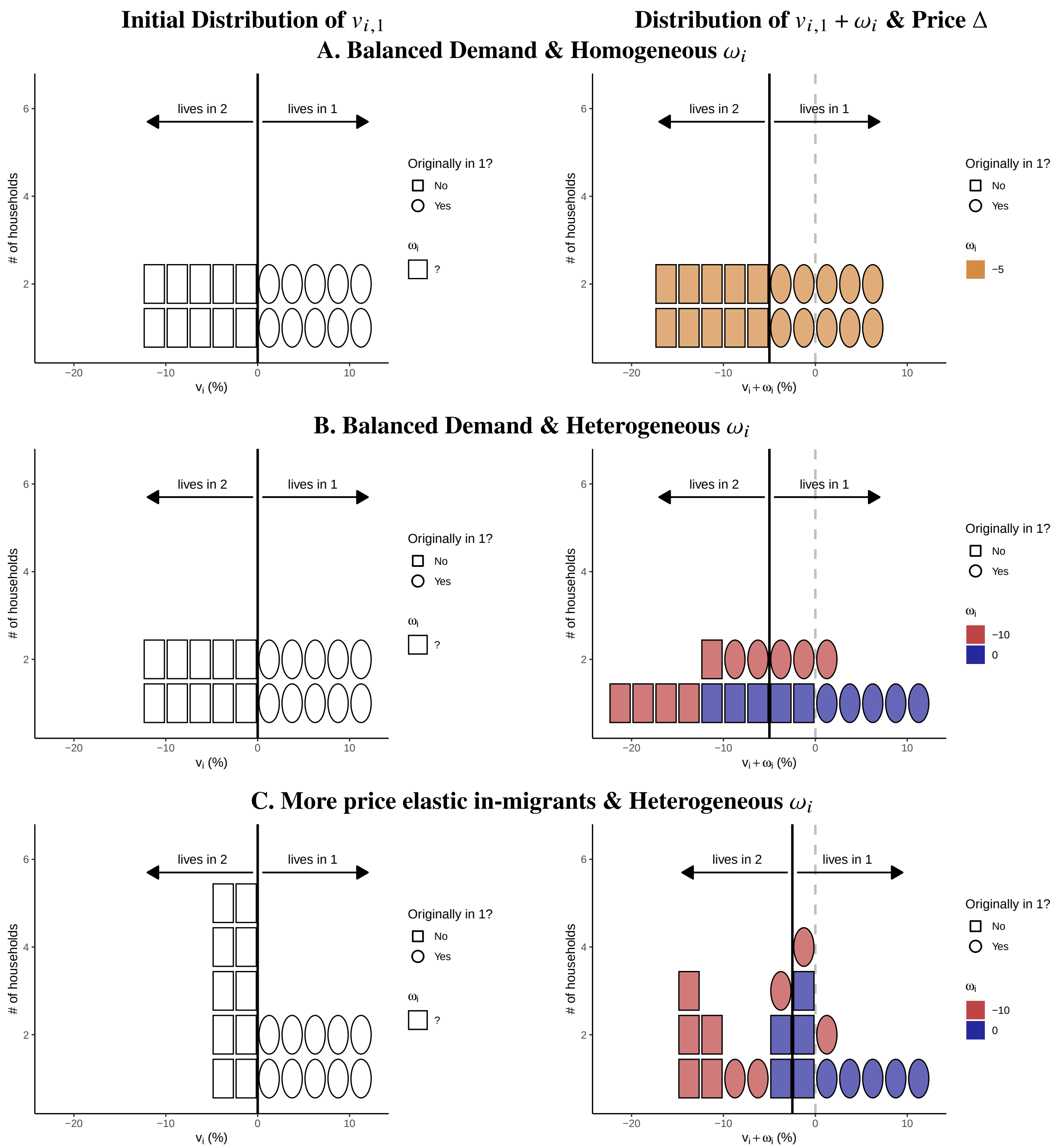
Figure A39 illustrates how the distribution of $v_{i,d}$ affects equilibrium price changes and re-sorting. I consider alternative distributions of $v_{i,d}$ and simulate equilibrium outcomes ω_i takes values -10% or 0% with equal probability. In the first row, $v_{i,d}$ is approximately balanced around 0. In the second, more households have $v_{i,d} < 0$, representing a larger mass of marginal potential in-migrants. In these simulations, I hold quantity fixed and represent the market-clearing price change with the thick black line. In the first case, $\Delta p = -5.2\%$; in the second, $\Delta p = -3.7\%$, even though wind preferences, W, are identical. Figure A40 illustrates how preference heterogeneity and demand curve shape jointly determine the extent of re-sorting after wind farm entry. With homogenous preferences there would be no re-sorting, which is contradicted empirically by the estimates in Figure A5. Holding preference heterogeneity fixed, smaller equilibrium price changes imply a larger re-sorting margin. Without observing the full preference distribution, it is impossible to determine whether the price effects in Section 4.1 over- or under-state true preferences. This also explains why similar amenity changes can produce very different price effects across locations, depending on the demand curve they face.

Figure A39: Relating the shape of demand curves and equilibrium price changes



Note: In each row, in the left panel I present alternative baseline demand curves for a treated location d. In the right panel, I present the new demand curve after wind farm entry where preferences are heterogeneous and may be -0.1 or 0 with equal probability. In this example, supply is in-elastic in the short run, so the equilibrium price, represented by the vertical line, must re-equilibriate to clear the market.

Figure A40: Illustration of how the shape of demand curves affect price and re-sorting



Note: In the first row, with homogeneous preferences, the price change is equal to the average preference and no households move in response. In the second row, the price change is equal to the average preference. In the third row, due to the shape of demand and preference heterogeneity, the price change does not equal the average preference. The posterior distribution of the ovals is identical in the second and third rows, however the equilibrium price change is smaller in magnitude in the third row so 20% and 30% of households move in response to the wind farm entry in the second and third rows respectively.

C.2 Can origin-destination shares be predicted by observable characteristics?

I assess how well observable characteristics predict origin-destination flows and compare this explanatory power to that of persistent, time-invariant heterogeneity. Using the main estimation sample from Section 4.4.1, I predict migration shares for all origin-destination pairs with non-zero flows at any time between 2000 and 2013.

Results are shown in Appendix Table A13. Columns (1) and (3) regress migration shares on log-transformed characteristic distance across six key observables. Larger differences across these dimensions are strongly associated with lower migration volumes, though the model explains relatively variation (R^2 of 0.147 and 0.177). Columns (2) and (4) use a more flexible specification, incorporating nonparametric functions of characteristic distances and their pairwise interactions. This only modestly improves explanatory power, raising the R^2 to 0.162 and 0.190. Finally, in Columns (3) and (6), adding origin-destination fixed effects increases the R^2 to 0.320 and 0.337.

I draw two main conclusions from this exercise. First, origin-destination fixed effects explain substantially more variation than observable characteristics alone. Secondly, the strong explanatory power of these fixed effects indicates that migration flows are persistent over time. This persistence likely reflects enduring unobserved characteristics and stable origin-specific preferences for both observable and unobservable features of each destination.

C.3 Can origin-destination FEs' index multidimensional unobservable heterogeneity?

In my main specification, I proxy for multi-dimensional preference heterogeneity using households' prior location choices. To assess the performance of this approach, I conduct a series of Monte Carlo exercise comparing my estimates of own- and cross-price elasticities to their true values. I simulate data from a random-coefficients logit model that my estimation framework deliberately mis-specifies. In an important deviation from Berry et al. (1995), I allow households to sort along two dimensions of unobservable heterogeneity. I consider a baseline setting with five locations, l, each characterized by two potentially time-varying unobservable characteristics, $x_{1,l,t}$ and $x_{2,l,t}$. Household i receives the following indirect utility,

$$u_{h,l,t} = 3 - \left(\beta_{1,h,t} - x_{1,l,t}\right)^2 - \left(\beta_{2,h,t} - x_{2,l,t}\right)^2 - \log\left(p_{l,t}\right) + \xi_{l,t} + \varepsilon_{h,l,t}, \quad (45)$$

where $\varepsilon_{h,l,t}$ are EV1 errors drawn from a distribution with standard deviation $1/\alpha$, and $\beta_{1,h,t}$ and $\beta_{2,h,t}$ are household h's potentially time-varying random components of utility. This framework generalizes many location-choice contexts, where households seek to minimize deviations from their ideal attributes–such as distance to workplaces and family, preferred climate, or neighborhood character. Both households' bliss points, as well as the characteristics of each location, may change over time.

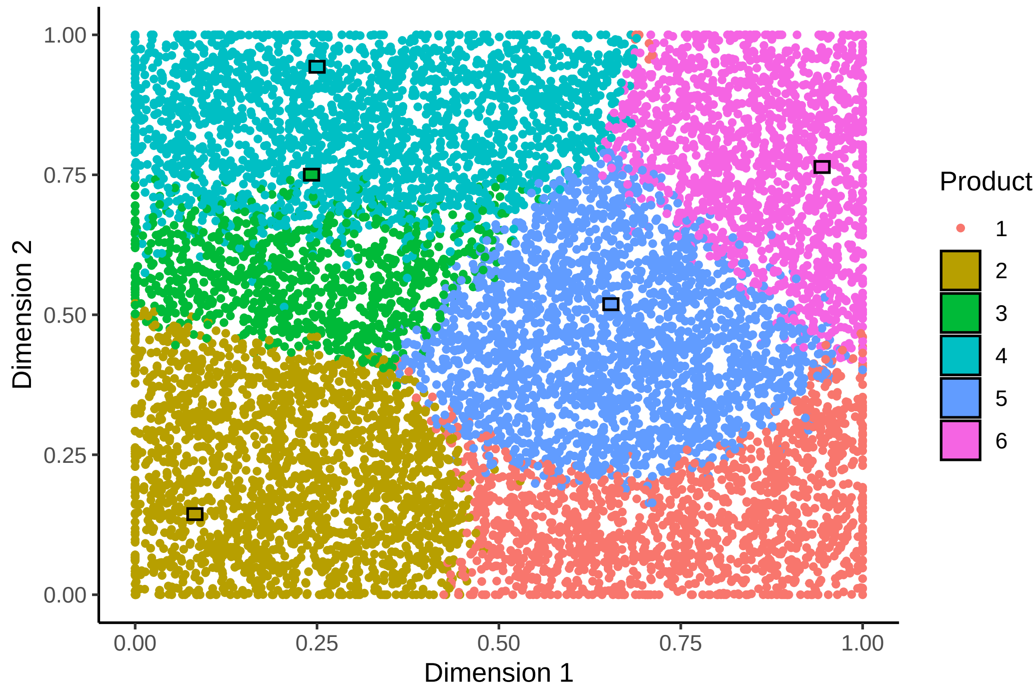
For each h and t I generate data as follows where $\beta_{1,h,t} = \min\left(1, \max\left(0, \beta^0_{1,h} + \beta^1_{1,h,t}\right)\right)$, $\beta^0_{1.h} \sim U([0,1])$, and $\beta^1_{1,h,t} \sim U([-r/2, r/2])$, and identically for $\beta_{2,h,t}$, $x_{1,h,t}$, and $x_{2,h,t}$. This allows for serial correlation in preferences and characteristics. In each period, I solve for an equilibrium price vector $p^*_{l,t}$ that ensures that all locations, including the outside option, have equal shares. This is analogous to a price equilibrium in short-run supply inelastic markets that clear with price. To allow for instrumental variables estimation of price elasticities, I set $p_{l,t} = p^*_{l,t} * z_{l,t}$ where $z_{l,t} \sim N(1, 0.02)$. I consider a variety of values for α and r that alter both the dispersion of utilities and how predictable next period's choice is given the prior period's choice.

Table A13: Predicting shares of in-state moves

Dependent Variable:		$\log\left(s^o_{d,t} + 10^{-8}\right)$			$\left[\log\left(\frac{N^o_t s^o_{d,t}+\iota_l}{N^o_t}\right) + \log\left(\frac{N^o_t s^o_{d,t}+\iota_u}{N^o_t}\right)\right]/2$	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Log(char. dist. +10^{-4})						
Distance (mi)	-1.019			-1.440		
	(0.002)			(0.003)		
HH income	-0.042			-0.059		
	(0.001)			(0.002)		
% college	-0.135			-0.189		
	(0.001)			(0.002)		
% senior	-0.022			-0.029		
	(0.001)			(0.001)		
% white	-0.136			-0.188		
	(0.001)			(0.002)		
% poverty	-0.048			-0.068		
	(0.001)			(0.002)		
Fixed-effects						
Origin tract × Year	Yes	Yes	Yes	Yes	Yes	Yes
Destination × Origin			Yes			Yes
Splines						
Char. dist. (3 d.f.)		Yes			Yes	
All interactions (2 d.f.)		Yes			Yes	
Observations	16,105,668	16,105,668	16,105,668	16,105,668	16,105,668	16,105,668
R^2	0.147	0.162	0.320	0.177	0.190	0.337

Note: Sample includes all origin-destination flows from 2000 – 2013 for 2500 randomly selected origin tracts for which the flow is *ever* non-zero. Standard errors are clustered at the origin tract × destination tract level. All variables, besides distance, are in z-scores.

Figure A41: Simulated choice regions



Note: Shown for α = 100 and r = 0.1. Both dimensions, for all households and all products, may be unobserved to the econometrician. The rectangles are the location of each product. Each dot is at a household's $\vec{\beta}$ and is colored by the product which maximizes their utility.

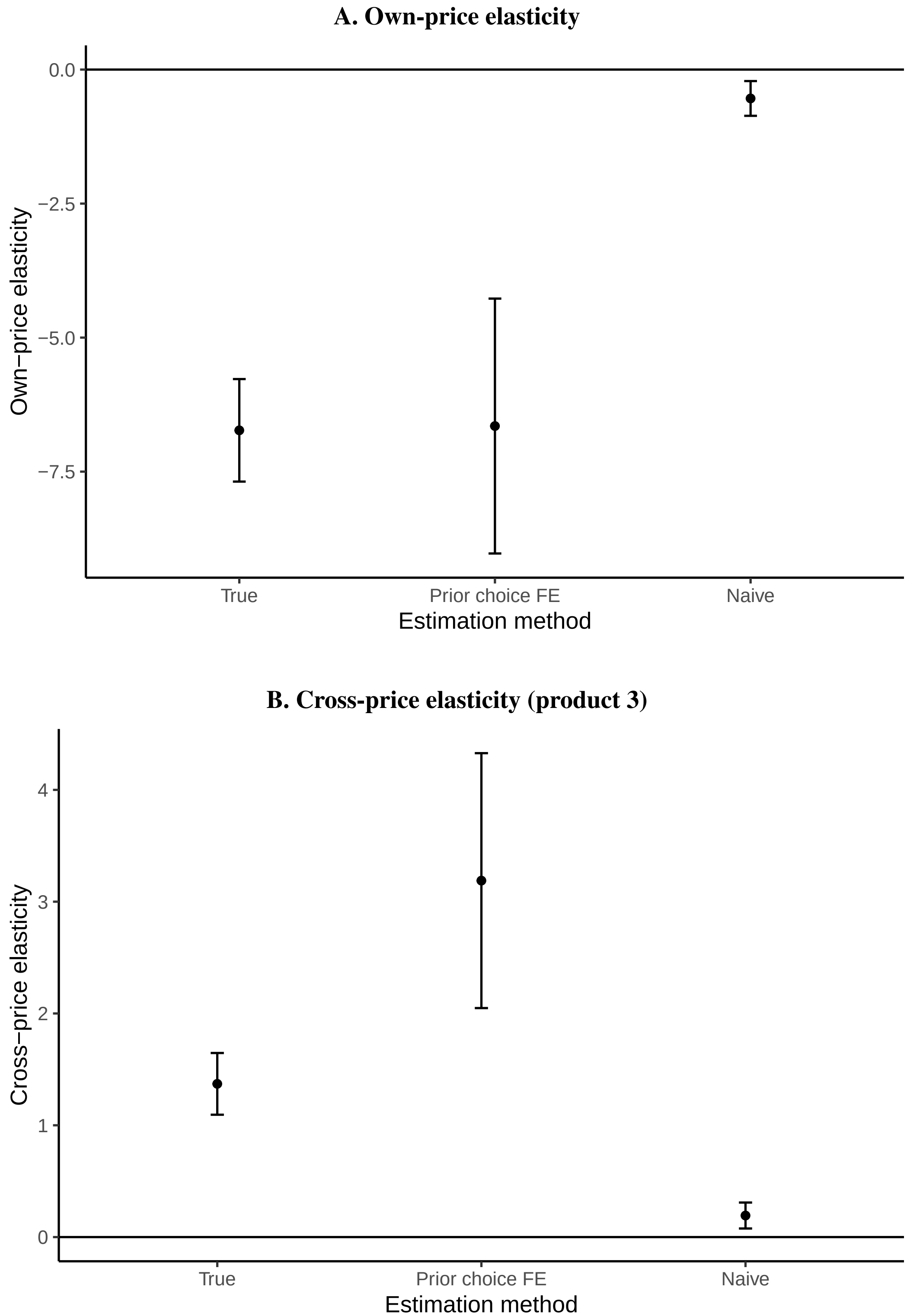
I estimate the following utility specifications

$$u^{\text{o.f.e.}}_{h,l,t,o} = \gamma_l^{o(h)} - \alpha \log\left(p_{l,t}\right) + \xi_{l,t}^{o(h)} + \varepsilon_{h,l,t}, \tag{46}$$

$$u^{\text{n}}_{h,l,t} = \beta_0 - \alpha \log\left(p_{l,t}\right) + \xi_{l,t} + \varepsilon_{h,l,t}, \tag{47}$$

using a Berry (1994) inversion and compare the estimated own- and cross-price elasticities to the true responses to a 5% increase in the price of location 2. In principle, one could specify a random coefficient on an indicator variable for each product, drawing from a sufficiently flexible distribution to match the data. In practice, however, without incorporating information on prior choices, this specification may be difficult to consistently estimate without far more data than is required for consistent estimation of Equations 46 and 47. In Figure A42, I compare the estimates from each strategy to the true elasticities. Overall, conditioning on prior choices and estimating a simple logit by group (as in Equation 46) more accurately reproduces the true substitution patterns than the pooled estimates. Importantly, this approach requires no additional information beyond a panel of consumer choices, yet allows for flexible unobserved heterogeneity and sorting along multiple unobserved dimensions.

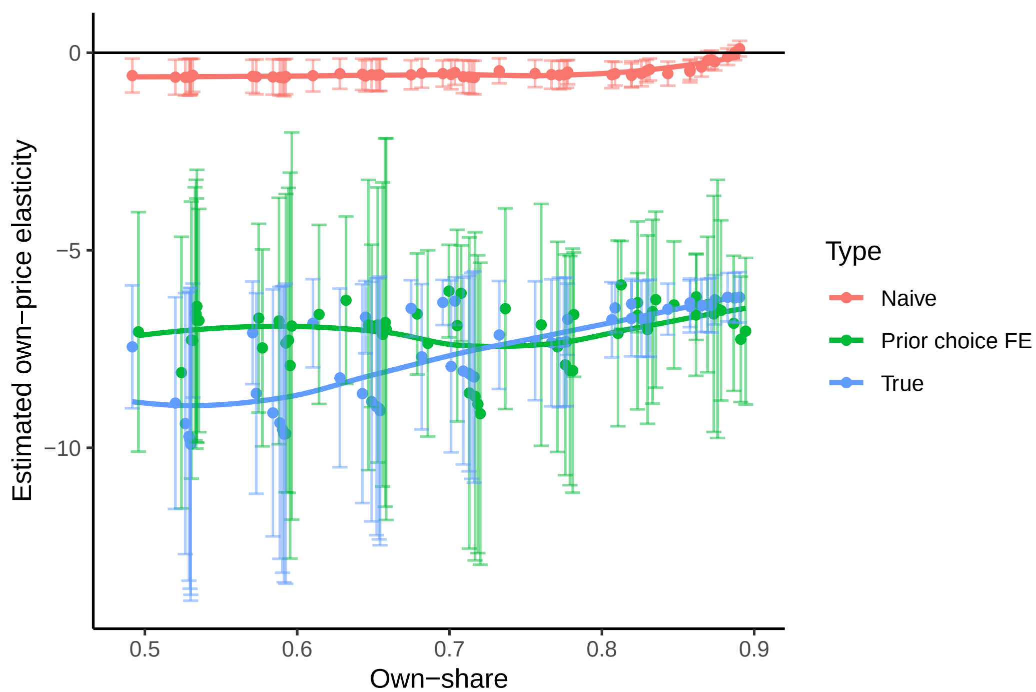
Figure A42: True price elasticities vs. estimates



Note: Both specifications are presented considering 20 simulated periods where α = 100 and r = 0.1. Each true price elasticity is calculated by increasing the price of product 2 by 5%.

Finally, I consider alternative values for both α and r. I plot their estimated own-price elasticities in Figure A43. I define the own-share as the average fraction of households h that choose the same location l in both t and $t+1$. This measure serves as a proxy for the informativeness of prior choices for future utility.[73] The deviation between the true and estimated own-price elasticities is largest when the own-share is smallest. In my sample, the average own-share is 95.4%. These Monte Carlo simulations suggest that when both consumer preferences and product characteristics are persistent, including product × prior choice fixed effects can be a powerful tool for recovering true price elasticities and substitution patterns. This approach performs well in settings where standard demand estimation methods may fall short. This method accommodates sorting along multiple dimensions of unobserved heterogeneity. Moreover, even if the product characteristics $x_{1,l,t}$ and $x_{2,l,t}$ were observe, it insulates against misspecification of the distribution of households' random coefficients $\beta_{1,h,t}$ and $\beta_{2,h,t}$.

Figure A43: Simulated elasticities and estimates



Note: I show the estimated price elasticities under a variety of specifications of α and r.

C.4 Cross-price elasticities by characteristic distance

A key implication of the demand model in Section 4.2—common to multinomial logit discrete-choice models—is that the cross-price elasticity of location l' with regard to price in location l is constant across all alternatives $l \neq l'$. In many empirical settings, this assumption is untenable and eliminates the variation of interest.[74] A central motivation of Berry et al. (1995) was to allow for the ability to recover flexible cross-

[73]The own-share and the R^2 of a regression of each household's utility from each product are almost exactly one-to-one. A 1 SD increase in own-share is associated with a 0.99 SD increase in the R^2.

[74]As discussed in Berry and Haile (2021) the standard multinomial logit "impose(s) strong a priori restrictions on demand elasticities—and, therefore, on markups, pass-through, and other key quantities of interest—that are at odds with common sense and standard economic models." I avoid this a priori restriction since although there are a priori restrictions on demand elasticities within type, these are quite flexible across types and lead to vastly heterogeneous demand elasticities.

price elasticities. As they note, the multinomial logit "model would necessarily predict that an increase in the price of BMW would generate equal increases in the demand for Yugos and for Mercedes. This contradicts the intuition which suggests that couples of goods whose characteristics are more "similar" should have higher cross-price elasticities." This observation naturally motivates a falsification test for the multinomial logit model: examining how the cross-price elasticity varies with the observable similarity between two products.

I empirically test this prediction of the model in Section 4.2 that cross-price elasticities are independent of the distance between observable characteristics. I examine the cross-price elasticity associated with changes in the price of the origin tract.[75] I restrict the sample to destinations at least 50 miles from the origin census tract to ensure that the price instruments for the origin tract are independent of those for the destination tract. Table A14 presents the central estimate of this cross-price elasticity, with a confidence interval that includes the value implied by the full model. To assess heterogeneity in cross-price elasticities I estimate the following specification:

$$\log\left(s_{d,t}^{o} + 10^{-8}\right) = \gamma_d^o + \phi_{s(d),t} + \beta_d^o \log\left(p_{o,t}\right) + \varepsilon_{d,t}^o, \tag{48}$$

where γ_d^o is a time-invariant origin-destination fixed effect, $\phi_{s(d),t}$ is a state, $s(d)$, by time fixed effect, and $\beta_d^o = \beta_0 + \beta_1 \delta\left(X_o, X_d\right)$ for some scalar observable X measured in o and d and δ is the Euclidean distance operator. I instrument for $\log\left(p_{o,t}\right)$ using the same instruments described in Section 4.4.1, interacting each instrument with $\delta\left(X_o, X_d\right)$ to capture heterogeneity across observable characteristic distances. Figure A44 plots the ratio of the estimated $\alpha_{d'}^{o'}$ when $\delta\left(X_{o'}, X_{d'}\right)$ is one standard deviation above the sample mean of $\delta\left(X_o, X_d\right)$, relative to overall the mean $\bar{\alpha}_d^o$. I find that this ratio is not statistically different than one for four of the five estimated cross-price elasticities. All five estimates of cross-price elasticity heterogeneity are quantitatively small, with the largest implying that a one standard-deviation greater difference in tract income is associated with a slightly less than 2.5% smaller cross-price elasticity. Overall, the multinomial logit model fits the data well once migration shares are modeled separately for each origin tract.

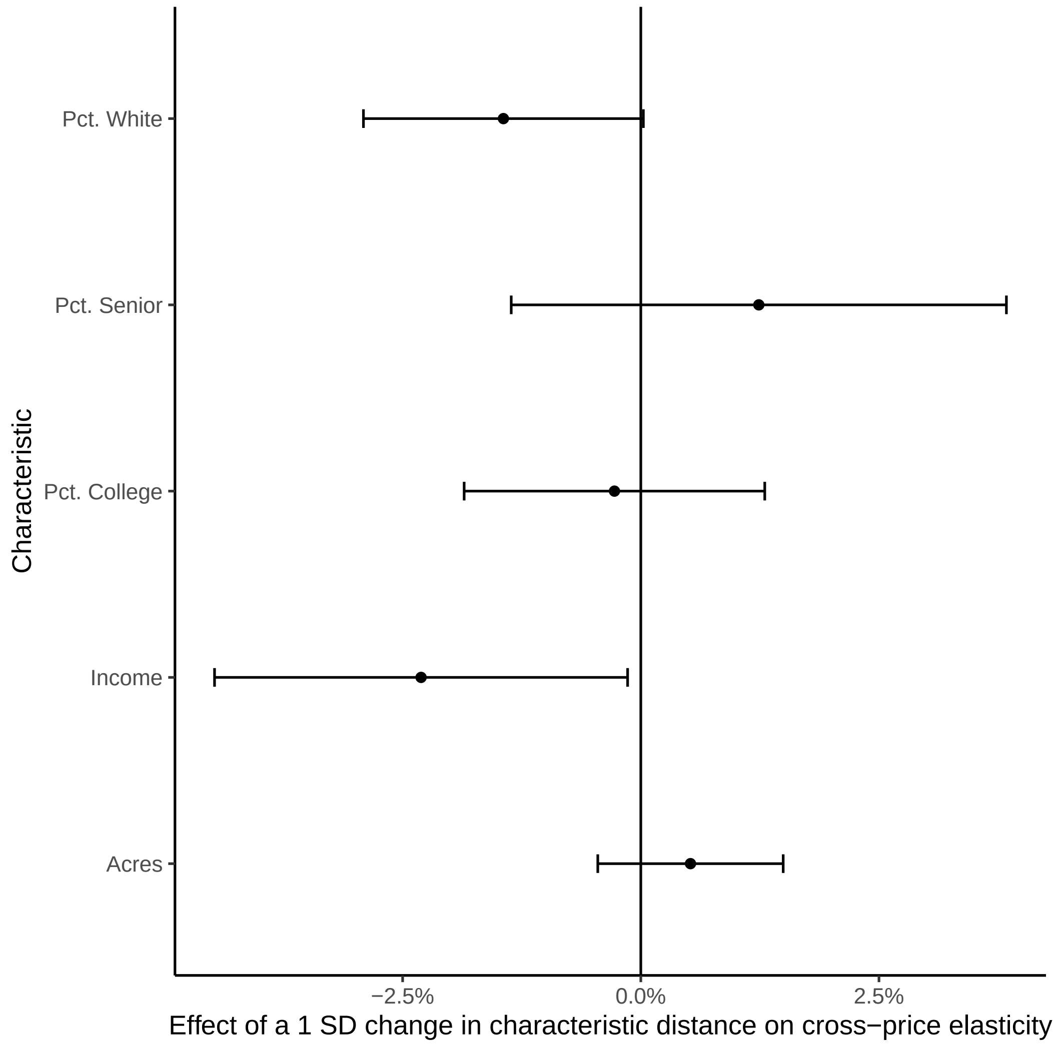
Table A14: Cross-price elasticity relative to origin price

Dependent Variables:	$\log\left(s_{d,t}^{o} + 10^{-8}\right)$	$\left[\log\left(\left(N_t^o s_{d,t}^o + \iota_l\right)/N_t^o\right) + \log\left(\left(N_t^o s_{d,t}^o + \iota_u\right)/N_t^o\right)\right]/2$
Model:	(1)	(2)
$\log\left(p_{o,t}\right)$	2.581	2.033
	(0.622)	(0.739)
State × Year FE	Yes	Yes
Destination × Origin FE	Yes	Yes
Observations	5,347,522	5,347,522

Note: Column (1) presents a naive smoothing of the shares. Column (2) targets the average of the bounds explained in Section 4.4.1. Both regression have a first stage F-statistic of 126.6. Standard errors clustered at the origin × destination level.

[75] The exact formula for the cross-price elasticity in this case is $\alpha^o s_{o,t}^o$, which illustrates why using origin prices, which have typically large choice shares, would be expected to have the largest cross-price elasticities.

Figure A44: The effect of a 1 SD increase in characteristic distance on cross-price elasticity



Note: Confidence intervals calculated from parametric bootstrap using the delta method. Standard errors clustered at the origin × destination level.

C.5 Can origin-destination FEs' allow for strategic moves?

I show that, under suitable conditions, the utility specification in Equation 3 can be interpreted as a dynamic discrete choice model. This approach is common in the literature on residential mobility, including Kennan and Walker (2011), Bayer et al. (2016), Diamond et al. (2019), Bilal and Rossi-Hansberg (2021), Davis et al. (2021), and Almagro and Dominguez-Iino (2025), who model location choice as a dynamic decision. I consider a model in which household i, from origin tract o, receives the following flow utility from living in tract d at time t

$$u^{o,F}_{i,j,d,t} = \underbrace{\omega_i w_{j,t}}_{\text{wind prefs}} + \underbrace{\gamma^{o,F}_{d,m_{i,j}}}_{\text{tract prefs.}} + \underbrace{\kappa^{o}_{d,m_{i,j},t}}_{\text{moving cost}} - \underbrace{\alpha^{o}\log(p_{d,t})}_{\text{price}} + \underbrace{\beta X_{d,t}}_{\text{chars.}} + \underbrace{\mu^{0}_{t}}_{\text{FE}} + \underbrace{\xi^{o}_{d,m_{i,j},t}}_{\text{unobs.}} + \underbrace{\varepsilon_{i,m_{i,j},d,t}}_{\text{T1EV}}, \tag{49}$$

where each period households re-draw idiosyncratic Type I Extreme Value shocks, and there are both common preferences for tracts $\gamma^{o,F}_{d,m_{i,j}}$ and unrestricted moving costs $\kappa^{o}_{d,m_{i,j},t}$. When a household relocates, their baseline preference type updates to be in accordance with their new origin location. Thus, household i's dynamic problem can be written recursively as,

$$V^{o}_{i,t} = \max_{d,j} u^{o,F}_{i,j,d,t} + \beta \mathbb{E}\left[V^{o}_{i,d,t+1}\right]. \tag{50}$$

I further assume that moving costs can be decomposed into a common origin-destination specific, time-invariant component and a state-level, time-varying component, so that $\kappa^{o}_{d,m_{i,j},t} = \kappa^{o}_{d,m_{i,j}} + \phi_{m_{i,j},s,t}$, where s indexes the state of destination d. I also assume that the expected flow value of living in location d is constant over time, i.e., $\mathbb{E}\left[V^{o}_{d}\right] = \mathbb{E}\left[V^{o}_{i,d,t}\right]$ for all i and t in the sample period. This assumption, rules out systematic changes over time in the attractiveness of d for households originating in o. In particular, this rules out dynamic changes in neighborhood character, as emphasized in Almagro and Dominguez-Iino (2025). However, it is consistent with the stylized facts in Garin et al. (2024), who show that while individuals' earnings change and neighborhood choices evolve, the overall neighborhood incomes are relatively static.

With these assumptions, the likelihood that a household coming from o at time t chooses to live in destination d (or move to house j) becomes

$$\pi^{o}_{i,j,d,t} = \frac{\exp\left(u^{o,F}_{i,j,d,t} + \beta \mathbb{E}\left[V^{o}_{d}\right]\right)}{1 + \sum_{d',j'} \exp\left(u^{o,F}_{i,j',d',t} + \beta \mathbb{E}\left[V^{o}_{d}\right]\right)}. \tag{51}$$

Collecting terms, I can write

$$\gamma^{o}_{d,m_{i,j}} = \gamma^{o,F}_{d,m_{i,j}} + \kappa^{o}_{d,m_{i,j}} + \beta \mathbb{E}\left[V^{o}_{d}\right] \tag{52}$$

and note that the specification estimated in Equation 3 nests this, somewhat restrictive, form of dynamics.

When a shock such as a wind farm entry occurs, I assume the resulting change in utility is both sudden and persistent. Under this interpretation, ω_i, reflects the combined flow utility and continuation value of living near a wind farm. The remaining components of $\mathbb{E}\left[V^{d}\right]$, unrelated to wind farms, then are separable and are observed into the baseline location preferences.

This implies that the instruments Z used for $\log\left(p_{d,t}\right)$ must be excluded from affecting continuation values. Because the continuation value, $\beta \mathbb{E}\left[V^{d}_{i,t+1}\right]$, is unobserved, if $\mathbb{E}\left[Z \cdot \left(\mathbb{E}\left[V^{d}_{i,t+1}\right] - \mathbb{E}\left[V^{d}\right]\right) | X\right] \neq 0$, then the exclusion restriction to identify α^{o} is violated. Thus, it is important to use instruments Z that generate primarily short-run, idiosyncratic variation in prices, rather than persistent long-run trends. Contemporaneous supply shocks, such as the death shocks in Section 4.4.1, satisfy this requirement. In contrast, standard instruments such as those in Bayer et al. (2007) or other variants of the Berry et al. (1995) instruments, rely on durable changes in nearby housing supply, which are persistent and therefore affect expectations of the future. This persistence makes such instruments more likely to violate the exclusion restriction in this setting.

C.6 Constructing moment inequalities for Section 4.3.1

I build two moment inequalities–one that *on average* serves as the upper bound and one that *on average* serves as the lower bound for $\delta^{o}_{d,w,t}$. These bounds rely on the existence of some upper (lower) bounds on the true choice probabilities ι_u (ι_l). I then choose choose some $\bar{\iota}_l \leq \iota_l \leq \iota_u \leq \bar{\iota}_u$,[76] and estimate parameters

[76] In practice, as suggested in Gandhi et al. (2023), I choose an extremely low $\bar{\iota}_l$ to be $1/\left(N^{\text{hh}}_{l} \cdot C_{S(l)} \cdot 100\right)$ where N^{hh}_{l} is the number of households, $C_{S(l)}$ is the number of census tracts in state $S(l)$, and 100 is an arbitrarily large smoothing parameter.

to satisfy the following conditional moment inequalities,

$$\mathbb{E}\left[\log\left(\left(N_t^o s_{d,w,t}^o + \bar{\iota}_u\right)/N_t^o\right) - \log\left(\pi_{d,w,t}^o\right)|z_{d,t}\right] \geq 0, \text{ and} \tag{53}$$

$$\mathbb{E}\left[\log\left(\left(N_t^o s_{d,w,t}^o + \bar{\iota}_l\right)/N_t^o\right) - \log\left(\pi_{d,w,t}^o\right)|z_{d,t}\right] \leq 0. \tag{54}$$

Where N_t^o are the number of individuals in o at time t and $z_{d,t}$ are discretized versions of my continuous instruments explained in more detail below.

I combine these inequalities with the orthogonality condition that $\mathbb{E}[\xi|z] = 0$ to solve for the parameters of $\delta_{m,d,t}^o - \xi_{m,d,t}^o$ to satisfy

$$\mathbb{E}\left[\log\left(\left(N_t^o s_{d,w,t}^o + \bar{\iota}_u\right)/N_t^o\right) - \log\left(\pi_{0,t}^o\right) - \left(\delta_{d,w,t}^o - \xi_{d,w,t}^o\right)|z_{d,t}\right] \geq 0, \text{ and} \tag{55}$$

$$\mathbb{E}\left[\log\left(\left(N_t^o s_{d,w,t}^o + \bar{\iota}_l\right)/N_t^o\right) - \log\left(\pi_{0,t}^o\right) - \left(\delta_{d,w,t}^o - \xi_{d,w,t}^o\right)|z_{d,t}\right] \leq 0, \tag{56}$$

where $\pi_{0,t}$ is the probability of choosing the outside option.[77] I note that since $\delta_{m,d,t}^o - \xi_{m,d,t}^o$ is linear as a function of a full vector of parameters $\hat{\theta}$ there is some $X_{o,d,m}^f$ such that $\delta_{m,d,t}^o - \xi_{m,d,t}^o = X_{o,d,m}^f{}'\theta$. I then form the following sample moments and solve for $\hat{\theta}$, as follows

$$\bar{m}_u(\theta, g) := \frac{1}{N_{JT}} \sum_t \sum_{o,d,w} \left(\log\left(\left(N_t^o s_{d,w,t}^o + \bar{\iota}_u\right)/N_t^o\right) - \log\left(\pi_{0,t}\right) - X_{o,d,w,t}^f{}'\theta\right) g\left(z_{d,t}\right), \tag{57}$$

$$\bar{m}_l(\theta, g) := \frac{1}{N_{JT}} \sum_t \sum_{o,d,w} \left(\log\left(\left(N_t^o s_{d,w,t}^o + \bar{\iota}_l\right)/N_t^o\right) - \log\left(\pi_{0,t}\right) - X_{o,d,w,t}^f{}'\theta\right) g\left(z_{d,t}\right), \tag{58}$$

$$\hat{\theta} = \arg\min_\theta \sum_g \mu(g) \left([\bar{m}_u(\theta, g)]_-^2 + [\bar{m}_l(\theta, g)]_+^2\right). \tag{59}$$

Where $[x]_- = \min\{0, x\}$, $[x]_+ = \max\{0, x\}$, and μ is any weighting of a set of instrumental indicator functions g.

As proposed by Gandhi et al. (2023), to identify the parameters given the moment inequalities, I discretize the instruments $Z_{d,t}^1$ and $Z_{d,t}^2$. I follow their procedure to do so and first transform $\tilde{Z}_{d,t}^c = \Phi\left(\hat{\Sigma}_Z^{-1/2} Z_{d,t}^c\right)$, where Φ is the CDF of the standard normal and $\hat{\Sigma}_Z$ is the sample covariance matrix of Z. I then construct a discretized grid of these instruments

$$\mathcal{G} = \left\{g\left(\tilde{Z}_{d,t}^1, \tilde{Z}_{d,t}^2\right) = \mathbb{I}\left\{\left(\tilde{Z}_{d,t}^1, \tilde{Z}_{d,t}^2\right) \in B_{a,r}\right\} : B_{a,r} \in \mathcal{B}\right\}, \tag{60}$$

$$\mathcal{B} = \left\{ \left(\times_{u=1}^2 \big((a_u - 1)/(2r), a_u/(2r) \big]\right) \times \{\zeta\} : a_u \in \{1, 2, ..., 2r\}, \right. \tag{61}$$

$$\left. \text{for } u = 1, 2,\ r = 6,\ \zeta \in \tilde{\mathcal{Z}} \right\}.$$

I choose $\mu(\{g\})$ to be the empirical frequency of each $B_{a,r} \in \mathcal{B}$. Finally, I create an identical discretized grid for the instruments beginning with $Z_{o,d,t}^{1,I} = Z_{o,d,t}^1 \cdot I_o$ and $Z_{d,t}^{2,I} = Z_{d,t}^2 \cdot I_o$ where I_o is origin o's income in 2000 in order to recover α_I.

This can be interpreted as essentially being a lower bound wherein 1 household would move to l in 100 years. I choose $\bar{\iota}_u$ so that each tract in state s is chosen with equal probability.

[77] As instructed in Gandhi et al. (2023), I define $\pi_{0,t}$ to be a simple modification of $s_{0,t}^o$ of $\max\left(s_{0,t}^o, 10^{-4}\right)$, which, per their proof is allowable so long as the modification is negligible relative to the estimation error in $s_{0,t}^o$.

C.7 Comparison of own-price elasticities

Appendix Figure A10 presents the histogram of own-price of elasticities, which has a mean of $\varepsilon_p = -0.311$. I compare this estimate to others in the residential demand literature. In my model, households choose where to live annually. In other models, this choice is made in other time spans. For example, Diamond (2016) models decennial location choice in accordance with the census. In each case, the scale parameter of the Type I Extreme Value errors adjust to match the migration frequency implied by the time interval.

Consider a destination d and an origin group o. Let $s^o_{d,t}$ denote share of people living in d from o at time t. Let $p_{d,t}$ denote price in d at time t. Consider a persistent 1% decrease in $p_{d,t}$ for a ten year period, holding the size of origin market o fixed. Because individuals re-draw Type I Extreme Value shocks each period, the population decreases by ε_p percent in response to a 1% price decrease each period. Over T years, the total decrease in the shares, given a stable 1% price decrease is $T \cdot \varepsilon_p$. Thus, I can translate my estimated price elasticity to a ten-year cumulative price elasticity of -3.11.

For comparability with other static residential demand estimates, I convert all elasticities to a common ten-year metric. Table A15 reports a selection of comparable estimates from similar models. My estimate lies within the range found in the literature.

Table A15: Comparison to other price elasticities

Paper	Setting	Time frame	ε_p	Ten-year ε_p	Instrument
This paper	United States	1 year	−0.311	−3.11	Nearby deaths
Diamond (2016)	United States	10 years	−2.71	−2.71	Bartik × supply elasticity
Hsiao (2023)	Jakarta	Cross-section	−9.12	-	Land ruggedness
Cook et al. (2025)	Chicago (renters)	3 years	−0.7	−2.33	Shift-share by demographics

Note: Diamond (2016) average elasticity calculated by weighing the college and non-college demand elasticities to rental prices of Table 5, Column (4) by the 2000 population shares from Table A.1. The elasticities from Hsiao (2023) and Cook et al. (2025) are known from correspondence with the authors.

C.8 Does the endowed option have a different price coefficient from alternatives?

In Section 4.2 I assume that each household's idiosyncratic utility shocks for all options in their choice set are drawn from the same Type I Extreme Value Type distribution. In principle, the coefficient measuring the effect of home prices on indirect utility may vary across products. This is most likely different for endowed options, which may have more salient price information, as in the model of Abaluck and Adams-Prassl (2021). Alternatively, substitution away from endowed homes in response to price changes may follow different patterns from overall out-migration. Either case would imply that the estimated coefficient on $\log\left(p_{d,t}\right)$ may be observable different for choices in which households do not move. Given the scope of my data, this implication is testable. In my full specification, I estimate $\alpha_0 = -3.32$ $[-3.02, -3.43]$. I estimate a comparable coefficient by restricting to the shares of endowed options. This has the added benefit of always having non-zero shares, allowing α_0^{own} to be recovered via a Berry (1994) inversion. Table A16 reports my estimate of $\hat{\alpha}_0^{\text{own}}$. Although this parameter is estimated imprecisely, given the smaller sample, the estimate is qualitatively similar and statistically indistinguishable from the baseline. Concerns related to price salience would predict that $\hat{\alpha}_0^{\text{own}} >> \hat{\alpha}_0$, which is not borne out in this case.

Table A16: Price coefficient of endowed option

Dependent Variable:	$\log\left(s^{o}_{d,t}\right) - \log\left(s^{o}_{oo,t}\right)$
Model:	(1)
Variables	
$\log\left(p_{d,t}\right)$	-2.93
	(1.25)
FEs	
Destination × Origin	Yes
County × Year	Yes
Fit statistics	
Observations	344,642
R^2	-0.44195
Within R^2	-11.583

Note: Additionally control for all parameters as in Table A4. Standard errors are clustered at the Destination × Origin level. I instrument for $\log\left(p_{d,t}\right)$ as in Table A4.

C.9 Estimating the population distribution of ω_i

I estimate $\hat{W}$ is by gridding the space of $\hat{W}$ into $G = 100$ grid points $\left\{w_g\right\}$with spacing $\Delta w = 0.015$ and minimizing a system of linear equations to match the observed series, with a penalization term to ensure the regularity of the tails. I denote the incumbent distribution of non-wind marginality as $V_{i,1}$ and I aggregate the distribution of non-incumbent wind marginality, $V_{i,2}$, as their population-weighted average.

I can approximate the convolution integral in Proposition 1 as

$$F_{V_{i,1}+W}\left(p_i\right) \approx \sum_{k=1}^{N} f_{V_{i,1}}\left(p_i - w\right) f_W\left(w\right) \Delta w \equiv \tilde{F}_{V_{i,1}+W}\left(p_i\right), \tag{62}$$

$$F_{V_{i,2}+W}\left(p_i\right) \approx \sum_{k=1}^{N} f_{V_{i,2}}\left(p_i - w\right) f_W\left(w\right) \Delta w \equiv \tilde{F}_{V_{i,2}+W}\left(p_i\right). \tag{63}$$

I note that in my setting, it is simple to differentiate my known demand curves to get

$$f_{V_i^o}\left(z\right) = \alpha^o \frac{\exp\left(\delta_i - \alpha^o z\right)\left(1 + \sum_j \exp\left(\bar{\delta}_j\right)\right)}{\left(1 + \exp\left(\delta_i - \alpha^o z\right) + \sum_j \exp\left(\bar{\delta}_j\right)\right)^2} \tag{64}$$

where δ_i is the relevant mean utility excluding changes in price, and $\bar{\delta}_j$ is some non-negative alternative mean utility at the average price.[78] I thus am able to solve for a grid f_W where for $\lambda = 0.1$ I enforce regularity of the tails as follows

$$\hat{f}_W = \min_{f_W}\left(\tau F_{V_{i,1}+W}\left(\tau_i^p\right) - \tilde{F}_{V_{i,1}+W}\left(p_i\right)\right)^2 + \left(\tau F_{V_{i,2}+W}\left(\tau_i^p\right) - \tilde{F}_{V_{i,2}+W}\left(p_i\right)\right)^2 - \lambda R\left(f_W\right) \tag{65}$$

where R applies Tikhonov regularization.

[78]The support of f_{V_i} is $(0, \infty)$ since z is in the space of $\log\left(p_i\right)$.

D Developer-government model appendix

D.1 Closed form policy function for exogenous transfers

I solve the model backwards by deriving closed form solutions for continuation values at each decision point in the regimes with exogenous transfers

When do developers proceed with construction? The developer builds if and only if the profit, net of sunk costs and transfers, is positive

$$\Pi_l + E - T_l > 0$$

When does the government block development? The government blocks development if and only if

$$V_l \times T_l + C_l \times P_l < -B_2,$$

or the value of the transfers and the cost of the externalities is worse than the cost of blocking.

How does the government decide to initially dissuade? If the government would be better off not allowing the process to proceed, or

$$\mathbb{E}\left[\mathbb{V}_d | C_{l,0}, \Pi_{l,0}\right] > -B_1$$

then they will optimally block at the first contact.

How does the developer decide to approach? The value to a developer of an approach, conditional on not being initially dissuaded, in the regimes with exogenous T_l is

$$\mathbb{E}\left[\mathbb{V}_e | C_{l,0}, \Pi_{l,0}\right] = \underbrace{\mathbb{E}\left[\max\left(\Pi_l - T_l + E, 0\right)\right]}_{\text{censored profit}} \mathbb{P}\left(\text{approve} | C_{l,0}, T_l\right) - \underbrace{E}_{\text{sunk cost}} .$$

The probability of final approval is solvable in closed form as

$$\mathbb{P}\left(\text{approve} | C_{l,0}, T_l\right) = \left(1 - \Phi\left(\frac{-C_{l,0} - B_2}{\sqrt{\mu^2 P_l + \nu^2 T_l}}\right)\right).$$

It is also possible to solve for the expected censored profit in closed form as

$$\begin{aligned} \mathbb{E}\left[\max\left(\Pi_l - T_l + E, 0\right)\right] &= \int_0^\infty x \mathbb{P}\left(\Pi_l - T_l + E = x\right) dx \\ &= \left(\Pi_{l,0} - T_l + E\right) \Phi\left(\frac{\Pi_{l,0} - T_l + E}{\sigma}\right) + \sigma \phi\left(\frac{\Pi_{l,0} - T_l + E}{\sigma}\right). \end{aligned}$$

If $r(l) = \text{b}$ then the constraint on the offer T_l guarantees approval, but the offered T_l may well make it not profitable to build, so

$$\mathbb{E}\left[\mathbb{V}_e^{\text{b}} | C_{l,0}, \Pi_{l,0}\right] = \mathbb{E}_{T_l}\left[\max\left(\Pi_l - T_l + E, 0\right)\right] - E.$$

I combine this to find that the value to a developer of an approach is

$$\mathbb{E}\left[\mathbb{V}_a | C_{l,0}, \Pi_{l,0}\right] = \mathbb{E}\left[\mathbb{V}_e^{\text{b}} | C_{l,0}, \Pi_{l,0}\right] \cdot \underbrace{\mathbb{I}\left\{\mathbb{E}\left[\mathbb{V}_d | C_{l,0}, \Pi_{l,0}\right] < -B_1\right\}}_{\text{not immediately dissuaded}},$$

which is non-zero if and only if they will not be immediately blocked. They then approach if and only if $\mathbb{E}\left[\mathbb{V}_a | C_{l,0}, \Pi_{l,0}\right] > e$, where e is the cost of an approach.

D.2 Characterizations of policy function for endogenous transfers

I solve the model backwards by deriving solutions, which will be approximated numerically, for continuation values at each decision point in the negotiation regime. I will denote T_g^* to be the government proposed transfer, and T_d^* to be the developer proposed transfer

When do developers proceed with construction? The developer builds if and only if the profit, net of sunk costs and transfers, is positive

$$\Pi_l + E - T^* > 0$$

When does the local government block development? The government blocks development if the developer proposed a transfer and

$$V_l \times T_d^* + C_l \times P_l < -B_2,$$

or the value of the transfers and the cost of the externalities is worse than the cost of blocking. If the government offered a TIOLI deal, they will block any rejection.

How much does the local government offer? With probability ρ, the government makes an offer

$$T_g^* = \arg\max_T \left(V \times T - C_l \times P_l\right) \mathbb{P}\left(\Pi_l + E - T > 0\right) + \left(1 - \mathbb{P}\left(\Pi_l + E - T > 0\right)\right)(-B_2).$$

I note that the posterior belief over the profit is such that $\Pi_l \sim N\left(\Pi_{l,0} + \frac{\sigma_f^2}{\eta^2+\sigma_f^2}\Pi_{l,1,g}, \frac{\eta^2\cdot\sigma_f^2}{\eta^2+\sigma_f^2}\right)$. The government solves for T by noting that the first-order-condition implies that

$$V\left[1 - \Phi\left(\frac{T - E - \Pi_{l,0} - \frac{\sigma_f^2\Pi_{l,1,g}}{\eta^2+\sigma_f^2}}{\sqrt{\frac{\eta^2\cdot\sigma_f^2}{\eta^2+\sigma_f^2}}}\right)\right] - \left(V \cdot T - C_l \cdot P_l + B_2\right)\left[\frac{1}{\sqrt{\frac{\eta^2\cdot\sigma_f^2}{\eta^2+\sigma_f^2}}}\phi\left(\frac{T - E - \Pi_{l,0} - \frac{\sigma_f^2\Pi_{l,1,g}}{\eta^2+\sigma_f^2}}{\sqrt{\frac{\eta^2\cdot\sigma_f^2}{\eta^2+\sigma_f^2}}}\right)\right] = 0,$$

which can be solved numerically, and must be such that $T_g^* \geq 0$.

What does the firm offer? With probability $1 - \rho$, the firm makes an offer

$$T_l^* = \arg\max_T \left(\Pi_l + E - T\right)\mathbb{P}\left(V \times T - C_l \times P_l > -B_2\right).$$

I write $Z = \frac{-B_2 + C_l \times P_l}{V}$. First, I note that as before, given the signal $c_{l,d}$, the developer holds a posterior belief over

$$c_l \sim N\left(c_0 + \frac{\mu^2}{\mu_c^2 + \mu^2}c_{l,d}, \frac{\mu_c^2 + \mu^2}{\mu_c^2 + \mu^2}\right).$$

I note that $V \sim N(1, \nu)$ and $C_l \sim N(c_0, \mu)$. For simplicity, I assume that ν is small,[79] which allows me to approximate Z with a first order Taylor expansion since $\frac{1}{V} \approx 1 - (V - 1)$. This implies a closed form for $Z \sim N\left(m_z, \sigma_z^2\right)$ where

$$m_z = -B_2 + \left(c_0 + \frac{\mu^2}{\mu_c^2 + \mu^2}c_{l,d}\right) \times P_l$$

and

$$\sigma_z^2 = \frac{\mu_c^2 + \mu^2}{\mu_c^2 + \mu^2}P^2 + \left(-B_2 + \left(c_0 + \frac{\mu^2}{\mu_c^2 + \mu^2}c_{l,d}\right) \times P_l\right)^2 \nu^2.$$

The developer solves for T by noting that the first-order-condition implies that

$$-\left[1 - \Phi\left(\frac{T - m_z}{\sigma_z^2}\right)\right] + \left(\Pi_l + E - T\right)\left[\sigma_z^2\phi\left(\frac{T - m_z}{\sigma_z^2}\right)\right] = 0,$$

[79] In estimating step one, I find this to be true empirically.

which can be solved numerically, and is constrained such that $T_l^* \geq 0$.
How does the government decide to initially dissuade? If the government would be better off not allowing the process to proceed, or

$$\mathbb{E}\left[\mathbb{V}_d | C_{l,0}, \Pi_{l,0}\right] > -B_1$$

then they will optimally block at the first contact. The government's

$$\begin{aligned}\mathbb{E}\left[\mathbb{V}_c | C_{l,0}, \Pi_{l,0}\right] =& \rho \mathbb{E}\left[\left(V \times T_c^* - C_l \times P_l\right) \times \left(\Pi + E - T_c^* \geq 0\right) - B_2 \left(0 > \Pi + E - T_c^*\right) \left(\Pi + E > 0\right)\right] + \\ & (1-\rho)\, \mathbb{E}\left[\max\left(V \times T_d^* - CP, -B_2\right)\right].\end{aligned}$$

How does the developer decide to approach? The value to a developer of an approach, conditional on not being initially dissuaded, is

$$\begin{aligned}\mathbb{E}\left[\mathbb{V}_d | C_{l,0}, \Pi_{l,0}\right] =& \rho \mathbb{E}\left[\max\left(\Pi + E - T_c^*, 0\right)\right] + \\ & (1-\rho)\, \mathbb{E}\left[\max\left(\Pi + E - T_d^*, 0\right)\right] - E.\end{aligned}$$

The value to a developer of an approach is

$$\mathbb{E}\left[\mathbb{V}_a | C_{l,0}, \Pi_{l,0}\right] = \mathbb{E}\left[\mathbb{V}_d | C_{l,0}, \Pi_{l,0}\right] \cdot \underbrace{\mathbb{I}\left\{\mathbb{E}\left[\mathbb{V}_c | C_{l,0}, \Pi_{l,0}\right] < -B_1\right\}}_{\text{not immediately dissuaded}},$$

which is non-zero if and only if they will not be immediately blocked. They then approach if and only if $\mathbb{E}\left[\mathbb{V}_a | C_{l,0}, \Pi_{l,0}\right] > e$, where e is the cost of an approach. Both $\mathbb{V}_c$, $\mathbb{V}_d$ must be simulated numerically.

D.3 Additional identification

D.3.1 Identification: no bargaining

I discuss the intuitive variation that is informative each of the remaining 13 parameters not discussed in Section 5.6.1.
Costs of planning and approaching: E, e. Variation that aids in informed E is the extent to which the inferred likelihood of being blocked, conditional on passing the first stage, affects decisions to contact the government in the first place. The overall level of implied initial contacts identifies e. Intuitively, the difference here is comparing how the likelihood of being rejected affects contact relative to the likelihood of a large negative final-period cost shock.
Noise in government costs and benefits: μ, ν. These parameters are symmetrically informed by the extent to which higher values of V_l and T_l lead to higher variance in the final decision to block.
Noise in profit: σ_ε, σ_Π. Intuitively σ_ε is informed by the noise that rationalizes the dispersion in $\Pi_{l,0} + \beta X_l$ of applied for locations, after conditioning out all other strategic aspects. Then, σ_Π is the ensuing additional noise, conditional on the follow-through selection of the unobserved component from the first stage. For intuition, consider a setting with no risk of the government refusing. In this case, the extent to which there are locations l and l' where $\Pi_{l,0} + \beta X_l < \Pi_{l',0} + \beta X_{l'}$ but l is applied for and l' is not will separately identify σ_ε from σ_Π. In other words, while higher σ_ε and σ_Π will both lead to a flattening of how predictive observable profit is for application, the extent to which observably worse projects receive applications and observably better projects do not will pin down this unobserved persistent component of profit.
Controls in profit: β_1, β_2, $,\beta_3$, β_{region}. The parameters β_1, β_2, and β_3 are informed by the effect of a marginal increase in agricultural profit/acre, RPS existence, and RPS amount compared to the effect of a dollar increase in $\Pi_{l,0}$. The census region fixed effects β_{region} are shifters that rationalizes the decisions to apply for and build the least observably productive locations by Census region, conditional on other parameters.

D.4 Policy functions with up-front negotiation

The firm now faces the problem of choosing an offer which can be described as

$$T_l^* = \arg\max_T \mathbb{E}\left[\max\left(\Pi_l + E - T, 0\right) - E\right] \mathbb{P}\left(V \times T - C_l \times P_l > 0\right).$$

This becomes

$$T_l^* = \arg\max_T \left(z\Phi\left(z/\sigma\right) + \sigma\phi\left(z/\sigma\right) - E\right) \mathbb{P}\left(V \times T - C_l \times P_l > 0\right),$$

where $z = \Pi_{l,0} + E - T$. The new first-order condition is now

$$\left(-\Phi\left(z/\sigma\right)\right)\left[1 - \Phi\left(\frac{T - m_z}{\sigma_z^2}\right)\right] + \left(z\Phi\left(z/\sigma\right) + \sigma\phi\left(z/\sigma\right) - E\right)\left[\sigma_z^2\phi\left(\frac{T - m_z}{\sigma_z^2}\right)\right] = 0,$$

which can be solved numerically, and is constrained such that $T_l^* \geq 0$.

D.5 Robustness to correlation of profit shocks

In section 5.1 I specify that the firm's profit is revealed in the following manner: in period 1 they observe $\Pi_{l,0} = \hat{\Pi}_l + \Pi_{l,\xi} + \beta X_l$ where $\hat{\Pi}_l$ is engineering productivity, X_l are other relevant covariates, and $\Pi_{l,\xi} \sim N\left(0, \sigma_\xi^2\right)$ is an unobservable quality. In period 2, after deciding on whether to contact the local government, they observe the full profit $\Pi_l = \Pi_{l,0} + \Pi_{l,1}$ where $\Pi_{l,1} \sim N\left(0, \sigma_f^2\right)$ is a final-period profit shock. I specify $\Pi_{l,\xi}$ and $\Pi_{l,1}$ as independent for ease of exposition. I can broaden my model to a setting in which

$$\left(\begin{array}{cc} \Pi_{l,\xi} & \Pi_{l,1} \end{array}\right) \sim N\left(\left[\begin{array}{c} 0 \\ 0 \end{array}\right], \left[\begin{array}{cc} \sigma_1^2 & \sigma_{1,2}^2 \\ \sigma_{1,2}^2 & \sigma_2^2 \end{array}\right]\right).$$

This allows for a covariance $\sigma_{1,2}$ between the initial unobservable quality and the final-period profit shock.

While this changes the interpretation of what is indicated about the information structure, it is possible to decompose the decision rule by the local government into one where behavior is isomorphic to the model with independent profit shocks. I note that while before $\mathbb{E}\left[\Pi_l|\Pi_{l,0}\right] = \Pi_{l,0} + \mathbb{E}\left[\Pi_{l,1}|\Pi_{l,\xi}\right] = \Pi_{l,0}$, this is no longer necessarily the case since $\mathbb{E}\left[\Pi_{l,1}|\Pi_{l,\xi}\right]$ may be non-zero. In a multivariate normal distribution, $\mathbb{E}\left[\Pi_{l,1}|\Pi_{l,\xi}\right] = \frac{\sigma_{1,2}^2}{\sigma_1^2}\Pi_{l,\xi}$. Thus, I can write

$$\mathbb{E}\left[\Pi_l|\Pi_{l,0}\right] = \hat{\Pi}_l + \beta X_l + \left(1 + \frac{\sigma_{1,2}^2}{\sigma_1^2}\right)\Pi_{l,\xi}$$

where I can define $\Pi'_{l,\xi} = \left(1 + \frac{\sigma_{1,2}^2}{\sigma_1^2}\right)\Pi_{l,\xi}$ and note that $\Pi'_{l,\xi} \sim N\left(0, \left(1 + \frac{\sigma_{1,2}^2}{\sigma_1^2}\right)^2 \sigma_1^2\right)$. In the final period,

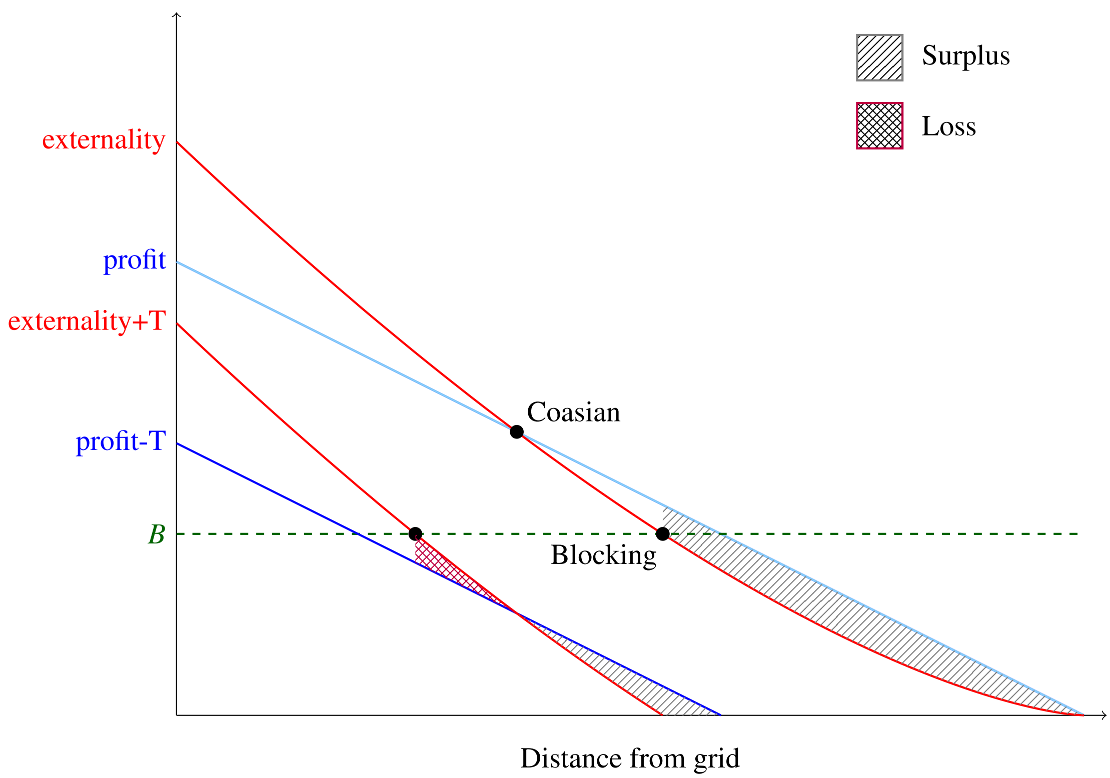
$$\begin{aligned} \Pi_l &= \hat{\Pi}_l + \beta X_l + \Pi_{l,\xi} + \Pi_{l,1} \\ &= \hat{\Pi}_l + \beta X_l + \left(\Pi_{l,\xi} + \mathbb{E}\left[\Pi_{l,1}|\Pi_{l,\xi}\right]\right) + \left(\Pi_{l,1} - \mathbb{E}\left[\Pi_{l,1}|\Pi_{l,\xi}\right]\right). \end{aligned}$$

I define $\Pi'_{l,1} = \Pi_{l,1} - \mathbb{E}\left[\Pi_{l,1}|\Pi_{l,\xi}\right]$ and note that $\Pi'_{l,1} \sim N\left(0, \sigma_2^2 - \frac{\left(\sigma_{1,2}^2\right)^2}{\sigma_1^2}\right)$. Thus, it is possible to write $\mathbb{E}\left[\Pi_l|\Pi_{l,0}\right] = \hat{\Pi}_l + \beta X_l + \Pi'_{l,\xi}$ and $\Pi_l = \mathbb{E}\left[\Pi_l|\Pi_{l,0}\right] + \Pi'_{l,1}$ where $\Pi'_{l,\xi}$ and $\Pi'_{l,1}$ are independent and normally distributed mean-zero errors with variances $\sigma_\xi^2 = \left(1 + \frac{\sigma_{1,2}^2}{\sigma_1^2}\right)^2 \sigma_1^2$ and $\sigma_f^2 = \sigma_2^2 - \frac{\left(\sigma_{1,2}^2\right)^2}{\sigma_1^2}$ respectively. So long as both the local government and the developer have rational expectations given the covariance of shocks, all behavior will proceed as before. Intuitively, non-zero covariance between the first-period shock and second-period shock collapses to a question of semantics: so long as agents are aware of this covariance–the problem continues to admit a structure of independent profit shocks, where the variance of expectation shocks need not be equal to the variance of first period information shocks.

D.6 Simple illustration of observed distances from local government threshold rules

In Figure A45 I present a simple Harberger-style illustration of the welfare losses stemming from rigid transfer amounts. In the figure, it may be the case that the hassle-cost of blocking is such that when the local governments are being paid a transfer, they allow for the construction of projects with negative social values.

Figure A45: Simple diagram of cost of coarse contracts



Note: This is a stylized example. Profit is decreasing in distance from the grid, due to higher cost of building roads and power lines. The externality is decreasing in distance from the grid due to decreasing population density–given that the grid often is close to population centers.

D.7 Do local governments' choices represent heterogeneity in residents' disutilities?

I measure how closely local governments' perceived costs of exposing households to wind farms align with the actual utility costs those households experience. Consider two extremes. In one, the idiosyncratic costs perceived by the local government are uncorrelated with the households' true utility costs, and the local governments' costs reflect statistical or political noise. At the other extreme, the local government may perfectly represents households' utility costs. In the first case, using the local government's private information does not improve the efficiency of siting. In the second case, this private information may be highly valuable for efficient allocation.

I measure this by comparing changes in home transaction prices after wind entry, across locations that differ in their model-implied estimates of the local governments' perceived costs.[80] In the model in Section 5, local governments allow wind development if $V_l T_l + \zeta_l \sum_{i \in \mathcal{I}(l)} d_i \geq -B_2$, meaning that the costs of blocking exceed the net costs of construction. In this model, smaller perceived costs of wind development correspond to smaller values of ζ_l. There are locations l where $T_l + \zeta_0 \sum_{i \in \mathcal{I}(l)} d_i$ is well above $-B_2$. In these locations, there is little selection along ζ_l, because only very large draws would prevent construction. Conversely, there are locations where $T_l + \zeta_0 \sum_{i \in \mathcal{I}(l)} d_i < -B_2$, so construction occurs only when ζ_l is very small. I compare how home prices respond to wind entry in locations with very small and very large model-implied probabilities that the local government blocks development.

I test for private information by comparing the model-implied posterior of ζ_l for each location to the observed price responses when wind farms were built in those areas. Local governments possessing private information is consistent with estimated price effects being smaller at lower values of ζ_l, conditional on local demand. For each treated census tract $d \in \mathcal{T}$,I calculate the posterior of ζ_l, conditional on construction, using the parameter estimates from Section 5.8. I denote this as $\hat{\zeta}_d = \mathbb{E}\left[\zeta_d | d = \text{built}\right]$.[81]

I estimate the heterogeneous treatment effects of wind farm entry on home prices and sales as a function of $\hat{\zeta}_d$. I only consider states with exogenous transfers since bargaining implies that higher, unobserved, payments should be associated with lower values of ζ_d which may confound of the estimation. I estimate the following heterogeneous difference-in-differences by constructing a stacked controls estimator of homes near turbines treated between five to ten years later, but have not been treated yet. I estimate the following specifications:

$$\log\left(p_{i,t}\right) = \tau^{\mathrm{k}} \cdot \left(\hat{\zeta}_d - \zeta_0\right) \cdot B_{i,t} + \beta_\zeta \left(\hat{\zeta}_d - \zeta_0\right) + \tau^r \cdot B^r_{i,t} + B_{i,t}\theta_1\left(\delta_i, \iota_{i,t-1}\right) + \theta_2\left(X_{i,t}, c\left(i\right), t, \delta_i, \iota_{i,t-1}\right) + \varepsilon_{i,t}, \tag{66}$$

For some property i, $p_{i,t}$ is the price at which it is transacted at time t, and $B^r_{i,t}$ is an indicator for the wind farm is built at time t by rule r. The estimand of interest is τ^k which is the treatment effect on price as a function of $\left(\hat{\zeta}_d - \zeta_0\right)$. In θ_1 and θ_2 I control for heterogeneous treatment effects of wind entry using Hermite splines with three degrees of freedom each for both distance from first turbine, δ_i, and outside demand, $\iota_{i,t-1}$. Both of which mediate the price effect, as shown in Figures A4 and 4. In θ_2, I also control linearly for characteristics of the home—acres, bedrooms, age, and square-feet—as $X_{i,t}$, as well as census tract, $c\left(i\right)$, year t, and three-year-bin-by-county fixed effects, as in Section 4.1.

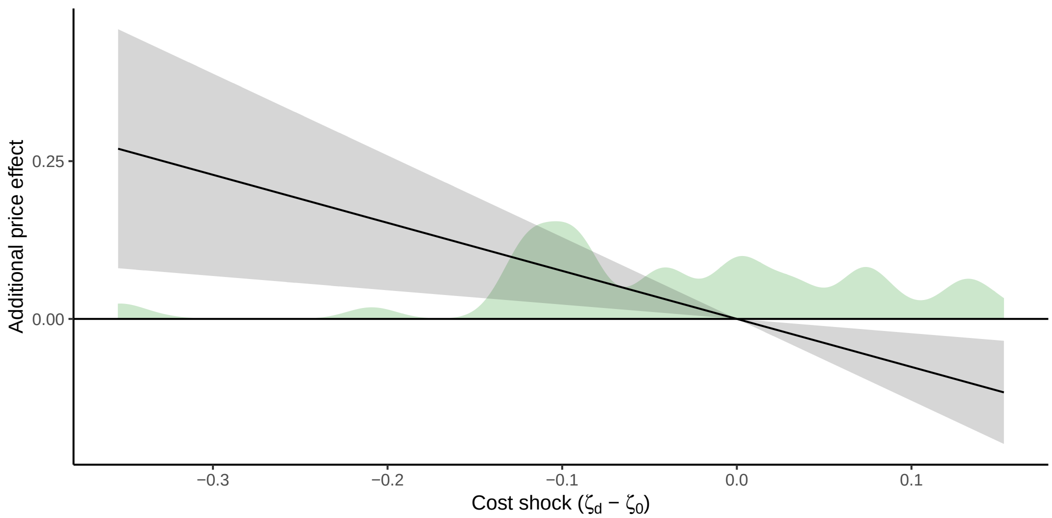
In Figure A46, I present the estimated effect. I find that in areas with lower values of $\zeta_d - \zeta_0$, the price drops by a smaller magnitude. This is consistent with the interpretation that the cost shocks have a real and positive correspondence with the actual utility costs. In Figure A47, I present a bin-scatter of the posterior mean of $\zeta_d - \zeta_0$ and the expected net cost to each location, showing that higher values of $\zeta_d - \zeta_0$ are associated with higher expected net costs.

Overall, I find that local governments' perceived costs of wind construction seem to be highly correlated with the true utility costs in that location, as proxied by home price effects. The existence of such private information suggests that eliciting local governments' preferences in a mechanism can be effective in targeting construction to areas with lower household costs.

[80] I interpret smaller price reductions, conditional on all observables including outside demand, to be associated with lower household utility costs.

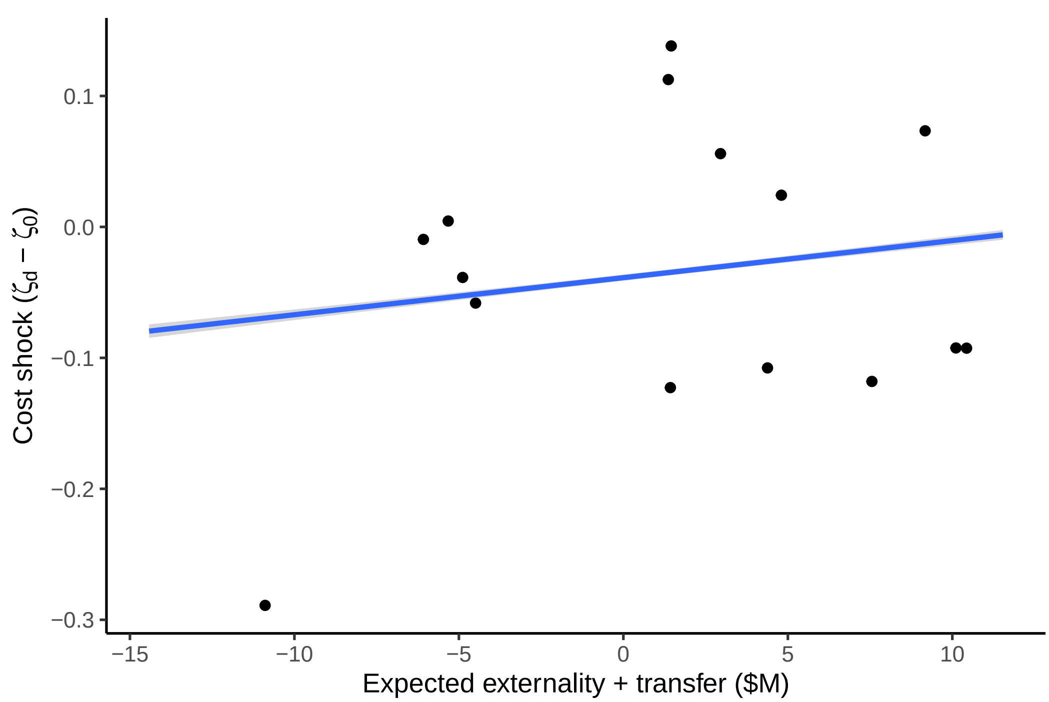
[81] I calculate this by simulating each location in the U.S. 6,000 times using the estimated model parameters from Section 5.

Figure A46: Effect heterogeneity by implied cost shocks $\zeta_d - \zeta_0$ on home prices



Note: Effect estimated using homes treated five to ten years after the treatment group as a control. Difference-in-difference price effect is estimated as an affine function of $\hat{\zeta}_d - \zeta_0$. Control for distance from turbine, outside demand ι, age, acreage, bedrooms, baths, distance to neighbors, census tract, and year. In green, I present the density of $\hat{\zeta}_d - \zeta_0$. The slope of this effect is -0.761 (0.273).

Figure A47: Bin-scatter of expected net local cost and the posterior of $\zeta_d - \zeta_0$



Note: Binscatter with 15 bins plotting each location's expected externality plus the transfer compared to the simulation of the posterior of $\zeta_d - \zeta_0$ conditional on successful construction.