INDIANA RENEWABLE ENERGY

Siting through Technical Engagement and Planning (R-STEP™)

A Hedonic Analysis of Large-Scale Photovoltaic Projects in Indiana

Produced for the Indiana R-STEP Collaborative by the Center for Business and Economic Research, Ball State University

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August 3, 2026

This material is based upon work supported by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy (EERE) through the **Renewable Energy Siting through Technical Engagement and Planning (R-STEP)** program. R-STEP is administered with support from the Partnership Intermediary Agreement (PIA) that the U.S. Department of Energy (DOE) has established with EnergyWerx.

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Table of Contents

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Note: We wish to thank attendees of the 2026 Mid-Continent Regional Science Association/IMPLAN conference session on regional sustainability, especially Laurie McKnight and Carlos Sandoval Machado, and comments from Vasundhara Guar and Ben Hoen at Lawrence Berkely National Laboratories and Eric Brunner at the University of Connecticut. Any remaining errors are our own. We thank Nathanael Bumgarner for research assistance.

Keywords: Solar Energy, Property Values, Renewable Energy, Externalities, Hedonic Pricing, Economic Impacts, Difference-In-Differences, Event Study, Indiana • JEL Codes: R31, R21, Q42, Q51

Abstract

This report examines the impact of utility scale solar projects on the sale price of homes in Indiana, using 2004-2024 residential real estate data from the Multiple Listing Service. Using two complementary difference-in-differences designs, we find negative but statistically insignificant aggregate impacts on residential sale prices. Taken together, our results suggest that proximity to solar projects has no statistically significant or economically significant negative impact on nearby home prices. However, heterogeneity analysis reveals weak evidence of negative effects of larger-capacity (> 3 MW AC) solar development on sale prices. We find no difference in the sale prices of homes close to solar projects in urban and rural areas or proximate to brownfields. The type of power producer appears to impact property values, with properties within 0.5 miles of investor-owned utilities experiencing positive effects.

Introduction

We analyze the proximity effect of large-scale photovoltaic projects (LSPVPs) on Indiana residential property values, from 2004 to 2024. Our purpose with this report is to more fully evaluate the economic consequences of the deployment of industrial scale solar energy facilities. Here we focus on the partial equilibrium effects of potential disamenities of these facilities as expressed by household willingness to pay to avoid exposure to large-scale solar energy facilities.

In Indiana, electric power capacity from solar photovoltaics increased from 3.5 MW (megawatts) in 2012 to 1,289 MW in 2023 (USEIA, 2024). Solar photovoltaics accounted for about 2% of Indiana's electricity generation in 2023, and it is expected to continue to grow as a component of the state's energy portfolio.

As the number of large-scale solar projects has increased, so has opposition to new projects. Over the past two decades, photovoltaics technology has become more efficient, so that more power is produced on a given acre of land. Bolinger and Bolinger (2022) estimate that median power density (MW/acre) has increased by 52% and 43% for fixed-tilt and tracking plants, respectively. Yet, LSPVPs use large plots of land, as Bolinger and Bolinger (2022) estimated that large-scale solar facilities directly occupy 3.6 to 5.6 acres per MW of AC-generating capacity, while overall project footprints are often larger due to required setbacks, buffers, access roads, and other supporting infrastructure. Nearby property owners and the public often have concerns related to various potential disamenities associated with solar farms. Potential disamenities include impacts on property values, displacement of greenfields or agricultural land, viewshed, loss of open space, impact on ecosystems and animal migration patterns, fire risk, drainage issues, and noise (Maddison et al., 2023; Bessette et al., 2024; Gaur et al., 2023; Uebelhor et al., 2021; Hernandez et al., 2014; Walston et al. 2016; Rose & Wollert, 2015). Lease payments to landowners are one of the benefits of solar projects and guarantee a steady stream of income over the life of the project. Environmental benefits, job creation, and payments-in-lieu-of-taxes (PILOTS) or economic development payments to local governments are other benefits.

This analysis provides state-specific estimates to inform Indiana's state and local officials and residents of the impact of LSPVPs on house values. We approach this with two empirical techniques — the first is a series of hedonic difference-in-difference estimates, and the second is a series of event studies examining the impact of distance from LSPVPs on the sale prices of residential properties over time.

Literature

Recent studies examining the impact of large-scale photovoltaic projects on house values have used larger datasets and longer time periods than previous studies and find varying effects over time, distance, and geographic areas. These studies have done more detailed analysis of the characteristics of the location (e.g., rural versus urban; greenfield versus brownfield). Elmallah et al. (2023) examined the relationship between LSPVPs and the sale price of residential properties in six states. A general summary of the results is that homes closest to LSPVPs (< 0.5 miles) experienced the most negative effect (-1.54% lower) on the sale price of homes compared to similar homes 2 to 4 miles away. A negative but smaller effect persisted for properties located 0.5 to 1 mile from the LSPVP (-0.82%). There was no effect on properties located more than 1 mile from the LSPVP. A closer look at the analysis shows that statistically significant, negative effects beyond 1 mile occurred in two of the six states, and an additional two showed some negative effects within 1 mile, and three states showed no effects or positive effects beyond 1 mile, providing evidence that there is variation among states. This analysis also shows that the results are driven by rural areas, which suggests that there is also intra-state variation in the impact.

Gaur and Lang (2023) examined the impact of LSPVPs in Massachusetts and Rhode Island, two densely populated states with renewable energy goals related to each state's renewable portfolio standards. Using the full sample (urban and rural areas), they found 1.5% to 3.6% lower sale prices depending on the specification and sample used for properties located within 0.6 miles of LSPVPs, compared to properties 1 or more miles away. Further analysis showed that these effects were driven by property transactions near solar farms located on greenfields (i.e., farm and forest land) and in rural areas. There was no statistically significant effect on properties located near LSPVPs in urban areas or near solar arrays that were not built on greenfields.

Hu et al. (2025) examined property transactions (including residential, large lots > 5 acres, agricultural, and vacant land) in 40 states. They found negative impacts up to 7.9% on sale prices of residential properties within 0.5 miles of solar projects, with larger negative effects for homes in viewshed (7.9% versus 7.2%) and lesser negative effects of 4.6% to 5.2% for properties within 3 miles of a solar project. They found that these negative effects fade after nine years and primarily affect properties in the Northeast. Further analysis showed a positive impact on properties located near solar projects on brownfields and no impact on large-lot residential properties. They found a positive effect (+19.8%) on the sale price of agricultural or vacant land within 2 miles of solar sites, which they attribute to increased demand from potential solar leases.[1] They did not find a difference in the effects of LSPVPs on the sale price of residential properties in urban and rural areas, which may be due to the way they measured urban and rural.[2]

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[1] The positive effect on agricultural land near solar fields could also result from higher lease prices for farmland, as land available for agricultural use decreases when solar farms become operational.

[2] Hu et al. (2025) classify properties as urban by distance to the nearest metropolitan area. If the distance is zero, the property is in a metro area. If the distance is greater than zero, the property is outside a metro area and is rural. Metro areas are determined by the OMB. Elmallah et al. (2023) use the 2010 Census definitions of urbanized areas and urban clusters, where urbanized areas have 50,000 or more people and urban clusters have at least 2,500 and less than 50,000 people. Rural is any area that does not meet these criteria. Gaur and Lang (2023) use municipal-level population density and classify areas with municipalities with a population density ≤ 850 per square mile as rural.

In their analysis of LSPVPs in Central Florida, Georgic et al. (2025) found that residential properties located within 750 meters (a little less than 0.5 miles) experienced a 6.86% decrease (almost $15,000) in sale price after the solar facility was operational. When the sample was limited to larger LSPVPs (> 50 MW) the effect increased to a -15.7% difference in sale price for properties within 750 meters of the solar facility, compared to properties between 750 meters and 2 miles from the solar facility. The effect dissipated after five years. The authors also examined the impact of different treatment distances, ranging from 500 to 1500 meters, and found a negative effect of around 7% for properties 750 to 1200 meters from a solar project, which then decreased reaching -2.6% at 1500 meters.

The studies above used data on residential property sale prices. Hao and Michaud (2024) used data on average home values of three-bedroom homes in ZIP codes containing LSPVPs and a randomly selected adjacent ZIP code in 11 Midwestern states and found that average home values in ZIP codes with solar projects are higher (+0.5% to 2.0%) than average home values in adjacent ZIP codes. They found that smaller solar projects have a more positive impact than larger projects. Because this study used average home values in ZIP codes as the variable of interest, explicitly controlling for distance between a solar site and property transaction was not possible. Information about the location of the LSPVP in a ZIP code relative to the adjacent ZIP code is also not included. ZIP codes are also far from uniform in size. Finding that ZIP codes with LSPVP facilities have 0.5% to 2.0% higher average home prices than adjacent ZIP codes after the solar site becomes operational fits with the hedonic literature described above, in that the impact is not particularly large.

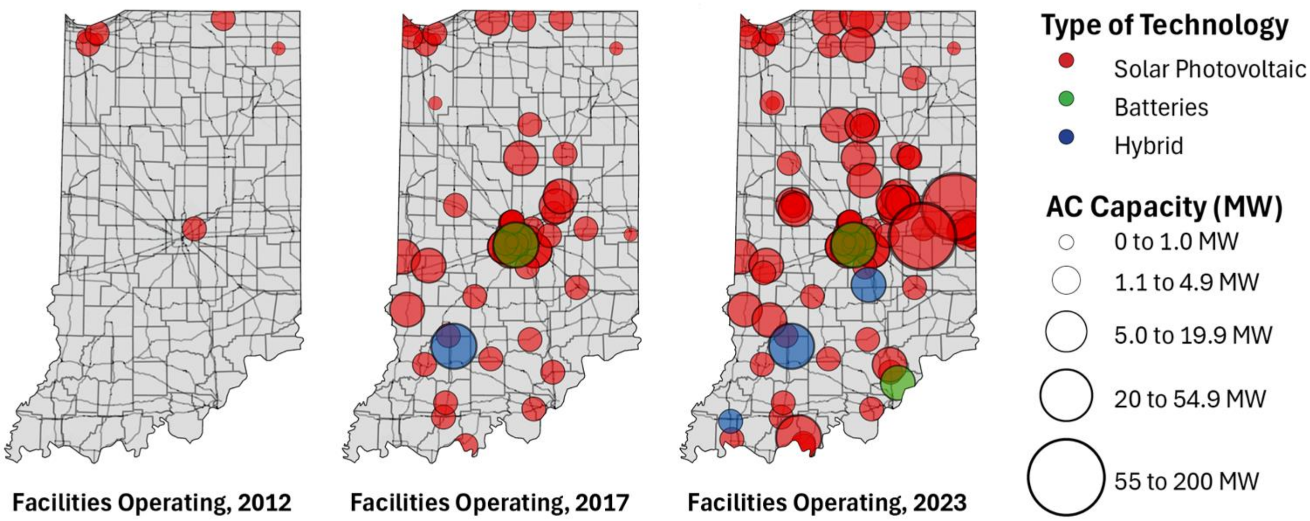
The results for the studies on LSPVPs show that properties closest to the solar farm are most affected, with less than a 10% difference in sale prices compared with properties further away. These studies suggest that the impact dissipates over space and time, and that rural areas are most affected with little or no impact in urban areas.

Few studies have examined the impact of large-scale solar projects on agricultural land values. Abashidze and Taylor (2023) studied agricultural parcels sold within 5 miles of 428 LSPVPs in North Carolina and found that proximity to solar farms had no statistically significant effect on nearby agricultural land values. They also tested how proximity to power lines affected the sale price of agricultural parcels and found that parcels closer to transmission lines had higher prices after solar projects became operational and interpret this as a signal that land near transmission lines may be suitable for future LSPVPs, which is capitalized into the price of this land (Abashidze & Taylor, 2023). In a working paper, Li et al. (2024) examined changes in the price of large parcels of agricultural land (> 10 acres) within 2 miles of electrical substations in New York State after the 2015 implementation of the state-administered Shared Renewables Program (SRP), which led to the growth of LSPVPs. They found that beginning in the second year after the implementation of the SRP program, prices of farmland within 2 miles of substations was 15% to 18% higher than similar property more than 2 miles from a substation. They find even higher price differences (> 20% difference) for agricultural land proximate to substations in areas with higher electricity prices. For parcels smaller than 10 acres, they find no difference in sale prices (Li et al., 2024).

Profile of Indiana Solar Projects

The first large-scale photovoltaic project in Indiana became operational in Marion County in 2011. As renewables have become an increasingly important source of energy, the number of large-scale (> 1 MW AC) solar projects increased to 91 by 2023, along with an additional 20 projects in development or in the planning process.[3] In addition, five battery storage facilities were operational, with two additional battery facilities under development. Of Indiana's 92 counties, 39 have LSPVPs. *Figure 1* illustrates the growth in the number of LSPVPs in the state 2012-2023. For corresponding data, see *Appendix Table A1*.

Figure 1. Large-Scale Photovoltaic Projects in Indiana by Year, Type, and Capacity



Source: Solar Energy Industries Association. Note: For corresponding data, see *Appendix Table A1*.

These projects have been built in both rural and urban areas. Starke and Pulaski counties (rural) are home to Mammoth Solar, expected to be the largest solar farm in the U.S. when completed. It is incorporating various agrivoltaics strategies and is projected to generate enough electricity to power 275,000 homes (Charron, 2023). Marion County (urban) has the world's largest airport-based solar farm — IND Solar Farm at the Indianapolis International Airport — where more than 87,000 solar panels generate 17.5 MW of power, which is enough electricity to power more than 3,200 homes for a year (World Record Academy, 2023).

[3] Over this period, emissions of sulfur dioxide, nitrogen oxide, and carbon dioxide by the electric power industry have decreased 96%, 77%, and 51% measured in short tons, respectively (USEIA, 2023, Table 7).

Data and Methodology

Data on Indiana solar projects were obtained from the major projects list of the Solar Energy Industries Association (SEIA), covering projects of 1 MW and above that began operating during 2011-2023. Residential property sale prices were derived from the Indiana Association of Realtors (IAR) Multiple Listing Service (MLS) data. The dataset from IAR provided one row of data for each residential property sold in Indiana in 2004-2024. For each sale, the data records the sale date, sale price, number of bedrooms, number of bathrooms, square feet, number of acres, basement indicator, school district, and the latitude-longitude coordinates of the property. To ensure data quality, we removed observations with obvious errors or missing values. Specifically, we dropped entries where the number of bedrooms or bathrooms were zero, missing, or greater than 20. Additionally, we excluded properties with implausible square footage or acres (e.g., 999999 or zero), and properties more than 100 years old. Finally, we improved focus on residential property transactions by dropping outlier observations where acreage was > 100 or < 0.10, square footage was > 5,500 or < 450, or transactions with sale prices < $10,000. Notably, our results are also robust to analyses on samples that include these outlier data points. We calculate spatial proximity as the Haversine distance between MLS property coordinates and the reported point centroid of each LSPVP.

To estimate the effect of LSPVPs on nearby residential property values, we use two complementary difference-in-differences (DiD) hedonic valuation models. These two models exploit different variation in the data, and the second method (our primary method) is robust to heterogeneous treatment effects that can plague two-way fixed effects DiD models (Goodman-Bacon, 2021). However, both methods lead to similar results.

First, we conduct a straightforward two-way fixed effects (TWFE) DiD design by limiting analysis to residential properties sold less than 0.5 miles from an LSPVP that was either operating or commenced operation within the time frame of our real estate data (2011-2024). Specifically, we model *Equation 1*:

$$\ln(\boldsymbol{P_{ismt}}) = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 T_{ismt}} + \boldsymbol{X_i \alpha} + \boldsymbol{\gamma_s} + \boldsymbol{\delta_m} + \boldsymbol{\phi_t} + \boldsymbol{\varepsilon_{ismt}} \qquad \textbf{(1)}$$

…where the dependent variable is the natural logarithm of sales price $\boldsymbol{P_{ismt}}$ for residential property sale $\boldsymbol{i}$ in school district $\boldsymbol{s}$ transacted in month $\boldsymbol{m}$ of year $\boldsymbol{t}$. $\boldsymbol{T_{ismt}}$ is a treatment indicator denoting whether a property sale occurred after the estimated construction start date of an LSPVP project, which we define as two years prior to the operation start date. This accounts for forward looking economic agents who may change behavior prior to the completion of a project if, for example, they forecast a future disamenity of LSPVP presence. $\boldsymbol{\gamma_s}$ denote school district fixed effects, $\boldsymbol{\delta_m}$ are month fixed effects, and $\boldsymbol{\phi_t}$ are year fixed effects. We utilize school district fixed effects rather than census tract or census block group fixed effects because, as of 2010 at the beginning of our panel, Indiana's 1,511 census tracts and 4,814 block groups would oversaturate the model given our sample size of less than 5,000 property sales less than 0.5 miles from an LSPVP project. School district fixed effects preserve statistical power while accounting for time-invariant geographic differences and factors related to school quality, which is an important unobserved amenity capitalized into residential property values (Brasington, 1999; Dhar and Ross, 2012). Lastly, $\boldsymbol{X_i}$ denotes a vector of house characteristics: number of bedrooms, number of bathrooms, square feet, number of acres, age of house, age of house squared, and an indicator for whether the house has a basement. Standard errors are clustered at the school district level. To assess dynamic effects and the possibility of pre-trends, we also estimate an event study model of *Equation 1*. We omit event year $\boldsymbol{k = -1}$, the last event-year before the estimated construction start date, so each coefficient is estimated relative to a pre-construction period.

The coefficient of interest is $\boldsymbol{\beta_1}$, which presents the DiD estimate of the effect of being close to an LSPVP after its construction. The identifying variation for this DiD design comes from comparing changes in house prices before and after LSPVP completion within a narrow (0.5-mile) geographic radius, leveraging the staggered timing of project completion across Indiana. Effectively, the model compares changes in sale prices for properties after a nearby LSPVP project is completed to changes in prices for properties whose nearby projects are not yet completed, while simultaneously accounting for time-invariant property and location characteristics and common time shocks. The strength of this design is that it uses properties near *future* LSPVPs as the control group, ensuring that treatment and control properties are more likely to share similar unobserved characteristics and satisfy parallel trends assumptions than properties located several miles away. Essentially, the location of solar projects is potentially endogenous because they are not randomly assigned. Instead, they are located in areas in a manner potentially reflective of land value growth potential, zoning laws, nearby brownfield sites, and other factors that may independently influence property value growth. However, this potentially cleaner comparison comes at the cost of reducing the possible sample size of property transactions.

Therefore, we show that the DiD results from *Equation 1* are quite similar to the DiD results from an alternative specification, which follows the empirical design of others (Droes et al., 2021; Elmallah et al., 2023) by relating treatment timing and differential effects by distance from LSPVPs. Specifically, we employ a stacked DiD design combined with spatial distance bins, which is robust to heterogeneous treatment effects and uses within-project cohort comparisons that do not utilize any forbidden control groups (Cengiz et al., 2019; Goodman-Bacon, 2021; Baker et al., 2022). We remain consistent with Elmallah et al. (2023) in using four distance bins to interact with treatment status: homes located [0, 0.5], [0.5, 1], [1, 2], and [2, 4] miles away from an LSPVP.

To implement the stacked estimator, we calculate an estimated construction start date, assuming construction begins two years before the official date of operation. The distance between the coordinates of each MLS home sale and LSPVP is calculated. Consistent with Elmallah et al. (2023), we retain only properties within 4 miles of an LSPVP. We keep transactions occurring in the window from five years before to seven years after the *estimated construction start date*, which is equivalent to seven years before and five years after the LSPVP *operation date*. We then create a separate stack for each unique LSPVP. Within each stack, properties in the closest three distance bins ([0, 0.5], [0.5, 1], and [1, 2] miles) serve as treated units, while properties in the outermost ring of [2,4] miles serve as the within-stack control group. Therefore, in this stacked DiD analysis, treatment versus control comparison is spatially linked by the LSPVP. Consistent with Elmallah et al. (2023), if a home sale belongs to more than one project cohort, we keep the project cohort with the minimum distance between LSPVP and the property.[4] Stacks are then appended for all LSPVPs to form the final dataset. The final stacked dataset covers 87 unique LSPVP stacks and includes approximately 220,000 home sales. We model *Equation 2* here:

$$\ln(P_{icdjqt}) = \beta T_{idt} + X_i\alpha + \delta_{dc} + \lambda_{tc} + \rho_{qc} + \phi_j + \epsilon_{icdjqt} \qquad (2)$$

…where the dependent variable in *Equation 2* is the natural logarithm of sale price P for residential property transaction i in project cohort c within distance bin d and school district j, transacting in quarter q of year t. T_{idt} is a vector of distance bin indicators for homes located [0, 0.5], [0.5, 1], and [1, 2] miles from an LSPVP, in which each indicator equals 1 if the home sold after the estimated construction start date of the nearest LSPVP. Consistent with Elmallah et al. (2023), the omitted distance bin indicator is properties located 2 to 4 miles from an LSPVP. X_i is the same vector of property characteristics used in *Equation 1*. δ_{dc} represents distance bin-by-project fixed effects. Here λ_{tc} represents sale year-by-project cohort fixed effects, and ρ_{qc} represents sale quarter-by-project cohort fixed effects. These stack-interacted fixed effects ensure that treatment effects are identified from within-project cohort variation in sale prices across distance bins. ϕ_j is a vector of school district fixed effects, although we show robustness to using Census tract fixed effects instead. The key coefficients of interest are the βs, which represent the average treatment effect of LSPVP on home sale prices for each distance bin relative to home sale prices 2 to 4 miles away from an LSPVP. Standard errors are clustered at the project cohort level.

To estimate the dynamics of treatment effects and assess the parallel trends assumption, we also estimate an event study specification of *Equation 2*. *Equation 3* is:

$$\ln(P_{icdjqt}) = \sum_{k=-5,k\neq-1}^{7} T_{k,idt}\gamma_k + X_i\alpha + \delta_{dc} + \lambda_{tc} + \rho_{qc} + \phi_j + \epsilon_{icdjqt} \qquad (3)$$

…where $T_{k,idt}$ is an indicator equal to 1 if property i in distance bin d transacted exactly k years relative to the estimated construction start date of the nearest LSPVP. Consistent with Elmallah et al. (2023), we include five years of lead indicators and seven years of lag indicators. The omitted category is $k = -1$, the last event-year before the estimated construction start year, which is calculated as the operating date minus 2 years to account for forward-looking individuals who may react to information of a new solar plant installation before the solar plant construction has finished. For comparison with the original Elmallah et al. (2023) presentation of dynamic results, *Appendix Figures B1-B2 and Tables B1-B2* report the same models re-centered on $k = 0$, the estimated construction start year. This changes the reference year but has a negligible effect on the path of event study estimates.

[4] See Elmallah et al. (2023) Footnote 5 for more detail.

Results and Discussion

Tables 1 and 2 present the descriptive statistics for the two primary empirical specifications used in this report.

Table 1. Descriptive Statistics of Home Sales < 0.5 Miles from LSPVP

Variable	Mean (Std Dev)
N	4,821
Sale Price ($)	130,849.74 (74,034.94)
Post Project	0.60 (0.49)
# of Bedrooms	2.98 (0.69)
# of Bathrooms	1.94 (0.78)
Square Feet	1,634.79 (632.39)
Lot Acreage	0.47 (1.85)
Age	51.55 (25.64)
Basement (1 = Yes)	0.32 (0.47)
Dist to Project (Miles)	0.35 (0.11)

Note: We calculate the mean for each variable with standard deviations in parentheses.

Table 1 presents descriptive statistics for the 4,821 property transactions underlying *Equation 1*, which includes only 2011-2024 home sales located within 0.5 miles of LSPVPs. This narrow geographic focus allows for a comparison of home sales near *future* project sites with those near *completed* sites, providing a potentially cleaner comparison for DiD at the cost of a smaller sample size.

Table 2. Descriptive Statistics, Sold Homes by Distance Bin from LSPVP in Stacked DiD Analysis

Variable	< 0.5 mi	0.5-1 mi	1-2 mi	2-4 mi
N	3,232 (1.4%)	12,614 (5.6%)	57,860 (25.5%)	153,131 (67.5%)
Sale Price (1000s)	123.38 (67.53)	120.12 (76.60)	124.09 (80.33)	154.02 (105.94)
Post Project	0.66 (0.47)	0.66 (0.47)	0.66 (0.47)	0.66 (0.47)
# of Bedrooms	2.96 (0.69)	2.99 (0.71)	3.07 (0.70)	3.18 (0.73)
# of Bathrooms	1.93 (0.79)	1.93 (0.81)	2.02 (0.83)	2.24 (0.89)
Square Feet	1,627.28 (631.74)	1,667.62 (682.62)	1,711.83 (721.66)	1,899.38 (852.51)
Lot Acreage	0.47 (2.12)	0.38 (1.28)	0.35 (1.06)	0.43 (1.35)
Age	52.09 (25.69)	55.41 (24.37)	52.32 (23.94)	46.34 (24.06)
Basement (1 = Yes)	0.34 (0.47)	0.37 (0.48)	0.33 (0.47)	0.36 (0.48)
Dist to Project (mi)	0.35 (0.10)	0.78 (0.14)	1.54 (0.28)	3.03 (0.57)

Note: We calculate the mean for each variable with standard deviations in parentheses.

Table 2 presents descriptive statistics for a much larger sample of transactions within 4 miles of an LSPVP, underlying the distance bin-based stacked DiD specification. Across most distance bins in *Table 2*, properties are generally similar in terms of most characteristics. However, properties farther from an LSPVP (like the 2-4 miles omitted category) exhibit higher mean sale prices and larger square footage compared to properties in the closer distance bins, suggesting a modest baseline difference in market characteristics.

It is important to note that the sample size in *Table 2* for the < 0.5 miles bin (N = 3,232) is less than the total transactions in *Table 1* (N = 4,821) because *Table 2* retains only transactions used in creating project cohort stacks for the stacked DiD analysis, where only transactions occurring between five years before and seven years after the estimated construction start date are retained.

Table 3. Effect of LSPVP Completion on Home Prices

Variable	Model 1	Model 2
Post	-0.009 (0.037)	-0.014 (0.034)
Adj. R^2	0.720	0.723
F-statistic	48.16	47.16
N	4,818	4,818
House Characteristics	Yes	Yes
School FE	Yes	Yes
Year FE	Yes	No
Month FE	Yes	No
Year-Month FE	No	Yes
Distance to Project	No	No

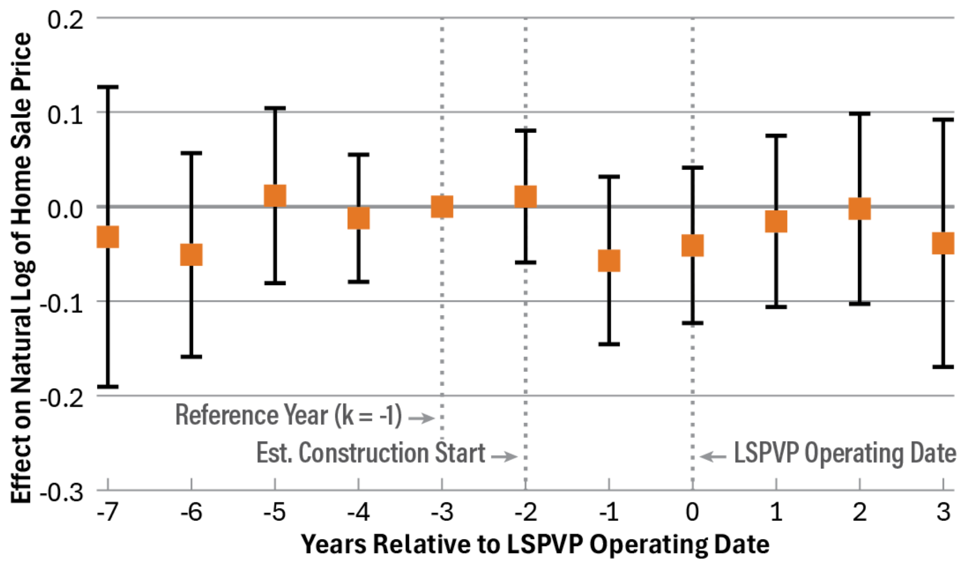
Note: Sample includes residential property sales within 0.5 miles of LSPVPs. Standard errors in parentheses are clustered at the school district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3 presents DiD estimates from two variations of *Equation 1*. Model 2 strengthens identification by using year-by-month fixed effects instead of separate year and month fixed effects. Results across all columns are negative, but statistically insignificant. The coefficient of -0.009 in Model 1 implies that LSPVPs reduced the sale price of homes by approximately 0.9% ($e^{(-0.009)} - 1$). While statistically indistinguishable from zero, this estimate is similar but slightly smaller in magnitude than the statistically significant 1.5% decrease in property values estimated by Elmallah et al. (2023). However, we note that the difference in estimated effects may come from differences in the underlying DiD variation used.

The estimates in *Table 3* come from models that leverage properties within the same distance band (0.5 miles) near *future* project sites as the comparison group, instead of a stacked DiD distance-based comparison used in a complementary model (as we test later in this report).

Does the Impact of a Solar Project Vary Over Time?

Figure 2. Event Study: Effect of LSPVP Completion on Sale Prices, Homes < 0.5 Miles



Note: Sample includes home sales within 0.5 miles of an LSPVP constructed during the sample period. The x-axis displays years relative to the LSPVP operating date. The omitted event-time category is ***k = -1***, plotted three years before operation and representing the last event-year before the estimated construction start. Estimated construction start is two years before facility operation. Standard errors are clustered at the school district level. Confidence intervals are 95%.

To examine the parallel trends assumption and assess potential dynamic effects, we present event study estimates from *Equation 1* (incl. home sales within 0.5 miles of an LSPVP) in *Figure 2,* using ***k = -1*** as the omitted last pre-construction year. The graph provides no evidence of significant pre-trends. Consistent with the main DiD results in *Table 3*, post-treatment estimates are relatively small and hover around zero with statistically insignificant estimates. There is some visual evidence in the event study that transaction prices decrease the year before operation start date, but the coefficient is statistically insignificant.

Table 4. Stacked DiD: Effect of LSPVP Construction and Proximity on Home Sale Prices

Column	1	2	3	4	5
Variable	Stacked	Stacked	Stacked	Stacked	TWFE
Dist to LSPVP: < 0.5 mi	-0.005 (0.027)	-0.004 (0.028)	-0.005 (0.023)	0.001 (0.023)	0.009 (0.034)
Dist to LSPVP: 0.5-1 mi	0.009 (0.020)	0.008 (0.019)	0.009 (0.015)	0.009 (0.019)	0.024 (0.025)
Dist to LSPVP: 1-2 mi	-0.012 (0.013)	-0.011 (0.013)	-0.012 (0.009)	-0.006 (0.011)	0.017 (0.016)
Adj. R^2	0.745	0.748	0.745	0.788	0.716
F-statistic	146.33	138.82	168.67	343.63	107.82
N	226,751	225,610	226,751	226,785	226,783
House Characteristics	Yes	Yes	Yes	Yes	Yes
Distance-Bin x Project Cohort FE	Yes	Yes	Yes	Yes	No
Sale Year x Project Cohort FE	Yes	No	Yes	Yes	No
Sale Quarter x Project Cohort FE	Yes	No	Yes	Yes	No
Sale Month x Project Cohort FE	No	Yes	No	No	No
School District FE	Yes	Yes	Yes	No	Yes
Census Tract FE	No	No	No	Yes	No
Cluster Level	Project Cohort	Project Cohort	School District	Project Cohort	School District

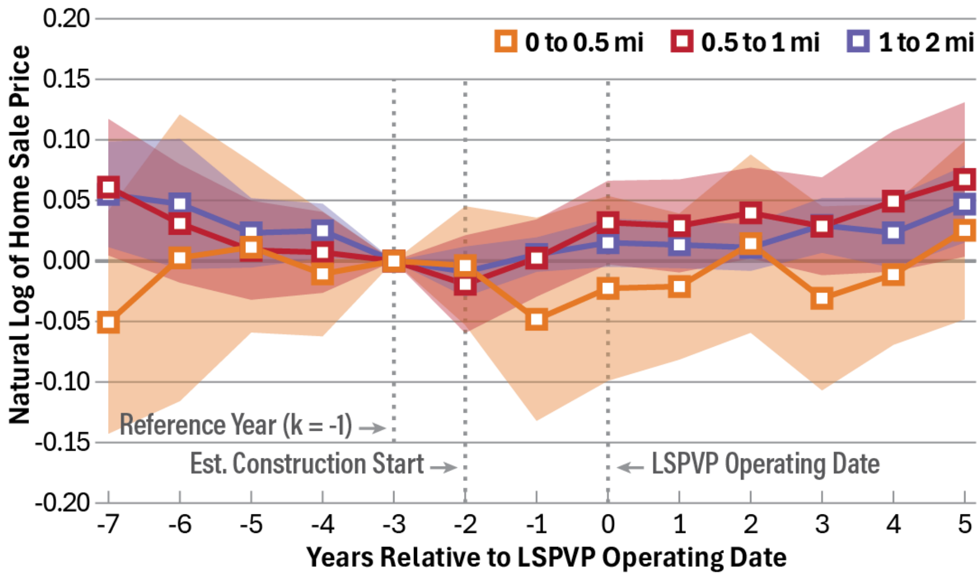
Note: Sample includes residential sales within 4 miles of LSPVPs. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4 shows results from the stacked DiD specification (*Equation 2*), which interacts LSPVP completion with distance bins, using property transactions 2 to 4 miles from an LSPVP as the omitted category (control group). Like results from *Table 3*, estimates are not statistically significantly different from zero, indicating that sale prices of homes within any of the distance bins shown in *Table 4* are not statistically different from sale prices of homes 2 to 4 miles from an LSPVP (the control group).

Estimates from our main stacked DiD model in Column 1 suggest that sale prices of houses less than 0.5 miles from an LSPVP decreases 0.5% after LSPVP construction. Column 2 shows that results are robust to using sale month by project cohort fixed effects instead of sale quarter by project cohort fixed effects. Column 3 shows that standard errors are similar when clustering at the school district level rather than the project cohort level. Column 4 shows that results are robust to using census tract fixed effects instead of school district fixed effects. Finally, standard TWFE estimates in Column 5 are similar in magnitude and direction as the more robust stacked DiD estimates. *Taken together, our results suggest that LSPVP construction has no statistically significant or economically significant negative impact on nearby home prices.*

While the six-state analysis of Elmallah et al. (2023) reports a stacked DiD estimate of -0.0154 and statistically significant for properties transacted less than 0.5 miles from an LSPVP, our respective estimate for Indiana is -0.005 and statistically insignificant. Our stacked DiD estimate for Indiana is consistent with the null effects that Elmallah et al. (2023) report for California, Connecticut, and Massachusetts for properties located within 0.5 miles of LSPVPs. In contrast, they find negative and statistically significant effects of LSPVP in Minnesota, North Carolina, and New Jersey ranging from -3.9% to -5.7% for properties located within 0.5 miles, smaller negative and significant effects within 0.5 to 1 mile of LSPVPs, and even smaller negative effects within 1 to 2 miles in Minnesota and North Carolina.

Figure 3. Stacked DiD Event Study: Effect of LSPVP Completion and Distance on Home Sale Prices



Note: We present stacked DiD event study estimates from *Equation 3* for each treated distance bin relative to the omitted control group of homes 2-4 miles from the nearest LSPVP. The x-axis displays years relative to the LSPVP operating date. The omitted reference year is ***k* = -1**, plotted three years before LSPVP operation and representing the last event-year before the estimated construction start. Confidence intervals of 95% appear as shaded bands. Standard errors are clustered at the project cohort level. Corresponding data available in *Appendix Table A3*.

Figure 3 presents the estimates from the stacked DiD event study specification (*Equation 3*). There are three separate lines for event study estimates of the three distance bins closer to LSPVPs, compared to the omitted 2-to-4-mile distance bin. There is light evidence of a downward trend in sale prices six to seven years before LSPVP operation, but there is little evidence of pre-trends in the five years prior to LSPVP operation. Moreover, event study estimates do not provide any evidence of a decline in transaction prices in the years after LSPVP construction or operation. Even estimates for properties less than 0.5 miles from an LSPVP are statistically insignificant in the year prior to operation start and in the year of operation start. The results suggest that LSPVPs have little impact on residential property values in Indiana. The signs on the coefficients for the closest properties are negative, but they are not statistically different from zero, indicating low levels of statistical certainty.

Does the Energy Capacity of a Solar Project Affect House Values?

We now explore the heterogeneous effects by the capacity of the LSPVP. See *Table 5*.

Table 5. Stacked DiD: Heterogeneity by Facility Capacity

Column	1	2	3	4
Variable	**< Median MW**	**≥ Median MW**	**× MW**	**× ln (MW)**
Dist to LSPVP: < 0.5 mi	0.057** (0.027)	-0.062* (0.036)	0.006 (0.039)	0.032 (0.042)
Dist to LSPVP: 0.5-1 mi	0.011 (0.028)	0.009 (0.027)	-0.012 (0.024)	-0.017 (0.031)
Dist to LSPVP: 1-2 mi	-0.016 (0.017)	-0.006 (0.017)	-0.029** (0.014)	-0.030* (0.018)
< 0.5 mi × MW	-	-	-0.002 (0.005)	-
0.5-1 mi × MW	-	-	0.005 (0.003)	-
1-2 mi × MW	-	-	0.004 (0.003)	-
< 0.5 mi × ln (MW)	-	-	-	-0.031 (0.026)
0.5-1 mi × ln (MW)	-	-	-	0.023 (0.019)
1-2 mi × ln (MW)	-	-	-	0.017 (0.016)
Adj. R^2	0.763	0.731	0.745	0.745
N	111,586	115,158	226,751	226,751

Note: Median capacity = 3 MW AC. Standard errors in parentheses clustered at the project cohort level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Stacked DiD estimates in Columns 1 and 2 that split the sample by below median versus above median capacity LSPVPs suggest that only above median capacity (> 3 MW AC) LSPVPs have a detrimental effect on home sale prices, whereas smaller LSPVPs may have a positive impact on nearby home sale prices. However, Columns 3 and 4 provide results from an interactive model. In these specifications, the interactions between LSPVP capacity or the logarithm of capacity and treatment distance bins for properties less than 0.5 miles from an LSPVP are negative, but not statistically significant. Overall, these results suggest that any negative impacts of LSPVPs on nearby home prices may be driven by larger capacity LSPVPs, though results are not definitive.

Does Rural or Urban Siting Affect the Impact of a Solar Project?

The impact of LSPVP completion may be a function of what the LSPVP facility displaces. We hypothesize that facilities will have a more negative effect on house prices in rural Indiana because the LSPVP facilities displace scenic land that potential homeowners may value.

To test this, we examine differences in residential property transactions near LSPVPs in urban, mixed, and rural areas as defined by Miller et al. (2022). Census tracts with less than 25% of the population residing in urban areas are defined as rural. Tracts with 25-75% of the population residing in urban areas are defined as mixed. Urban areas are tracts with at least 75% of the population living in urban areas.

To assess heterogeneous effects by urbanicity, we examine our alternative specification, which estimates differential effects by distance from LSPVP. See *Table 6*.

Table 6. Stacked DiD: Effect of LSPVP Completion and Proximity on Home Prices by Urbanicity

Column	**1**	**2**	**3**
Variable	**Rural**	**Mixed**	**Urban**
Distance to LSPVP: < 0.5 mi	0.055 (0.049)	-0.047 (0.103)	-0.001 (0.031)
Distance to LSPVP: 0.5-1 mi	-0.064 (0.046)	-0.002 (0.053)	0.011 (0.021)
Distance to LSPVP: 1-2 mi	-0.005 (0.029)	0.022 (0.017)	-0.017 (0.014)
Adj. R^2	0.673	0.708	0.746
N	5,861	20,497	200,242

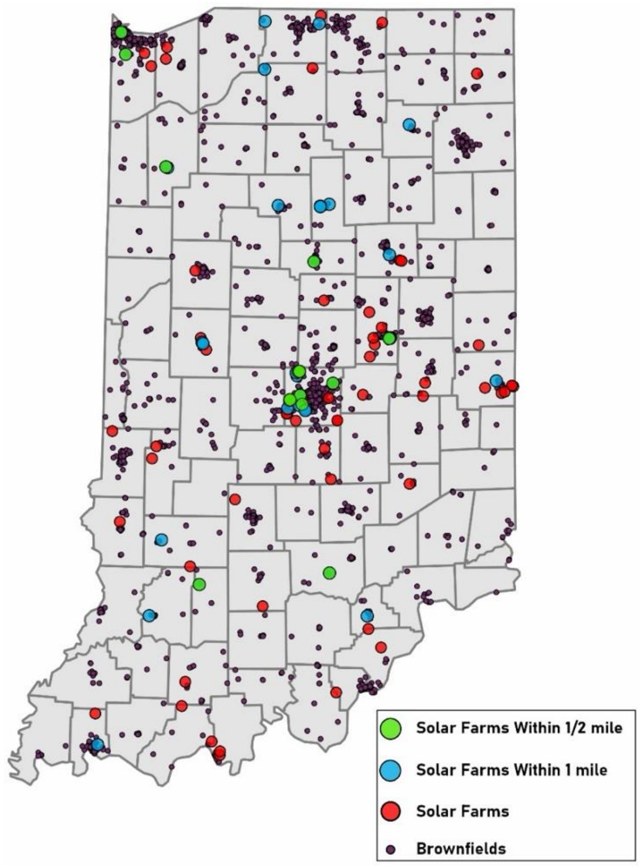
Note: Standard errors in parentheses clustered at the project cohort level. All models include all covariates and fixed effects from the baseline stacked DiD specification. $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Estimates in Columns 1-3 show a positive but insignificant effect of LSPVP on house prices in rural areas less than 0.5 miles away, relative to houses 2 to 4 miles from LSPVP. The coefficients are negative for mixed and urban properties within 0.5 miles of LSPVP, but these effects are not statistically significant, suggesting that LSPVP projects have a limited effect on the sale price of nearby homes compared to homes further from the solar project.

Does a Solar Project's Proximity to a Brownfield Affect House Values?

Next, we assess heterogeneous effects by LSPVP proximity to brownfield sites using data from the Indiana Department of Environmental Management. Brownfield sites are often abandoned, vacant, or underutilized properties that are marred with environmental contaminants.

Figure 4. Indiana's Brownfield Sites and Completed LSPVPs, 2023



Source: IDEM and SEIA. Note: For corresponding data, see *Appendix Table A4*.

Figure 4 maps the locations of brownfield sites and solar farms (LSPVP) that were completed by 2023. Brown dots mark the location of more than 2,500 brownfield sites in Indiana. Green dots denote LSPVP within 0.5 miles of a brownfield, blue dots denote LSPVP within 1 mile of a brownfield, and red dots denote LSPVP beyond 1 mile of a brownfield.

If LSPVP completion reduces local property values via displacing scenic land, then one should expect larger negative effects of LSPVP completion in areas further from brownfield sites. Meanwhile, LSPVP completion near brownfield sites may have a positive impact on local property values, as developments near brownfield sites may serve as a welcome alternative to contaminated land that may sit vacant or underdeveloped due to high brownfield site remediation costs. In their analysis, Hu et al. (2025) found that solar projects located on brownfields lead to a positive and statistically significant impact on residential property values for homes within 3 miles of these projects. Using a choice experiment survey of Rhode Island residents, Gaur et al. (2023) found that residents prefer solar developments to occur on commercial/industrial land or brownfield/covered landfill areas instead of farms or forest lands.

To estimate heterogeneous effects by proximity to brownfield sites, we calculate the distance between each brownfield site and LSPVPs in Indiana.[5] See *Table 7*. We create separate indicator variables equal to 1 if the LSPVP is located within 0.5 mile or 1 mile from a brownfield site.

Table 7. Stacked DiD: Effect of LSPVP Completion and Proximity to Brownfield Sites

Column	1	2	3	4
Variable	**Brownfield < 0.5 Mi**	**No Brownfield < 0.5 Mi**	**Brownfield < 1 Mi**	**No Brownfield < 1 Mi**
Distance to LSPVP: < 0.5 mi	-0.008 (0.059)	-0.002 (0.032)	0.023 (0.034)	-0.032 (0.039)
Distance to LSPVP: 0.5-1 mi	0.004 (0.037)	0.011 (0.023)	0.014 (0.026)	0.000 (0.031)
Distance to LSPVP: 1-2 mi	-0.029 (0.030)	-0.001 (0.011)	-0.015 (0.022)	-0.005 (0.008)
Adj. R^2	0.761	0.738	0.742	0.751
N	72,780	153,966	124,639	102,109

Note: Standard errors in parentheses clustered at the project cohort level. All models include all covariates and fixed effects from the baseline stacked DiD specification. Columns 1 and 3 restrict the sample to project cohorts whose LSPVP lies within 0.5 miles (1 mile, respectively) of a brownfield site. Throughout the stacked DiD analysis sample, there were 716 property transactions that occurred in project cohorts in which an LSPVP was less than 0.5 miles from a brownfield site and 1,703 that occurred in project cohorts less than 1 mile from a brownfield site. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7 presents results from a distance-based, stacked DiD model that is estimated separately by proximity to brownfield sites. Estimates in Columns 1 and 2 suggest that a negative but insignificant effect on properties within 0.5 miles of an LSPVP regardless of whether the LSPVP is on a brownfield or not. Columns 3 and 4 present results from a similar split by proximity less than or greater than 1 mile from a brownfield site. Estimates suggest positive effects of LSPVP completion for properties within 1 mile of brownfield sites (Column 3) and 0.5 miles of an LSPVP site, while estimates in Column 4 suggest LSPVP completion has a negative (-3.2%) effect on property values when homes are within 0.5 miles of an LSPVP but not near a brownfield site. However, both effects are statistically insignificant. In sum, the results suggest that LSPVPs located near brownfields do not have a differential effect on the average sale price of residential properties in Indiana.

[5] These distances are calculated from the latitude and longitude provided in the datasets for each brownfield and LSPVP site, which are likely to be the centroid of each site. We cannot say definitively that the LSPVP is "on" a brownfield.

Does the Type of Power Provider Affect House Values?

The SEIA dataset provides information on entity type, which allows us to examine the relationship between home sale prices and proximity to LSPVP for three types of providers. Independent power producers own facilities to generate electricity for sale to utilities and end users, often operating through power purchase agreements.[6] Political subdivisions are municipal-owned utilities that operate primarily through the Indiana Municipal Power Agency. Investor-owned utilities are privately-owned, for-profit companies, and their stock is publicly traded.[7] Additionally, one federally owned utility, two commercial utilities, and several rural electric cooperatives operate in Indiana, but sample sizes were too small for statistical analysis.

Table 8. Effect of LSPVP Completion and LSPVP Entity Type

Variable	Independent Power Producer	Political Subdivision (Municipal-Owned)	Investor-Owned Utility
Distance to LSPVP: < 0.5 mi	-0.012 (0.038)	-0.043 (0.054)	0.079^{**} (0.030)
Distance to LSPVP: 0.5-1 mi	0.022 (0.024)	-0.005 (0.050)	0.044^{*} (0.022)
Distance to LSPVP: 1-2 mi	-0.003 (0.013)	0.004 (0.013)	0.026 (0.028)
Adj. R^2	0.747	0.698	0.761
N	126,444	27,796	38,519

Note: Standard errors in parentheses clustered at the project cohort level. All models include all covariates and fixed effects from the baseline stacked DiD specification. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8 displays the results from the distance-based DiD model and shows that effects differ by entity type. Homes within 0.5 miles of investor-owned utilities experienced an 8.2% increase in sale price, and homes within 0.5 to 1 mile experienced a 4.5% increase after the LSPVP became operational, relative to homes 2 to 4 miles away.[8] This positive result may occur because investor-owned utilities better design and maintain their solar facilities to minimize disamenity effects.

Another likely explanation for the observed positive relationship between home prices and large investor-owned LSPVPs is the offsetting capitalization of property tax revenues in the taxing districts. Within Indiana's local tax system, the large business personal property assessment of an LSPVP may work to reduce property tax rates for all properties within a taxing district. This would be partially capitalized into all properties within those overlapping districts. This capitalization would partially offset any negative effects of proximity. However, for properties where the disamenity of an LSPVP is negligible, the expected reduction in property tax rates would potentially result in a positive effect on home prices through capitalization. We do not possess property-level tax rates to assess this effect, so we must defer this question to later work.

[6] A few examples of independent power producers are Cypress Creek Renewables, Mammoth North LLC, and Ecos Energy LLC.

[7] Investor-owned utilities operating in the state include Northern Indiana Public Service Company (NIPSCO), Indiana-Michigan Power (I&M), Duke Energy, Indianapolis Power& Light, and Vectren.

[8] The calculation is $(e^{0.079}) - 1 = approximately\ 8.2\%$ and a similar calculation for the 0.5 to 1 mile distance.

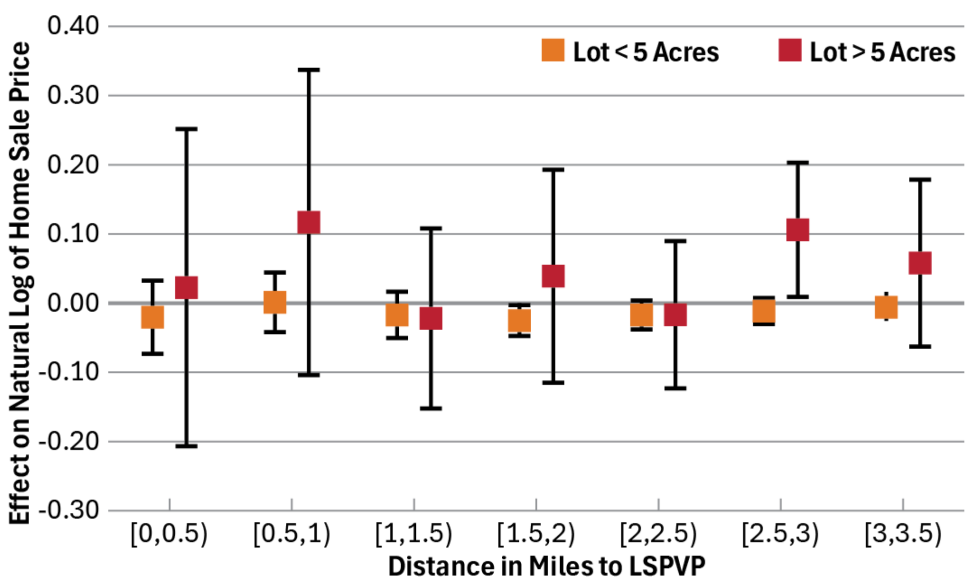
Are Homes on Large Lots Affected Differently by Proximity to a Solar Project?

As a final robustness check to the two primary DiD specifications, we also show that results are robust to the use of distance decay DiD models inspired by Hu et al. (2025), modified so that properties 3.5 to 4 miles from an LSPVP serve as the control group, consistent with the rest of our report and that of Elmallah et al. (2023), which limits analysis to transactions within 4 miles of an LSPVP. Specifically, we estimate in *Equation 4*:

$$\ln(P_{it}) = \beta_0 + \beta_1 Post_{it} + \sum_{m=1}^{M-1} \beta_2^m T_i^m + \sum_{m=1}^{M-1} \beta_3^m (Post_{it} \times T_i^m) +$$
$$\sum_k \delta_k X_{it}^k + \sum_k \gamma_k (Post_{it} \times X_{it}^k) + \tau_{ct} + \varepsilon_{it} \quad (4)$$

…where $\ln(P_{it})$ is the natural logarithm of sale price of property i transacted in year t. $Post_{it}$ indicates a sale transacted after the estimated construction start of the nearest LSPVP. Consistent with analysis above, we use two years prior to the operating date as the construction start date. The vector X_{it} of length k controls for the same property characteristics as the two main DiD specifications. Each property characteristic control is included on its own as well as interacted with $Post_{it}$, consistent with Hu et al. (2025). The distance decay model uses proximity-bin indicators, T_i^m, which partition the area around each LSPVP into M 0.5-mile rings. The outermost ring, T_i^M, spans 3.5 to 4 miles and is omitted to serve as the control group. The coefficients of interest, β_3^m, are estimated for the $M-1$ rings closer to the LSPVP and estimate treatment effects of LSPVP construction on sale prices as a function of distance, with effects expected to decay as properties move closer to the control ring. Consistent with Hu et al. (2025), the model absorbs Census tract by year fixed effects, τ_{ct}, for smaller properties (< 5 acres) and county-LSPVP-year fixed effects for larger properties (> 5 acres). Following Hu et al. (2025) methodology, we cluster standard errors using two-way clustering at the Census tract and year levels or county-site and year levels, respectively.

Figure 5. Distance Decay DiD: Effect of LSPVP Completion on Home Sale Prices



Note: This figure presents distance decay DiD estimates from *Equation 4*. Each marker presents estimated effects of LSPVP construction based on a binary treatment indicator that is interacted with the respective proximity bin. The 95% confidence intervals are calculated using two-way clustering described above. The control group is defined as properties in the [3.5,4) mile proximity bin.

Figure 5 presents the estimated distance decay coefficients following Hu et al. (2025), estimated separately for homes on less than 5 acres versus homes on more than 5 acres. Confidence intervals for estimates regarding homes on less than 5 acres are noticeably larger due to a much smaller sample size of large-lot homes in Indiana near LSPVPs. For homes on less than 5 acres, the proximity bin effects are slightly negative across most distance rings close to LSPVPs, but are statistically insignificant at conventional levels, providing no evidence of statistically significant reductions in sale prices even for homes nearest to LSPVPs. For large-lot homes (> 5 acres), estimated effects of LSPVPs are positive across most proximity bins but are similarly statistically insignificant.

These estimates are consistent with Hu et al. (2025), who find that negative effects of LSPVPs on property values are driven almost entirely by the northeast region of the U.S. and that results are statistically insignificant with positive point estimates in the U.S. Midwest. The positive signs on large lot estimates (> 5 acres), though statistically imprecise, are consistent with the mechanisms emphasized by Hu et al. (2025), whereby LSPVPs may potentially depress nearby home values via reduced residential amenities while raising values of larger lots via improved land use potential through solar leasing or expansion. Moreover, the results from our two primary DiD specifications are remarkably consistent with this alternative distance decay DiD model inspired by Hu et al. (2025), reinforcing our central finding that proximity to LSPVPs in Indiana has no economically meaningful or statistically significant effect on nearby home prices.

Conclusions

Our estimates from two complementary DiD hedonic valuation models and event studies reveal no statistically significant negative effects of LSPVP completion on home prices in Indiana. The results of the TWFE DiD models (*Table 3*) and the stacked DiD models (*Table 4*) consistently point to small (potentially negative) but statistically insignificant results with relatively small standard errors that show that LSPVPs do not have a large negative impact on nearby house prices in Indiana.

While these results indicate a lack of negative effects on nearby residential properties examined in this study, this does not preclude any negative effects occurring on individual properties. Regression results are averages, so some nearby properties may have been negatively impacted. Properties within 0.5 miles is the closest distance with sample sizes large enough to conduct statistical analysis.

Other studies show that the effects of solar on local property values vary by region. Elmallah et al. (2023) find large and statistically significant negative effects in North Carolina and New Jersey, but positive statistically insignificant estimates for California and Connecticut. Hu et al. (2025) find that negative effects of solar are concentrated in the Northeast, while Midwest estimates are positive and statistically insignificant. Our statistically insignificant results for Indiana are consistent with the Hu et al. (2025) results for the broader Midwest, suggesting that variation in local siting conditions and local housing markets matter.

We also examine heterogeneous effects based on the size of the solar development, location in an urban or rural area, and proximity to brownfield sites. Analysis of the production capacity of the LSPVP (measured in MW AC) suggests that larger LSPVPs have a statistically significant negative effect (-6%) on sale prices in a split-sample model, but this result is not robust across various specifications.[9] Unlike Elmallah et al. (2023), we find no evidence of negative effects of LSPVP proximity on property values in rural areas where scenic land may be displaced. Our results are more consistent with those of Hu et al. (2025), who found no statistically significant effects of LSPVP on residential property values in the Midwest U.S.

Our model results found no statistically significant effect of LSPVPs on sale price after solar farms become operational at any distance in urban, mixed, or rural areas. Moreover, our results provide no evidence that LSPVPs have a positive effect on the sale price of properties located near brownfields. Location near a brownfield had no statistically significant effect on the sale price of residential properties, although this result might be due to a relatively small sample size for properties closest to LSPVPs and brownfields. Finally, the type of energy provider appears to affect property values with properties within one mile of investor-owned utilities experiencing positive effects. This positive effect may result from the capitalization effects operating through the property tax system and/or design and maintenance of the solar facilities to reduce disamenity effects.

[9] The calculation is $(e^{-0.062}) - 1$ = approximately -6%.

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Appendix

Contents

Corresponding Data for Figures 1-5 (Tables A1-A5)

Table A1. LSPVP, Battery, and Hybrid Facilities in Indiana by Year, Type, and Capacity

Source: SEIA. Note: Corresponds with the maps of facilities in operation by 2012, 2017, and 2023 in Figure 1.

Operating Year	Facility Name	County	Type	AC Capacity MW
2011	M. G. Emmett J. Bean Federal Center	Marion	Solar PV	1.9
2012	Lincoln Solar	Lake	Solar PV	1.5
2012	Hobart Solar, LLC	Lake	Solar PV	1
2012	Waterloo Solar, LLC	DeKalb	Solar PV	1
2012	Valparaiso Solar, LLC	Porter	Solar PV	1
2012	Portage Solar	Porter	Solar PV	1.5
2012	Middlebury Solar	Elkhart	Solar PV	1.5
2013	IND Community Solar Farm 1st Phase	Marion	Solar PV	10
2013	Indy Solar I, LLC	Marion	Solar PV	10
2013	Indy Solar II, LLC	Marion	Solar PV	10.1
2013	Indy Solar III, LLC	Marion	Solar PV	8.6
2013	East Chicago	Lake	Solar PV	2
2013	Griffith	Lake	Solar PV	2
2014	Indianapolis Motor Speedway Solar PV	Marion	Solar PV	9
2014	Maywood Photovoltaic Project	Marion	Solar PV	8
2014	Rockville Solar I, LLC	Marion	Solar PV	2.8
2014	Rockville Solar II, LLC	Marion	Solar PV	2.7
2014	IND Solar Farm (Phase IIA)	Marion	Solar PV	7.5
2014	Duke Building 87	Marion	Solar PV	2.7
2014	Duke Building 98	Marion	Solar PV	2.7
2014	Duke Building 129	Marion	Solar PV	3.4
2014	IMPA Richmond Solar Park	Wayne	Solar PV	1
2014	IMPA Frankton Solar Park	Madison	Solar PV	1
2014	IMPA Rensselaer Solar Park	Jasper	Solar PV	1
2015	Lenape II	Marion	Solar PV	4
2015	Belmont	Marion	Solar PV	3.8
2015	Marion Solar LNG	Marion	Solar PV	1.5
2015	IMPA Peru Solar Park	Miami	Solar PV	3
2015	IMPA Tell City Solar Park	Perry	Solar PV	1.1
2015	IMPA Crawfordsville Solar Park	Montgomery	Solar PV	3
2015	IMPA Pendleton Solar Park	Madison	Solar PV	2
2015	INDY III	Marion	Solar PV	2.5
2015	Indy Grocers	Marion	Solar PV	1
2015	Scotland Solar RES	Greene	Solar PV	1.1
2015	Lanesville Solar RES	Harrison	Solar PV	1.1
2015	McDonald Solar Farm, LLC	Vigo	Solar PV	5.2
2015	Pastime Farm, LLC	Clay	Solar PV	5.2
2016	*Harding Street*	*Marion*	*Batteries*	*20*
2016	OlivePV	St Joseph	Solar PV	5

Operating Year	Facility Name	County	Type	AC Capacity MW
2016	Deer Creek PV	Grant	Solar PV	2.5
2016	Twin Branch PV	St Joseph	Solar PV	2.6
2016	New Castle Solar RES	Henry	Solar PV	1.1
2016	New Haven Solar RES	Spencer	Solar PV	1.1
2016	Ellettsville Solar RES	Monroe	Solar PV	1.1
2016	Henryville Solar RES	Clark	Solar PV	1.1
2016	Johnson Co. Solar RES	Johnson	Solar PV	1.1
2016	IMPA Huntingburg Solar Park	Dubois	Solar PV	2
2016	IMPA Washington Solar Park	Daviess	Solar PV	4
2016	Sullivan Solar, LLC	Sullivan	Solar PV	5.2
2016	Kokomo Solar 1, LLC	Howard	Solar PV	5.4
2017	Spring Mill Solar RES	Lawrence	Solar PV	1.1
2017	Decatur Co. Solar RES (IN)	Decatur	Solar PV	1.1
2017	Jackson Co. Solar RES	Jackson	Solar PV	1.1
2017	IMPA Anderson Solar Park	Madison	Solar PV	5
2017	Crane Solar Facility	Martin	Hybrid	22
2017	Greenfield Solar Park	Hancock	Solar PV	2.8
2017	IMPA Anderson Solar Park 2	Madison	Solar PV	8.1
2018	Oak Hill Solar Array	Vanderburgh	Solar PV	2
2018	Volkman Road Solar Array Hybrid	Vanderburgh	Hybrid	3
2018	Richmond Solar Site 2	Wayne	Solar PV	7.4
2018	Rensselaer Solar Site 2	Jasper	Solar PV	3.8
2018	Staunton	Clay	Solar PV	4
2019	Tipton Solar Park	Tipton	Solar PV	5.3
2019	Crawfordsville 2 Solar Park	Montgomery	Solar PV	7.9
2019	Crawfordsville 3 Solar Park	Montgomery	Solar PV	4.8
2019	Richmond Solar Park 3	Wayne	Solar PV	6.5
2019	Tippecanoe Solar Power Plant	Tippecanoe	Solar PV	1.6
2019	Camp Atterbury Microgrid Hybrid	Johnson	Hybrid	7
2020	Scottsburg Solar Park	Scott	Solar PV	7.1
2020	Gas City Solar Park	Grant	Solar PV	2.5
2020	Crawfordsville Solar Park 4	Montgomery	Solar PV	2.3
2020	Tell City Solar Park	Perry	Solar PV	3.2
2020	Richmond Solar Park 4	Wayne	Solar PV	7.1
2020	Crawfordsville 5 Solar Park	Montgomery	Solar PV	9.8
2020	Centerville Solar Park	Wayne	Solar PV	1.1
2020	*Nabb Battery Energy Storage System*	*Clark*	*Batteries*	*5*
2021	Columbia City Solar Park	Whitley	Solar PV	4.3
2021	St. Joseph Solar	St Joseph	Solar PV	20
2021	Logansport Solar	Cass	Solar PV	16
2021	Troy Solar	Spencer	Solar PV	50.4
2021	Anderson 3	Madison	Solar PV	8.7
2021	Anderson 5	Madison	Solar PV	3
2021	Peru 2	Miami	Solar PV	9.5
2021	Richmond 5	Wayne	Solar PV	9
2021	Anderson 4	Madison	Solar PV	7.8
2021	Riverstart Solar Park LLC	Randolph	Solar PV	200
2022	Anderson 6	Madison	Solar PV	6.8
2022	Peru 3	Miami	Solar PV	2.9
2022	Walkerton	St Joseph	Solar PV	1.1
2022	Linton	Greene	Solar PV	5.4
2022	Bremen	Marshall	Solar PV	6.8
2023	Bellflower Solar 1	Henry	Solar PV	152.5
2023	Gas City 2	Grant	Solar PV	1.8

Table A2. Event Study: Effect of LSPVP Completion on Home Prices

Note: Data corresponds with Figure 2. Year 0 = Start of facility operation. Confidence Interval (CI) is 95%.

Year	Estimate	Std Error	CI Lower	CI Upper
-7	-0.0320	0.0794	-0.1906	0.1266
-6	-0.0510	0.0539	-0.1588	0.0567
-5	0.0115	0.0464	-0.0811	0.1042
-4	-0.0123	0.0337	-0.0797	0.0550
-3	0.0000	0.0000	0.0000	0.0000
-2	0.0107	0.0349	-0.0590	0.0804
-1	-0.0571	0.0444	-0.1457	0.0316
0	-0.0410	0.0411	-0.1231	0.0411
1	-0.0156	0.0453	-0.1062	0.0750
2	-0.0022	0.0504	-0.1029	0.0984
3	-0.0388	0.0655	-0.1697	0.0921

Table A3, Panel 1. Stacked DiD Event Study, Distance Bin 0-0.5 Miles

Note: Data corresponds with the 0-0.5 Miles Distance Bin in Figure 3. Year 0 = Start of facility operation. Confidence Interval (CI) is 95%.

Year	Dist Bin	Estimate	Std Error	CI Lower	CI Upper
-7	0-0.5 mi	-0.0506	0.0469	-0.1426	0.0414
-6	0-0.5 mi	0.0026	0.0604	-0.1157	0.1209
-5	0-0.5 mi	0.0114	0.0359	-0.0590	0.0818
-4	0-0.5 mi	-0.0107	0.0263	-0.0622	0.0409
-3	0-0.5 mi	0.0000	0.0000	0.0000	0.0000
-2	0-0.5 mi	-0.0038	0.0250	-0.0528	0.0451
-1	0-0.5 mi	-0.0482	0.0428	-0.1320	0.0357
0	0-0.5 mi	-0.0226	0.0389	-0.0989	0.0537
1	0-0.5 mi	-0.0211	0.0307	-0.0814	0.0391
2	0-0.5 mi	0.0143	0.0375	-0.0592	0.0878
3	0-0.5 mi	-0.0309	0.0387	-0.1068	0.0450
4	0-0.5 mi	-0.0112	0.0296	-0.0692	0.0468
5	0-0.5 mi	0.0254	0.0375	-0.0481	0.0989

Table A3, Panel 2. Stacked Event Study, Distance Bin 0.5-1 Mile

Note: Data corresponds with the 0.5-1 Mile Distance Bin in Figure 3. Year 0 = Start of facility operation. Confidence Interval (CI) is 95%.

Year	Dist Bin	Estimate	Std Error	CI Lower	CI Upper
-7	0.5-1 mi	0.0609	0.0287	0.0046	0.1172
-6	0.5-1 mi	0.0310	0.0249	-0.0178	0.0797
-5	0.5-1 mi	0.0088	0.0208	-0.0320	0.0497
-4	0.5-1 mi	0.0071	0.0170	-0.0263	0.0404
-3	0.5-1 mi	0.0000	0.0000	0.0000	0.0000
-2	0.5-1 mi	-0.0192	0.0205	-0.0594	0.0211
-1	0.5-1 mi	0.0024	0.0162	-0.0294	0.0342
0	0.5-1 mi	0.0317	0.0176	-0.0027	0.0662
1	0.5-1 mi	0.0290	0.0196	-0.0094	0.0673
2	0.5-1 mi	0.0396	0.0191	0.0022	0.0770
3	0.5-1 mi	0.0287	0.0206	-0.0117	0.0690
4	0.5-1 mi	0.0493	0.0296	-0.0087	0.1073
5	0.5-1 mi	0.0673	0.0325	0.0036	0.1310

Table A3, Panel 3. Stacked Event Study, Distance Bin 1-2 Miles

Note: Data corresponds with the 1-2 Miles Distance Bin in Figure 3. Year 0 = Start of facility operation. Confidence Interval (CI) is 95%.

Year	Dist Bin	Estimate	Std Error	CI Lower	CI Upper
-7	1-2 mi	0.0550	0.0222	0.0115	0.0985
-6	1-2 mi	0.0471	0.0274	-0.0066	0.1007
-5	1-2 mi	0.0232	0.0146	-0.0054	0.0518
-4	1-2 mi	0.0249	0.0114	0.0025	0.0473
-3	1-2 mi	0.0000	0.0000	0.0000	0.0000
-2	1-2 mi	-0.0089	0.0105	-0.0295	0.0118
-1	1-2 mi	0.0053	0.0072	-0.0089	0.0194
0	1-2 mi	0.0151	0.0101	-0.0048	0.0350
1	1-2 mi	0.0133	0.0098	-0.0059	0.0325
2	1-2 mi	0.0111	0.0098	-0.0081	0.0304
3	1-2 mi	0.0294	0.0115	0.0068	0.0520
4	1-2 mi	0.0232	0.0148	-0.0058	0.0523
5	1-2 mi	0.0470	0.0162	0.0153	0.0787

Table A4. Number of Brownfield Sites and Completed LSPVPs by County

Note: Data corresponds with Figure 4. We include solar photovoltaic and hybrid facilities that were completed and in operation by 2023.

County	# of Brownfield Sites	# of Solar Facilities (incl. PV & Hybrid)
Adams	12	0
Allen	121	0
Bartholomew	32	0
Benton	8	0
Blackford	9	0
Boone	41	0
Brown	2	0
Carroll	6	0
Cass	31	1
Clark	50	1
Clay	13	2
Clinton	20	0
Crawford	7	0
Daviess	13	1
Dearborn	10	0
Decatur	8	1
DeKalb	21	1
Delaware	83	0
Dubois	15	1
Elkhart	116	1
Fayette	10	0
Floyd	28	0
Fountain	4	0
Franklin	3	0
Fulton	17	0
Gibson	13	0
Grant	32	3
Greene	12	2
Hamilton	46	0
Hancock	9	1
Harrison	11	1
Hendricks	21	0
Henry	37	2
Howard	35	1
Huntington	15	0
Jackson	11	1
Jasper	8	2
Jay	10	0
Jefferson	13	0
Jennings	3	0
Johnson	31	2
Knox	13	0
Kosciusko	26	0
Lagrange	9	0
Lake	211	4
LaPorte	54	0
Lawrence	9	1
Madison	86	8
Marion	550	18
Marshall	14	1
Martin	3	1
Miami	15	3
Monroe	51	1
Montgomery	14	5
Morgan	11	0

County	# of Brownfield Sites	# of Solar Facilities (incl. PV & Hybrid)
Newton	8	0
Noble	16	0
Ohio	2	0
Orange	8	0
Owen	2	0
Parke	15	0
Perry	9	2
Pike	7	0
Porter	31	2
Posey	9	0
Pulaski	11	0
Putnam	13	0
Randolph	16	1
Ripley	10	0
Rush	22	0
Saint Joseph	93	4
Scott	7	1
Shelby	14	0
Spencer	6	2
Starke	9	0
Steuben	9	0
Sullivan	34	1
Switzerland	1	0
Tippecanoe	49	1
Tipton	10	1
Union	1	0
Vanderburgh	69	2
Vermillion	25	0
Vigo	46	1
Wabash	18	0
Warren	2	0
Warrick	11	0
Washington	5	0
Wayne	22	6
Wells	4	0
White	5	0
Whitley	23	1

Table A5, Panel 1. Distance Decay DiD, Lot Type < 5 Acres

Note: Data corresponds with Figure 5. Confidence Interval (CI) is 95%.

Lot Type	Distance Bin	Estimate	Std Error	CI Lower	CI Upper
Residential < 5 Acres	[0,0.5)	-0.0204	0.0253	-0.0732	0.0324
Residential < 5 Acres	[0.5,1)	0.0012	0.0206	-0.0418	0.0443
Residential < 5 Acres	[1,1.5)	-0.0170	0.0160	-0.0504	0.0164
Residential < 5 Acres	[1.5,2)	-0.0252	0.0107	-0.0476	-0.0029
Residential < 5 Acres	[2,2.5)	-0.0171	0.0100	-0.0380	0.0038
Residential < 5 Acres	[2.5,3)	-0.0115	0.0090	-0.0303	0.0073
Residential < 5 Acres	[3,3.5)	-0.0059	0.0056	-0.0177	0.0059

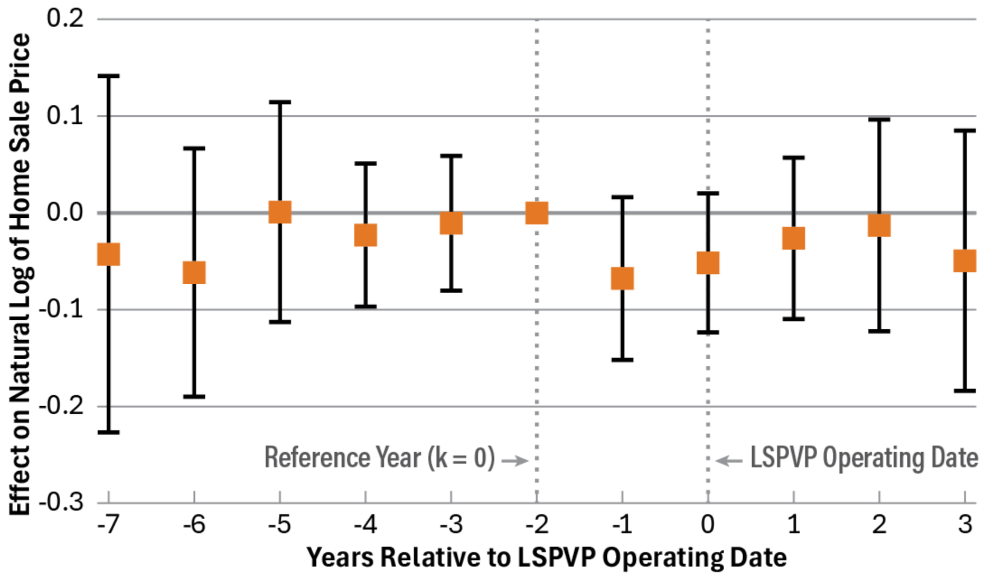
Table A5, Panel 2. Distance Decay DiD, Lot Type ≥ 5 Acres

Note: Data corresponds with Figure 5. Confidence Interval (CI) is 95%.

Lot Type	Distance Bin	Estimate	Std Error	CI Lower	CI Upper
Large Lot ≥ 5 Acres	[0,0.5)	0.0223	0.1099	-0.2069	0.2516
Large Lot ≥ 5 Acres	[0.5,1)	0.1167	0.1057	-0.1039	0.3372
Large Lot ≥ 5 Acres	[1,1.5)	-0.0220	0.0624	-0.1522	0.1081
Large Lot ≥ 5 Acres	[1.5,2)	0.0389	0.0737	-0.1150	0.1927
Large Lot ≥ 5 Acres	[2,2.5)	-0.0168	0.0510	-0.1232	0.0897
Large Lot ≥ 5 Acres	[2.5,3)	0.1061	0.0465	0.0091	0.2030
Large Lot ≥ 5 Acres	[3,3.5)	0.0579	0.0579	-0.0629	0.1786

Additional Tests (Figures B1-B2 and Tables B1-B2)

Figure B1. Event Study: Effect of LSPVP Completion on Home Prices (k = 0)



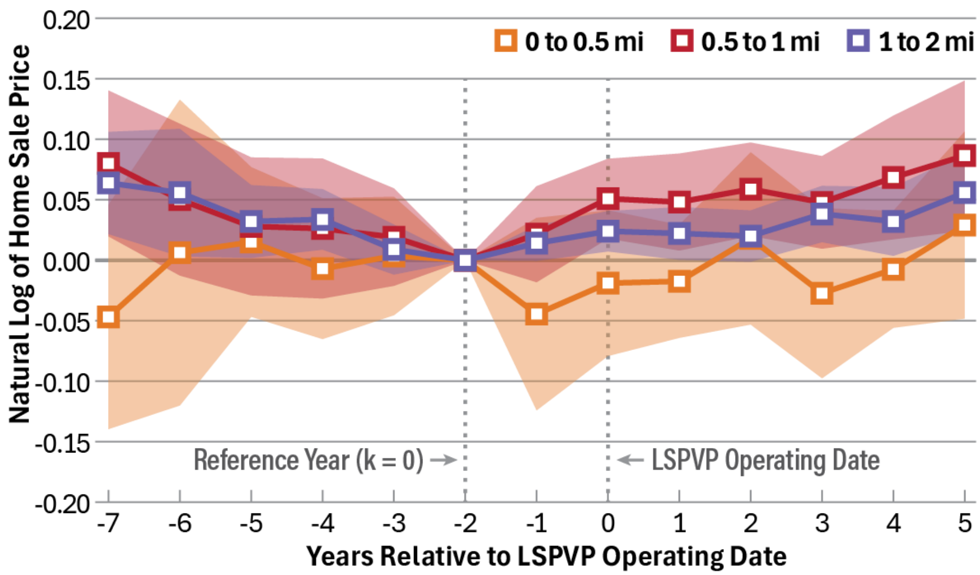
Note: The sample includes home sales within 0.5 miles of an LSPVP constructed during the sample period. The x-axis displays years relative to the start of facility operations. The omitted event-time category is ***k = 0***, two years before the LSPVP operation date. Standard errors are clustered at the school district level. Confidence Interval (CI) is 95%. Corresponding data in *Appendix Table B1*.

Table B1. Event Study: Effect of LSPVP Completion on Home Prices (k = 0)

Note: Data corresponds with *Figure B1*. The omitted event-time category is ***k = 0***, two years before the LSPVP operation date. Year 0 = Start of facility operation. Confidence Interval (CI) is 95%.

Year	Estimate	Std Error	CI Lower	CI Upper
-7	-0.0427	0.0922	-0.2269	0.1414
-6	-0.0617	0.0642	-0.1900	0.0666
-5	0.0008	0.0569	-0.1127	0.1144
-4	-0.0230	0.0370	-0.0970	0.0509
-3	-0.0107	0.0349	-0.0804	0.0590
-2	0.0000	0.0000	0.0000	0.0000
-1	-0.0678	0.0421	-0.1519	0.0163
0	-0.0517	0.0360	-0.1236	0.0201
1	-0.0263	0.0417	-0.1097	0.0571
2	-0.0129	0.0548	-0.1224	0.0965
3	-0.0495	0.0673	-0.1840	0.0850

Figure B2. Stacked DiD Event Study: Effect of LSPVP Completion on Home Prices (k = 0)



Note: We present stacked DiD event study estimates from *Equation 3* for each treated distance bin relative to the omitted control group of homes 2-4 miles from the nearest LSPVP. The x-axis displays years relative to the start of LSPVP facility operations. The omitted reference year is ***k = 0***, which is two years before the LSPVP operating date and is the estimated start of construction. Confidence intervals of 95% shown as shaded bands. Standard errors are clustered at the project cohort level. Corresponding data available in *Appendix Tables B2, Panels A-C*.

Table B2, Panel 1. Stacked DiD Event Study, Distance Bin 0-0.5 Miles

Note: Data corresponds with homes in the 0-0.5 Miles Distance Bin in *Figure B2*. The omitted event-time category is ***k = 0***, two years before the LSPVP operation date. Year 0 = Start of facility operation. Confidence Interval (CI) is 95%.

Year	Dist Bin	Estimate	Std Error	CI Lower	CI Upper
-7	0-0.5 mi	-0.0469	0.0473	-0.1395	0.0458
-6	0-0.5 mi	0.0063	0.0645	-0.1200	0.1327
-5	0-0.5 mi	0.0151	0.0315	-0.0467	0.0769
-4	0-0.5 mi	-0.0070	0.0297	-0.0651	0.0512
-3	0-0.5 mi	0.0036	0.0250	-0.0454	0.0525
-2	0-0.5 mi	0.0000	0.0000	0.0000	0.0000
-1	0-0.5 mi	-0.0445	0.0406	-0.1240	0.0350
0	0-0.5 mi	-0.0189	0.0307	-0.0791	0.0413
1	0-0.5 mi	-0.0174	0.0238	-0.0641	0.0292
2	0-0.5 mi	0.0180	0.0363	-0.0531	0.0892
3	0-0.5 mi	-0.0272	0.0358	-0.0975	0.0430
4	0-0.5 mi	-0.0075	0.0247	-0.0558	0.0408
5	0-0.5 mi	0.0291	0.0394	-0.0482	0.1064

Table B2, Panel 2. Stacked Event Study, Distance Bin 0.5-1 Mile

Note: Data corresponds with homes in the 0.5-1 Mile Distance Bin in *Figure B2*. The omitted event-time category is ***k = 0***, two years before the LSPVP operation date. Year 0 = Start of facility operation. Confidence Interval (CI) is 95%.

Year	Dist Bin	Estimate	Std Error	CI Lower	CI Upper
-7	0.5-1 mi	0.0801	0.0307	0.0198	0.1403
-6	0.5-1 mi	0.0501	0.0320	-0.0126	0.1128
-5	0.5-1 mi	0.0280	0.0291	-0.0290	0.0850
-4	0.5-1 mi	0.0262	0.0295	-0.0316	0.0841
-3	0.5-1 mi	0.0191	0.0205	-0.0211	0.0594
-2	0.5-1 mi	0.0000	0.0000	0.0000	0.0000
-1	0.5-1 mi	0.0216	0.0202	-0.0181	0.0612
0	0.5-1 mi	0.0509	0.0168	0.0180	0.0839
1	0.5-1 mi	0.0481	0.0204	0.0081	0.0882
2	0.5-1 mi	0.0588	0.0197	0.0202	0.0973
3	0.5-1 mi	0.0478	0.0195	0.0096	0.0861
4	0.5-1 mi	0.0684	0.0261	0.0174	0.1195
5	0.5-1 mi	0.0865	0.0317	0.0244	0.1485

Table B2, Panel 3. Stacked Event Study, Distance Bin 1-2 Miles

Note: Data corresponds with homes in the 1-2 Miles Distance Bin in *Figure B2*. The omitted event-time category is ***k = 0***, two years before the LSPVP operation date. Year 0 = Start of facility operation. Confidence Interval (CI) is 95%.

Year	Dist Bin	Estimate	Std Error	CI Lower	CI Upper
-7	1-2 mi	0.0639	0.0215	0.0217	0.1061
-6	1-2 mi	0.0559	0.0269	0.0032	0.1086
-5	1-2 mi	0.0321	0.0153	0.0020	0.0621
-4	1-2 mi	0.0338	0.0128	0.0088	0.0588
-3	1-2 mi	0.0089	0.0105	-0.0118	0.0295
-2	1-2 mi	0.0000	0.0000	0.0000	0.0000
-1	1-2 mi	0.0141	0.0074	-0.0005	0.0287
0	1-2 mi	0.0240	0.0085	0.0073	0.0407
1	1-2 mi	0.0222	0.0111	0.0004	0.0439
2	1-2 mi	0.0200	0.0108	-0.0012	0.0412
3	1-2 mi	0.0383	0.0119	0.0150	0.0615
4	1-2 mi	0.0321	0.0145	0.0037	0.0605
5	1-2 mi	0.0559	0.0166	0.0234	0.0883