David L. Hawkins

190 Cane Run Cemetery Road

Munfordville, Ky 42765

RECEIVED

AUG 1 8 2025

PUBLIC SERVICE
COMMISSION

August 13, 2025

Kentucky State Board on Electric Generation and Transmission Siting

211 Sower Boulevard

P. O. Box 615

Frankfort, Ky 40602

Re: Opposition to Wood Duck Solar, LLC Project (Case No. 2024-00337)

Dear Members of the Siting Board,

This letter is submitted to express strong opposition to the proposed Wood Duck Solar, LLC project in Barren County, Kentucky. This project, which seeks a certificate of construction for an approximately 100-megawatt solar generating facility on over 2,300 acres of land, raises serious concerns across multiple fronts.

The specific scale, location, and potential impacts are highly detrimental to our community and its irreplaceable natural resources. We urge the Siting Board to deny the application based upon the following key arguments, which are supported by public filings, local testimony, and the criteria for project evaluation outlined in **KRS 278.710(1)**.

1. **Significant Negative Impact on Scenic Surroundings and Property Values**

The proposed industrial-scale solar facility, spanning thousands of acres, will irrevocably alter the pastoral and scenic landscape of Barren County. The installation of vast arrays of solar panels and associated infrastructure will introduce an industrial presence into a rural, agricultural community, creating a significant and lasting visual blight. This directly contradicts the board's duty to consider the "impact of the facility on scenic surroundings, property values, [and] the pattern and type of development of adjacent property" as stated in **KRS 278.710(1)(a).** Furthermore, my submission at the July 15, 2025 public hearing in this case specifically contested the developer's property value analysis, arguing that it failed to adequately account for the project's scale and the resulting negative impact on adjacent land values. I cited **current, independent research by Nino Abashidze of the University of Wyoming which was issued on May 29, 2025** that found an approximately 8.7% reduction in value for homes within one mile of a solar farm. She also found reduced housing market liquidity and stated that her methodology was more accurate than other common types of analysis. Attached is the full document for your review. Keep in mind that the Kirkland report utilized by the developer was bought and paid for by Wood Duck/Geenex and therefore lacks independence. The negative effect on the aesthetic character of the area is a primary concern for local residents, who have clearly stated that their quality of life and investments in their homes and land are at risk. This scattered-site development is totally inappropriate for the proposed area. How will property owners be compensated for the loss in value of their properties if this project gains your approval?

2. **Irreversible Loss of Prime Agricultural Land**

The proposed location for the Wood Duck Solar project encompasses over 2,300 acres of what is currently productive farmland. This land is a vital economic and cultural resource for Barren County. Converting this acreage to an industrial solar facility represents a permanent loss of agricultural capacity. This conversion will have a long-term economic impact on the local agricultural sector and the food supply chain. Current research from Columbia University, New York states "The USDA figures show that one agricultural related job is lost for every 9 acres taken out of production". Approximately 250 agriculture jobs will be lost to the Wood Duck Solar project contrasted with an estimated 3 permanent jobs created by the project. How will those who lose their livelihood because of the loss of farmland be made whole?

3. **Threat to Mammoth Cave National Park and Karst Aquifer System**

Perhaps the most critical environmental concern is the potential impact of the project on the unique and fragile ecosystem of Mammoth Cave National Park, a UNESCO World Heritage Site. The karst geology of the area means that any chemical spills or runoff from the solar panels, battery storage, or construction activities could quickly enter the groundwater and contaminate the cave's aquifer. This poses a direct threat to the federally endangered Kentucky Cave Shrimp and over 160 other species of aquatic wildlife that depend on the pristine waters of the cave system. It is undisputed that the solar panels proposed to be used by Wood Duck contain lead and the manufacturer warns that "a release of, and exposure to, lead can take place when (i) when the different components of the solar modules are disassembled, in particular for recycling purposes, and (ii) in instances of fire. Lead may damage fertility or the unborn child, causes damage to organs through prolonged or repeated exposure, is very toxic to aquatic life with long lasting effects, may cause cancer, is very toxic to aquatic life, and may cause harm to breast-fed children". Yes, the warning about toxicity to aquatic life is repeated in the same paragraph by the manufacturer. It is also undisputed that most of the project site has 4 inch water lines that are insufficient to support a hydrant or provide sufficient volume to suppress a solar fire. Barren County's own regulations required that commercial properties be served by at least a 6 inch line. This farmland becomes a commercial project if Wood Duck gains approval and 6 inch water lines are mandated. In reviewing the recent communications between Wood Duck and Mammoth Cave National Park, I was struck by the realization that the most serious, over-riding concern was not addressed at all. How is

Mammoth Cave protected from a release of lead, or other contaminants such as chemicals or glass shards, in the event of a fire caused by lightning, arson, equipment malfunction, or another type of incident? The answer is that it is not protected and this tremendous resource would suffer unfathomable, unrecoverable harm. The risk is too great and I ask, once again, that you deny the project and protect the community and its irreplaceable treasures.

4. **Inadequate Decommissioning Plan and Financial Responsibility**

A major point of concern for residents is what happens to the land once the solar facility reaches the end of its useful life. The filings in this case have not provided sufficient guarantees that a comprehensive and fully funded decommissioning plan is in place. Without a robust and independently verified financial guarantee, the financial burden could fall on local taxpayers and landowners. The lack of a clear, legally binding, and well-funded decommissioning plan is a significant risk that the Siting Board must address before granting a certificate. Will you prevent Wood Duck from controlling the process of establishing the amount and type of the decommissioning security?

5. **Failure to Respect Local Community Concerns and Lack of Zoning**

The developer has proceeded with this project despite widespread local opposition, which was clearly demonstrated at the public hearing held on July 15, 2025 and is further evidenced by the volume of comment letters to you in opposition to the project. The absence of comprehensive land-use restrictions or zoning in Barren County has been exploited by the developer, who has circumvented a process that would have prioritized community input and local concerns. Barren County Planning and Zoning failed to adequately vet the project or seek public input before rubber stamping Wood Duck's requests. I attended both public information meetings and they were a farce. Wood Duck utilized a "divide and conquer" strategy by having their representatives engage each attendee individually so that attendees couldn't ascertain the answers being given to other questions. There were no group information presentations or Q&A sessions. All we heard were non-answers and that our concerns were being heard. No substantive information was shared. Wood Duck's outreach to the community has been inadequate and ineffective, but did serve to hold back community opposition until Paula Pedigo and others were able to discover the complicity of the judge-executive and Wood Duck in stifling community dissent. This has created a situation where a state-level decision is being made on a project that profoundly affects a local community that feels unheard and unprotected. The Siting Board has a responsibility to consider the public comments and the strong sentiment of the local community, which has raised valid questions that deserve answers. The project's failure to secure local support demonstrates a disregard for the principles of responsible community development. This project is now tainted by its failure to adequately inform the citizenry about the details of its plans. Are citizen's rights to be trampled by approval of this project? You have the power to say no.

6. **Impact on Amish Neighbors**

Included in the public comments from the July 15, 2025 public hearing and later submissions are letters and petitions signed by 141 Amish community members that are negatively impacted by the proposed project. In the writings they detail how profoundly their way of life will be adversely affected by Wood

Duck's solar farm. It is incumbent on all involved to respect the Amish way of life and help to protect their culture. Will you stop this infringement by Wood Duck?

7. **Impact on Wildlife and the Indiana Bat**

Just today an article appeared on The Cool Down with the headline "Scientists raise alarm over unexpected wildlife behavior around solar farms: 'Leading them off course'". The article states that rapid expansion of solar farms" has brought unexpected consequences for migrating birds and bats that could threaten biodiversity if left unaddressed. Researchers at Murdoch University have called for wildlife-friendly solar farm designs after discovering that solar farms could confuse birds and bats during migration. The researchers also found that the panels may attract insects, creating artificial feeding grounds that can disrupt natural hunting and foraging behavior. This disruption can increase the risk of bird collisions and shift wildlife behavior in unintended way. As solar capacity grows, land requirements expand significantly. This can reduce available habitat for wildlife, degrade soil health, and threaten nearby pollinators, which are essential to crop production, biodiversity, and ecosystem resilience. Fencing is another concern. While designed to protect solar infrastructure, it can block animal migration routes or trap small wildlife". A copy of this article is attached. The Indiana bat is a protected species that inhabits the project area. The Amish neighbors are dependent on venison as part of their food supply. Will you protect wildlife by denying approval to Wood Duck?

In conclusion, the proposed Wood Duck Solar project is an ill-suited development for its location. The potential harm to the local economy, environment, and community significantly outweighs any perceived benefits. In this letter are seven reasons to deny approval to Wood Duck. Any single reason is sufficient to justify disapproval, but the seven reasons taken as a whole provide overwhelming justification and we respectfully request that the Kentucky State Board on Electric Generation and Transmission Siting deny the application for a certificate of construction for the Wood Duck Solar, LLC project.

Sincerely,

David L. Hawkins

enclosures

Search the web

Cub Run 81°F

Discover Following News Local Science Technology Crime Politics Entertainment L Personalize

162

93

The Cool Down Follow 166.6K Followers

Scientists raise alarm over unexpected wildlife behavior around solar farms: 'Leading them off course'

Story by Calvin Coffee • 20h • 3 min read Summarize

Feedback

Unseen consequences will need to be addressed

Solar energy is crucial in our transition away from pollution-heavy power, but its rapid expansion has brought unexpected consequences for migrating birds and bats that could threaten biodiversity if left unaddressed.

What's happening?

Researchers at Murdoch University have called for wildlife-friendly solar farm designs after discovering that solar panel farms could confuse birds and bats during migration.

In a new report published in Renewable and Sustainable Energy Reviews, ecologists explained that solar panels often reflect light in a way that mimics bodies of water. Known as polarized light pollution, it can mislead birds into landing or veering off course.

"The reflective glare from solar panels mimics the appearance of water bodies, confusing migrating birds and leading them off course," professor Trish Fleming, lead author of the report, said.

The researchers also found that the panels may attract insects, creating artificial feeding grounds that can disrupt natural hunting and foraging behavior. This disruption can increase the risk of bird collisions and shift wildlife behavior in unintended ways.

Why is this important?

While solar panels offer clear environmental benefits, unique surprises are bound to arise with large-scale land use.

In 2023, solar panels covered about 0.025% of the Earth's surface. But as solar capacity grows, land requirements expand significantly. Generating 1 megawatt, which can power 2,000 typical U.K. homes for an hour, usually requires around 2 to 6 hectares, or about 5 to 15 acres, of land, which can significantly disrupt habitats.

Related video: 'Wind theft' threatens offshore wind farms and climate goals, warn scientists (KameraOne USA)

This can reduce available habitat for wildlife, degrade soil health, and threaten nearby pollinators, which are essential to crop production, biodiversity, and ecosystem resilience.

Fencing is another concern. While designed to protect solar infrastructure, it can block animal migration routes or trap small wildlife, especially in desert ecosystems.

What's being done about it?

With any new technology, unseen consequences will need to be addressed; it's a natural part of the cycle of development. Fortunately, solutions are already being tested.

Do you think solar farms are an eyesore?

Definitely

Not at all

It depends where they are

I've never seen one

Click your choice to see results and speak your mind.

Nano-coating solar panels to reduce polarized light pollution could prevent birds from mistaking the technology for bodies of water, Fleming said. "These coatings alter the way light is reflected, making the panels less visually disruptive to wildlife."

Designers can also integrate strategies for fencing, such as including wildlife corridors and gaps, while preserving native plants and natural washes to support biodiversity on and around solar farms, allowing desert life to continue to thrive.

As the world moves toward cleaner energy with solar, wind, and more, it's essential that we design with biodiversity and ecological awareness in mind. Responsible solar development that protects wildlife can ensure this technology remains a win for people and the planet.

The Local Cost of Clean Energy: Evidence from Solar Farm Siting and Home Prices

Nino Abashidze*

May 29, 2025

Abstract

Local opposition to utility-scale solar farms often stems from concerns about declining nearby home values. This paper quantifies the impact of solar farm construction on residential property prices in North Carolina, one of the leading U.S. states for utility-scale solar capacity. Using detailed housing transaction data and a hedonic difference-in-differences framework, we estimate the causal effect of new solar farm operations on neighboring home sale prices. We employ a refined measure of spatial exposure—using street-network (road) distance rather than straight-line distance to define proximity—to better capture actual visual exposure in treatment assignment. Our results indicate that the arrival of a solar farm leads to an approximately 8.7% reduction for homes within one mile relative to similar homes farther away. We also find evidence that local housing market activity declines after a solar farm becomes operational: the number of homes sold in the nearby area falls by roughly 6%, suggesting reduced housing liquidity in the vicinity of the new solar facility.

Keywords: solar farms; residential property values; hedonic method; network distance; renewable siting.
JEL Codes: Q42; Q51; R31; C21

*University of Wyoming. *Corresponding author:* nabashid@uwyo.edu

1 Introduction

Solar energy expansion in the United States is widely supported,[1] yet utility-scale solar projects frequently encounter resistance from local communities. Although solar farms contribute to climate goals and rural economic development, nearby residents often worry that these large ground-mounted installations could degrade scenic views, alter rural character of their communities, and depress property values (Johnson, 2012; Cignoli, 2012). These concerns have manifested in court cases and zoning hearings, where neighbors describe visible solar arrays as an undesirable local disamenity.

Despite rapid growth in solar deployment, relatively few empirical studies have quantified the local spillover effects of utility-scale solar on residential real estate. The existing evidence is mixed and contradictory. For example, Gaur and Lang (2023), using repeat-sales data in Massachusetts and Rhode Island, find modest home value declines of roughly 1.5–3.6% within 0.6 miles of new solar farms. In contrast, Hao and Michaud (2024) document small positive effects (0.5–2.0%) in parts of the Midwest, where solar facilities may be less visible or better integrated with local land use. Maddison et al. (2022), in a study of England and Wales, find that homes located within 750 meters of large (>5 MW) solar farms experienced price declines of approximately 5.4%. Guignet and Hellerstein (2023), using a nationwide hedonic framework, find no consistent solar-specific effect after accounting for neighborhood and locational features.[2,3]

This paper contributes new evidence to the emerging literature by estimating the causal effect of solar farm development on nearby residential property values in North Carolina,

[1]Kennedy (2016), "Americans strongly favor expanding solar power to help address costs and environmental concerns," Pew Research Center: http://pewrsr.ch/2dK9KKQ.

[2]Abashidze and Taylor (2023) examine the effect of utility-scale solar systems on nearby agricultural land values in North Carolina. They find no direct positive or negative spillover effects but suggest that solar farm construction may indirectly influence land values by signaling the land's suitability for future solar development, particularly in proximity to electric transmission lines.

[3]By contrast, a robust body of research has shown that rooftop solar installations tend to increase home values. Households with installed photovoltaic (PV) systems often receive price premiums upon sale, reflecting both energy savings and buyer preferences for environmentally friendly features. See, for example, Qiu et al. (2017); Hoen et al. (2017); Dastrup et al. (2012); Adomatis and Hoen (2016); and Wee (2016).

one of the leading U.S. states for utility-scale solar capacity. Using a difference-in-differences framework and detailed transaction data from Zillow Research (2017),[4] we compare price effects for homes located near solar farms to those slightly farther away, before and after each project becomes operational. We build on recent literature by using street-network (rather than straight-line) distance to define exposure. This approach may better capture how residents actually experience the visual externality of solar farms, particularly in settings where visibility is shaped by local siting ordinances. For example, solar ordinances in North Carolina often mandate vegetative buffers between farms and homes, but not along public roads (Lovelady, 2014). This implies that road-facing exposure may be the primary channel through which residents encounter the disamenity, especially during daily commutes.

We find that homes located within one mile of a new solar farm experience sale price declines of approximately 8–12%, with the largest effects concentrated within 0.5 miles. These statistically and economically significant effects are robust across specifications. The estimated effects are substantially larger than those reported in a multi-state study by Lawrence Berkeley National Laboratory (Laboratory, 2023), which found an average 1.5% price reduction within 0.5 miles of solar farms and significant effects in only a subset of states, including North Carolina. A likely explanation is that the LBNL analysis relies on broad distance bands and Euclidean proximity, which may attenuate localized variation. By contrast, our approach leverages high-resolution street-network distance and parcel-level data to capture exposure more precisely. In addition to price effects, we also document a roughly 6% drop in home sales volume following solar farm construction, which may reflect reduced housing demand or market activity in affected neighborhoods. Finally, we explore heterogeneity in treatment effects based on prior land cover and find no statistically significant differences between sites converted from forest versus grassland.

Together, these results contribute to a growing body of evidence on the localized impacts

[4]Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group.

of renewable energy infrastructure. In particular, this study adds to the literature by (1) introducing a network-based exposure measure grounded in road accessibility; (2) using highly detailed spatial and temporal data on both home sales and solar installations in a high-growth solar market; (3) providing evidence from the Southeastern U.S., a region largely absent from prior research; and (4) examining outcomes beyond price - specifically, the effect on transaction frequency. These findings offer new insight into how solar development reshapes local housing markets and can inform land-use policy, community planning, and solar siting strategies.

The remainder of the paper is organized as follows. Section 2 describes the data, including the novel road-distance exposure metric. Section 3 outlines the empirical strategy and identification assumptions. Section 4 presents the baseline results and robustness checks (e.g., alternative distance measures, sample windows, and farm characteristics). Section 5 concludes with a discussion of policy implications.

2 Data

To conduct our analysis, we integrate two primary datasets—residential property transactions from Zillow's ZTRAX database and detailed solar farm location data from the North Carolina Clean Energy Technology Center. Below, we describe each data source, the procedures used to link them spatially, and our sample selection criteria.

2.1 *Housing Transactions*

Our primary housing market data come from Zillow's Transaction and Assessment Dataset (ZTRAX)[5], which provides comprehensive geocoded records of single-family home sales across the United States. For our analysis, we extract all arms-length transactions

[5]Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author(s) and do not reflect the position of Zillow Group.

recorded in North Carolina from 1997 through 2017 and restrict the sample to sales that include a consistent set of property characteristics (e.g., lot size, living area, number of bedrooms, and bathrooms) and have non-missing geographic coordinates for the property address. Transactions with prices below $20,000 or above the 99th percentile of the price distribution are excluded from the analysis (Haninger et al., 2017; Taylor et al., 2016), as these prices likely do not represent market values. Short-term resales (sales occurring within two years of a previous sale) are also removed from the analysis, as these may reflect speculative behavior or atypical market conditions rather than stable valuations (Haninger et al., 2017).

To capture local socioeconomic context, demographic information from the American Community Survey (ACS) is integrated into the analysis. Specifically, each home sale is linked to block-group-level demographics, including median household income, racial and ethnic composition, and educational attainment levels. These variables serve as essential neighborhood controls in the subsequent analyses.

2.2 *Solar Farms*

Information on solar farm locations is sourced from the North Carolina Clean Energy Technology Center, which maintains a comprehensive inventory of solar installations statewide. Each project record includes location coordinates, generation capacity, and confirmed operational start dates through 2017.

To precisely delineate the spatial boundaries of these solar installations, we manually digitize panel footprints using high-resolution satellite imagery Google Earth and Google Maps. This digitization ensures accurate exposure measurement by capturing actual physical extents rather than relying on approximations such as parcel centroids. Our final dataset includes verified spatial polygons for 428 utility-scale solar farms, representing the near-universe of large-scale solar development in North Carolina over the study period.

To further characterize solar installations, we overlay each digitized polygon onto the

2006 National Land Cover Database (NLCD). This allows us to classify the pre-solar land cover of each installation site, focusing primarily on whether the land was previously forest or grassland. These distinctions enable heterogeneity analyses that test whether property-value impacts vary based on the original landscape type converted to solar use.

2.3 *Sample Construction*

To focus on localized housing market effects, we restrict the sample to homes located within two Euclidean miles of at least one solar farm. This initial spatial boundary is consistent with prior studies assessing the localized effects of environmental disamenities and energy infrastructure (e.g., Gaur and Lang (2023); Haninger et al. (2017); Hoen et al. (2015); Currie et al. (2015), which find that housing price effects tend to dissipate beyond this range. Limiting the analysis to homes in close proximity ensures that the control group is drawn from the same general neighborhood context as the treated homes, minimizing confounding differences in broader housing market conditions. To ensure the estimated effects are not influenced by the presence of multiple nearby facilities, we restrict the sample to homes located within two miles of only one solar farm.

In addition to structural characteristics from ZTRAX and neighborhood demographics from ACS, we include several locational controls to account for spatial amenities and disamenities that could independently influence property values. These include distances to major roads, bodies of water, and public open spaces, which we calculate using GIS-based overlays with state geographic data layers.

Table 1 provides descriptive statistics for our final sample of 15,939 home transactions across 249 distinct solar farm areas, highlighting the typical housing characteristics and contextual attributes of the analyzed homes. The average home in the sample is 32 years old and is sold for \$153,000 (inflation-adjusted to 2017 dollars) with about 3 bedrooms and 2 bathrooms, and the mean living area is 1,670 square feet on a lot of 0.9 acres. The nearby solar farms vary widely in scale, from small 1 MW projects to large installations of 80 MW capacity, with an average capacity of about 5–6 MW. Given typical land use intensity for utility-scale solar, a project with 5–6 megawatts of capacity generally occupies between 25 and 30 acres. Most of these installations ($\approx 60\%$) are built on previously agricultural open space, while the remainder are sited on forested land.

3 Empirical Strategy

The non-experimental nature of our data presents challenges in identifying the causal effect of solar farm construction on residential property values. In particular, solar farms are not randomly sited across space: their locations may reflect unobserved local characteristics, such as land suitability, zoning, or development potential, that also influence nearby home prices. For example, if solar farms tend to be built in less affluent or more rural areas where property values are already lower, a naïve comparison of house prices near versus far from solar farms may overstate the disamenity effect. This is because underlying spatial and economic conditions, not the solar farm itself, could drive observed price differences.

To address these identification concerns and mitigate bias from unobserved heterogeneity, we adopt a difference-in-differences (DiD) research design with rich fixed effects. Specifically, we include solar farm fixed effects to control for all time-invariant factors specific to the area surrounding each installation, such as baseline amenity levels, land quality, or proximity to infrastructure. We also incorporate county-by-year fixed effects to capture local housing market trends and policy shocks that vary across time and geography. These controls allow us to isolate the change in house prices associated with the solar farm construction from broader trends or persistent spatial differences.

Our identification strategy compares housing price trends before and after a solar farm becomes operational for homes located in close proximity to the facility relative to homes located slightly farther away within the same local area. This strategy relies on a parallel trends assumption: that is, in the absence of solar farm development, treated and control homes would have followed similar price trajectories. Formally, we estimate variations of the following hedonic DiD regression model:

$$\ln(P_{itcs}) = \beta_0+\beta_1\text{Treat}_{ics}+\beta_2\text{Post}_{itcs}+\beta_3(\text{Treat}_{ics}\times\text{Post}_{itcs})+X_{itc}\theta+Z_{itc}\varphi+\mu_s+\lambda_{tc}+\varepsilon_{itcs} \quad (1)$$

where $\ln(P_{itcs})$ is the natural log of the sale price of house i, sold in year t, located in county c, and whose nearest solar farm is s. The indicator $Treat_{ics}$ equals one if house i is located near solar farm s (regardless of whether the project is yet to be built), and ${}_{itcs}$ equals one if the sale occurred after the farm became operational. The coefficient of interest, β_3, captures the difference-in-differences estimate: the change in log sale price for homes near a solar farm after construction, relative to price changes for homes farther away during the same period. A negative β_3 implies that the solar farm's introduction reduced nearby property values, beyond broader market trends captured by the control group.

The vectors X_{itc} and Z_{itc} control for housing characteristics and neighborhood demographics, respectively. We include solar farm fixed effects, μ_s, to account for all time-invariant differences across project sites. County-by-year fixed effects, λ_{tc}, control for local housing market shocks or policy shifts that vary across counties and time, ensuring treated and control homes are compared under common regional trends. We cluster standard errors at the solar farm level to account for spatial correlation in the error term among homes linked to the same installation. We also explore alternative fixed-effects structures to assess the sensitivity of the results to the specification of temporal controls.

3.1 *Defining Treatment and Control Groups*

In line with prior disamenity studies (e.g., Linden and Rockoff (2008); Muehlenbachs et al. (2015)), we define treatment and control areas based on proximity to the solar farm. Homes within a certain distance of a solar installation are considered "treated" (exposed to the solar farm's externalities), while homes farther away serve as the control group. Because the appropriate distance cutoff is not known a priori, we determine it empirically rather than assume an arbitrary radius. Following the approach of Haninger et al. (2017), we first regress the (log) sale price on housing attributes, solar farm fixed effects, and county-by-year fixed effects to obtain price residuals purged of observable factors. We then use a nonparametric local linear regression to examine how these residuals differ before vs. after the solar farm's construction as a function of distance from the farm (Cameron and Trivedi, 2005; Haninger et al., 2017)[6]. The intuition is that if the solar farm impacts property values up to a certain distance, we should observe a divergence between pre- and post-construction price residuals for homes nearer than that threshold, but no difference for homes farther away.

The local polynomial analysis indicates that any divergence in pre- versus post-treatment housing prices disappears beyond roughly one mile from the solar farm (Figure 1). In other words, solar farm construction has no statistically discernible effect on home values beyond approximately one mile. Based on this evidence, we define the treatment group as homes located within one mile of the nearest solar farm, and the control group as homes located beyond one mile. It is important to note that distance is measured along the street network (i.e., driving distance on roads) rather than straight-line Euclidean distance. This choice is motivated by the nature of visual externalities: solar farms are typically buffered from direct view of adjacent properties by vegetation (as encouraged by local ordinances – see Lovelady (2014)), but they remain visible to observers traveling along nearby roads. A network-distance measure thus may better capture actual exposure to the installation (Taylor, 2017). As a robustness check, we also implement a "donut" specification that excludes transactions occurring in the 1.0–1.5 mile range, ensuring that our results are not sensitive to including homes near the cutoff threshold. Table 2 summarizes the number of home sales by treatment status and time period.

[6] A local linear polynomial estimator minimizes the locally weighted sum of squared residuals. We use the Gaussian kernel for weighting and Silverman's rule of thumb (Silverman, 2018) to determine the bandwidth.

3.2 *Identification Assumptions and Validity*

The DiD strategy relies on the parallel trends assumption. That is, in the absence of treatment, housing prices in the treatment group would have followed the same trajectory as those in the control group. This identification assumption requires that, after controlling for observable differences, any change in the price gap between treated and control homes can be attributed to the introduction of the solar farm. Figure 2 provides a graphical check of this assumption by plotting the house price residual trends for treatment and control groups over time (with time measured relative to the solar farm's operation start date). The two groups exhibit statistically indistinguishable price trends in the pre-construction period, consistent with parallel trajectories prior to treatment. After the solar farm becomes operational, however, the trends diverge: there is no change in the price residuals for control homes, but the treated homes experience a pronounced downward shift. This post-treatment divergence is significant for roughly the first three years after the solar farm's opening (diminishing by the fourth year, as fewer treated homes are sold by that time).

We further assess identification validity using an event-study approach, which relaxes the constant treatment effect assumption. Specifically, we re-estimate the model allowing the treatment–control price differential to vary with each year relative to the solar farm's introduction (including solar-farm-by-year fixed effects to absorb common shocks). The resulting coefficients (plotted in Figure 3 with 90% confidence intervals) reinforce the evidence that treated and control homes followed similar trends prior to solar farm construction. In contrast, beginning in the first year after the solar farm becomes operational, a clear negative impact on treated home prices emerges and persists in subsequent years. There is a slight dip in the relative price of treated homes about one year before the opening (event time -1), which could indicate anticipation effects or disruptions during the construction period. These patterns are evidence that pre-treatment trends were parallel. This evidence further supports the validity of the research design's identification assumption.

4 Results

4.1 *Baseline Results*

Table 3 presents the baseline DiD estimates of equation 1 for the effect of solar farm construction on nearby house prices. In all specifications, the treated group is defined as homes within one mile by road of a solar farm and the control group as homes beyond one mile from that same site. Standard errors are clustered at the solar-farm level to allow for spatial correlation among observations tied to the same site, and the results are robust to alternative clustering at the county level as well (results not reported). In support of the parallel trend assumption, the pre-treatment differences between the groups are negligible. The coefficient on the *Treat* dummy (which captures any baseline price gap between homes that will be treated compared to controls) is small and not significantly different from zero in most specifications.

Our preferred specification (column (12) of Table 3) includes both solar-farm fixed effects and county-by-year fixed effects, along with the full set of housing and neighborhood characteristics. The coefficient on the interaction term *Treat* $\times$ *Post* is negative and statistically significant, indicating a substantial decline in home values for properties near the solar farm after it becomes operational. In our preferred model, the point estimate implies that the opening of a solar farm leads to approximately an 8–9% reduction in sale price for homes within one mile, relative to comparable homes in the control group.

We explore the price effect at varying proximity thresholds as well. Notably, the price impacts are highly localized: homes immediately adjacent to the solar farm experience the largest drop in value. For example, when we restrict the treatment group to houses within 0.5 miles of the solar installation (and exclude those 0.5–1 mile away), the estimated effect is around 12-14% (Table 3, columns 1 - 4). This suggests a distance gradient, where properties closest to the solar farm suffer the greatest capitalized losses, while those a bit farther out (between half a mile and one mile) see a smaller impact. Beyond one mile, we detect no price changes attributable to the solar farm, consistent with our earlier distance analysis.

Table 4 reports results for a "donut" approach, where houses located between 1 and 1.5 miles from solar farms are excluded from the control group to mitigate potential spillover effects at intermediate distances. Relative to the baseline estimates reported in Table 3, the "donut" method produces treatment effects that are larger in absolute magnitude and statistically significant.

We also examine whether solar farm development may be capitalized into home prices prior to project completion. That is, if nearby residents anticipate the disamenity, price effects might emerge before the farm becomes operational. To test this, we estimate equation 1, which introduces a construction-period dummy for homes sold shortly before the solar farm's opening. While we lack data on the precise start of construction, we follow (Kikuma et al., 2018) and assume either a one- or two-year lead time. Columns (1)–(4) of Table 5 define the construction period as one year before operation; columns (5)–(8) extend it to two years.

Results show that sales prices in the treatment group are slightly lower than in the control group during the year preceding solar farm operation, but these differences are not statistically significant. When extending the lead to two years, point estimates remain small and imprecise. Across both specifications, the coefficient on the construction-period dummy is near zero and insignificant. Overall, we find no consistent evidence of pre-construction price effects, suggesting that home values in treated and control areas were comparable in the one to two years prior to solar farm operation. Importantly, the main post-treatment effect (*Post* × *Treat*) remains stable in both magnitude and significance, confirming that our baseline results are not confounded by anticipatory price adjustments.

4.2 *Robustness Checks*

We conduct a series of additional analyses to ensure that our findings are not driven by specific modeling choices or data limitations. In each case, the results continue to support the conclusion that solar farms have a localized negative impact on home prices. Below we summarize key robustness checks.

Alternative Distance Metric: We re-estimate the model using Euclidean (straight-line) distance to define proximity. Across all specifications, this yields small, inconsistent, and statistically insignificant estimates (Appendix Table A1). This supports the use of street-network distance as a more accurate proxy for exposure, as it better captures visual access, such as from roads. Homes located within 0.5 miles "as the crow flies" but shielded by trees or lacking road access show no price response, while homes within 1 mile by road exhibit significant value declines. This suggests that visual exposure, not simple geographic proximity, drives the observed effect.

Housing Supply Adjustment: A potential concern is that the housing market may respond on the supply side to solar farm construction. For example, if homeowners delay sales or developers reduce nearby building activity, prices could be affected over time. To address this, we restrict the sample to narrower post-treatment windows. One test includes only sales within one year of solar farm opening; others limit the window to two or three years. Since housing supply is relatively inelastic in the short run, these tests help isolate demand-side effects before supply adjustments take hold. Across all windows (Table 6), we continue to observe negative treatment effects of 7–11%, though significance declines in the one-year sample due to limited observations. Importantly, point estimates remain consistent with the baseline, suggesting our results are not driven by supply-side shifts.

Extended Control Radius: Our baseline sample includes home sales within a two-mile Euclidean radius of each solar farm. As a robustness check, I expand this radius to three miles, enlarging the pool of potential control observations by including homes located between two and three miles away. The treated group remains defined using a one-mile network distance. Results (reported in Appendix Table A2) remain qualitatively unchanged: the coefficient on $Post \times Treat$ is negative and statistically significant, with a magnitude very close to that of the two-mile sample estimate. This finding suggests that including more distant control observations (unlikely to be affected by the solar farms) does not dilute the estimated effect, reinforcing the interpretation of a localized impact. Additionally, it implies that minor differences in neighborhood context between the 1–2 mile and 2–3 mile rings are already captured by the fixed effects.

4.3 Heterogeneity Analysis

We next explore whether the impact of solar farms on property values varies with certain observable factors related to the solar installations or their surroundings. In particular, we examine three dimensions of potential heterogeneity:

Solar Farm Size: We test whether the effect differs for larger vs. smaller solar farms. Many of the installations in our sample are modest in size ($\leq$5 MW capacity), and there are relatively few home sales near the handful of larger projects (>5 MW). To investigate whether larger solar farms drive the primary results, we re-estimate the model after excluding observations associated with these larger facilities. The estimated treatment effect remains unchanged, suggesting that the main findings are primarily driven by numerous smaller-scale solar farms (column 1 of Table 7). Consequently, we find no evidence of systematically different impacts arising from the few larger installations. However, given the limited number of observations around larger projects, caution is warranted when drawing definitive conclusions regarding size-specific effects.

Local Electricity Buyer: We consider whether community attitudes or perceived benefits might differ based on who purchases the power generated by the solar farm. In North Carolina, some solar farms sell electricity to investor-owned utilities (e.g., Duke Energy), while others contract with local electric cooperatives or municipal utilities. One might hypothesize that if a solar farm's power is sold locally (to a co-op/municipal utility), nearby residents could view the project more favorably, perhaps due to targeted outreach by the co-op or an expectation of local energy benefits, compared to a scenario where power is sold to a large external utility. To test this, we create an indicator for solar farms with local utility off-takers (co-ops or municipals) and interact it with the treatment variables. The regression results (Table 7, column 2) show no meaningful difference in the price effect: the coefficient on the triple interaction (*Treat* $\times$ *Post* $\times$ *LocalUtility*) is near zero and insignificant. The main *Treat* $\times$ *Post* effect in these models remains negative and significant, and its magnitude is only slightly smaller than in the baseline. In sum, whether the solar farm's electricity is sold to a local co-op/municipality or to a large utility does not appear to change the effect on nearby home prices.

Prior Land Use (Visual Buffering): We investigate whether the land cover of the solar farm site before development influences the magnitude of the externality. Converting a forested plot into a solar farm could have a different visual/scenic impact than converting an open field, for example. On one hand, replacing a forest with rows of solar panels might be more jarring (homes lose a wooded view they once had), potentially leading to larger price drops. On the other hand, a former forest site might retain surrounding trees as natural buffers, whereas a farm built on open grassland relies on newly planted vegetative screens that might be less effective initially. To test for differential effects, we classify each solar site based on its pre-construction land cover: forest vs. grassland/agricultural. We then interact these indicators with the treatment effect. The results (Table 7, column 3) reveal no statistically significant heterogeneity by land cover. The estimated solar farm effect is slightly larger in magnitude for the forested sites, but the difference is not significant, the interaction terms for *Post* $\times$ *Treat* $\times$ *Forest* and *Post* $\times$ *Treat* $\times$ *Grassland* both have confidence intervals that include the baseline effect. We conclude that, at least on average, the negative effect on home prices does not depend strongly on whether a solar farm is built on former forest versus open land. Any visual differences created by these land conversions do not translate into a discernible difference in home value responses.

We also explore other potential dimensions of heterogeneity. For example, comparing effects between more densely populated and very rural areas, or examining differences across housing value tiers. These exploratory analyses did not reveal clear patterns, partly due to limited statistical power when partitioning the sample. We stratify solar farms by community characteristics within two Euclidean miles, including education level, racial composition, ethnicity, and average income. Estimates reveal that the treatment effect is fairly homogeneous across these different community profiles (Appendix Table A3).

4.4 Additional Outcomes: Housing Market Activity

Beyond price effects, we examine whether solar farm openings have any impact on the liquidity of the nearby housing market, specifically whether homes transact less frequently once a solar farm is in operation. A reduction in sales volume could occur if homeowners are reluctant to sell (or buyers are hesitant to purchase) due to the disamenity, resulting in fewer transactions in the treated area post-treatment. To investigate this, we follow an approach similar to Currie et al. (2015) and analyze annual home sales counts in treated vs. control areas. Specifically, we aggregate the number of single-family home sales in each year, for the treated area and the control area, for each solar farm. We then re-estimate our DiD model with the log of sales count as the dependent variable.

The results, reported in Table 8, indicate a decline in housing sales activity near the solar farms. In our preferred specification with site and county-by-year fixed effects, the *Treat* × *Post* coefficient corresponds to about a 6% decline in the number of homes sold within one mile, relative to the control group, following the solar farm's construction. In other words, the volume of transactions in the immediate vicinity drops significantly after the solar farm comes online, compared to the trend in slightly more distant areas. This finding is consistent across alternative specifications as well. The decline in sales volume suggests a reduction in housing market liquidity near the solar farms.

5 Conclusion

We provide new evidence that utility-scale solar farm development can significantly depress nearby home values. Using a rigorous difference-in-differences design with high-resolution housing sales data from North Carolina, we find that homes within roughly one mile (by road) of a new solar installation sell for lower prices after the farm becomes operational, relative to comparable homes slightly farther away. The estimated impact is substantial: on the order of 8% to 12% price depreciation for properties in close proximity (with the largest losses occurring within 0.5 miles). A back-of-the-envelope calculation illustrates the economic significance of these findings: the average home within one mile of a solar farm experiences a property value reduction of approximately $11,900 following solar farm construction. These effects are highly localized, as we detect no significant price changes beyond about a one-mile distance after controlling for site fixed effects and neighborhood trends.

Our results show larger local disamenity effects than most prior studies that rely on straight-line distance measures. For example, a recent multi-state analysis by Lawrence Berkeley National Lab (Laboratory, 2023) reported only a 1.5% average price reduction within 0.5 miles of utility-scale solar sites. Likewise, previous U.K. research found modest effects limited to large solar farms (> 5 MW) (Maddison et al., 2022), while we document substantial price declines even around smaller installations. This contrast highlights the importance of accurately measuring proximity using road-network distance and demonstrates the sensitivity of impacts to local development context.

From a policy perspective, our findings indicate that renewable energy infrastructure entails meaningful local costs. Homeowners near solar farms experience reduced property equity, which may lead to community resistance. Mitigation or compensation strategies, such as targeted property tax abatements, direct payments, or community benefit agreements, could help address these localized economic impacts. Additionally, enhancing visual buffers or setbacks could alleviate aesthetic concerns, potentially reducing negative price effects.

Our analysis captures the net property value effect of converting land into solar installations but cannot fully separate the visual impact of solar panels from losses associated with the previous land use, such as open farmland or forest. Future studies should investigate whether these effects persist, fade, or intensify over longer periods as communities adapt. Examining outcomes across different regional or regulatory contexts, such as varying zoning or community engagement standards, could further identify factors influencing property value impacts. Overall, while utility-scale solar farms offer significant societal benefits, recognizing and addressing their localized costs will help policymakers ensure an optimal clean-energy transition.

6 Acknowledgments

The author(s) thank the Property and Environment Research Center for partial support of this research during a summer graduate fellowship.

7 Declaration of generative AI and AI-assisted technologies in the writing process.

During the preparation of this manuscript, the author(S) used OpenAI's generative AI tool to enhance readability, clarity, and language precision. After employing this AI tool, the author(s) thoroughly reviewed, edited, and verified the generated content, and take(s) full responsibility for the published article.

8 Data Availability

The Zillow transaction and assessment data and the solar farm data obtained from the NC Clean Energy Technology Center are proprietary and subject to confidentiality agreements. Researchers interested in using these datasets must obtain licenses directly from Zillow Research (research@zillow.com) and from the NC Clean Energy Technology Center (https://nccleantech.ncsu.edu/). All replication codes (Stata .do files) are publicly available in the replication package accompanying this paper.

References

Abashidze, N. and Taylor, L. O. (2023). The effect of utility-scale solar systems on nearby agricultural land values. *Journal of Environmental Economics and Management.* Forthcoming.

Adomatis, S. and Hoen, B. (2016). An analysis of solar home paired sales across six states. *The Appraisal Journal*, 84(1):27–42.

Cameron, A. C. and Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications.* Cambridge University Press, New York.

Cignoli, M. (2012). Neighbors sue saying homeowners' solar panels have hurt their property values. `http://www.saratogian.com/article/ST/20120322/NEWS/303229959`. Accessed: 2018-03-26.

Currie, J., Davis, L., Greenstone, M., and Walker, R. (2015). Environmental health risks and housing values: Evidence from 1,600 toxic plant openings and closings. *American Economic Review*, 105(2):678–709.

Dastrup, S. R., Zivin, J. G., Costa, D. L., and Kahn, M. E. (2012). Understanding the solar home price premium: Electricity generation and 'green' social status. *European Economic Review*, 56(5):961–973.

Gaur, V. and Lang, C. (2023). The impact of utility-scale solar farms on residential property values. *Energy Policy.* Forthcoming.

Guignet, D. and Hellerstein, D. (2023). Utility-scale solar facilities and residential property values: A national hedonic analysis. *Energy Economics.* Forthcoming.

Haninger, K., Ma, L., and Timmins, C. (2017). The value of brownfield remediation. *Journal of the Association of Environmental and Resource Economists*, 4(1):197–241.

Hao, Y. and Michaud, G. (2024). Do solar farms enhance or diminish nearby property values? evidence from the midwestern united states. *Renewable and Sustainable Energy Reviews*. Forthcoming.

Hoen, B., Adomatis, S., Jackson, T., Graff-Zivin, J., Thayer, M., Klise, G. T., and Wiser, R. (2017). Selling into the sun: Price premium analysis of a multi-state dataset of solar homes. *Energy Economics*, 67:147–158.

Hoen, B., Brown, J. P., Jackson, T., Thayer, M. A., Wiser, R., and Cappers, P. (2015). Spatial hedonic analysis of the effects of us wind energy facilities on surrounding property values. *The Journal of Real Estate Finance and Economics*, 51:22–51.

Johnson, L. (2012). Solar panel boom pits neighbor against neighbor. `https://www.scientificamerican.com/article/solar-panel-boom-pits-neighbor/`. Accessed: 2018-03-26.

Kennedy, B. (2016). Americans strongly favor expanding solar power to help address costs and environmental concerns. `https://www.pewresearch.org/short-reads/2016/10/05/americans-strongly-favor-expanding-solar-power-to-help-address-costs-and/-environmental-concerns/`. Accessed: 2019-05-22.

Kikuma, I., Rublev, E., and Tan, X. (2018). Siting of utility-scale solar in north carolina. *MA project, Duke University*.

Laboratory, L. B. N. (2023). Impact of utility-scale solar projects on residential property values: Multi-state analysis. Technical report, Lawrence Berkeley National Laboratory, Berkeley, CA. LBNL Technical Report.

Linden, L. and Rockoff, J. E. (2008). Estimates of the impact of crime risk on property values from megan's laws. *American Economic Review*, 98(3):1103–1127.

Lovelady, A. (2014). Planning and zoning for solar in north carolina. Technical report, University of North Carolina School of Government, Chapel Hill, NC.

Maddison, D., Rehdanz, K., and Welsch, H. (2022). The effect of utility-scale solar energy systems on residential property values in england and wales. *Environmental and Resource Economics*, 83:531–560.

Muehlenbachs, L., Spiller, E., and Timmins, C. (2015). The housing market impacts of shale gas development. *American Economic Review*, 105(12):3633–3659.

Qiu, Y., Wang, Y. D., and Wang, J. (2017). Soak up the sun: Impact of solar energy systems on residential home values in arizona. *Energy Economics*, 66:328–336.

Silverman, B. W. (2018). *Density estimation for statistics and data analysis.* Routledge.

Taylor, L. O. (2017). *Hedonics.* Springer.

Taylor, L. O., Phaneuf, D. J., and Liu, X. (2016). Disentangling property value impacts of environmental contamination from locally undesirable land uses: Implications for measuring post-cleanup stigma. *Journal of Urban Economics*, 93:85–98.

Wee, S. (2016). The effect of residential solar photovoltaic systems on home value: A case study of hawai 'i. *Renewable energy*, 91:282–292.

Table 1: The summary statistics of the variables used in the analysis.

	Mean	SD	Min	Max
Structural Characteristics				
real price (2017 dollars)	153,118	85,085	20,000	510,721
lot size (acres)	0.9	1.6	0.01	19.9
living area (sq ft)	1,670	638	432	7,692
age at time of sale	32	27	1	161
bedrooms	3	1	1	9
bathrooms	2	1	1	6
Location Characteristics				
Euclidean distance to solar farm (miles)	1.34	0.46	0.014	2.00
street network distance to solar farm (miles)	2.45	1.08	0.019	8.85
capacity of nearest solar farm	4.4	4.1	1	80
distance to nearest river (miles)	0.27	0.18	0	1.30
distance to nearest lake (miles)	1.30	1.13	0	9.39
distance to nearest open space (miles)	9.62	5.71	0	35.26
distance to nearest major road (miles)	0.64	0.65	0	6.33
Demographics				
White (%)	66.9	23.1	0	100.0
Hispanic (%)	9.6	11.0	0	69.1
Bachelor's degree (%)	15.9	9.7	0	55.2
Average Income ($)	57,951	17,530	16,544	187,967

Note: The number of sales for the full dataset is 15,939. Zero distance means that the house is adjacent to river, lake, open space, and/or major road. Note, several houses are located in census block groups with zero white and/or Hispanic population. Furthermore, in some block groups no individuals have bachelor or higher education.

Table 2: Transaction counts for house sales analysis by distance and time period.

	Euclidean Distance		Street Network Distance	
Treatment Status	Pre	Post	Pre	Post
Treated ($\leq 1 mile$)	2,532	1,186	703	259
Controls (>1 mile)	8,594	3,627	10,423	4,554
Total	11,126	4,813	11,126	4,813

Note: Controls (> 1 mile) include house sales located between one and two Euclidean miles or between 1 and 8.85 miles by street network.

Table 3: The effect of solar farm construction on house values.

	Treated ($\leq 0.5 miles$)				Treated ((0.5; 1] miles)				Treated ($\leq 1 mile$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treat	0.020	0.066*	0.044	0.061*	-0.007	0.000	0.018	-0.011	-0.002	0.016	0.023	0.006
	(0.042)	(0.035)	(0.035)	(0.034)	(0.033)	(0.035)	(0.035)	(0.037)	(0.026)	(0.028)	(0.027)	(0.029)
Post	0.118**	0.074	0.074*	0.043**	0.120**	0.077*	0.075*	0.043**	0.120**	0.078*	0.076*	0.049**
	(0.055)	(0.046)	(0.043)	(0.022)	(0.055)	(0.046)	(0.043)	(0.021)	(0.055)	(0.046)	(0.043)	(0.021)
Post X Treat	-0.110	-0.147**	-0.123*	-0.125*	-0.150***	-0.120**	-0.137***	-0.084*	-0.135***	-0.122***	-0.127***	-0.087**
	(0.069)	(0.074)	(0.072)	(0.075)	(0.053)	(0.049)	(0.051)	(0.049)	(0.044)	(0.043)	(0.044)	(0.042)
Adjusted R2	0.578	0.630	0.612	0.651	0.580	0.630	0.613	0.651	0.581	0.630	0.614	0.651
Observations	15,264	15,264	15,264	15,264	15,666	15,666	15,666	15,666	15,939	15,939	15,939	15,939
Year fixed effects	Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes	
Solar Farm characteristics	Yes				Yes				Yes			
Solar Farm fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
County fixed effects			Yes				Yes				Yes	
County by Year fixed effects				Yes				Yes				Yes
F-testb	0.01	0.93	0.45	1.22	0.22	0.53	1.17	0.66	0.07	0.68	1.08	0.84
(P-test)	0.92	0.34	0.50	0.27	0.64	0.47	0.28	0.42	0.79	0.41	0.30	0.36

Note: The estimates are based on equation 1. The sample includes houses located within two-Euclidean miles from the nearest solar farm. The treatment and control groups are defined based on street network measure. The dependent variable is the natural log of sales price for houses sold between 1997 and 2017. The sample includes 249 solar farms built between 2009 and 2017. A control group includes houses located beyond one street network mile of the solar farm. All models include house, neighborhood, and location characteristics. F-test for $Post + Post\ x\ Treat = 0$. Finally, robust standard errors clustered by solar farm are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Table 4: "Donut" Approach: The effect of solar farm construction on house values.

	Treated ($\leq 0.5miles$)				Treated ((0.5; 1] miles)				Treated ($\leq 1miles$)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treat	0.014	0.053	0.039	0.047	-0.015	-0.006	0.010	-0.024	-0.011	0.009	0.015	-0.007
	(0.041)	(0.033)	(0.034)	(0.032)	(0.035)	(0.037)	(0.036)	(0.039)	(0.028)	(0.030)	(0.028)	(0.030)
Post	0.122**	0.081*	0.083*	0.051**	0.124**	0.083*	0.083*	0.051**	0.124**	0.084*	0.083*	0.055**
	(0.056)	(0.048)	(0.044)	(0.023)	(0.057)	(0.048)	(0.044)	(0.022)	(0.056)	(0.048)	(0.044)	(0.022)
Post X Treat	-0.132*	-0.168**	-0.141**	-0.139*	-0.156***	-0.122**	-0.142***	-0.079	-0.140***	-0.124***	-0.131***	-0.081*
	(0.069)	(0.073)	(0.071)	(0.076)	(0.055)	(0.051)	(0.053)	(0.051)	(0.046)	(0.044)	(0.046)	(0.043)
Adjusted R2	0.576	0.629	0.609	0.651	0.579	0.629	0.610	0.651	0.580	0.629	0.611	0.652
Observations	13,687	13,687	13,687	13,687	14,072	14,072	14,072	14,072	14,345	14,345	14,345	14,345
Year fixed effects	Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes	
Solar Farm characteristics	Yes				Yes				Yes			
Solar Farm fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
County fixed effects			Yes				Yes				Yes	
County by Year fixed effects				Yes				Yes				Yes
F-testb	0.02	1.28	0.67	1.37	0.26	0.39	1.01	0.29	0.09	0.53	0.88	0.35
(P-test)	0.90	0.26	0.41	0.24	0.61	0.53	0.32	0.59	0.77	0.47	0.35	0.55

Note: The sample includes houses located within two-Euclidean miles from the nearest solar farm. The treatment and control groups are defined based on street network measure. The dependent variable is the natural log of sales price for houses sold between 1997 and 2017. The sample includes 249 solar farms built between 2009 and 2017. A control group is defined based on a "donut" approach. A control group includes houses located beyond 1.5 street network mile of the solar farm. All models include house, neighborhood, and location characteristics. F-test for *Post* + *Post x Treat* = 0. Finally, robust standard errors clustered by solar farm are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Construction Period: The effect of solar farm construction on house values.

	Construction = 1 year before the solar farm operation start date				Construction = 2 years before the solar farm operation start date			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treat ($\leq 1mile$)	0.001	0.027	0.032	0.015	-0.005	0.022	0.027	0.007
	(0.027)	(0.031)	(0.030)	(0.032)	(0.030)	(0.036)	(0.034)	(0.036)
Construction	-0.028	-0.020	-0.030*	0.009	0.007	0.006	0.004	0.002
	(0.017)	(0.016)	(0.015)	(0.020)	(0.016)	(0.014)	(0.015)	(0.020)
Post	0.107*	0.065	0.059	0.052**	0.125**	0.082*	0.078*	0.050**
	(0.058)	(0.047)	(0.043)	(0.022)	(0.061)	(0.047)	(0.043)	(0.024)
Construction X Treat	-0.020	-0.059	-0.048	-0.049	0.010	-0.020	-0.013	-0.003
	(0.046)	(0.050)	(0.048)	(0.051)	(0.039)	(0.044)	(0.043)	(0.045)
Post X Treat	-0.138***	-0.133***	-0.136***	-0.096**	-0.132***	-0.128***	-0.131***	-0.088*
	(0.045)	(0.045)	(0.046)	(0.044)	(0.047)	(0.048)	(0.049)	(0.047)
Adjusted R2	0.581	0.631	0.614	0.651	0.581	0.630	0.614	0.651
Observations	15,939	15,939	15,939	15,939	15,939	15,939	15,939	15,939
Year fixed effects	Yes	Yes	Yes		Yes	Yes	Yes	
Solar Farm characteristics	Yes				Yes			
Solar Farm fixed effects		Yes		Yes		Yes		Yes
County fixed effects			Yes				Yes	
County by Year fixed effects				Yes				Yes

Note: Note: The estimates are based on equation 1. The sample includes houses located within two-Euclidean miles from the nearest solar farm. The treatment and control groups are defined based on street network measure. The dependent variable is the natural log of sales price for houses sold between 1997 and 2017. In columns (1) to (4), construction period equals one if a house is sold one year prior to the solar farm operation start date, while in columns (5) to (8), construction period equals one is a house is sold one or two years prior to solar farm operation start date. All models include house, neighborhood, and location characteristics. F-test for *Post + Post x Treat* = 0. Finally, robust standard errors clustered by solar farm are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Robustness Check: Housing Supply Adjustment.

	1 Year Post Construction				2 Years Post Construction				3 Years Post Construction			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treat ($\leq 1mile$)	-0.015	0.009	0.012	0.006	-0.013	0.010	0.016	0.004	-0.008	0.013	0.020	0.006
	(0.026)	(0.029)	(0.026)	(0.029)	(0.025)	(0.028)	(0.026)	(0.029)	(0.026)	(0.028)	(0.027)	(0.029)
Post	0.056	0.051*	0.027	0.056**	0.070*	0.056*	0.037	0.048**	0.114**	0.087*	0.074*	0.063***
	(0.035)	(0.029)	(0.026)	(0.025)	(0.039)	(0.033)	(0.029)	(0.021)	(0.054)	(0.047)	(0.044)	(0.021)
Post X Treat	-0.096	-0.108*	-0.114*	-0.079	-0.082*	-0.094**	-0.090*	-0.074	-0.110***	-0.104**	-0.109**	-0.078*
	(0.064)	(0.064)	(0.063)	(0.065)	(0.044)	(0.047)	(0.046)	(0.045)	(0.040)	(0.041)	(0.042)	(0.041)
Adjusted R2	0.597	0.636	0.622	0.655	0.591	0.633	0.618	0.651	0.585	0.630	0.614	0.649
Observations	12,567	12,567	12,567	12,567	14,292	14,292	14,292	14,292	15,269	15,269	15,269	15,269
Year fixed effects	Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes	
Solar Farm characteristics	Yes				Yes				Yes			
Solar Farm fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
County fixed effects			Yes				Yes				Yes	
County by Year fixed effects				Yes				Yes				Yes

Note: The estimates are based on equation 1. The sample includes houses located within two-Euclidean miles from the nearest solar farm. The treatment and control groups are defined based on street network measure. The dependent variable is the natural log of sales price for houses sold between 1997 and 2017. Columns (1) to (4), removes sales occurring one year post solar farm construction. Columns (5) to (8) removes sales occurring two years post solar farm construction. Columns (9) to (12) removes sales occurring three years post solar farm construction. All models include house, neighborhood, and location characteristics. Finally, robust standard errors clustered by solar farm are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Heterogeneity Analysis

	SF capacity $\leq$ 5 MW	Electric Coops	Forest and Grass Coverage
	(1)	(2)	(3)
Treat ($\leq$ 1 mile)	0.004	0.012	0.005
	(0.029)	(0.019)	(0.029)
Post	0.047**	0.047**	0.049**
	(0.023)	(0.023)	(0.021)
Post × Treat	-0.081*	-0.072*	-0.086**
	(0.042)	(0.037)	(0.042)
Treat × Coop		-0.054	
		(0.056)	
Post × Coop		0.028	
		(0.051)	
Post × Treat × Coop		-0.062	
		(0.085)	
Treat × Forest			-0.154
			(0.094)
Post × Forest			-0.029
			(0.042)
Post × Treat × Forest			0.191
			(0.230)
Treat × Grass			-0.000
			(0.067)
Post × Grass			0.012
			(0.029)
Post × Treat × Grass			0.124
			(0.087)
Adjusted R^2	0.655	0.651	0.651
Observations	15,034	15,939	15,372

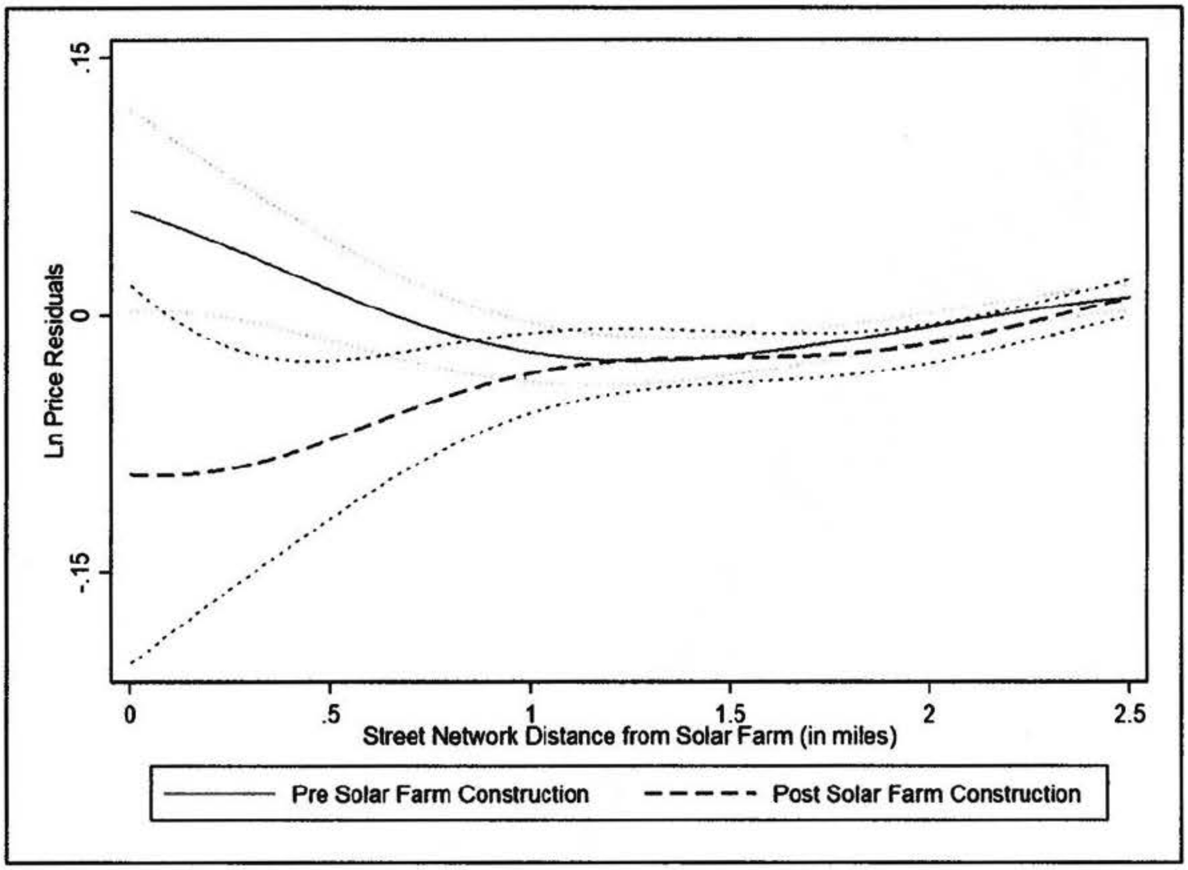
Note: The estimates are based on equation 1. The sample includes houses located within two-Euclidean miles from the nearest solar farm. The treatment and control groups are defined based on street network measure. The dependent variable is the natural log of sales price for houses sold between 1997 and 2017. Column (1) drops sales around solar farms larger than 5 MW capacity; Column (2) incorporates interaction terms between a binary indicator Coop (that equals one if a house is located around solar farms that sell power to either electric co-ops or municipality owned electric utilities) and post, treat, and post x treat variables; Column (3) includes land characteristics of parcels before the construction of the solar farm (forest and grassland indicators). All specifications include county-by-year fixed effects and solar farm fixed effects. All models include house, neighborhood, and location characteristics. Finally, robust standard errors clustered by solar farm are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Housing Market Activity: The effect of solar farm construction on sales counts

	(1)	(2)	(3)	(4)
Treat ($\leq 1mile$)	-2.688***	-2.693***	-2.690***	-2.690***
	(0.013)	(0.015)	(0.014)	(0.014)
Post	0.001	-0.002	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.003)
Post X Treat	-0.058***	-0.055***	-0.057***	-0.057***
	(0.014)	(0.015)	(0.014)	(0.014)
Adjusted R2	0.996	0.996	0.996	0.997
Observations	15,939	15,939	15,939	15,939
Year fixed effects	Yes	Yes	Yes	
Solar Farm characteristics	Yes			
Solar Farm fixed effects		Yes		Yes
County fixed effects			Yes	
County by Year fixed effects				Yes

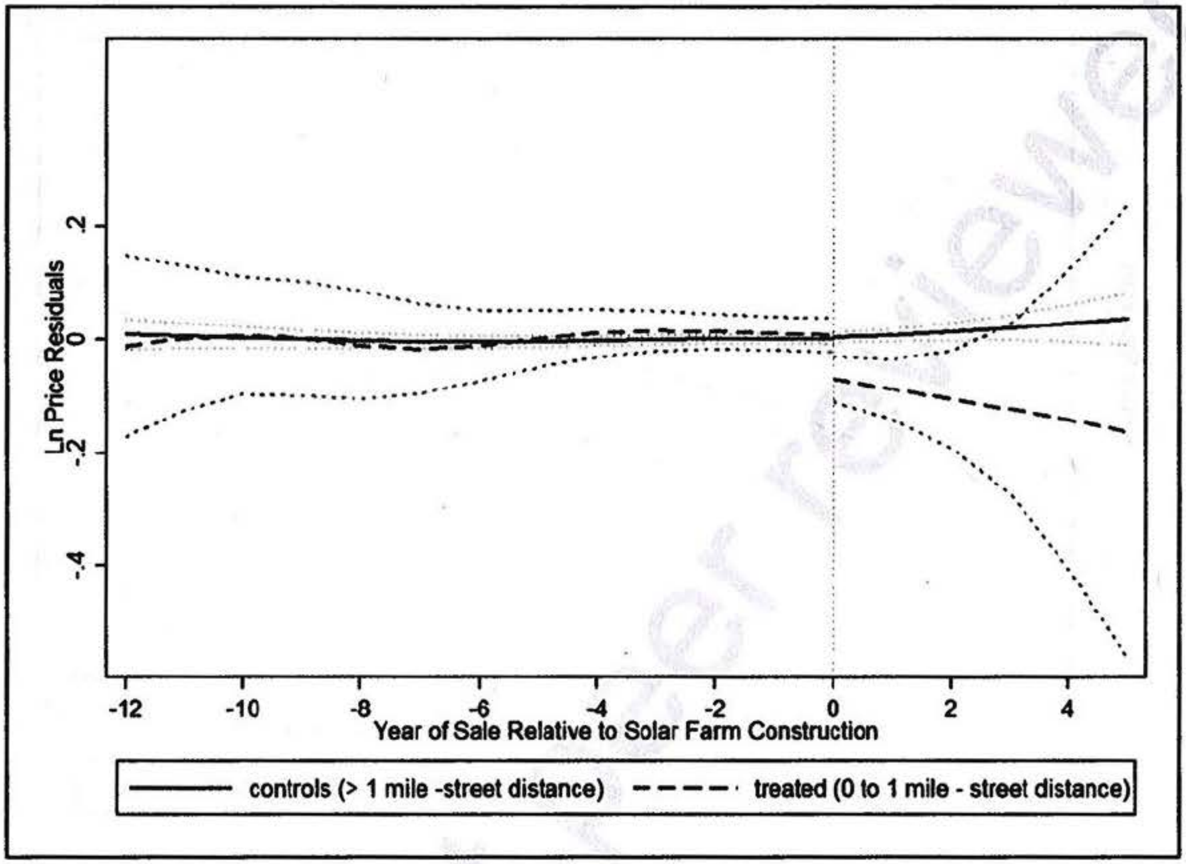
Note: The sample includes houses located within two-Euclidean miles from the nearest solar farm. The treatment and control groups are defined based on street network measure. The dependent variable is the natural log of sales count aggregated by solar farm by year of sale by treatment status. All models include house, neighborhood, and location characteristics. Finally, robust standard errors clustered by solar farm are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Figure 1. Price function estimates pre- and post- solar farm construction



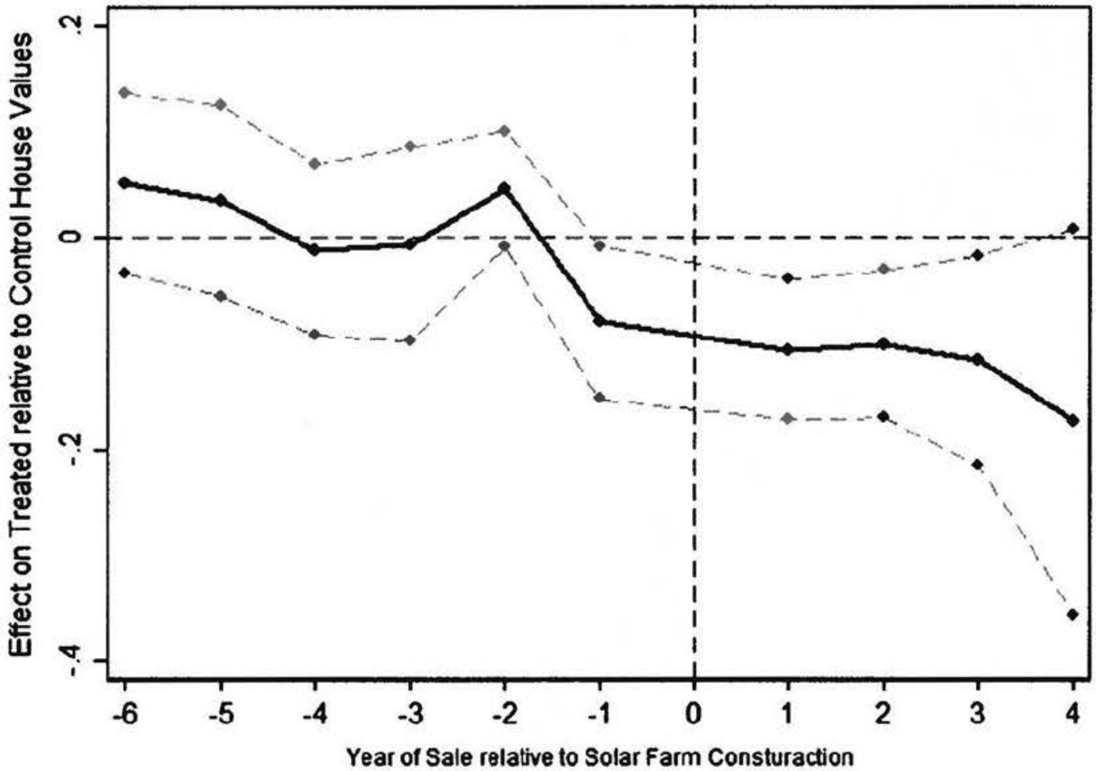
Note: The sample includes houses located within two-Euclidean miles from the nearest solar farm. The figure is restricted to sales within 2.5 miles of the solar farm based on street network distance measure. The figure includes 90 percent confidence intervals.

Figure 2. Price function estimates relative to solar farm construction date



Note: The sample includes houses located within two-Euclidean miles from the nearest solar farm. Treatment and control groups are defined based on street network distance measure. The figure includes 90 percent confidence intervals.

Figure 3. Event study: the effect of solar farm construction on housing values



Note: The sample includes houses located within two-Euclidean miles from the nearest solar farm. Treatment and control groups are defined based on the street network distance measure. The point estimates for the average treatment effect are provided along with 90 percent confidence intervals.

Appendix

Table A1: Euclidean Distance: The effect of solar farm construction on house values.

	Treated (0.5 miles)				Treated ((0.5; 1] miles)				Treated (1 miles)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Treat	0.002	0.015	0.013	0.005	-0.026	-0.028	-0.030	-0.026	-0.017	-0.020	-0.019	-0.019
	(0.025)	(0.022)	(0.021)	(0.022)	(0.029)	(0.023)	(0.024)	(0.024)	(0.024)	(0.020)	(0.020)	(0.020)
Post	0.116**	0.073	0.079*	0.041*	0.114**	0.068	0.073*	0.031	0.121**	0.067	0.074*	0.043
	(0.053)	(0.045)	(0.042)	(0.021)	(0.054)	(0.048)	(0.044)	(0.021)	(0.055)	(0.046)	(0.043)	(0.026)
Post X Treat	-0.037	-0.042	-0.033	-0.022	0.013	0.017	0.017	0.015	-0.004	0.001	0.002	0.007
	(0.032)	(0.030)	(0.032)	(0.030)	(0.029)	(0.028)	(0.028)	(0.026)	(0.024)	(0.023)	(0.024)	(0.023)
Adjusted R2	0.592	0.641	0.622	0.661	0.579	0.630	0.613	0.651	0.580	0.630	0.613	0.634
Number of observations	13,344	13,344	13,344	13,344	14,816	14,816	14,816	14,816	15,939	15,939	15,939	15,939
Year fixed effects	Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes	
Solar Farm characteristics	Yes				Yes				Yes			
Solar Farm fixed effects		Yes		Yes		Yes		Yes		Yes		Yes
County fixed effects			Yes				Yes				Yes	
County by Year fixed effects				Yes				Yes				Yes

Note: The sample includes houses located within two-Euclidean miles from the nearest solar farm. The treatment and control groups are defined based on Euclidean distance measure. The dependent variable is the natural log of sales price for houses sold between 1997 and 2017. The sample includes 249 solar farms built between 2009 and 2017. A control group includes sales located beyond one-Euclidean mile of the solar farm. All models include house, neighborhood, and location characteristics. Finally, robust standard errors clustered by solar farm are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Table A2: The effect of solar farm construction on house values (three-Euclidean miles).

	Treated ($\leq 1 miles$)			
	(1)	(2)	(3)	(4)
Treat	-0.028	0.000	0.002	-0.012
	(0.029)	(0.029)	(0.027)	(0.031)
Post	0.082	0.038	0.043	0.008
	(0.054)	(0.034)	(0.032)	(0.015)
Post X Treat	-0.110**	-0.097**	-0.115***	-0.064
	(0.047)	(0.044)	(0.044)	(0.043)
Adjusted R2	0.581	0.623	0.613	0.637
Observations	32,413	32,413	32,413	32,413
Year fixed effects	Yes	Yes	Yes	
Solar Farm characteristics	Yes			
Solar Farm fixed effects		Yes		Yes
County fixed effects			Yes	
County by Year fixed effects				Yes

Note: The sample includes houses located within three-Euclidean miles from the nearest solar farm. The treatment and control groups are defined based on street network measure. A control group includes houses located beyond 1 mile of the solar farm. The dependent variable is the natural log of sales price for houses sold between 1997 and 2017. All models include house, neighborhood, and location characteristics. Finally, robust standard errors clustered by solar farm are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Heterogeneity analysis by demographics.

	Education (1)	Race (white) (2)	Race (Hispanic) (3)	Income (4)
Post X Treat ($\leq 1mile$)	-0.061	-0.074	-0.060	-0.060
	(0.057)	(0.056)	(0.070)	(0.057)
Post X Treat X (Above Median)	-0.072	-0.028	-0.045	-0.065
	(0.080)	(0.082)	(0.086)	(0.080)
Adjusted R2	0.651	0.651	0.651	0.651
Observations	15,939	15,939	15,939	15,939

Note: The sample includes houses located within three-Euclidean miles from the nearest solar farm. The treatment and control groups are defined based on street network measure. A control group includes houses located beyond 1 mile of the solar farm. The dependent variable is the natural log of sales price for houses sold between 1997 and 2017. All models include house, neighborhood, and location characteristics. Finally, robust standard errors clustered by solar farm are in parentheses where *** p<0.01, ** p<0.05, * p<0.1.