Zine, Natalie

From:	Vincent C. Argento [redacted]
Sent:	Friday, August 29, 2025 8:58 AM
To:	Zine, Natalie
Subject:	EX: Petition 4666
Attachments:	hu-et-al-impact-of-large-scale-solar-on-property-values-in-the-united-states-diverse-effects-and-causal-mechanisms.pdf; Solar_land_value_impacts_Update-1.pdf; ssrn-5280613.pdf

Hello Natalie:

Attached are 3 Studies and/or reports that I would like submitted in opposition of Petition 4666. I plan to speak at the Zoning Board of Appeals meeting scheduled for September 2, 2025 when this petition is presented. I will submit the Request to Speak Form electronically shortly.

Thank you.

Yours very truly,

Vince

Vincent C. Argento

[redacted]

PNAS RESEARCH ARTICLE | ECONOMIC SCIENCES

Impact of large-scale solar on property values in the United States: Diverse effects and causal mechanisms

Chenyang Hu[a], Zhenshan Chen[a,1], Pengfei Liu[b], Wei Zhang[a], Xi He[a], and Darrell Bosch[a]

Affiliations are included on p. 9.

Edited by Catherine Kling, Cornell University, Ithaca, NY; received September 10, 2024; accepted April 24, 2025

As the renewable energy transition continues into less receptive communities, local opposition is expected to intensify, potentially slowing the process. Since the local impacts are neither well quantified nor widely recognized, we lack policies and common practices to mitigate the potential associated welfare loss in affected communities. Based on a nationwide dataset combining property transactions and large-scale solar photovoltaic (LSSPV) sites, we analyze the heterogeneous effects of LSSPV on property prices and the associated causal pathways. Difference-in-differences estimates show that LSSPV significantly increases agricultural or vacant land value by about 19.4% within a 2-mile radius, while simultaneously reducing residential property values within 3 miles by about 4.8%. The estimated average negative impact on home values is primarily driven by site proximity and diminishes with both distance and time. Effect estimates are more robust to alternative specifications when proximity pairs with visibility rather than invisibility, but no evidence suggests visibility significantly amplifies the proximity effect. Heterogeneous effect estimates indicate that high solar lease potential, being in heavily Democratic-leaning counties, and brownfield redevelopment largely mitigate the negative residential value impact. The analysis reveals no significant heterogeneity across a few factors, including varying site visibility, directional orientation of properties relative to the LSSPV site, and different tracking systems. Evidence indicates that the negative impact on residential values might mainly stem from negative perceptions, but channels through physical conditions cannot be entirely dismissed. Our assessment provides benchmark information for local externality mitigation plans, potentially reducing community opposition and expediting the renewable energy transition.

solar energy | economic valuation | econometric analysis | renewable energy transition

Significance

Large-scale solar projects are crucial for decarbonizing the US economy, but growing local resistance may impede the renewable energy transition. We estimate the impact of large-scale solar on property prices and the underlying pathways using 8.8 million sales and 3,699 solar sites in the United States. Exposure to solar sites decreases nearby residential home values but increases land values. For large-lot homes, the increase in land value largely mitigates the negative residential impact. Varying county political leaning and land use histories result in significantly different residential value impacts. Empirical evidence indicates that the current negative residential impact might represent a stigma effect attached to solar sites. Our findings provide important insights for addressing local resistance against large-scale solar projects.

As the cost of solar energy continues to decline (1), solar is likely to remain the leading source of renewable energy in the United States (2). Although the climate benefits of large-scale solar photovoltaic (LSSPV) are widely recognized, the siting of LSSPV projects has encountered increasing local resistance (3–5). As the renewable energy transition deepens into less receptive communities, local opposition is expected to intensify and slow down the transition process. Anecdotal and qualitative evidence suggests that the local concerns are primarily driven by negative aesthetic impacts, decreased property values, environmental injustice, and adverse impacts on local agriculture (3, 6, 7). However, these negative impacts are not well quantified, and we lack policies or common practices to mitigate the potential welfare loss in affected communities.

LSSPV facilities can significantly alter local amenities in residential areas. Recent studies suggest that proximity to a solar site may reduce home values (8, 9) due to diminished amenities such as adverse visual impact (10). The geometric and highly reflective surfaces of LSSPV facilities can be seen as unattractive and disruptive, particularly in natural or agrarian settings (11). There are other potential disamenities associated with LSSPV that may not be revealed immediately after site installation, including disrupted ecosystems and wildlife habitats (12, 13), increased soil erosion and water runoff, and degraded air quality (14). Moreover, negative perceptions of disamenities could lead to property value losses that are unrelated to actual levels of physical disamenities, a phenomenon known as the stigma effect in the housing market (15, 16).

Solar development can affect land prices considerably. An LSSPV facility typically requires between 5 and 10 acres per MWac of generating capacity. Agricultural land has been the most common land type for LSSPV development, due to its suitability, such as being flat, dry, cleared of natural vegetation, and close to electric infrastructure (17, 18). A recent projection from the American Farmland Trust shows that solar projects could occupy over 7 million acres by 2040, with 83% of new installations on farmlands and ranchlands, half of which are on highly productive land (19). If we consider the potential future surge in

Author contributions: C.H., Z.C., and P.L. designed research; C.H. and Z.C. performed research; C.H. and Z.C. contributed new reagents/analytic tools; C.H. and Z.C. analyzed data; C.H. processed geographic data and aggregated the data; Z.C. provided property data, processed geographic data and edited the paper; P.L. and W.Z. provided property data and edited the paper; X.H. provided property data and edited paper; D.B. edited the paper; and C.H., Z.C., and P. L. wrote the paper.

The authors declare no competing interest.

This article is a PNAS Direct Submission.

[1]To whom correspondence may be addressed. Email: zhenshanchen@vt.edu.

This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2418414122/-/DCSupplemental.

Published June 9, 2025.

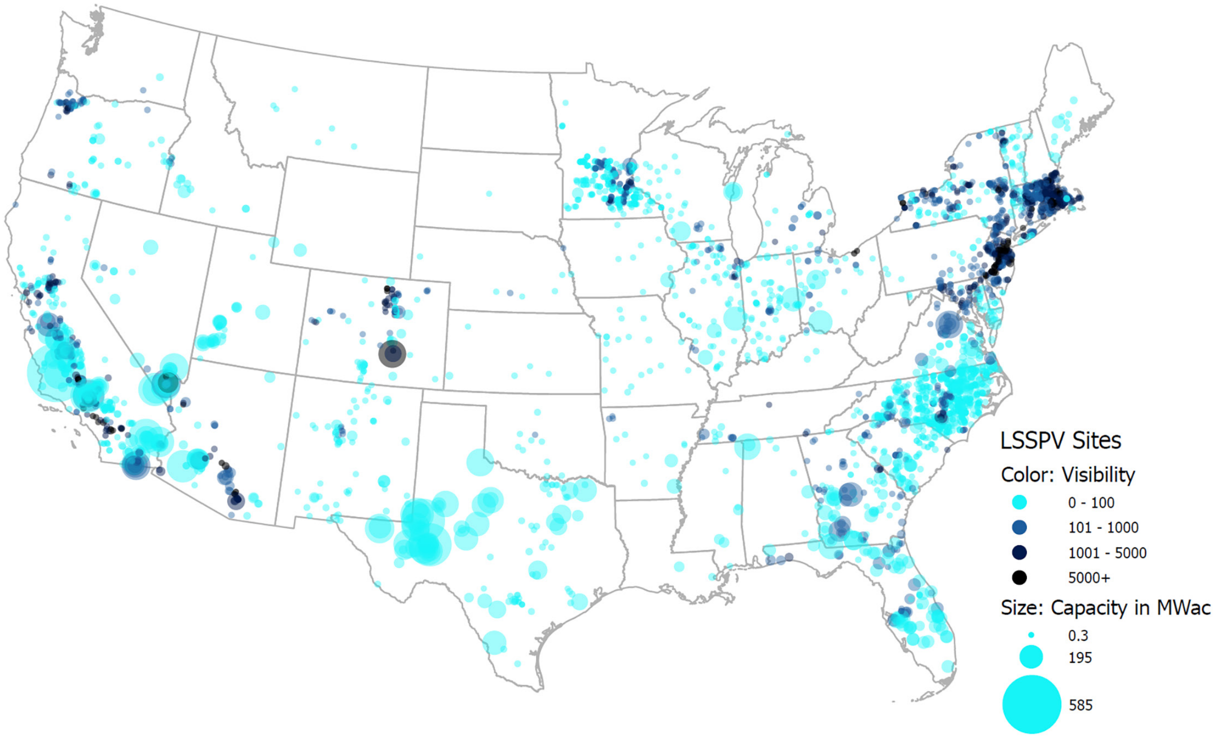


Fig. 1. Map of LSSPV locations, capacity, and visibility. The size of circles indicates the capacity of each LSSPV site. The colors represent the visibility of each site. Visibility is measured in the number of local (<6 miles) residential homes with a view of that LSSPV site.

energy demand, e.g., electrifying the transportation sector and establishing AI data centers, the required farmland for solar energy production could be much higher than the projected 5.8 million acres. In the long run, the land use competition between solar development and agricultural production is likely to increase the scarcity of farmlands, especially at the urban fringe. In the short run, leasing the land for solar energy production provides higher financial returns than traditional agricultural operations, which may drive up farmland prices and elevate farming costs.

Existing studies provide suggestive evidence that visual impacts and loss of property values are the two leading concerns for local oppositions (3, 10).[*] These local impacts of LSSPV represent classically defined externalities, as no widely established mechanism exists for solar site owners to compensate neighboring communities for potential negative effects. Quantifying these externalities is important to establishing solar siting procedures that adequately compensate the community and allow socially optimal allocations of resources. More importantly, as solar sites are initially developed in receptive communities, siting efforts are expected to become more challenging when the renewable energy transition continues. Studies have suggested that a major proportion of proposed LSSPV projects were denied or withdrawn due to local resistance (5, 10).[†] Clarifying and addressing the externalities of LSSPV development will help alleviate local opposition to solar development and accelerate the energy transition.

Utilizing property-level transaction data and detailed LSSPV site information, we present a comprehensive nationwide analysis to estimate and quantify the externalities of LSSPV facilities facing nonresidential and residential properties. We employ a Difference-in-Differences (DID) identification framework to investigate the effects of solar projects on nearby property values. Previous studies have employed similar methods to investigate the property value effects of solar site exposure in a few selected states (8, 9, 20). While viewshed analyses and visual impact investigations are prevalent for wind site studies (e.g., refs. 21–25), previous solar studies have not measured site visibility or quantified the associated visual impact, despite some indicating its relevance (e.g., ref. 26). In contrast to previous solar studies focusing on site proximity, we additionally assess the impact of site visibility and its interaction with proximity. Specifically, we create a geospatial database showing the visibility from every residential home to nearby LSSPV facility in the contiguous United States (Fig. 1, see *Data and Methods* for details). With the average effects showing the general size of welfare changes in the neighborhood, we further differentiate the impact mechanisms and provide information for a compensation plan for the local externalities generated by LSSPV sites.

Our analysis demonstrates that LSSPV sites affect local residential property values and land values differently. We separately analyze transactions on three types of properties. The first type is residential properties (hereafter "residential homes" or "residential") with a lot size under five acres (i.e., the typical minimum acreage requirement for a solar lease), where LSSPV effects primarily stem from impacts related to residential amenities. The second type involves agricultural or vacant land above five acres (hereafter "agricultural land" or "ag-land"), where LSSPV effects mainly result from potential solar lease-induced land use value changes. The third

[*]Crawford et al. (3), based on 33 interviews with residents, found that the top three of residents' most common concerns of large-scale solar are "negative aesthetic impact", "decreased property values", and "misuse of agricultural land". Moreover, a survey conducted in 2023 by Nilson et al. (10) shows that 123 developers report visual concerns to be the most common concern for utility-scale solar, followed by property value loss and agricultural land loss.

[†]An earlier study from Mulvaney (5) showed that nearly half of the LSSPV projects proposed from 2005 to 2016 in the Southwest US were denied or withdrawn, largely due to local resistance. A survey conducted in 2023 by Nilson et al. (10) suggests that among solar industry respondents across the US, 95% agree that community opposition will get in the way of decarbonization goals. The same survey shows that about 40% of planned solar projects were canceled while the remaining 60% were delayed by at least 6 months in the last 5 y, and local ordinances and community opposition are among the leading causes of cancellation.

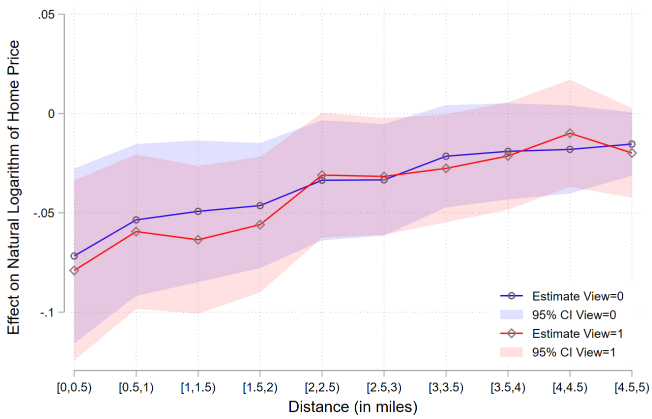


Fig. 2. Effects of proximity and view on residential home value. The blue line connects the coefficient estimates of proximity bins without view, obtained by interacting the proximity bins, the binary posttreatment indicator, and the no-visibility indicator (i.e., equals 1 if no site view). The red line connects coefficient estimates of proximity bins with view, obtained by interacting the proximity bins, the binary posttreatment indicator, and the visibility indicator (i.e., equals 1 if with site view). The number of observations (N) in this analysis is 8,303,074, excluding singleton observations on the census-tract by year level. The 95% CIs are constructed with two-way clustered SEs at the census tract and year level. The control group is properties in the 5-to-6-mile proximity bin.

type includes properties over five acres with residential structures (hereafter "large-lot homes"), where LSSPV effects may include both residential amenity and land use value impacts. Within the analysis of each property type, we further investigate the impact heterogeneity across a range of dimensions, including rural–urban status, census region, lot size, county political leaning, median household income, solar site scale, site historical land use, state siting regulation, among others. To make sure our estimates are not specific to the five-acre segregation criterion, we conducted robustness checks in *SI Appendix*.[‡]

1. Results

1.1. LSSPV Impact on Residential Home Value. We first present the results for residential properties under five acres, which include approximately 8.3 million property transactions within a 6-mile radius of LSSPV sites from 15 y before the installation of each site through 2020. Further analytical details are provided in *Data and Methods*.

1.1.1. Residential proximity and visibility. We first use distance decay specifications within the DID framework (see Section 3.5 for model details) to decide the proper treatment variable, assuming solar site exposure is determined by proximity and visibility. The view-specific distance decay results (Fig. 2) show that proximity is the major driver of the negative residential value impact. We find that, without LSSPV view, LSSPV proximity reduces residential sales price by up to 7.2% within a 0.5-mile radius, and the bin-specific estimates gradually decrease with distance and remain statistically significant up to 3 miles from the LSSPV site. Having LSSPV in the viewshed of a home incurs slightly more negative effects (i.e., up to 7.9% within 0.5 miles) compared to the pure proximity effects,[§] and the bin-specific effects also diminish with distance. Beyond 3 miles, both the proximity effect and the visibility effect become indistinguishable from zero, suggesting that visibility does not independently generate negative impacts in the absence of proximity.

1.1.2. Residential treatment—site within 3 miles. As shown in Table 1 column (1), when examining the average treatment effect of proximity within 3 miles (regardless of visibility), the estimate is 4.8% and statistically significant at the 5% level. We further investigate the interaction between proximity and visibility in column (2). When the solar site is visible and within 3 miles, property values, on average, decrease by about 5.2%. The corresponding effect of an invisible site is estimated at 4.6%. While both estimates are statistically significant at the 5% level, a statistical test shows that the difference between them is not significant at all (test *P*-value = 0.746), indicating that site visibility may not impose a significant additional average effect beyond proximity and supporting the validity of proximity-based specifications in prior studies (e.g., refs. 8 and 9). We also checked an alternative specification that excludes no-view properties within the 3-mile radius in column (3) of Table 1, which provides a similar interaction effect of visibility and proximity. These average effect analyses, combined with the distance decay results, suggest that site proximity alone largely drives the residential home effect. Consequently, site proximity within a 3-mile radius [as presented in Table 1 column (1)] serves as the principal treatment variable, representing LSSPV exposure, in subsequent event study and heterogeneity analyses. Examining the sensitivity of estimates to alternative control group specifications in *SI Appendix*, Table S6, we find that the interaction effect of visibility and proximity remains robust across the board, while the pure proximity effect becomes insignificant in some of the alternative

Table 1. DID Estimates for Residential Homes

	(1)	(2)	(3)
	ProxT	ProxT × ViewT	ProxT × ViewT
ProxT	−0.076**		
	(0.022)		
β_3: ProxT × Post	−0.048*		
	(0.020)		
ProxT × 0.ViewT		−0.078**	
		(0.022)	
ProxT × 1.ViewT		−0.070**	−0.044
		(0.023)	(0.029)
$\beta_3^{no\_view}$: ProxT × 0.ViewT × Post		−0.046*(0.020)	
β_3^{view}: ProxT × 1.ViewT × Post		−0.052*	−0.046+
		(0.020)	(0.023)
N	4975808	4975808	2444983
Covariates	Yes	Yes	Yes
Census Tract × Year	Yes	Yes	Yes

Test (H_0: $\beta_3^{no\_view} = \beta_3^{view}$): z-Statistic = 0.324 *P*-value = 0.746

Note: In Column (1), ProxT, standing for site proximity below 3 miles, is used as the treatment. In Column (2), proximity without view (ProxT×0.ViewT) and proximity with view (ProxT×1.ViewT) are used as treatment. In Column (3), properties that satisfy ProxT = 1 and ViewT = 0 are excluded. β_3 s represent the treatment effects specified in Section 3.5.1. SE, two-way clustered at census tract and year level, are reported in parentheses: $^{+}P < 0.1$, $^{*}P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$. Census tract by year fixed effects and property-level covariates are included in all specifications but not displayed. The control group is properties in the 5-to-6-mile proximity bins of the LSSPV sites, and properties located within 3 to 5 miles from the LSSPV sites are excluded. The number of observations, N, is calculated excluding singleton observations on the census-tract by year level. The coefficient for Post is omitted due to collinearity with fixed effects.

[‡]The results are presented in *SI Appendix*, Table S8, which suggest that the main estimates are robust to alternative acreage thresholds for segregating the small-lot properties and large-lot properties (e.g., 5 miles to 0.3 miles for small-lot properties and 5 miles to 9 miles for large-lot properties). Therefore, the main conclusions of this study are not sensitive to changes in the five-acre threshold.

[§]As pointed out in the *Data and Methods* section below, our visibility measure potentially overrepresents the true visibility especially when the viewpoint and the target are close, limited by structural elevation data availability (36). This measurement bias introduces attenuation in the treatment variable, potentially leading to an underestimation of the visibility impact (and hence the difference between visibility and proximity impact in Fig. 2).

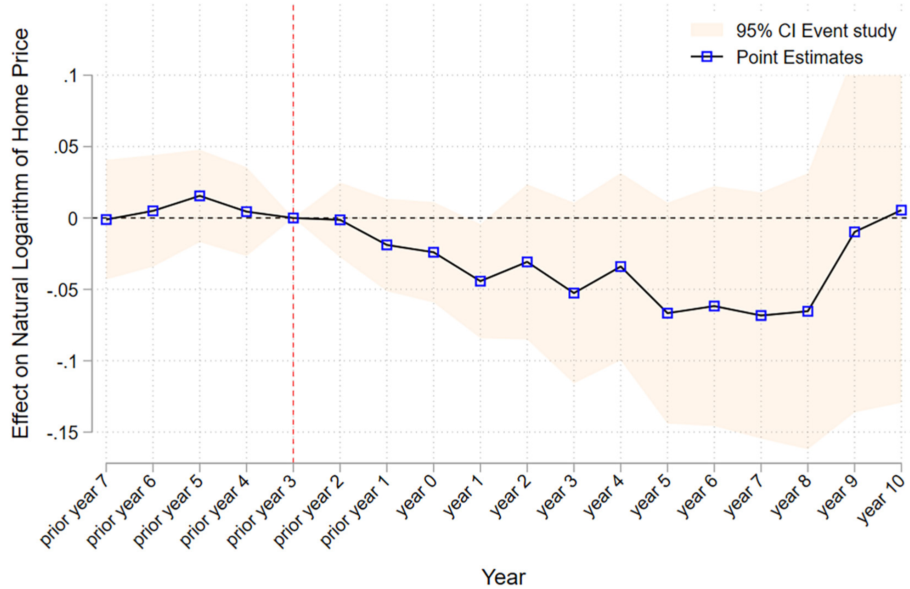


Fig. 3. Event study on residential home value. The treatment (LSSPV site within 3 miles) effect on residential home values is illustrated across different years relative to the year of LSSPV installation. The blue squares on the black line indicate the coefficient estimates, obtained by interacting the treatment variable with year indicators. The reference year is defined as 3 y before the LSSPV installation, and the control group is properties in the 5-to-6-mile proximity bin. The shaded areas represent the 95% CIs, constructed using two-way clustered SEs at the census tract and year level.

specifications. This implies that site visibility appears to reinforce the proximity effect in the sense that it improves the robustness of the home value effect estimate across various alternative control group specifications. To provide a comprehensive view of the proximity effect, we present both the specifications from column (1) and column (2) in the pretrend tests and robustness checks in the *SI Appendix*. Pretrend tests with placebo treatments in *SI Appendix*, Table S5 show that the parallel trend assumptions are satisfied for all specifications in Table 1. More robustness checks in *SI Appendix*, Tables S8 and *S9* confirm that all estimates in Table 1 remain consistent when applying alternative sample selection criteria based on acreage and the number of observations per tract-year cluster.

1.1.3. Residential event-study results. We explore the timing of the LSSPV exposure effect (i.e., site visible within 3 miles) based on an event study where the base year is specified as 3 y prior to the LSSPV installation[¶] (Fig. 3). The average negative price impact on residential homes is minor after the base year but becomes pronounced following the installation. The effect generally maintains its magnitude over time and fades after the ninth year postinstallation. There are potential explanations for the observed effect dynamics. Right after the base year, the gradual dissemination of the LSSPV site information may not have reached many home buyers or led them to fully realize the potential negative price impact of the site, but the installation event makes the impacts clear and manifested in the market. The diminishing effect after 9 y might come from the shrinking sample size as most of the LSSPV sites were developed after 2010. However, if the diminished effect is true, it does not necessarily imply that the negative amenity impacts disappear after 9 y since many of the negative impacts, such as soil erosion and dust pollution, may take a long time to manifest (14, 27, 28). A more plausible explanation of the faded price impact may be linked to residential sorting and demographic shifts (29–31), as individuals less concerned about LSSPV facilities move into the affected neighborhoods. This indirectly suggests that the negative price impact might be more closely related to psychological factors than to the amenities themselves, which will be explored further in subsequent analyses and discussions.

1.1.4. Residential Effect Heterogeneity. We explore the heterogeneity of LSSPV exposure effect on residential homes across various dimensions, as shown in *SI Appendix a*nd Fig. 4.[#] We observe noticeable heterogeneity across census regions, county political leaning, county median household income, and historical land use of the LSSPV sites. Statistical tests results are available in *SI Appendix,* Table S10. LSSPV sites in the Northeast region impose significantly more negative impacts than those in other regions. Heavily Democratic-leaning counties (over 65% Democratic votes in 2016) experience a positive LSSPV effect (+0.0374, insignificant), which is significantly different from more politically conservative counties (−0.0538, significant at the 5% level). Greenfield LSSPV development leads to a negative effect (−0.0466, significant at the 10% level), while brownfield redevelopments lead to a positive residential value effect (+0.225, significant at the 10% level), significantly different from the effect of Greenfield LSSPV.[||] Observed differences along other dimensions are not statistically significant. Moreover, we observe almost zero heterogeneity across different rural status, different lot sizes, different site capacities, and different levels of site visibility. A higher level of visual exposure ("High View" in Fig. 4) or directly facing the solar panels (i.e., in the south of the solar panels,

[¶]This approximately represents the time when some residents may become aware of the upcoming LSSPV site through permitting, contracting, community engagement, or other site preparation activities.

[#]We also investigate the heterogeneous pure proximity and visible proximity effects in *SI Appendix* Fig. S7. The results show that both effects have very similar heterogeneities as the main results in Fig. 4: the negative property value impact is significantly higher in more politically conservative counties, and brownfield sites may have a positive property value impact.

[||]Brownfields include sites such as hazardous waste facilities, abandoned contaminated areas, and inactive mines (53). Solar projects on brownfields often require site cleanup, which can reduce negative externalities and undesirability of these sites and positively affect property values. This aligns with Gaur et al. (54), who found that residents are willing to pay more for solar projects on brownfields, as these sites are otherwise undesirable. Meanwhile, respondents in Gaur et al. request compensation for solar project developed on greenfields, suggesting that they perceive brownfields as the more appropriate land type for LSSPV development than greenfields.

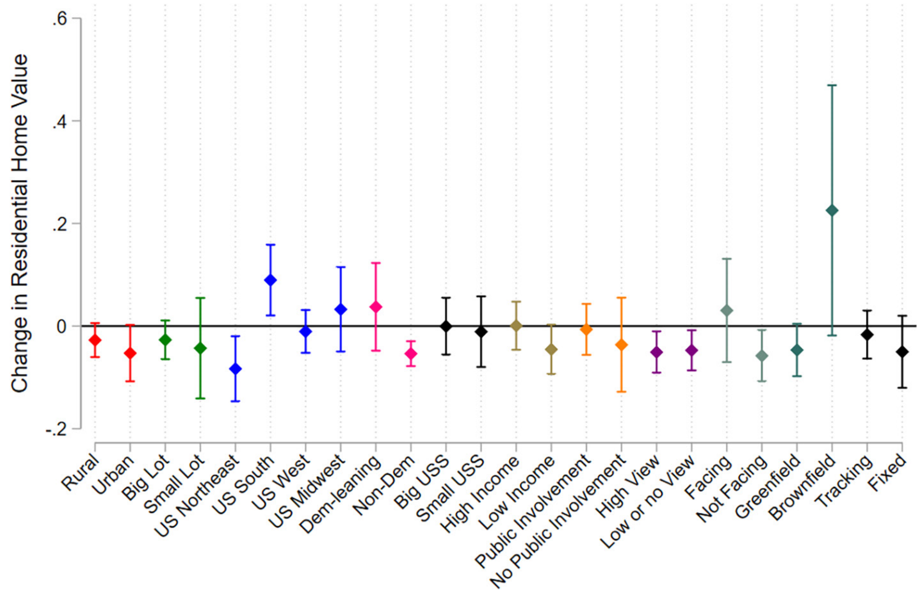


Fig. 4. Heterogeneous effects of LSSPV exposure by different dimensions. Diamonds are the point estimate of the effect of LSSPV on nearby residential home values based on DID models. The treatment is LSSPV within 3 miles, and the control group is properties in the 5-to-6-mile proximity bin of the LSSPV site. The 95% CIs of the estimates are shown as bars, having clustered SEs at the census tract and year level. Check *SI Appendix* for the details of all factors investigated here. More heterogeneity checks differentiating visible and invisible sites are available in *SI Appendix*, Fig. S7.

"Facing" in Fig. 4) does not lead to a more negative residential value effect, providing further evidence that more view exposure may not lead to significantly more negative impacts. While we lack direct data on glint and glare effects, indirect evidence suggests they may not be a primary mechanism, as we find no evidence to support that being exposed to a site with tracking systems (i.e., potentially more susceptible to glare impacts, "Tracking" in Fig. 4) or facing the solar panels lead to more negative impacts. Instead of visual levels or details, impacts appear to stem from psychological factors, such as negative perceptions of industrialization and altered scenic views. These negative perceptions are expected to be amplified by conservative ideology or mitigated by progressive ideology, aligning with the empirical finding that more politically conservative counties are associated with more negative impacts.

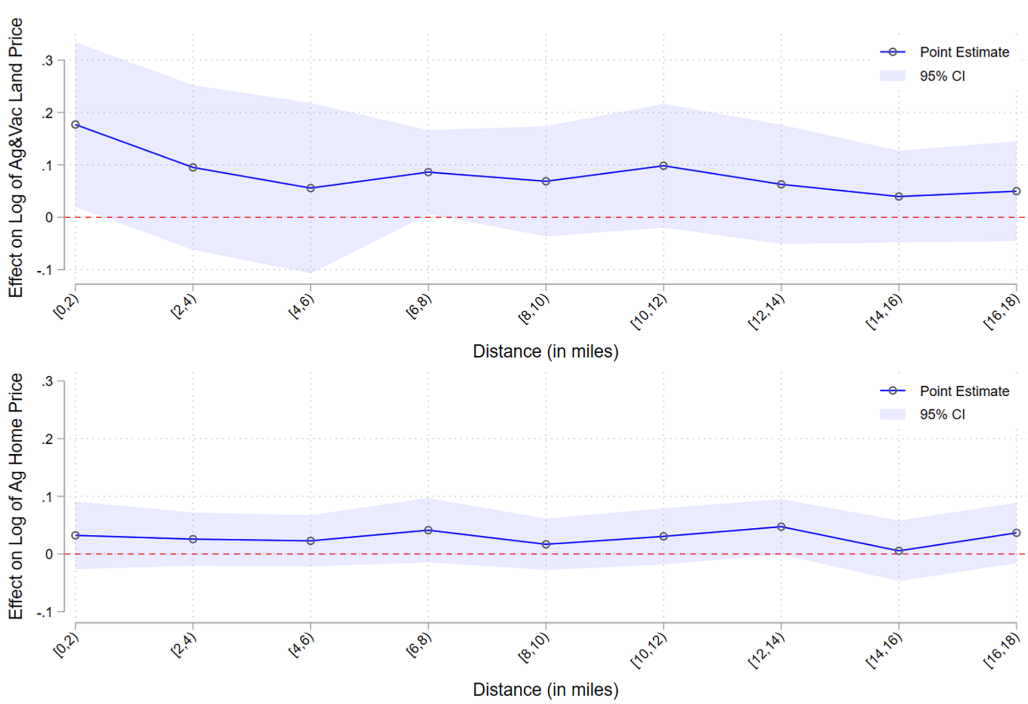


Fig. 5. Distance decay results for agricultural/vacant land and large-lot homes. The top subfigure shows estimates for agricultural and vacant land above five acres. The bottom subfigure shows estimates for large-lot homes, defined as properties over five acres with residential structures. The results show the value effects of LSSPV for a range of proximity bins, defined with 2-mile intervals. The blue line connects the coefficient estimates of proximity bins, obtained by interacting the proximity-bin indicators with the binary posttreatment indicator. The treatment groups are properties within these proximity bins, while the control group is properties within the 18-to-20-mile proximity bin. The 95% CIs are constructed with two-way clustered SEs at the county-site and year level.

1.2. LSSPV Impact on Agricultural Land Value. Our Ag-land analyses show that having LSSPV sites within 2 miles of agricultural or vacant land increases the sales price per acre by an average of 19.4%,[**] which is statistically significant at the 5% level (Fig. 5). The positive effect rapidly declines and becomes insignificant beyond 2 miles, similar to estimates in ref. 32. This positive effect is likely due to the demand increase from potential solar leases, as further expansion of existing LSSPV sites is less costly than constructing new sites and likely involve nearby agricultural or vacant land. Pretrend tests in *SI Appendix,* Table S5 show that the parallel trend assumptions are satisfied. Robustness checks in *SI Appendix,* Table S7 suggest that our main ag-land estimate is robust against different control group selection criteria. Event-study results in *SI Appendix,* Fig. S5 show that the positive land value effect manifests 3 y after the site installation and fades away 6 y later. *SI Appendix,* Fig. S6 presents our analysis of heterogeneous ag-land effects. We find that LSSPV sites of larger than-median scale have virtually zero effect on land value, while sites of smaller scale display a positive effect on land value (significant at the 10% level). Considering that smaller sites have a larger potential for expansion, this observation seems to confirm our speculation that the nearby land value increase is mainly driven by the potential of future solar lease. We also find that agricultural or vacant lots of large acreage bear virtually zero effect while smaller lots show a significantly (at the 5% level) positive effect. However, these differences are not statistically significant. More robustness checks in *SI Appendix,* Table S8 suggest that our land value estimates remain consistent when applying alternative sample selection criteria based on acreage. Finally, robustness checks in *SI Appendix,* Table S9 reveal that when focusing solely on county-site-year clusters containing more than a few sales, the land price effect of LSSPV rises dramatically, reaching 86.1% when excluding less-than-20-land-sales clusters (corresponding to a coefficient of 0.621). Given that we have excluded sales of land hosting LSSPV sites, the mechanism behind this substantial effect on land prices remains unclear but warrants further investigation.

1.3. LSSPV Impact on Large-Lot Home Value. Our empirical results show that LSSPV sites have a dual effect: they decrease residential property values via reduced residential amenity, while simultaneously increasing nearby land prices due to enhanced land use potential. For large-lot residential homes with over five acres of land, we expect the LSSPV to impact property values through both channels. Our distance decay analysis (Fig. 5, *Bottom*) suggests that the overall LSSPV impact on large-lot home price is close to zero and statistically insignificant for all nearby proximity bins. Robustness checks in *SI Appendix*, Tables S8 and S9 confirm that these large-lot-home estimates remain small and insignificant when applying alternative sample selection criteria based on acreage and the number of observations per tract-year cluster. Therefore, the LSSPV property value impacts via amenity reduction and increased land use potential seem to offset each other in residential homes with over five acres of land.

2. Discussion

This study provides a comprehensive nationwide assessment of the externalities associated with LSSPV installations in the United States focusing on their impacts on property values. We leverage a rich property transaction dataset with detailed geospatial information of LSSPV sites to estimate the effects on both residential properties and agricultural/vacant land. We apply advanced geospatial methods to overcome computational challenges and develop a comprehensive nationwide database on LSSPV visibility. Our findings reveal that LSSPV installations negatively affect the value of residential properties located within 3 miles, while increasing prices for agricultural and vacant land within 2 miles. Moreover, when the impacts through reduced residential amenity and increased land use potential coexist, the LSSPV effect on large-lot homes is indistinguishable from zero. We also explore the dynamics and heterogeneities of the local property value effects of LSSPV.

Our analyses and heterogeneity checks indicate that a nearby solar site may act as a stigmatizing nuisance (i.e. a psychological disamenity, see refs. 15, 16, 33) and 34). Evidence supporting this claim includes the minimal variation in effects across different levels of site visibility, in effects across properties to the south and to the north of the site, and in effects across sites with different tracking systems, as they suggest that the view details of solar sites (including view extent, the exact view composition, and potential difference in glare effects) do not significantly impact residential values. The negative impact on nearby residences appears to operate primarily through psychological channels rather than through the degree of visibility or specific visual details. Considering disamenities other than visual impact, the scale of the site likely results in different disamenity levels and impacts, but this is also not observed (i.e., "Big USS" vs. "Small USS" in Fig. 4). One explanation can be linked to negative perceptions that solar sites are industrial/commercial uses that alter rural land use and scenic views (15). The disparities in effects between brownfield and greenfield sites align with this mechanism. Another piece of evidence is the significantly higher property value loss in more conservative counties compared to Democratic-leaning counties. This disparity is likely due to solar sites being more aligned with progressive values prevalent in Democratic-leaning counties and less frequently associated with negative perceptions. However, we cannot entirely rule out causal channels related to actual disamenity variations. First, our nationwide analysis may obscure heterogeneities under certain conditions – for example, sites with a larger scale may have a stronger negative effect in the Northeast but a weaker one in the West, potentially canceling out in a pooled sample. Second, unexplored physical channels, such as vegetation and soil management practices (e.g., refs. 9 and 27), might also contribute to the negative LSSPV impact on residential values.

Our findings highlight the complex interplay between the benefits and costs of LSSPV development. In *SI Appendix,* Table S11, we performed a back-of-the-envelope calculation to estimate the benefits and costs of LSSPV solar sites included in our analysis, including the mitigation value (i.e., avoided social cost of carbon emission), the appreciation of nearby agricultural or vacant land value, the value loss of nearby residential properties, and the agricultural production loss on land utilized for hosting LSSPV. The results suggest that the assessed benefits of existing LSSPV significantly outweigh the assessed total costs. The carbon mitigation benefit is the major benefit (about $22.2 billion annually), while the loss in residential home value is the dominant cost (about -$4.1 billion annually). Therefore, property value losses constitute a major proportion of negative externalities of LSSPV. While the expansion of solar energy is crucial for the renewable energy transition, it is imperative to address the localized externalities to ensure equitable outcomes for affected communities. Quantitative evidence, such as that generated by this study, can inform policymakers and stakeholders in designing compensation mechanisms and siting strategies that mitigate negative impacts while promoting the broader adoption of solar energy.

[**]The coefficient estimate is 0.177, which reflects the effect on the logarithm of price. When this is converted to the actual proportional price effect, the result is $e^{0.177} - 1 = 19.4\%$.

To illustrate how our results or similar studies could be used to develop a community compensation plan, we design a prototype evidence-based community compensation plan for a site proposal in (*SI Appendix,* Fig. S12). First, property value impact studies should be carefully conducted with empirical data from comparable solar sites (e.g., similar size, similar demographics, in counties or states of similar regulations, etc.), where the effect of distance decay, dynamics, and heterogeneities across a wide range of dimensions should be analyzed. The sample choice of LSSPV sites needs to balance site similarity and statistical power of analysis. Second, based on the property value study, compensation specifics should be decided for different properties in the neighborhood. Taking our main results as an example, compensation rates could be set at 5.2% of the annualized property value for 10 y for residential homes within 3 miles of the LSSPV site with a site view, 4.8% for those without a view, and 19.4% of annual agricultural land rental costs[††] for 4 y for leasing farmers within 2 miles. Third, the community compensation plan can involve communication with stakeholders ahead of the permitting process, and stakeholders' input should be involved in the revision process before reaching a final plan. A comprehensive compensation plan should also consider local externalities that might not visibly manifest in property prices. We would like to stress that the specific community compensation plan developed based on our nationwide study here should be merely taken as an example, and we recommend conducting targeted studies to determine appropriate community compensation plans for a specific LSSPV site.

3. Data and Methods

The analysis primarily utilizes data of three categories: The US LSSPV data, the real estate transaction and assessment records, and geospatial data.

3.1. LSSPV Data. The LSSPV data acquired from the US Large Scale Solar Photovoltaic Database (USPVDB) (35) contain 3,699 LSSPV facilities investigated in the study. This dataset provides detailed information on LSSPV site footprint, area, capacity, and installation year, spanning from 1986 to 2021 (*SI Appendix,* Fig. S1 shows the total acreage developed per year, and *SI Appendix,* Table S1 shows the summary statistics of LSSPV projects). The facility polygons are digitized along the boundaries of the solar arrays, within an accuracy of 10 m.

3.2. Property Transaction. The property data are purchased from CoreLogic through a data agreement. CoreLogic data contain comprehensive information on property and transactions from the whole United States and enables researchers to work on property-level research questions. We developed a process to exclude non-arm's-length transactions (i.e., purging price outliers, foreclosure sales, multiple sales, sales between relatives, sales involving institutional buyers or sellers, and others as detailed in *SI Appendix*) so that our analyses only include transactions reflecting fair market values. The transaction prices are adjusted for inflation to reflect their values in 2017 dollars using the Consumer Price Index data from the US Bureau of Labor Statistics. We also exclude potential home flipping events by removing transactions of the same property that occur within 120 d of each other. As the majority of LSSPV sites have been developed within the past decade, we keep transactions up to 15 y before the installation of nearest LSSPV to make the time frame generally centered around the LSSPV development. The final dataset for analysis comprises both single-family residential properties and agricultural or vacant land, spanning 40 states[‡‡] from 1993 to 2020. To avoid the potential impact from market disequilibrium, we drop observations during the Great Recession (i.e., 2008 to 2010). *SI Appendix,* Tables S2–S4 show the summary statistics of residential homes, agricultural and vacant land, and large-lot homes, respectively. *SI Appendix,* Figs. S2–S4 illustrate the distribution of post-LSSPV-installation transactions of residential homes, agricultural or vacant land, and large-lot homes, respectively, across different proximity bins.

3.3. Geospatial Data. The geospatial data consist of a collection of geographic layers obtained from the US Census Bureau TIGER/line geodatabase (USCB TIGER) and US Energy Information Administration (EIA), which includes shapefiles of primary roads, transmission lines, and metropolitan areas. To support heterogeneity analyses, we also collected data on median household income, median land values, political leanings, and state-level siting policies, among other factors (see *SI Appendix* for details).

To acquire solar site proximity and other (dis)amenities, we generated geographic variables that represent the Euclidian distance between a property and the boundary of the nearest five solar sites, transmission line, primary road, and metropolitan area. The geographic variables were then matched with the property data. To alleviate identification concerns that attributes of control observations (i.e., properties far away from sites) might considerably deviate from treated observations (i.e., properties with solar site exposure), we only kept residential homes that are less than or equal to 6 miles away from the nearest solar sites. For properties above five acres (i.e., agricultural land or large-lot homes), we use a 20-mile radius inclusion criterion due to the general low density and low transaction volumes of such properties. The final sample includes 8.3 million transactions for residential homes, 68 thousand transactions for agricultural or vacant land, and 416 thousand transactions for large-lot homes.

3.4. Visibility Analysis. We establish a visibility database for LSSPV across the continental United States and investigate the property value effect of LSSPV visibility. We calculate the visibility from residential properties to large-scale solar sites within 6 miles. This visibility analysis proceeds in three steps. First, we acquire Digital elevation models (DEMs) of the continental United States from the Shuttle Radar Topographic Mission (SRTM) produced by NASA.[§§] Our analysis uses the 2018 version of SRTM DEMs at a resolution of 90 m by 90 m. The DEMs employed reflect terrain elevation but may not capture structures (e.g., houses or trees), and hence could overstate visibility especially when the viewpoint and the target are close (36). Nonetheless, the employed DEMs are the best available public data for our analysis, as structural elevation data (e.g., Light Detection and Ranging, or LiDAR, data) are not available for most solar sites and their neighborhoods.

Second, we calculate the viewsheds from solar sites to decide the areas from which the sites are visible, utilizing the duality of vision following ref. 21 (i.e., if and only if viewpoint A has a view on target B, a viewpoint on B has a view on target A). This approach greatly reduces computational effort since the number

[††]Note that this compensation assumes that the land price increase will induce a similar change in land rent costs. If land rent data is available, it could be used as the outcome in a similar DID study to decide the land rental cost impact of LSSPV site, which could serve as the baseline of the compensation to leasing farmers.

[‡‡]The other ten states (i.e., Alaska, Hawaii, Idaho, Kansas, Louisiana, Maine, Mississippi, Montana, Utah, and Wyoming) are excluded from the final analysis due to the absence of LSSPV sites, a lack of available transactions near LSSPV sites, or their non-continental status.

[§§]DEMs provide crucial information on the ground topography of the study area. The Shuttle Radar Topographic Mission by NASA employs remote sensing technology to gather laser light measurements of the earth's surface. The mission started in 2000, with a goal to create the first near-global topographical map of Earth and collect data on nearly 80 percent of the planet's land surfaces. Data are available at https://srtm.csi.cgiar.org/.

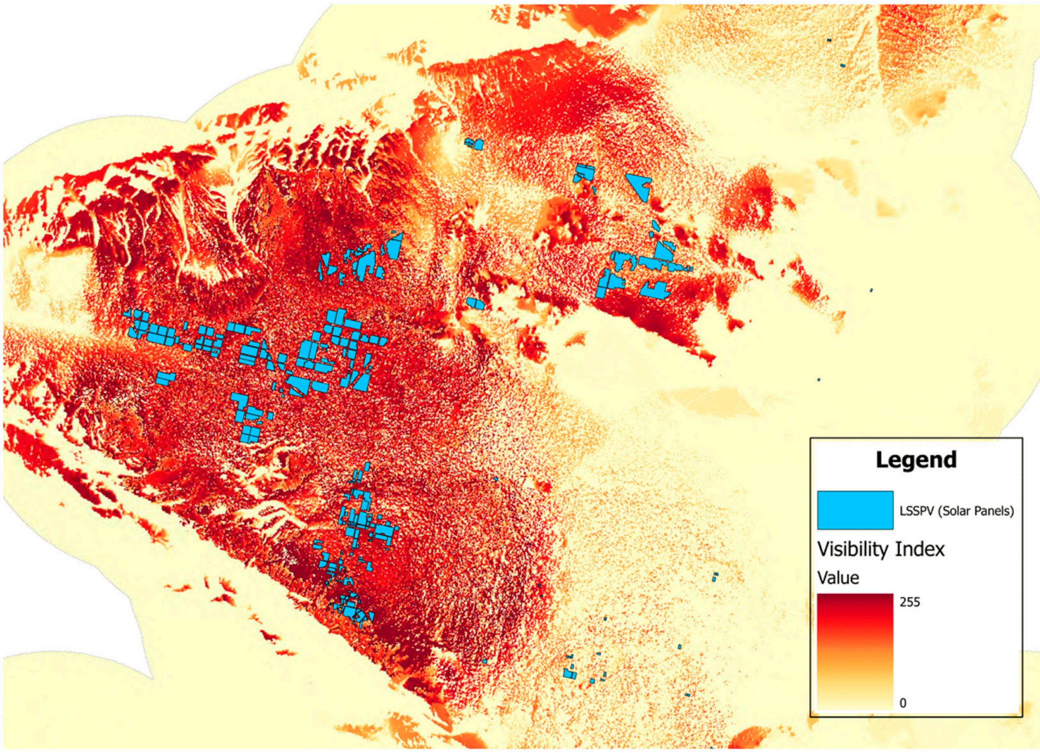


Fig. 6. Surface of Visibility Index. The visibility index measures the number of visible perimeter points of nearby solar sites. Intuitively, the red color denotes regions with solar view, and regions in darker red can see a larger area of solar panels.

of solar sites (3,699) is much smaller than the number of properties (about 5.9 million). Unlike the wind turbines that require height specifications for accurate viewshed analyses, LSSPV sites span broad areas, necessitating a proper way to account for partial views of a large solar site. Specifically, we set viewpoints along the perimeter of each site, where the viewpoints are defined with a random start point, an interval distance D, and a height of two meters. In practice, D is set at 500 m to balance the computation workload and the accuracy of partial view accounting.

Third, we aggregate the viewsheds from all site perimeter viewpoints and overlay the aggregated viewshed layer with properties to calculate the visibility variables. The aggregation of viewsheds will generate the visibility index (Fig. 6) for each geographic unit defined by the raster resolution (90 m by 90 m). Overlaying with the property layer, the visibility index will represent the number of perimeter viewpoints that can see a property, or the number of solar site perimeter points that the property has view on based on the duality of vision. This property-specific visibility index quantifies the extent of solar site visibility for each property and can be converted into a binary visibility variable that serves as the treatment variable in a DID model. For more details of the visibility analysis, refer to *Visibility Analysis* Details section in *SI Appendix*.

3.5. Econometrics: Property Value Effect Models. Previous studies have used econometric models to analyze and identify a variety of characteristics that could consistently influence property values, such as the productivity of the farmland (e.g., ref. 37), the influences of urbanization (e.g., ref. 38), and environmental factors (e.g., refs. 39–41). To estimate the impact of solar projects on nearby property values, it is crucial to control for potential confounders. We employ a DID approach to investigate the effects of LSSPV installation on nearby property values. Intuitively, this approach compares the change in property values before and after installation for properties close to the LSSPV site against the value change for properties farther away but still within the defined vicinity.

3.5.1. Analyses for residential homes. The general DID framework of our residential home study is as follows:

$$\ln(P_{it}) = \beta_0 + \beta_1 Post_{it} + \beta_2 T_i + \beta_3 Post_{it} \times T_i + \delta_k \sum_{k=1}^{K} X_{it}^k + \gamma_k \sum_{k=1}^{K} (Post_{it} \times X_{it}^k) + \tau_{ct} + \varepsilon_{it}. \quad [1]$$

In Eq. **1**, each observation corresponds to a transaction of residential home i that occurred in year t, with the dependent variable being the natural logarithm of transaction price $\ln(P_{it})$. $Post_{it}$ is a binary indicator that denotes whether the transaction of residential home happened after the LSSPV installation. T_i is the binary indicator that denotes whether a residential home was assigned to a treatment group, and the exact definition of treatment is explained below. The coefficient β_3 associated with the interaction term between $Post_{it}$ and T_i captures the impact of LSSPV installation on the outcome variable, which resembles a proportional change in the residential home prices. Previous studies show that the proximity to transmission lines could have an impact on the value of nearby property (42), and this impact could change after an LSSPV installation in the vicinity (20). To account for housing and lot characteristics that could affect home values and the estimation of β_3, we include property-level control variables X_{it}^k and $Post_{it} \times X_{it}^k$ (43, 44), where X_{it}^k include total bedroom number, total bathroom number, building age, and natural logarithms of distances to the nearest transmission line, the nearest primary road, and the nearest metropolitan area. To absorb the time-varying external location-specific shocks in the housing market, we incorporate fixed effects on the census tract by year level, denoted as τ_{ct}. All SE are two-way clustered at the census tract and year level.

To detect the proper site-proximity treatment in the average effect models (i.e., Eq. **1**), we employed a distance decay version of the DID approach, as shown in Eq. **2**. The distance decay study uses proximity intervals ($T_i^m, \forall m \leq M-1$) as the treatment variables instead of a single binary treatment (as T_i in Eq. **1**). The distance-decay model shown in Fig. 2 uses 0.5-mile intervals from 0 to 6 miles, with properties in the 5 to 6 mile ring (i.e., T_i^M) serving as the control group. To investigate the role of visibility, we further interact the proximity intervals with a binary visibility variable to produce the results in Fig. 1 (i.e., the treatment variables become $T_i^m \times 1(View=1)$ and $T_i^m \times 1(View=0)$). The model specifications in Eq. **2** are identical to Eq. **1** except for differences in the treatment variables,

$$\ln(P_{it}) = \beta_0 + \beta_1 Post_{it} + \sum_{m=1}^{M-1} \beta_2^m T_i^m + \sum_{m=1}^{M-1} \beta_3^m Post_{it} \times T_i^m + \delta_k \sum_{k=1}^{K} X_{it}^k + \gamma_k \sum_{k=1}^{K} (Post_{it} \times X_{it}^k) + \tau_{ct} + \varepsilon_{it}. \quad [2]$$

Based on the proximity cut-off point suggested in the distance decay results, we specify a proximity treatment (i.e., results suggest properties within 3 miles) for the average treatment model in Eq. **1**. Moreover, we can test the average treatment effect of the interaction between visibility and proximity, by slightly modifying Eq. **1** to allow for two treatment groups [i.e., effects shown as β_3^{view} and $\beta_3^{no\_view}$ in Table 1 column (2)]. The empirical results of these specifications decide the appropriate treatment to use for subsequent studies, where the control group specification will also be consistent with the exploratory specifications.[¶¶] Details of subsequent event study and heterogeneity analyses are presented in *SI Appendix*.

Our DID model relies on the assumption that the LSSPV siting process is independent of the price trends over time conditional on the covariates (i.e., the parallel trends assumption). We conduct pretrend tests with placebo treatments by setting a pseudo-post variable mimicking a fake installation event 6 y before the actual installation and dropping observations that are actually treated after the actual site installation. Null effect estimates from the placebo tests support the plausibility of the parallel trends assumption. Moreover, the event study model could also display pretreatment effects where pretreatment trend differences would show up and suggest a violation of the parallel trends assumption.

3.5.2. Analyses for agricultural land and large-lot homes. We use a distance-decay model to detect the cut-off proximity for the treatment variable in the DID analysis for agricultural or vacant land and large-lot homes as the potential impact mechanism is related to site proximity. The ag-land distance-decay model is built on Eq. **2** with three key differences. First, the outcome variable is the natural logarithm of land price per acre. Second, the control variables X_{it}^k do not include house characteristics. Finally, based on the volume of ag-land transactions, the proximity intervals are selected every two miles from 0 to 20 miles, the fixed effects used are on the county-site (i.e., an interaction between county and the LSSPV site identifier)[##] by year level, and the SE are two-way clustered at the county-site and year level. We also conduct the event study and heterogeneity analyses using the treatment variable suggested by the ag-land distance-decay model. Furthermore, we conduct pretrend tests for the ag-land analysis to check the plausibility of parallel trends assumption. The large-lot-home analysis retains the outcome and control variables from the residential analysis while adopting the same proximity bins and fixed effects used in the ag-land analysis. More details of ag-land and large-lot-home analyses are provided in *SI Appendix*.

[¶¶]This is to say, if pure proximity with a 3-mile cut-off point is decided as the most meaningful treatment to use, the control group in the main average effect model will be properties within the 5-to-6-mile proximity bin. This would involve the exclusion of properties within the 3-to-5-mile bin from the analyses. The subsequent event study and heterogeneity analysis models will follow the same sample and covariate specifications as the main model.

[##]The site identifier is based on the nearest LSSPV site. If a group of properties are within a 20-mile radius of the same site and the site is the nearest site to all of them, they share the same identifier. They span a relatively large region, potentially covering more than one county. To control for both site-level and county-level shocks, we use the county-site by year fixed effects here.

Data, Materials, and Software Availability. Our replication package (https://github.com/Starfallchen/SolarViewHedonic) provides all code used in this study, including Stata and Python code for raw data processing, geospatial variable processing, viewshed analysis, data aggregation, and estimation analysis (45). All analyses are conducted in Stata 18MP (https://www.stata.com/order/) (46) and Python 3.9.18 https://www.python.org/downloads/release/python-3918/) (47). The replication package also shares datasets that are from unrestricted data sources. The property transaction data are acquired from CoreLogic Solutions, LLC (https://www.corelogic.com/360-property-data) (48). Restricted by contract with CoreLogic, all variables derived from raw CoreLogic data will not be shared. To replicate our study, we recommend acquiring CoreLogic national-level property data with transactions from 1993 to 2020 and applying the data processing code in the replication package. Other raw data are from publicly available sources. The large-scale solar site data are available at the US Large Scale Solar Photovoltaic Database webpage: https://eerscmap.usgs.gov/uspvdb (49). Digital Elevation Models in the viewshed analysis are produced by NASA's Shuttle Radar Topographic Mission and available at https://srtm.csi.cgiar.org (50). Geospatial data on states, counties, census tracts, primary roads, and metropolitan areas are from US Census Bureau TIGER/line geodatabase, available at https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-geodatabase-file.html (51). Geospatial data on transmission lines are obtained from US Energy Atlas hosted by Energy Information Administration, available at https://atlas.eia.gov/search (52). Data for heterogeneity analysis are drawn from multiple public sources, with details described in the *SI Appendix*.

ACKNOWLEDGMENTS. We gratefully acknowledge financial support from the Sustainable Agricultural Systems Grant 2019-68012-29904 and Hatch projects 7006196, 7006059, and 1024040 from the United States Department of Agriculture National Institute of Food and Agriculture. We sincerely thank editor Catherine Kling and two anonymous reviewers for their insightful and valuable feedback. Property data were acquired from CoreLogic. The results and opinions are those of the author(s) and do not reflect the position of funding institutions.

Author affiliations: [a]Department of Agricultural and Applied Economics, Virginia Polytechnic Institute and State University, Blacksburg, VA 24060; and [b]Department of Environmental and Natural Resource Economics, University of Rhode Island, Kingston, RI 02881

1. US Energy Information Administration, *Levelized Cost of New Generation Resources in The Annual Energy Outlook 2022* (US Energy Information Administration, Washington, DC, 2022).
2. U. E. I. Administration, Solar accounted for 70% of new U.S. electric generation capacity in 2023 (2024). Accessed: 2024-08-04.
3. J. Crawford, D. Bessette, S. B. Mills, Rallying the anti-crowd: Organized opposition, democratic deficit, and a potential social gap in large-scale solar energy. *Energy Res. & Soc. Sci.* **90**, 102597 (2022).
4. M. Eisenson, J. Elkin, H. Singh, N. Schaffir, *Opposition to Renewable Energy Facilities in The United States: June 2024 edition*. (Columbia University in the City of New York, NY, 2024).
5. D. Mulvaney, Identifying the roots of green civil war over utility-scale solar energy projects on public lands across the American Southwest. *J. Land Use Sci.* **12**, 493–515 (2017).
6. T. Sharpton, T. Lawrence, M. Hall, Drivers and barriers to public acceptance of future energy sources and grid expansion in the united states. *Renew. Sustain. Energy Rev.* **126**, 109826 (2020).
7. R. S. Nilson, R. C. Stedman, Reacting to the rural burden: Understanding opposition to utility-scale solar development in Upstate New York. *Rural Sociol.* **88**, 578–605 (2023).
8. V. Gaur, C. Lang, House of the rising sun: The effect of utility-scale solar arrays on housing prices. *Energy Econ.* **122**, 106699 (2023).

9. S. Elmallah, B. Hoen, K. S. Fujita, D. Robson, E. Brunner, Shedding light on large-scale solar impacts: An analysis of property values and proximity to photovoltaics across six us states. *Energy Policy* **175**, 113425 (2023).
10. R. Nilson, B. Hoen, J. Rand, *Survey of Utility-scale Wind and Solar Developers Report* (Energy Markets and Policy, 2024).
11. N. Sánchez-Pantoja, R. Vidal, M. C. Pastor, Aesthetic impact of solar energy systems. *Renew. Sustain. Energy Rev.* **98**, 227–238 (2018).
12. J. E. Lovich, J. R. Ennen, Wildlife conservation and solar energy development in the desert southwest, united states. *BioScience* **61**, 982–992 (2011).
13. H. Sawyer *et al.*, Trade-offs between utility-scale solar development and ungulates on western rangelands. *Front. Ecol. Environ.* **20**, 345–351 (2022).
14. F. Bastida, J. L. Moreno, T. Hernandez, C. García, Microbiological activity in a soil 15 years after its devegetation. *Soil Biol. Biochem.* **38**, 2503–2507 (2006).
15. L. O. Taylor, D. J. Phaneuf, X. Liu, Disentangling property value impacts of environmental contamination from locally undesirable land uses: Implications for measuring post-cleanup stigma. *J. Urban Econ.* **93**, 85–98 (2016).
16. J. McCluskey, G. C. Rausser, Stigmatized asset value: Is it temporary or long-term? *Rev. Econ. Stat.* **85**, 276–285 (2003).
17. R. R. Hernandez, M. K. Hoffacker, M. L. Murphy-Mariscal, G. C. Wu, M. F. Allen, Solar energy development impacts on land cover change and protected areas. *Proc. Natl. Acad. Sci. USA* **112**, 13579–13584 (2015).
18. V. V. Katkar, J. A. Sward, A. Worsley, K. M. Zhang, Strategic land use analysis for solar energy development in new york state. *Renew. Energy* **173**, 861–875 (2021).
19. A. F. Trust, Advancing smart solar in the next farm bill. (2023), Accessed: May 4, 2024.
20. N. Abashidze, L. O. Taylor, Utility-scale solar farms and agricultural land values. *Land Econ.* **99**, 327–342 (2023).
21. W. Guo, L. Wenz, M. Auffhammer, The visual effect of wind turbines on property values is small and diminishing in space and time. *Proc. Natl. Acad. Sci.* **121**, e2309372121 (2024).
22. C. Lang, J. J. Opaluch, G. Sfinarolakis, The windy city: Property value impacts of wind turbines in an urban setting. *Energy Econ.* **44**, 413–421 (2014).
23. M. D. Heintzelman, R. J. Vyn, S. Guth, Understanding the amenity impacts of wind development on an international border. *Ecol. Econ.* **137**, 195–206 (2017).
24. S. Gibbons, Gone with the wind: Valuing the visual impacts of wind turbines through house prices. *J. Environ. Econ. Manag.* **72**, 177–196 (2015).
25. Y. Mei, P. Liu, L. Meng, L. Lin, Evaluate the impacts of wind farm facilities on land values with geographically-linked microdata in china. *Environ. Resour. Econ.* **87**, 465–489 (2024).
26. D. Maddison, R. Ogier, A. Beltrán, The disamenity impact of solar farms: a hedonic analysis. *Land Econ.* **99**, 1–16 (2023).
27. R. R. Hernandez *et al.*, Environmental impacts of utility-scale solar energy. *Renew. Sustain. Energy Rev.* **29**, 766–779 (2014).
28. J. Li, G. S. Okin, L. Alvarez, H. Epstein, Quantitative effects of vegetation cover on wind erosion and soil nutrient loss in a desert grassland of southern new mexico, USA. *Biogeochemistry* **85**, 317–332 (2007).
29. H. S. Banzhaf, R. P. Walsh, Do people vote with their feet? An empirical test of Tiebout's mechanism *Am. Econ. Rev.* **98**, 843–863 (2008).
30. A. Bernstein, S. B. Billings, M. T. Gustafson, R. Lewis, Partisan residential sorting on climate change risk. *J. Financial Econ.* **146**, 989–1015 (2022).
31. A. Shertzer, R. P. Walsh, Racial sorting and the emergence of segregation in american cities. *Rev. Econ. Stat.* **101**, 415–427 (2019).
32. Z. Li, W. Zhang, A. Ortiz-Bobea, *The Impact of Large-scale Solar Development on Farmland Values: Evidence from New York State* (SSRN Working Paper, 2024).
33. E. Goffman, *Stigma, Notes on The Management of Spoiled Identity* (Simon and schuster, 2009).
34. G. Link, J. C. Phelan, Conceptualizing stigma. *Annu. Rev. Sociol.* **27**, 363–385 (2001).
35. K. Fujita *et al.*, *United States Large-scale Solar Photovoltaic Database V1. 0 (November, 2023): Us Geological Survey and Lawrence Berkeley National Laboratory Data Release* (Us geological survey and lawrence berkeley national laboratory, 2023).
36. C. Lang, L. Dong, M. Peach, Elevation data are insufficient for assessing viewshed externalities of wind turbines. *Proc. Natl. Acad. Sci.* **121**, e2408344121 (2024).
37. L. Chen, R. M. Rejesus, S. Aglasan, S. Hagen, W. Salas, The impact of no-till on agricultural land values in the united states midwest. *Am. J. Agric. Econ.* **105**, 760–783 (2023).
38. G. Livanis, C. B. Moss, V. E. Breneman, R. F. Nehring, Urban sprawl and farmland prices. *Am. J. Agric. Econ.* **88**, 915–929 (2006).
39. Z. Chen, C. A. Towe, Pricing coastal amenities and flood hazards. *Land Econ.* **100**, 109–126 (2024).
40. C. Towe, Z. Chen, The impact of recreational homes on agricultural land use. *Land Econ.* **99**, 17–37 (2023).
41. R. T. Melstrom, The effect of land use restrictions protecting endangered species on agricultural land values. *Am. J. Agric. Econ.* **103**, 162–184 (2021).
42. Q. Lu, N. Cheng, W. Zhang, P. Liu, Disamenity or premium: Do electricity transmission lines affect farmland values and housing prices differently? *J. Hous. Econ.* **62**, 101968 (2023).
43. D. A. Keiser, J. S. Shapiro, Consequences of the Clean Water Act and the demand for water quality. *Q. J. Econ.* **134**, 349–396 (2019).
44. H. S. Banzhaf, Difference-in-differences hedonics. *J. Polit. Econ.* **129**, 2385–2414 (2021).
45. C. Hu *et al.*, Data and code for "Impact of large-scale solar on property values in the United States: Diverse effects and causal mechanisms." GitHub. https://github.com/Starfallchen/SolarViewHedonic. Deposited 5 May 2025.
46. StataCorp, Stata 18 MP (StataCorp LLC, College Station, TX, 2024). https://www.stata.com/order/. Accessed 17 May 2024.
47. Python Software Foundation, Python 3.9.18. https://www.python.org/downloads/release/python-3918/. Accessed 11 December 2023.
48. CoreLogic, 360 Property Data: Real estate transaction and property information database. https://www.corelogic.com/360-property-data. Accessed 5 June 2024.
49. United States Geological Survey, U.S. Large-Scale Solar Photovoltaic Database (USPVDB). https://eerscmap.usgs.gov/uspvdb. Accessed 20 March 2024.
50. A. Jarvis, HI. Reuter, A. Nelson, E. Guevara, Shuttle Radar Topography Mission (SRTM) data. CGIAR Consortium for Spatial Information. https://srtm.csi.cgiar.org. Accessed 4 May 2024.
51. U.S. Census Bureau, TIGER/Line Geodatabases: Geographic data files. https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-geodatabase-file.html. Accessed 2 May 2024.
52. U.S. Energy Information Administration, EIA Atlas: Energy infrastructure and resources data. https://atlas.eia.gov/search. Accessed 20 March 2024.
53. U.S. Environmental Protection Agency, *About the Brownfields Program* (U.S. Environmental Protection Agency, 2024), https://www.epa.gov/brownfields/about.
54. V. Gaur, C. Lang, G. Howard, R. Quainoo, When energy issues are land use issues: Estimating preferences for utility-scale solar energy siting. *Land Econ.* **99**, 343–363 (2023).

Updated Impact of Proximity to Solar Farms on Property Values

Ashley Cate, PhD Candidate, Life Sciences Communication,
(acate@wisc.edu)

Inder Majumdar, PhD Student, Agricultural and Applied Economics
(imajumdar@wisc.edu)

Paul Mitchell, Professor, Agricultural and Applied Economics
(pdmitchell@wisc.edu, 608-320-1162)

Original version : April 28, 2025
Updated version: June 11, 2025

Wisconsin Rural Partnerships Institute, College of Agricultural and Life Sciences
University of Wisconsin-Madison

This work is supported by the Institute for Rural Partnerships Program project award no. 2023-70500-38915 from the U.S. Department of Agriculture's National Institute of Food and Agriculture. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy.

Context

In response to stakeholder questions, this report summarizes the academic and non-academic literature about the impact of Wisconsin solar farms on nearby property values (both farmland and homes). We found several studies that examined impacts on home values and three that analyzed the impacts of solar farms on agricultural land values. Published results were generally mixed – studies found positive, negative or no statistical effect of solar farms on nearby property values or sales prices. However, a new comprehensive study (Hu et al. 2025) likely settles the academic debate for the time being, so we have updated our April report to reflect these new findings. We summarize the results from these studies and then discuss implications for Wisconsin and the importance of public perception for these effects.

Highlights

- Based on a new comprehensive study, agricultural land values jump 19.4% for properties within 2 miles of large-scale solar farms, but this effect is temporary, peaking 3 years after installation and dissipating within 6 years.
- Based on this same study, residential properties within 3 miles of a large-scale solar farm experience price declines of 4.8%, but this effect fades within 9 years of installation.
- We found no comprehensive study that specifically covered Wisconsin.
- Larger effects seem possible for agricultural land in Wisconsin because more areas have specialized agricultural needs with more limited availability of land to replace losses.
- Public perception of large-scale solar farms and proximity play a key role in these effects, while perceptions of community-scale solar farms remain unclear.

Primary Findings

Early peer-reviewed research produced mixed findings – some found positive effects, while others found negative effects or no statistically significant effects. The new comprehensive analysis of Hu et al. (2025) reveals a consistent pattern: farmland prices jump near large-scale solar installations while nearby home prices dip, and both effects diminish with distance and time. This is the average effect – home and farmland values are highly variable because the specific context for each property matters.

Hu et al.'s (2025) study covers 40 states with a comprehensive database for both agricultural and residential parcels and a thorough analysis that supersedes previous studies for the time being. For agricultural land, Hu et al. (2025) finds an average price increase of 19.4% for parcels within 2 miles of large-scale solar installations, but this effect disappears beyond 2 miles. This price effect is also temporary, peaking 3 years after installation and dissipating within 6 years. They interpret these price patterns as the option value – agricultural and non-vacant lands can be added to the existing solar farm, but as one moves further away and as the installation matures, this option value declines.

If a similar study were conducted for Wisconsin, we expect effects similar to the Hu et al. (2025) pattern, but to vary in magnitude and by location. Wisconsin has many areas devoted to specialized agricultural uses. Intensive dairy regions need land for manure, and crops like potatoes, vegetables, cranberries, and ginseng require special types of land. Loss of land to solar farms in these areas would likely have a larger impact on surrounding farmland values because alternative land to replace these losses is limited. However, the effect would likely be smaller in areas with more traditional agricultural land use for which substitute land is available nearby. Hu et al. (2025) also show that price increases are most evident for smaller parcels, because they can host incremental expansions of large-scale solar installations. By contrast, almost no price effect is observed for larger parcels.

For residential land, Hu et al. (2025) find drops of 7.2% in value for parcels within half a mile of a large-scale solar farm and 4.8% for those within 3 miles, and no statistically significant effect beyond that distance. Prices for residential properties return to their baseline about 9 years after solar construction. We anticipate similar effects in Wisconsin, a 4%-7% decline in residential property values within half a mile of large-scale solar farms that disappears after about 9 years.

Public perception plays an important role. Whether real or perceived, farmers and homeowners near solar farms are concerned about actual or potential effects on the value of their land and perceptions of potential buyers. In rural areas, opposition to solar farms is often explained by the perception that solar farms use rural resources for the benefit of urban areas – a phenomenon known as the "rural burden". However, not all solar farms are the same. Smaller community-scale solar farms are built to serve a community or a set subscriber base, while larger utility-scale solar farms are designed to provide electricity for cities or regions often further away. Since most research focuses on large-scale solar farms, it is unclear how results and perceptions would differ for community-scale solar farms. In the context of the "rural burden", community-scale solar farms could plausibly be seen favorably in rural and agricultural areas, as a source of pride for energy independence. Hu et al. (2025) finds some evidence supporting this effect, but the topic remains largely unexplored empirically. Understanding these effects on property values in Wisconsin would require survey or focus group work that is outside the scope of this assessment.

Updated Impact of Proximity to Solar Farms on Property Values

Context
Renewable energy technologies, such as solar panels, wind turbines, and biofuel technologies have gained increased attention in recent years, but not all renewable energy technologies are the same. Solar is more controversial because installing a solar farm requires a fundamental land-use change compared to producing wind energy or biofuels (Geiger 2025; Maguire et al. 2024). Attention commonly focuses on potential impacts on nearby home and agricultural land values. For this brief report, we searched both the academic and non-academic research to summarize what others have found. We found several studies that examined impacts on home values and a few that analyzed the impacts of solar farms on agricultural land values. The comprehensive study of Hu et al. (2025) was just published and likely settles much of the academic debate for the time being, and so we have updated our April report to reflect this new research. This report summarizes the research and briefly discusses possible implications for Wisconsin. Finally, we discuss the importance of public perception for these effects on property values.

Impacts on agricultural land prices
Abashidze and Taylor (2023) examined agricultural land sales in North Carolina and found no direct effect of the distance from a solar farm on the sale price of agricultural land. They find some weak statistical evidence that agricultural land parcels nearer to transmission power lines may increase in value after a solar farm is built nearby. They propose that solar farm installation potentially creates a signal to solar farm developers of the suitability of adjacent agricultural land for future development as a solar farm.

An unpublished master's thesis (Kunwar 2024) analyzed the effect that the distance to a solar farm had on prices for farmland sales in Indiana. The study found that being one mile nearer to a solar farm increased the price of farmland by 1.4%. For higher value farmland (in the top 20%), the effect was larger, a 1.6% increase, and only 0.9% for lower value land (in the bottom 20%). The thesis did not discuss how far this effect extended before it dissipated. Also, the regression analysis explained only about 18% of the variation in land prices, indicating that farmland values are highly variable and many other factors besides those included in their analysis affect prices.

Hu et al. (2025) find that the price of land within 2 miles of a solar farm increases 19.4% on average, with the effect becoming statistically insignificant beyond 2 miles. The increase appears three years after installation and fades roughly six years later, consistent with the hypothesis that these land value changes are driven by option value for possible future solar leases rather than a permanent change. Analysis shows that the price increases are concentrated on smaller parcels as they cost less to add to existing solar arrays. Large land parcels show no price response as they are more costly to add to an array, while parcels near mega-arrays also show no price response because the already large array is less likely to expand.

Discussion of impacts on agricultural land prices
Surprisingly little research exists on the effects of solar farms on farmland values. Abashidze and Taylor (2023) found no solid evidence of an impact in North Carolina. Kunwar's (2024) preliminary results are consistent with expectations (solar farms increase nearby farmland values), but the impact seems small: an average change of 1.4% per mile, with a range of 0.9% to 1.6%. The newly published Hu et al. (2025) study used an extensive multi-state database and comprehensive analytical methods, and so the research results summarized above supersede the

other analyses, which is why this report needed updating. In short, the value of farmland within 2 miles of a large-scale solar farm increases 19.4% on average – but the effect disappears beyond 2 miles, peaks about 3 years after solar farm installation, and fades roughly after 6 years. This pattern is consistent with an option value – land prices increase because the solar array may expand onto these nearby lands in the near future. This option value has a limited reach from the solar farm and eventually it fades as it becomes clear the solar farm will not expand further. Nonetheless, large scale installations have a sizable effect on farmland prices within a certain distance. The option value is highest for small parcels near smaller solar farms, because these parcels are lower cost to add to the array and smaller solar farms still have room to expand.

To give some idea of what this effect could mean in the state, we apply Hu et al.' (2025) estimates to 2024 land values in Wisconsin. The average value for agricultural land in Wisconsin in 2024 was $6,600/ac (USDA NASS 2025). Schlesser (2025) summarizes actual farmland sales data in Wisconsin in 2024. Her discussion and Figure 2 suggest that the lowest 20% had prices below about $3,000/ac and the top 20% had prices above about $9,500. Applying the 19.4% average effect to these land values gives $6,600 x 0.194 = $1280/acre price increase for average farmland, with a range of $3,000 x 0.194 = $582/acre to $9,500 x 0.194 = $1,843/acre. These gains are substantial compared to historical estimates but are spatially limited and temporary.

These are average effects based on this new national evidence. We expect larger effects in parts of Wisconsin with high-value and unique agricultural land uses, particularly in areas with lots of dairy or specialty crop production. Areas with intensive dairy production need farmland for manure application, the Central Sands and Lower Wisconsin River Valley are used for intensive potato and vegetable production, and several areas of the state are used for important specialty crops like seed potatoes, cranberry and ginseng. Loss of land in these areas to solar farms would likely have a larger impact on surrounding farmland values than in the Hu et al. (2025) study because they are high-value uses and have limited availability of alternative land for replacement if lost. However, we note that this hypothesis has not been examined empirically.

Impacts on home prices

Hu et al. (2025) analyzed prices for 8.3 million individual home sales in forty US states and found that, on average, homes within a half-mile of a large-scale solar farm experienced a 7.2% reduction in value, homes within 3 miles experienced a 4.8% reduction in value, and homes beyond that distance had no statistically significant reduction in value. Elmallah et al. (2023) used data from six states (not including Wisconsin) and found smaller home price decreases (2.3% within a quarter-mile, 1.5% within a half-mile), but the pattern was the same. In Hu et al. (2025), home price decreases were larger in the Northeastern U.S., in politically conservative counties (based on 2016 party voting shares), and for residential parcels on land that was previously agricultural, but negligible for solar farms that are brownfield redevelopments or located in left-leaning counties (based on 2016 party voting shares).

Smaller, single-state studies show mixed or null effects. Specific to the Midwest, a real estate impact study in Illinois by McGarr and Lines (2018) compared sales of single-family homes adjacent to solar farms to sales of comparable homes not adjacent to solar farms. They found no consistent negative impact on home sales prices or other influential market indicators attributable to adjacency to solar farms. Hao and Michaud (2024) used aggregate data to examine the impact of 70 Midwest solar farms on average home values in the same zip code, finding a 0.5% to 2.0% increase in average home values in zip codes with a solar farm. They propose that solar farms increase tax revenues that are used to build amenities such as better schools and public services, which then increase nearby home values. Specific to Wisconsin, the market analysis of MaRous and Company (2021) examined the potential impacts of a proposed solar farm in Dane County and found that the market data indicated that there would be no negative impact on rural residential property values. This study also found that data did not substantiate local landowners' concerns about noise and visual impacts from an existing solar farm on land values.

Taken together, the Hu et al. (2025) study confirms the expected disamenity effect on values for homes close to large-scale solar farms, while the findings of Elmallah et al. (2023) and single-state studies show how local contexts might abate the penalty. The results are highly variable, suggesting that the specific context for each home matters. The fact that the smaller studies did not find an effect is not surprising. Home values are highly variable and identifying effects with highly variable data is statistically difficult with small samples. Hao and Michard (2024) admit their results are counter to what most research finds; we have developed an academic critique beyond the scope of this report that would explain their unusual results as a statistical issue.

The role of public perception

The evidence put forth in these studies is often mixed, with the high variability in land values and home prices indicating that the specific context of each sale matters. The implication is that public perception plays an important role in how the proximity to solar farms impacts residential home prices and farmland values. Whether real or perceived, land and homeowners adjacent to solar farms are concerned about potential buyers passing on their home and land because of its proximity to a solar farm (Breese, 2025a; Breese, 2025b). In rural areas specifically, there is opposition to solar farm development that is best explained by the perception of the development being extractive of rural natural resources (i.e., land) for the benefit of urban areas – a phenomenon known as the "rural burden" (Nilson and Stedman, 2023). Hu et al. (2025) show that visibility itself adds no extra penalty once distance is controlled, lending credibility to the notion that the price discount might not be driven by glare, noise, or other physical health concerns, but perception. Public perception can and will influence the acceptability of solar projects so that citing ordinances may want to take it into consideration.

Not all solar farm projects are the same – notable differences exist between utility-scale and community-scale solar. Community-scale solar projects are usually smaller and established for a particular community or subscriber base, while utility-scale solar projects are larger and designed to provide a significant amount of electricity for cities or regions (Geiger, 2025). Most of the studies reviewed in this report were for utility-scale solar farms and it is not entirely clear how their results would differ for a community-scale solar farm. However, considering the root of the rural burden and the main concerns associated with solar farms such as change in land-use and visible disamenities, community-scale solar projects could plausibly be perceived more favorably in rural and agricultural areas. As a result, we believe that the distinction between community-scale and utility-scale solar projects is likely quite important in many contexts.

Caveats

We emphasize that extrapolation of some of these findings to Wisconsin is predicting out of sample, which can lead to serious errors. We found very few studies specific to Wisconsin and suggest that additional research to examine these effects in the unique Wisconsin context may be warranted to address this issue. Such work could include econometric analysis of home and land sales data, as well as surveys or focus groups to better understand public perceptions.

References

Abashidze, N., and L. Taylor. 2023. Utility-Scale Solar Farms and Agricultural Land Values. Land Economics, 99(3):327–342. https://muse.jhu.edu/pub/19/article/900217

Breese, T. 2025a. Some critics of Indiana solar farms say they drive down home values. But is it true? WHAS11. https://www.whas11.com/article/news/local/indiana/indiana-solar-farms-do-they-cause-home-values-to-drop/417-735eccd2-42e2-4cd7-9c35-66a57779ecbc

Breese, T. 2025b. How Indiana's solar farm debate impacts America's energy crisis. WHAS11. https://www.whas11.com/article/news/investigations/focus/america-energy-crisis-solar-power-farms-electricity/417-65642d0b-b291-41a3-9deb-cfb5c88244e5

Elmallah, S., B. Hoen, K. Fujita, D. Robson, and E. Brunner. 2023. Shedding light on large-scale solar impacts: An analysis of property values and proximity to photovoltaics across six U.S. states. Energy Policy, 175:113425. https://doi.org/10.1016/j.enpol.2023.113425

Geiger, D. 2025. A fundamental land-use change in the Midwest. American Farmland Owner. https://www.americanfarmlandowner.com/post/a-fundamental-land-use-change-in-the-midwest

Hao, S., and G. Michaud. 2024. Assessing property value impacts near utility-scale solar in the Midwestern United States. Solar Compass, 12:100090. https://doi.org/10.1016/j.solcom.2024.100090

Hu, C, Z. Chen, P. Liu, W. Zhang, X. He, and D. Bosch. 2025. Impact of Large-scale Solar on Property Values in the US: Diverse Effects and Causal Mechanisms. Proceedings of the National Academy of Sciences 122 (24) e2418414122 https://www.pnas.org/doi/10.1073/pnas.2418414122.

Kunwar, B. 2024. Impact of Commercial and Utility-Scale Solar Energy on Farmland Price. Unpublished Master's Thesis, Purdue University, West Lafayette, IN. https://hammer.purdue.edu/articles/thesis/_b_IMPACT_OF_COMMERCIAL_AND_UTILITY-SCALE_SOLAR_ENERGY_ON_FARMLAND_PRICE_b_/26076679?file=47193625.

Maguire, K., S. Tanner, J. Winikoff, and R. William. 2024. Utility-Scale Solar and Wind Development in Rural Areas: Land Cover Change (2009-20). USDA Economic Research Service. https://ers.usda.gov/sites/default/files/_laserfiche/publications/109209/ERR-330.pdf?v=53361

MaRous and Company. 2021. Market Impact Analysis—Koshkonong Solar Energy Center, Dane County, Wisconsin. https://apps.psc.wi.gov/pages/viewdoc.htm?docid=409444

McGarr, P., and A. Lines. 2018. Property value impact study: Proposed solar farm—Kane County, IL. CohnReznick LLP. https://www.kanecountyil.gov/FDER/Zoning%20Petitions%20Documents/Cohen%20Reznick%20Presentation.pdf

Nilson, R., and R. Stedman. 2023. Reacting to the Rural Burden: Understanding Opposition to Utility-Scale Solar Development in Upstate New York. Rural Sociology 88(2):578-605. https://doi.org/10.1111/ruso.12486

Schlesser, H. 2025. Wisconsin Agricultural Land Prices 2024, University of Wisconsin Extension. https://farms.extension.wisc.edu/articles/wisconsin-agricultural-land-prices/

US Department of Agriculture National Agricultural Statistics Service. 2025. Agricultural Land Values. Washington, DC. https://usda.library.cornell.edu/concern/publications/pn89d6567

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* × *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 ($Post \times Treat$) 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* $\times$ *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 ($\leq 0.5 miles$)				Treated ((0.5; 1] miles)				Treated ($\leq 1 miles$)			
	(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 ($\leq 1 mile$)	-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 ≤ 5 MW	Electric Coops	Forest and Grass Coverage
	(1)	(2)	(3)
Treat (≤ 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

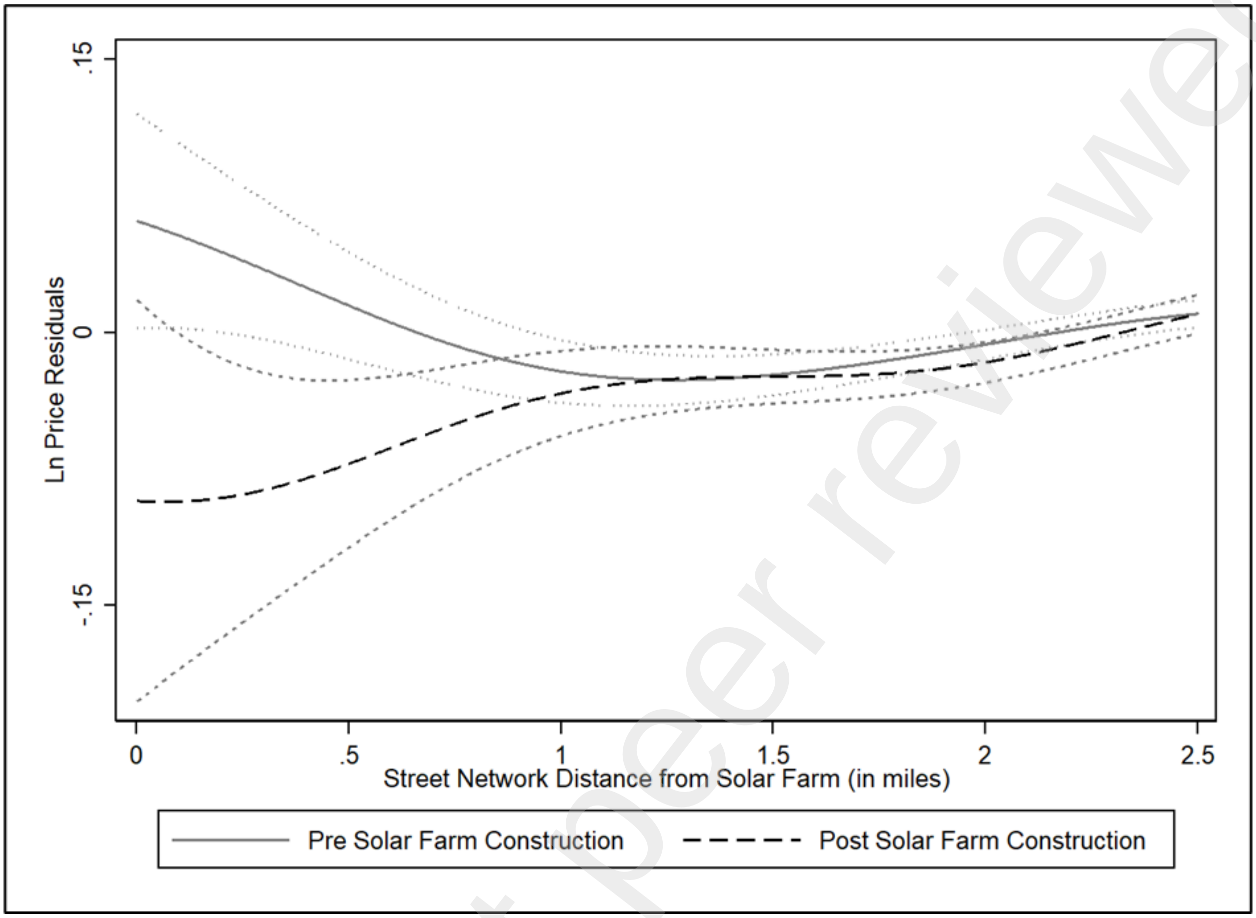
Note: The estimates are based on equation 1. The sample includes houses located within two-Euclidean miles from the nearest solar farm. The treatment and control groups are defined based on street network measure. The dependent variable is the natural log of sales price for houses sold between 1997 and 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

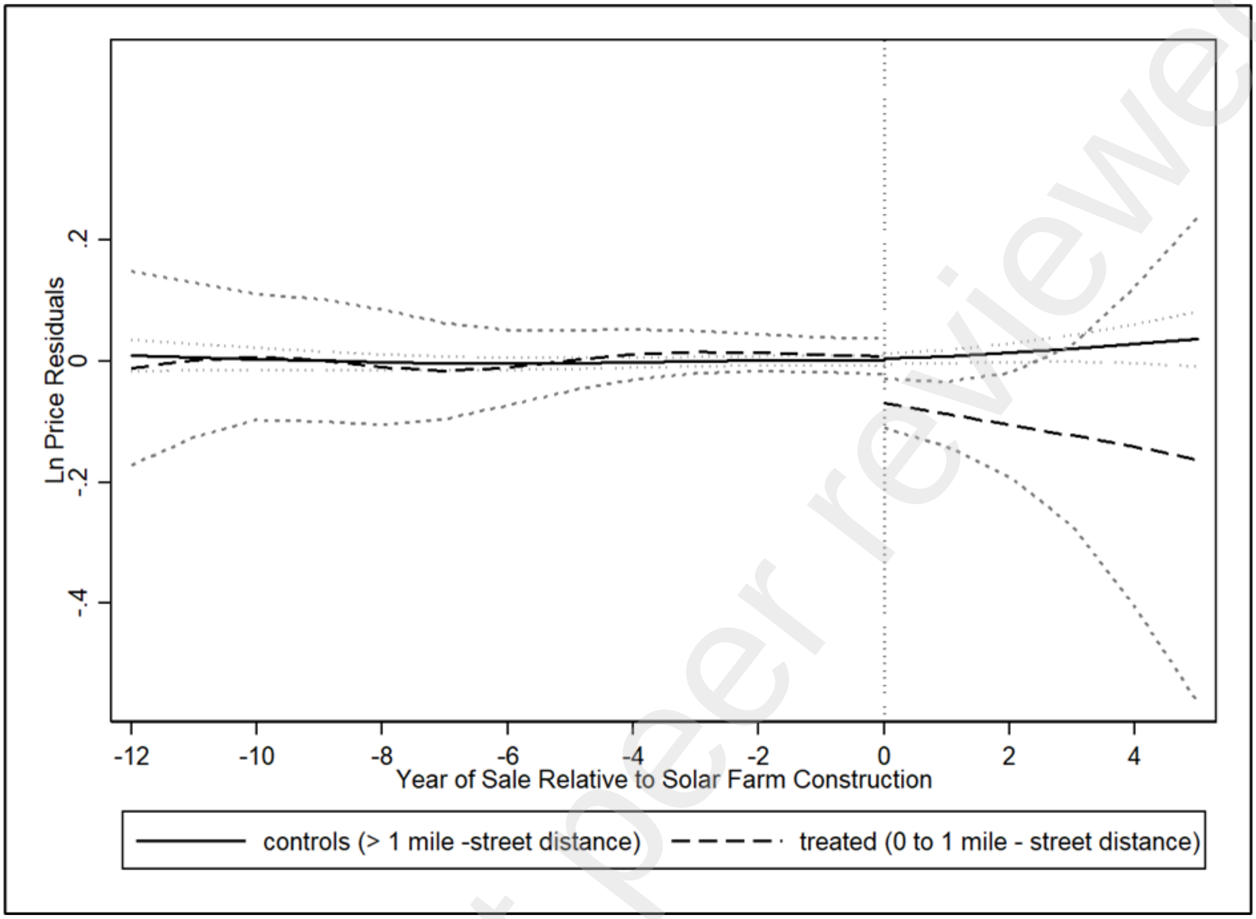
Note: The sample includes houses located within two-Euclidean miles from the nearest solar farm. The treatment and control groups are defined based on street network measure. The dependent variable is the natural log of sales count aggregated by solar farm by year of sale by treatment status. All models 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



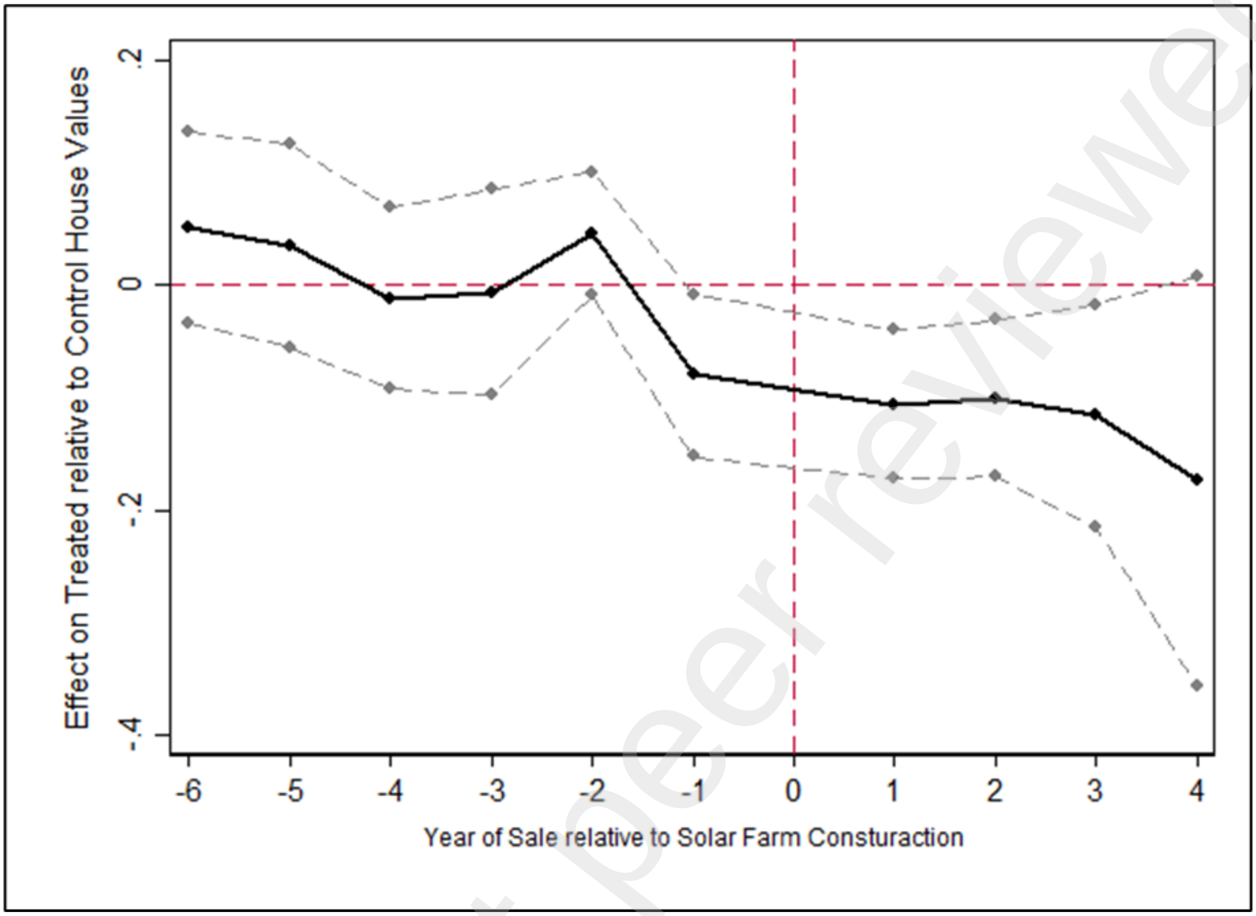
Note: The sample includes houses located within two-Euclidean miles from the nearest solar farm. The figure is restricted to sales within 2.5 miles of the solar farm based on street network distance measure. The figure includes 90 percent confidence intervals.

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.