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Shedding light on large-scale solar impacts: An analysis of property values and proximity to photovoltaics across six U.S. states

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ABSTRACT

We examine the impact of large-scale photovoltaic projects (LSPVPs) on residential home prices in six U.S. states that account for over 50% of the installed MW capacity of large-scale solar in the U.S. Our analysis of over 1,500 LSPVPs and over 1.8 million home transactions answers two questions: (1) what effect do LSPVPs have on home prices and (2) does the effect of LSPVP on home prices differ based on the prior land use on which LSPVPs are located, LSPVP size, or a home's urbanicity? We find that homes within 0.5 mi of a LSPVP experience an average home price reduction of 1.5% compared to homes 2–4 mi away; statistically significant effects are not measurable over 1 mi from a LSPVP. These effects are only measurable in certain states, for LSPVPs constructed on agricultural land, for larger LSPVPs, and for rural homes. Our results have two implications for policymakers: (1) measures that ameliorate possible negative impacts of LSPVP development, including compensation for neighbors, vegetative shading, and land use co-location are relevant especially to rural, large, or agricultural LSPVPs, and (2) place- and project-specific assessments of LSPVP development and policy practices are needed to understand the heterogeneous impacts of LSPVPs.

1. Introduction

Large-scale photovoltaic projects (LSPVP), defined here as ground-mounted photovoltaic generation facilities with at least 1 MW of DC generation capacity, are an increasingly prevalent source of renewable energy. LSPVPs accounted for over 60% of all new solar capacity in the United States in 2021, and, as the largest resource by capacity in interconnection queues, are projected to continue growing (Bolinger et al., 2021). However, the local economic impacts of LSPVPs are poorly understood (Mai et al., 2014), despite surveys showing that local public support for large-scale solar is strongly related to perceived economic impacts, including the impact on property values (Carlisle et al., 2014). Concerns surrounding the property value impacts of solar power are reflected in solar industry and environmental advocacy communication that challenge the conception that solar power reduces property values (Center for Energy Education, n.d.; Solar Energy Industries Association, 2019), and in attempts by neighbors of solar plants to claim solar panels as a private nuisance (Westgate, 2017).

The purpose of this paper is to provide some of the first comprehensive evidence on the impact of LSPVPs on residential home values. Specifically, we seek to answer two related research questions: (1) what effect, if any, do LSPVPs have on residential home prices and (2) does the effect of LSPVPs on home prices differ based on the prior land use on which a LSPVP is located, the size of the LSPVP, or the urbanicity of a home's location? To address these questions we use data from CoreLogic on over 1.8 million residential property transactions that occurred within six years before and after a LSPVP was constructed in the five U.S. states with the highest concentration of LSPVPs as measured by number of installations: California (CA), Massachusetts (MA), Minnesota (MN), North Carolina (NC), and New Jersey (NJ), as well as in Connecticut (CT), chosen for its relatively high population density (i.e., urbanicity) near LSPVPs. We then combine the transaction data with other geospatial datasets including an original dataset of LSPVP footprints developed by the project team for this research, a suite of environmental amenities and dis-amenities, urban, rural, and suburban classifications, and historic land cover data. We identify the arguably causal impact of LSPVPs on residential property values using a difference-in-differences identification strategy that compares the sale price of residential homes located in close proximity to a LSPVP (e.g. 0–0.5 miles away) both before and after a LSPVP is constructed to the sale price of homes located farther away from a LSPVP (e.g. 2–4 miles away).

Our paper makes several important contributions. First, we examine the impacts of LSPVPs in a large set of U.S. states that account for the

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Abbreviations

A/D	amenities and dis-amenities
API	Application Programming Interface
CA	California
CT	Connecticut
DC	direct current
dB	decibel
DiD	difference-in-difference
EIA	Energy Information Administration
FE	fixed effects
GHG	greenhouse gas
LSPVP	large-scale photovoltaic project
MA	Massachusetts
MN	Minnesota
MW	megawatt
NJ	New Jersey
NLCD	National Land Cover Database
NY	New York
NC	North Carolina
PV	photovoltaic
RI	Rhode Island
RPS	Renewable Portfolio Standard
SB	Senate Bill
U.K.	United Kingdom
U.S.	United States
USDA	United States Department of Agriculture

majority of U.S. LSPVP capacity, most of which, to our knowledge, have not previously been studied with respect to the impact of LSPVPs on property values. Existing research on the property value impacts of LSPVPs provides mixed results from a limited set of geographies. Where researchers do find an adverse impact of LSPVPs on property values, as in studies from the Netherlands and from the U.S. states of RI, MA, and NC, they theorize a change in property values due to visual intrusion from panels (Abashidze, 2019; Dröes and Koster, 2021; Gaur and Lang, 2020) and land use change (Gaur and Lang, 2020). Conversely, one study based in the U.K. finds no statistically significant effect of LSPVPs on property values (Jarvis, 2021). Expanding the geographic scope of the literature, then, facilitates both generalization (Brinkley and Leach, 2019) and more location-specific policy insights.

Second, we investigate whether the effect of LSPVPs on home prices is heterogenous with respect to LSPVP area, prior LSPVP land use, and home urbanicity. One of the major concerns surrounding LSPVPs, as well as one of the major opportunities to explore the co-benefits of LSPVP development, are its land use requirements (Hernandez et al., 2014a; Hernandez et al., 2014b; Katkar et al., 2021). In particular, more adverse home price impacts might be found where LSPVPs displace green space (consistent with results that show higher property values near green space (Crompton, 2001)) or where LSPVPs are larger in area, and thus more visually intrusive. While some previous studies (Gaur and Lang, 2020) find that greenfield solar development is primarily responsible for their observed decrease in home prices when compared to brownfield development, our constructed dataset of LSPVP footprints allows us to more precisely identify the prior land use of a LSPVP (for instance, breaking up the "greenfield" category into agricultural and non-agricultural land uses). Our dataset of LSPVP footprints additionally allows us to accurately characterize the area of each LSPVP.

In section 2, we introduce the policy context for LSPVP development in the study area and review the existing literature on property value impacts of LSPVPs. In section 3, we detail the data used in this study, the geospatial methods used to combine datasets, and the difference-in-differences approach to assessing property value impacts of LSPVPs. In section 4, we present our base model, event study, and heterogeneity analysis results. In section 5, we summarize and discuss our findings. In section 6, we note the limitations of our study and describe avenues for future work. Finally, in section 7, we review the key conclusions and policy implications of our study.

2. Background and relevant literature

2.1. Policy context

The study area is defined as the six states of CA, CT, MA, MN, NC, and NJ. The states in the study area were chosen based on number of installations: CA, NC, MA, MN, and NJ represent the top five states in terms of number of >1 MW DC solar installations through 2019. Together, these states contain over 2,000 solar projects, or approximately 53% of the total MW DC capacity in the United States through 2019. We additionally include CT because of its relatively high population density near solar projects (U.S. Energy Information Administration, 2021a).

All six states face increasing demands for large-scale solar along with intensifying land use and permitting constraints on solar development. Both CA and CT have ambitious Renewable Portfolio Standards (RPSs), aiming for 100% of electricity retail sales to be supplied by renewable sources by 2045 and 2040, respectively (Schwartz and Brueske, 2020; U. S. Energy Information Administration, 2021a). In CA, this necessitates, by some estimates, a tripling of California's renewable energy production; of those possible renewable resources, solar PV is both the least expensive and has the largest technical potential in the state (Schwartz and Brueske, 2020). Though MA, MN, and NJ have less ambitious renewable energy development goals, state reports still estimate that building solar PV is a key strategy to meeting both MA and MN's GHG reduction and renewable electricity sourcing targets (Jones et al., 2020; Putnam and Perez, 2018), and NJ introduced legislation in 2021 that aims to double existing solar installations through incentives (NJ Department of Environmental Protection, 2021). NC's solar future is less definite: although the state has, historically, been a leader in solar installations, the dominant electric utility in the state, Duke Energy, has proposed an integrated resource plan that largely privileges fossil generation over renewables. This plan is currently under review by the NC Utility Commission, with challenges from multiple environmental groups (Southern Environmental Law Center, 2021).

State reports identify persistent LSPVP land use and permitting challenges. In CA, for instance, San Bernardino county voted to ban utility-scale solar farms on over a million acres of private land (Schwartz and Brueske, 2020), citing concerns about the industrializing impact of solar projects on rural or desert landscapes (Roth, 2019). Tradeoffs between land use and LSPVP development are also observed at the state level in CT, MN, and NJ. In CT, Public Act 17–218, enacted in 2017, limits PV development on forest and prime farmland[1]; this has resulted in a reduced number of approved commercial PV projects per year (CT Council on Environmental Quality, 2020). Before the passage of this act, in 2016, the CT Council on Environmental Quality reported that solar PV was the single largest type of development displacing agricultural and forest land (CT Council on Environmental Quality, 2017). MN, too, prohibits solar development on prime farmland: the state's Prime

[1] Both CT Public Act 17–218 and the MA Prime Farmland Rule cite 7 CFR 657 for the definition of "prime farmland"; 7 CFR 657 is a periodically updated set of federal regulations, administered by the Department of Agriculture, that defines prime and important farmlands (Legal Information Institute, n.d.).

Farmland Rule includes solar development as one of the prohibited industrial uses of select agricultural land (Bergan, 2021). The MN Prime Farmland Rule is currently being contested: legislation that allows more PV development on farmland is now under consideration in the MN legislature (Bergan, 2021), and the MN Department of Commerce has, in the past, issued guidance for developers on how to make their case for an exception to the rule (Birkholz et al., 2020). In NJ and NC, too, concerns about farmland preservation and LSPVPs have appeared in discussions among agricultural stakeholders, although neither state has adopted prime farmland legislation like CT or MN (American Farmland Trust, 2021; Cleveland and Sarkisian, 2019). In MA, state reports refer to siting difficulties due to high population densities, expensive land for development that is disconnected from transmission, and opposition to disturbance of natural land (Jones et al., 2020).

In summary, while LSPVP installations are prevalent in the six states analyzed in this, these states also represent regions where an increasing need for LSPVP is met with restrictions, opposition, and land-use tradeoffs. These restrictions are often specific to farmland, although concerns do extend to other landscapes (like high density areas, deserts, and forests). Investigating property value impacts of LSPVPs, both overall and by prior land use and installation size, can potentially provide policymakers, practitioners, and developers with valuable information on how LSPVPs affect residents' willingness to pay for properties located near LSPVPs. To the extent that these concerns represent possible burdens of LSPVP development, investigating property value impacts of LSPVPs also helps us understand how these burdens are distributed. These insights, in turn, can guide policy or best practices that seek to mitigate adverse impacts of LSPVP development to enable build-out that meets climate and clean energy goals.

2.2. Relevant literature

The property value impacts of LSPVPs have received only recent, limited attention (Abashidze, 2019; Al-Hamoodah et al., 2018; Dröes and Koster, 2021; Gaur and Lang, 2020; Jarvis, 2021). Studies on LSPVPs and property values employing difference-in-differences (DiD) analyses find mixed results. Studies based in the U.S., specifically, MA and RI (Gaur and Lang, 2020) and NC (Abashidze, 2019), and the Netherlands (Dröes and Koster, 2021), find a statistically significant negative effect for homes near solar projects compared to homes further away. One study, based in the U.K., finds no statistically significant effect of LSPVP proximity on home property values (Jarvis, 2021). Although none of the existing studies find evidence of an increase in sales prices for homes near solar projects, Abashidze (2019) finds an increase in agricultural land value for land in close proximity to transmission lines after a solar farm is built in the area. To our knowledge, only Gaur and Lang (2020) investigate the impact of prior land use using a DiD framework, finding that greenfield solar construction is associated with a statistically significant reduction in sale prices in both rural and non-rural areas, with greater reductions observed in rural areas. One study using a contingent valuation survey finds that respondent willingness to pay for large-scale solar developments is a function of prior land use, where brownfield solar developments are more desirable than greenfield developments (Lang et al., 2021). Both Jarvis (2021) and Abashidze (2019) find no evidence of heterogeneity in home price impacts by income or other socio-economic indicators.

The mixed results to date in the LSPVP and property value literature motivates studies that look at previously understudied geographies to develop a more comprehensive view of the possible property value impacts of LSPVPs. The existing literature also orients us to relevant heterogeneity analyses, including heterogeneity by prior land use. We extend this literature by looking at a more specific set of prior land uses beyond greenfield and brownfield, as well as by looking at heterogeneity of effects by LSPVP size and urbanicity.

3. Methods

3.1. Data

This project utilized five major sources of data, shown on the left-most side of Fig. 1. First, to characterize and locate LSPVPs, we utilized the U.S. Energy Information Administration's Form 860 (U.S. Energy Information Administration, 2021b), which provides latitude-longitude data on solar plants, their installed capacities (in megawatts, MW), and their operation start date. We kept only solar plants within the study area with an installed capacity over 1 MW and eliminated rooftop installations, leaving us with 1,630 solar plants. Second, to understand the impact of prior LSPVP land use on property values, we used land use data from the United States Geological Survey (USGS)'s Multi-Resolution Land Characteristics (MRLC) Consortium's National Land Cover Database (NLCD) from 2006 (Multi-Resolution Land Characteristics Consortium, 2006). Third, for information about home sales, we used transaction data from CoreLogic (CoreLogic, n.d.), which provided information on location, property characteristics and transaction characteristics. We filtered this dataset for only relevant, complete records; the criteria used to screen data are outlined in Table A.1. Fourth, to identify amenities or disamenities (herein referred to as A/D), or landscape characteristics that could positively or negatively impact the price of a home, we used the data sources summarized in Table A.2. Finally, to understand the impact of urbanicity on property value impacts, we used the U.S. Census Bureau's (U.S. Census Bureau, n.d.) urban-urban cluster-rural classification (a metric based on population density, where urban areas are the most dense, followed by urban clusters, then rural areas). These data sources were validated and combined to produce a final analytic dataset. Fig. 1 graphically depicts the data preparation steps, which we describe below.

Step 1: To obtain a polygon representation of each LSPVP from the EIA point data, we first verified installation locations using satellite imagery from Esri and DigitalGlobe and revised project centroid coordinates where necessary. We manually drew polygons around the boundaries of each LSPVP based on satellite imagery; for projects that consisted of multiple, non-contiguous groups of panels, we drew a multipart polygon around the boundaries of each group of panels. We calculated a construction start year for each LSPVP, assuming construction begins one year before the EIA-provided operation start date. Fig. A.1 shows an example of two LSPVPs and their corresponding polygons; Fig. 2 shows the location of LSPVP sites as well as the density of transacted homes for the six states in the study area.

Additionally, in this step we determined the predominant prior land use type of each LSPVP. We first determined the distribution of prior land cover types by area for each LSPVP; each LSPVP polygon is composed of some proportion of the NLCD land cover classes shown in the right-most column of Table 1 (15 of the 16 possible NLCD classes showed up in our sample). Each LSPVP's distribution of NLCD classes was grouped and summed as per the left-most column of Table 1, and each LSPVP was assigned the predominant prior land use type that constituted 50% or more of its land cover. If no single predominant prior land use type accounted for 50% or more of an LSPVP's prior land cover by area, that LSPVP was assigned a predominant prior land use type of "mixed".[2] Fig. 3 shows (a) the proportion of displaced LSPVP area and

[2] For instance, a solar installation on land that was, in 2006, 15% barren land, 25% cultivated crops, 25% herbaceous, and 35% hay/pasture, would be generalized as 60% agriculture and 40% greenfield, and would be given the predominant prior land use type of "agriculture". A solar installation on land that was, in 2006, 15% barren land, 25% developed, high intensity, 25% herbaceous, and 35% hay/pasture, would be generalized as 35% agriculture, 40% greenfield, and 25% brownfield, a would be assigned the predominant prior land use type of "mixed", because no single category amounted to greater than 50%.

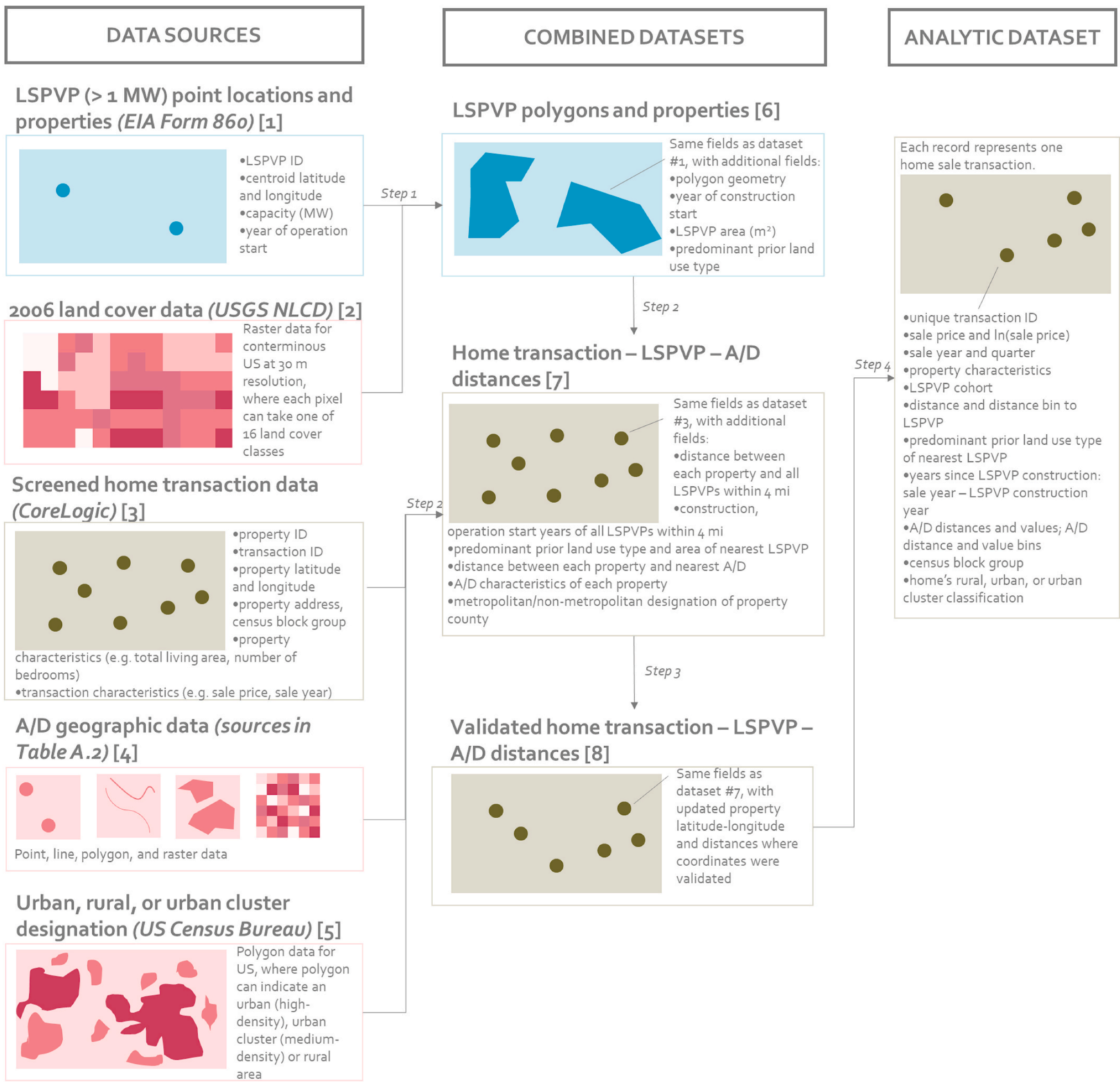

Fig. 1. Data sources and data preparation steps.

Table 1
Grouping of NLCD classes into predominant land use types; LSPVPs are assigned a predominant prior land use of "mixed" if their area does not contain 50% or more of the NLCD classes within a single predominant prior land use type.

Predominant prior land use type	NLCD classes
Agriculture	Cultivated Crops; Hay/Pasture
Brownfield	Developed, High Intensity; Developed, Low Intensity; Developed, Medium Intensity
Greenfield	Barren land; Deciduous forest; Developed, Open Space; Emergent Herbaceous Wetlands; Evergreen Forest; Herbaceous; Mixed Forest; Open Water; Shrub/Scrub; Woody Wetlands

Table 2
Transaction count by state in final analytic dataset.

State	Number of transactions
CA	933,037
CT	34,313
MA	291,325
MN	75,394
NC	204,134
NJ	297,756
6 state total	1,835,961

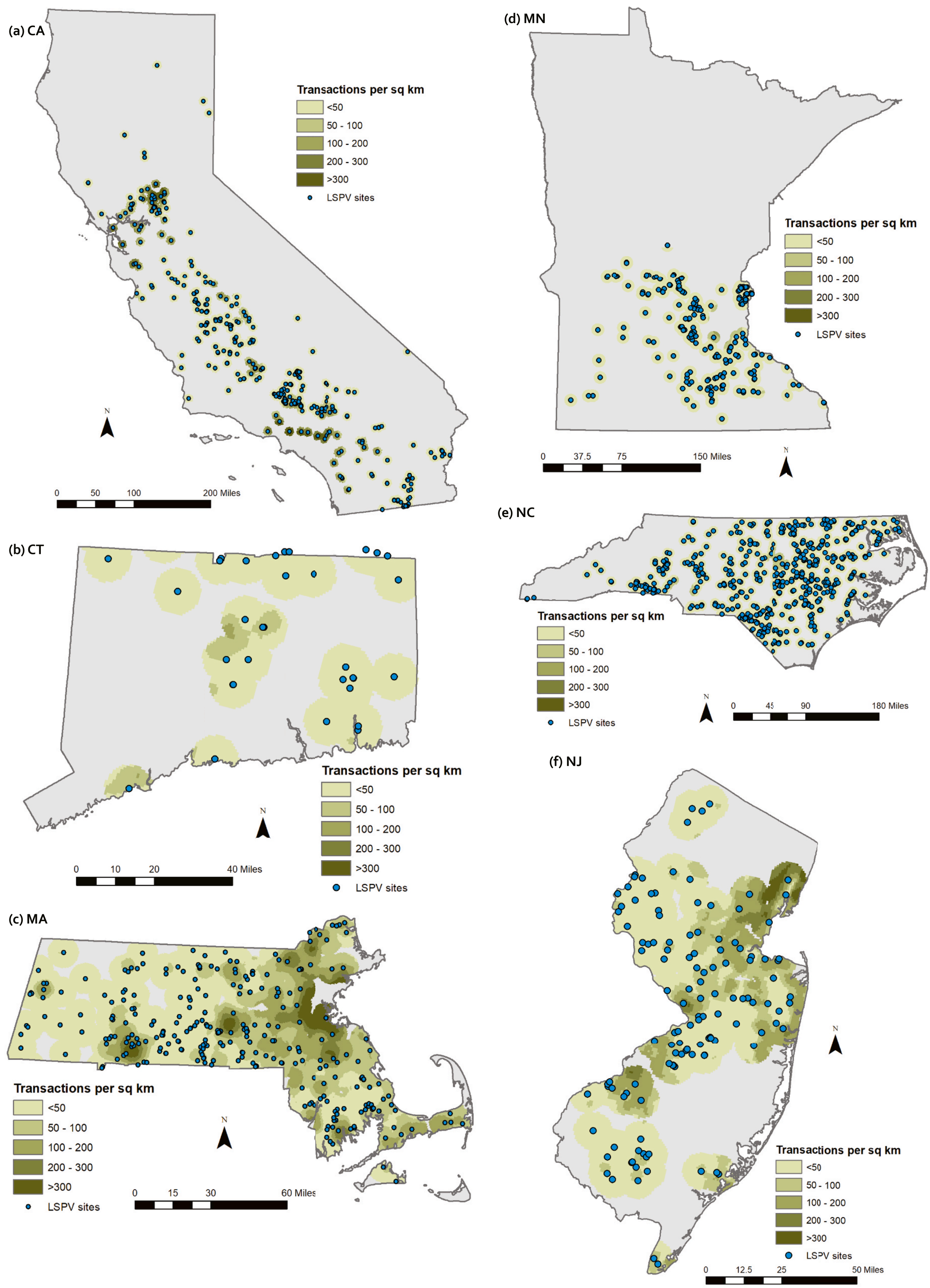

Fig. 2. Heat map of transacted home density within 5 miles of LSPVP sites in individual states.

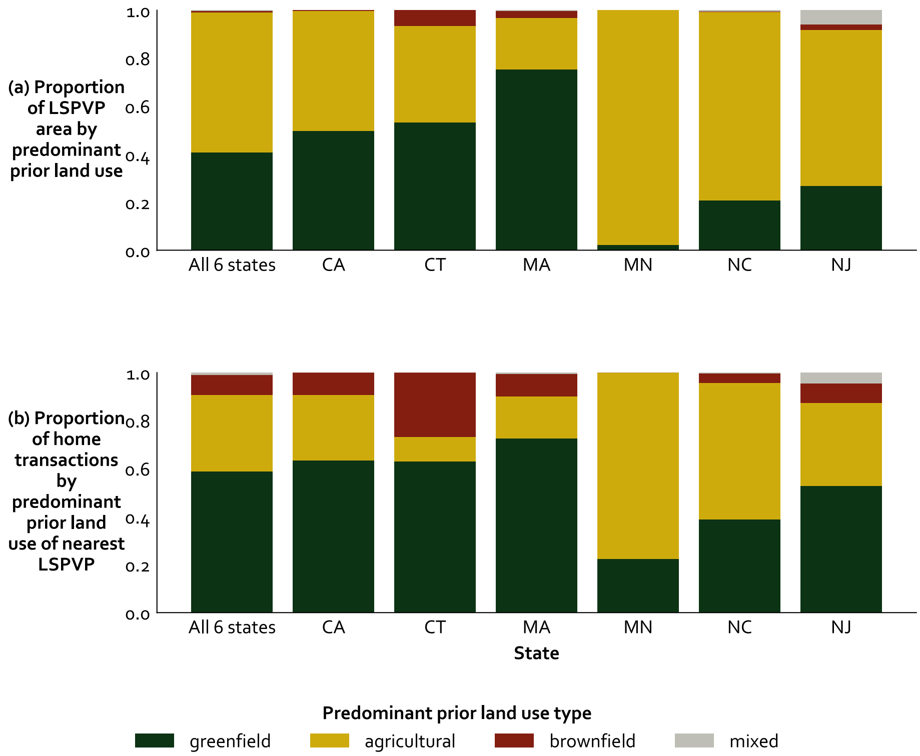

Fig. 3. Distribution of predominant prior land use by (a) LSPVP area and (b) number of homes near LSPVPs.

(b) the proportion of transactions near LSPVPs by predominant prior land use type.

Step 2: For each home we calculated the geodesic distance to the polygon boundary of the nearest LSPVP and to all A/D locations. We also determined underlying A/D characteristics, where appropriate, such as flood zone status and road/airport sound levels. Finally, we determined the urbanicity of each home's location. Fig. 4 shows the distribution of homes by state and urban, urban cluster, or rural designation.

Step 3: We validated the coordinates of select homes[3] that were sited near LSPVPs or A/D using the Google Geocoding API (Google Maps Platform, n.d.), which takes as input an address and returns a set of coordinates as well as a precision indicator. We dropped from our analysis any home transactions where there was inconsistency in the coordinates between CoreLogic and the Google Geocoding API. For some homes, we replaced the CoreLogic coordinates with coordinates from the Google Geocoding API where Google returned a high precision indicator.[4]

Step 4: Given validated coordinates and distances, we retained only the home transactions that were suitable for use in the final analysis. Specifically, we eliminated (1) properties that host a LSPVP (i.e. their coordinates fall within the boundaries of a LSPVP polygon), (2) properties that are over four miles away from a LSPVP, and (3) properties that transacted over 6 years before or after the operation start date of a LSPVP. We also calculated three sets of key values used in the analysis: the transaction's project cohort, LSPVP distance bin, and years since LSPVP construction.

The project cohort refers to the unique ID of the LSPVP that is nearest to a home transaction within 4 miles, and for which the operation start date occurred up to 6 years before or after a LSPVP began construction. If a given transaction belonged to more than one cohort, we retained only the nearest project cohort for that transaction.[5] The distance between the transacted home and the nearest LSPVP was binned into 4 categories: [0 mi, 0.5 mi), [0.5 mi, 1 mi), [1 mi, 2 mi), and [2 mi, 4 mi]. To calculate the number of years since LSPVP construction, we subtracted the LSPVP year of construction start from the sale year (recall that the construction start year is assumed to be the operation start year minus 1 year). The years since LSPVP construction were categorized into 1-year bins (i.e. a sale occurred [−5 years, −4 years), [−4 years, −3 years), …,[5 years, 6 years), [6 years, 7 years] since LSPVP construction). Our final analytic dataset consists of 1,836,053 transactions near 1,522 different LSPVPs.

Table 2 and Fig. 5 summarize the number of transactions, and the number and size of LSPVPs, respectively, by state. The final dataset contains a number of continuous and categorical property and transaction characteristics (e.g. sale price, sale year, number of bathrooms). Summary statistics for those continuous variables are shown in Table 3 for all six states; summary statistics for individual states are shown in Table A.3 to Table A.8. The categorical property characteristic variables are listed in Table A.9. Finally, Fig. 6 shows the total number of transactions within each distance bin by years since LSPVP construction and indicates that the sample has a robust set of transactions in all distance bins throughout the full sample period. While the home-level

[3] We selected properties that were <0.5 miles from an LSPVP or A/D; within a flood zone with at least 1% chance of flooding, or within an area with road or aviation noise exceeding 55 dB. Of the properties that satisfied these conditions, only those with an area greater than 1 acre or those with missing or non-unique coordinates were validated.

[4] We dropped home transactions from our analysis if the difference between the coordinates provided by the Google Geocoding API and CoreLogic was greater than 2 times the distance between that home and its nearest PV plant or A/D. We additionally dropped any duplicate coordinates within 0.5 mi of a PV plant. Where the Google Geocoding API returned a "rooftop" precision indicator, we replaced the CoreLogic coordinates with Google coordinates; for those homes, we recalculated distances to LSPVP and A/D using the process described in Step 2.

[5] In other words, if transaction T_1 is 0.5 miles from $LSPVP_1$ and 2 miles from $LSPVP_2$, and transacted within 6 years of the operation start date of both $LSPVP_1$ and $LSPVP_2$, we consider transaction T_1 to belong to the $LSPVP_1$ project cohort.

Fig. 4. Distribution of urban, urban cluster, and rural classifications by number of home transactions.

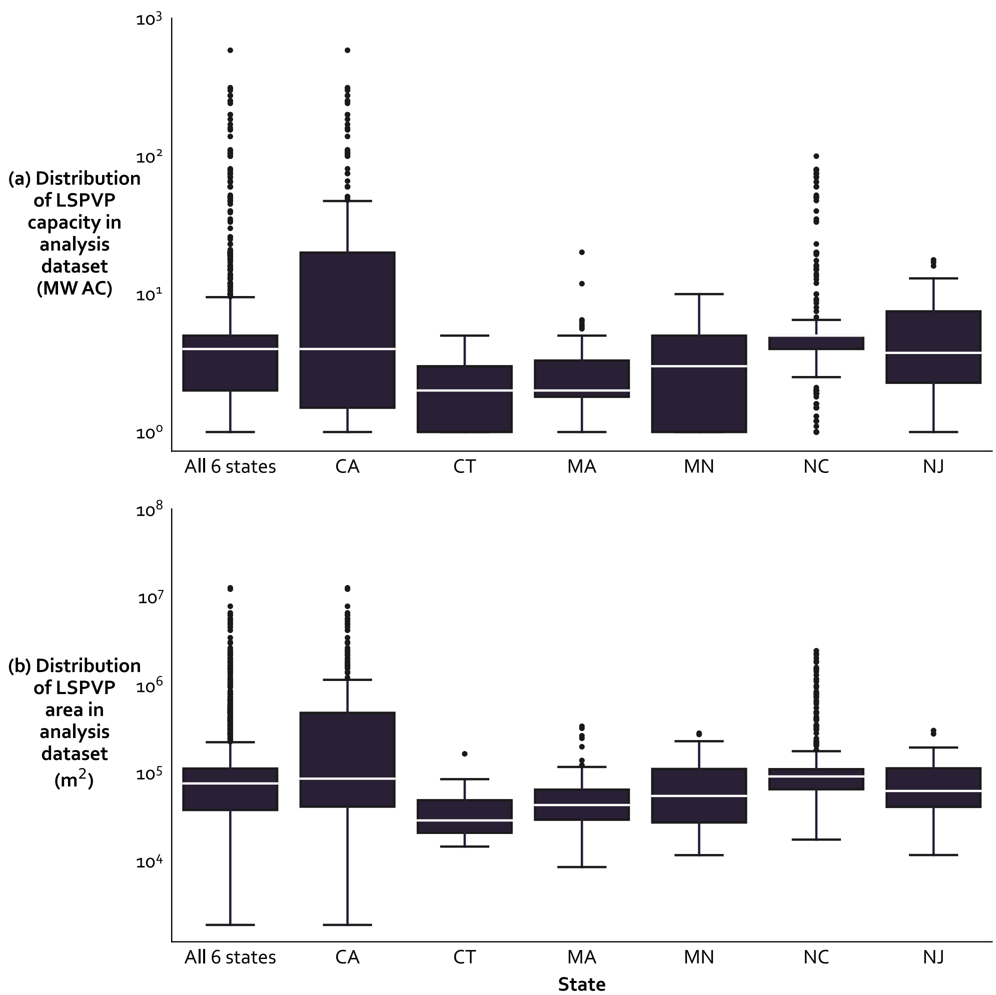

Fig. 5. Distribution of (a) capacity in MW AC and (b) ground-mount area in m^2 of unique LSPVPs in analysis dataset by state. Line represents median value; box limits represent 1st to 3rd quartiles; whiskers represent 4x the inter-quartile range.

transaction data used in this study is protected by a non-disclosure agreement and cannot be made publicly available, our dataset of LSPVP locations and associated sizes and prior land uses is available on Github (Elmallah et al., 2022).

3.2. Model specifications

3.2.1. Base difference-in-difference model

To examine the relationship between LSPVPs and residential property values we utilized a difference-in-differences (DiD) identification strategy that relates the timing of treatment (being close to an LSPVP post construction) to home prices for homes located [0 mi, 0.5 mi), [0.5 mi, 1 mi), and [1 mi, 2 mi) away from a LSPVP. Specifically, we first created 1,522 unique datasets, each representing a unique LSPVP and the residential home transactions that occurred within four miles of the LSPVP and transacted within 6 years before or after the first year of operation of the LSPVP. We call each of these unique datasets a “project cohort.” We then stacked the 1,522 project cohorts to create our final

Table 3
Summary of dependent variables and property and transaction characteristics in full analysis dataset.

Variable	Description	Mean	Std. dev.	Min.	Med.	Max.
Sp	Sale price ($)	$406,552.22	$340,123.75	$5050.00	$321,000.00	$3,998,000.00
Lsp	log of sale price	12.65	0.74	8.53	12.68	15.2
Lsf	Living area (ft^2)	1936.53	1002.05	102	1720.00	120,215.00
acres	Land area (acres)	0.455	0.873	0.006	0.19	14.14
Age	Age of home at time of sale (years)	44.08	30.86	0	40	212
agesq	Age of home at time of sale, squared ($years^2$)	2895.66	3708.86	0	1600.00	44,944.00
salesqtr	Quarter of sale	2.27	0.87	1	2	4
salesyr	Year of sale	2015	3	2003	2015	2020

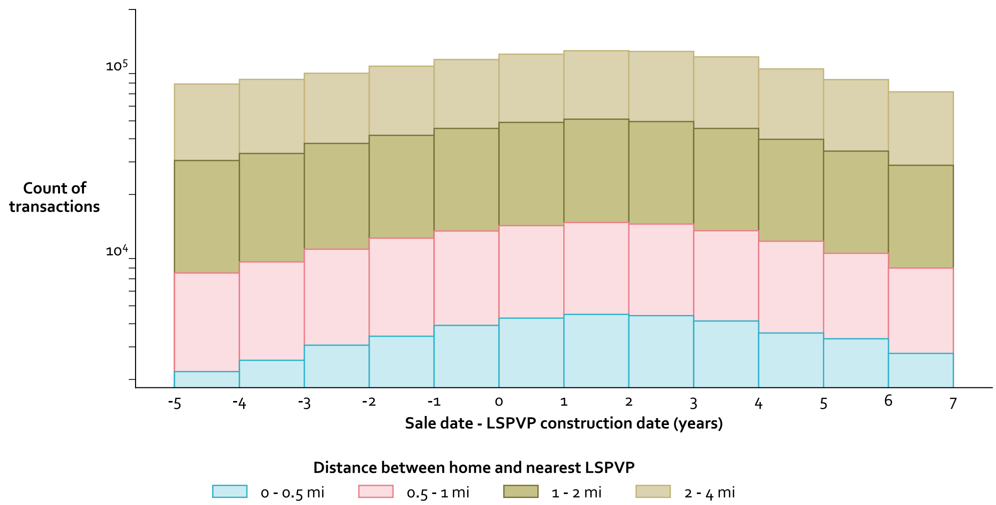

Fig. 6. Count of transactions in final analysis dataset by distance between transacted home and nearest LSPVP.

analytic dataset and specify a stacked difference-in-differences specification of the following form:

$$ln\left(P_{icdjqt}\right) = \beta\, \boldsymbol{T}_{idt} + \boldsymbol{X}_i \alpha + \delta_{dc} + \lambda_{tc} + \rho_{qc} + \varphi_j + \varepsilon_{icdjqt} \tag{1}$$

The dependent variable in (1) is the natural log of sales price P for residential home transaction i that belongs to a project cohort c within distance bin d and census block group j, that transacted in quarter q of year t. T_{idt} is a vector consisting of 3 distance bin indicators for homes located [0 mi, 0.5 mi), [0.5 mi, 1 mi), [1 mi, 2 mi) from a LSPVP, where each distance bin is interacted with an indicator for whether the home sale occurred after LSPVP construction. The omitted category for the distance bin indicators is homes located 2 to 4 miles from a LSPVP. δ_{dc}, λ_{tc} *and* ρ_{qc} are, respectively, distance bin-by-project cohort fixed effects (FEs), transaction year-by-project cohort FEs and transaction quarter-by-project cohort FEs. φ_j is a vector of census block group FEs, and ε_{icdjqt} is a random disturbance term. Finally, X_i is a vector of individual home characteristics including living square footage, land area, the age of the home at the time of sale, age squared, the number of full bathrooms and stories, the type of air conditioning (AC) and heating, the construction type and exterior wall type of the home, indicators for fireplaces and new construction, the type of garage, and the type of view a home has. The standard errors in (1) are clustered at the project cohort level.

The coefficients of primary interest in (1) are the β s which represent the DiD estimates of the effect of treatment (being close to an LSPVP post construction) on home prices for homes located [0 mi, 0.5 mi), [0.5 mi, 1 mi), and [1 mi, 2 mi) away from an LSPVP, respectively. Our DiD identification strategy is both transparent and intuitive. Specifically, each of the 1,522 project cohorts represents a unique quasi-experiment where the treatment group is homes located within [0 mi, 0.5 mi), [0.5 mi, 1 mi), and [1 mi, 2 mi) from a LSPVP and the control group is homes located 2 to 4 miles from a LSPVP. For each of these 1,522 quasi-experiments, our DiD framework then compares the sale price of homes located close to a LSPVP to the sale price of homes located farther away before and after LSPVP construction. The inclusion of distance bin-by-project cohort FEs, δ_{dc}, transaction year-by-project cohort FEs, λ_{tc}, and transaction quarter-by-project cohort FEs, ρ_{qc}, imply that our estimates are identified based only on within-project cohort variation in sale prices and distance from a LSPVP. Our coefficients of primary interest, β s, therefore represent the average treatment effect over the 1,522 quasi-experiments for homes located within each of our specified distance bins.

Another advantage of our stacked DiD framework is that it avoids the potential biases that can arise in standard DiD and event study models in the presence of staggered timing of treatment with heterogeneous treatment effects. Specifically, several recent studies have shown that DiD specifications relying on the staggered timing of treatment for identification may be biased in the presence of heterogeneous treatment effects due to the contamination of treatment effects from early versus later adopters from other relative time periods (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Sun and Abraham, 2021). As discussed by Cengiz et al. (2019) and Goodman-Bacon (2021), our stacked DiD model avoids this potential source of bias by ensuring that treatment effects are based only on within-project cohort comparisons.

3.2.2. Robustness checks

We investigated the robustness of the base model given by (1) to the choice of spatial FEs, time FEs, and treatment and control categories with three alternative specifications. Our first robustness check added a distance bin for homes located within 0.25 miles of a LSPVP.

Specifically, we augmented the distance bins in (1) to include four (rather than three) indicators for homes located in the [0 mi, 0.25 mi),[6] [0.25 mi, 0.5 mi), [0.5 mi, 1 mi), and [1 mi, 2 mi) distance bins; the indicator equals 1 if a transaction occurred within that distance bin in the same year or after LSPVP construction started, and 0 otherwise. This specification allows us to investigate the presence of a home price effect at even smaller distances. In our second robustness check we replaced the year-by-project cohort and quarter-by-project cohort FEs in the base model by a single vector of quarter-by-year-by-project cohort FEs to allow for more granular trending of home values across quarters and years. In our third robustness check we added the vector of A/D variables, consisting of distance and value bins described in section 3.1 to account for any potential correlation between the A/D variables and the timing and location of a LSPVP that may bias our base model estimates.[7]

3.2.3. Event study model

In addition to the base model specification in (1), we specified an event-study model, which allowed us to test the parallel trends assumption underlying the difference-in-differences model and to allow treatment effects to evolve non-parametrically post-construction. Specifically, we estimated a model of the following form:

$$\ln\left(P_{icdjqtk}\right) = \sum_{k=-5}^{7} T_{k,idt}\gamma_k + \boldsymbol{X}_i\kappa + \delta_{dc} + \lambda_{tc} + \rho_{qc} + \varphi_j + \eta_{icdjqtk} \tag{2}$$

where $T_{k,idt}$ represents a series of lead and lag indicators for when a LSPVP began construction for each of the three distance bins defined in (1). We re-centered $T_{k,idt}$ so that $T_{0,idt}$ always equals one in the year the LSPVP began construction. We included a series of indicators from 1 to 5 years prior to a LSPVP being constructed ($T_{-5,idt}$ to $T_{-1,idt}$), and a series of indicators for 1–7 years after construction ($T_{1,idt}$ to $T_{7,idt}$). The omitted category for our treatment indicators (i.e. the reference year for all estimates) is the year of construction start for a LSPVP ($T_{0,idt}$). $\eta_{icdjqtk}$ is a random disturbance term and all other terms are as defined in (1).

The coefficients of primary interest in (2) are the $\gamma_k^{'}s$. The estimated coefficients on the lead treatment indicators (γ_{-5}, …, γ_{-1}) indicate whether the parallel trends assumption, which underlies all causal claims based on DiD models, appears to hold. Specifically, if LSPVP installation induces exogenous changes in home values, these lead treatment indicators should be small in magnitude and statistically insignificant, implying that the price of homes located close to a LSPVP (within 2 miles) were trending in a similar way to homes located farther away (2 to 4 miles) prior to LSPVP construction. The lagged treatment indicators ($\gamma_1, \ldots, \gamma_7$) allow the effect of distance to a LPSVP on home prices to evolve over time in the post treatment period in a non-parametric way.

3.2.4. Heterogeneity analyses

We conduct four heterogeneity analyses using the baseline model given by (1). First, we examined potential heterogeneity across states by estimating (1) separately for each of the six states in our sample. Second, we investigated the relationship between prior LSPVP land use and property value impacts by dividing our sample into four groups: home transactions near LSPVPs that were predominantly agricultural, greenfield, brownfield, or mixed land use prior to LSPVP construction. Third, we investigated the relationship between urbanicity and property value impacts by dividing our sample into one of the following U.S. Census Bureau designations: urban, urban clusters, or rural. Finally, we investigated the relationship between project size (area in square meters) and property values by applying the base model (1) to two subsets of the data: home transactions near LSPVPs below the 50th percentile of LSPVP areas and above the 50th percentile of LSPVP areas, where the 50th percentile is calculated from the set of unique LSPVPs in our sample.

4. Results

4.1. Base model and robustness check results

Table 4 shows results for the base model given by (1) and the robustness checks described above. As shown in column 1, we find an average 1.5% reduction in house prices for homes within 0.5 miles of a LSPVP that transacted post-LSPVP construction, and an average 0.82% reduction in home prices for homes 0.5–1 mi away from a LSPVP. Both estimates are statistically significant at the 5 percent level or better. As shown in column 2, we additionally find an average 2.3% reduction in home prices within 0.25 mi of a LSPVP. In both models, the estimated treatment effects for homes located 1 to 2 miles from a LSPVP are quite small in magnitude and statistically insignificant, suggesting that the impact of LSPVPs on home values fades relatively quickly with distance from a LSPVP. Further, all effects are monotonically ordered from closest distances to further away, which meets a priori expectations and provides us additional confidence in the model. As shown in columns 3 and 4 of Table 4, altering the time FEs by including quarter-by-year-by-project cohort FEs or controlling for other A/D does not notably alter the estimates from the base model.

4.2. Event study results

In Fig. 7 we present results from our event study specification given by (2), with coefficient estimates of our three distance bins shown as lines, and 95% confidence intervals shaded in similar colors. Homes located 2–4 miles from a LSPVP are once again the omitted category. Despite some noise in the estimates based on sales that occurred four or five years prior to LSPVP construction, in general there is very little evidence that home values were trending lower prior to the construction of a LSPVP: all of the estimated pre-treatment effects are small in magnitude and statistically insignificant. The lack of differential trending prior to the installation of a LSPVP provides evidence that our main identification assumption—the parallel trends assumption—holds. Fig. 7 also shows a relatively clear decline in home values that starts shortly after the beginning of LSPVP construction and continues up to six years post construction. The negative impact of LSPVPs on home values is particularly pronounced for homes located 0 to 0.5 miles from a LSPVP where we see home values declining by 4 percent six years after LSPVP construction.[8]

4.3. Heterogeneity analyses results

Fig. 8 shows results from all the heterogeneity analyses alongside the base model results; for ease of visualization, only the coefficients and 95% confidence interval for the 0–0.5 distance bin are shown, while Table 5 through Table 8 show more detailed results for each heterogeneity analysis. As shown in Table 5, which shows base model results for individual states, changes in sales price are not statistically significant for CA, CT, and MA. However, MN, NC, and NJ, show a statistically

[6] A total of 6,252 transactions occurred both within 0.25 mi of an LSPVP and after that LSPVP was constructed.

[7] For A/D distance bins, the omitted category is [2 mi, 4 mi) from a home; for noise levels, the omitted category is the <45 dB category; for flood zone, the omitted category is the missing category.

[8] When investigating results for individual states, both for the event study (section 3.2.3) and the heterogeneity analyses (section 3.2.4), our results largely agreed with the results for the full 6 state sample. However, our individual state estimates suffer from small sample sizes in individual time and distance categories for the event study and in individual subcategories for the heterogeneity analyses, so results are less reliable. Therefore, we do not present them in this paper. Results for individual states are available upon request from the authors.

Table 4
Average effect of LSPVP construction and proximity on home prices for all six states. Standard errors are clustered at the project cohort level and are in parentheses. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1

Dependent variable: the logarithm of house prices	Base model (1)	Including 0–0.25 mi distance bin	Including quarter-year-project cohort FEs	Including amenities and disamenities vector
Distance between home and LSPVP: [0 mi, 0.25 mi)		−0.0226*** (0.00767)		
Distance between home and LSPVP: [0.25 mi, 0.5 mi)		−0.0133** (0.00641)		
Distance between home and LSPVP: [0 mi, 0.5 mi)	−0.0154** (0.00630)		−0.0171*** (0.00642)	−0.0170*** (0.00589)
Distance between home and LSPVP: [0.5 mi, 1 mi)	−0.00820** (0.00413)	−0.00820** (0.00413)	−0.00941** (0.00424)	−0.00987** (0.00403)
Distance between home and LSPVP: [1 mi, 2 mi)	−0.000841 (0.00226)	−0.000841 (0.00226)	−0.00179 (0.00234)	−0.00131 (0.00225)
Home characteristics	✓	✓	✓	✓
Distance-project cohort FEs	✓	✓	✓	✓
Sale year-project cohort FEs	✓	✓		✓
Sale quarter-project cohort FEs	✓	✓		✓
Census block group FEs	✓	✓	✓	✓
Sale year-sale quarter-project cohort FEs			✓	
Amenities and disamenities				✓
Observations	1,832,888	1,832,888	1,826,915	1,778,533
R^2	0.835	0.835	0.839	0.835

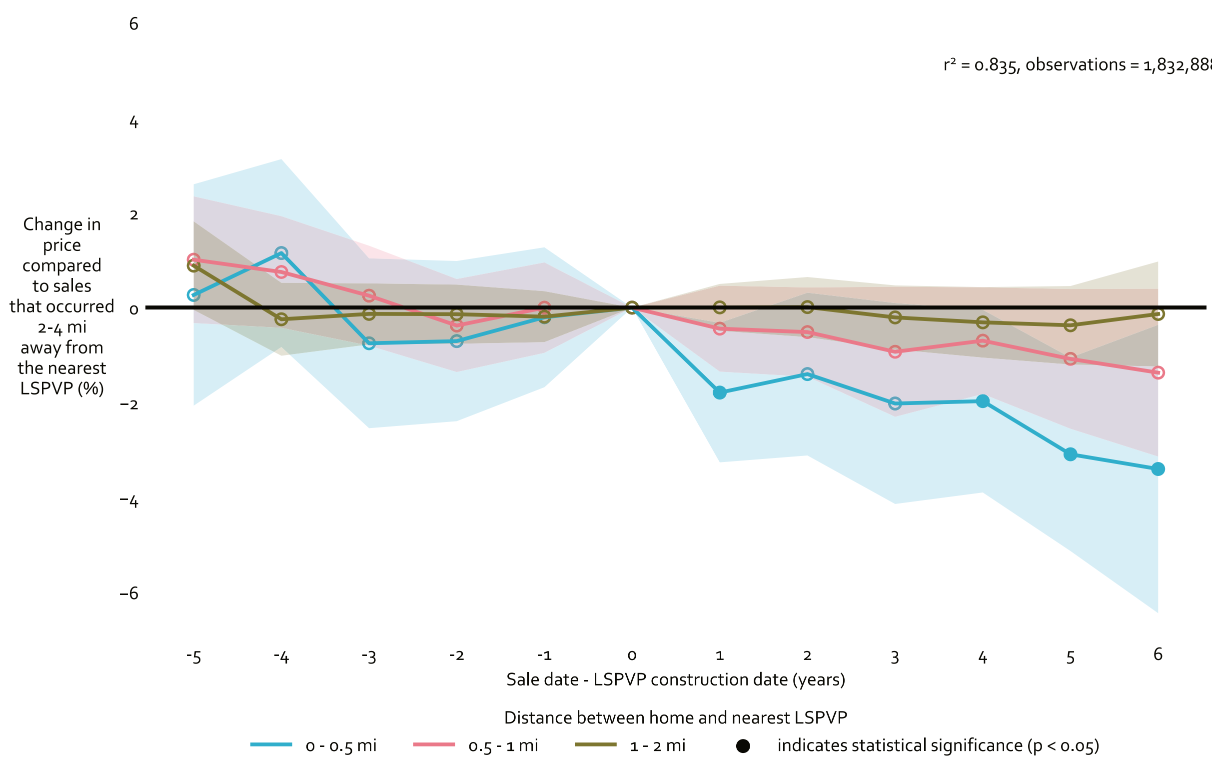

Fig. 7. Average effect of proximity to LSPVP by year of sale relative to year of LSPVP construction; shaded area represents 95% confidence interval; x-axis label represents lower bound of year range (e.g. −5 refers to all transactions that occurred [-5, −4) years before the construction date of the nearest LSPVP).

significant negative effect of 4%–5.6%, more than double that of the average across all states in the base model. In Table 6, where we examine potential heterogeneity by predominant prior land use of the nearest LSPVP,we find that statistically significant home value reductions are only observed for homes nearest to LSPVPs that are sited on previously agricultural land.[9] These findings are consistent with the results in

[9] We also tested the base model for a sample of only homes nearest to LSPVPs on previously forested land (NLCD classes of Deciduous Forest, Evergreen Forest, or Mixed Forest) and found no statistically significant results with $p < 0.1$.

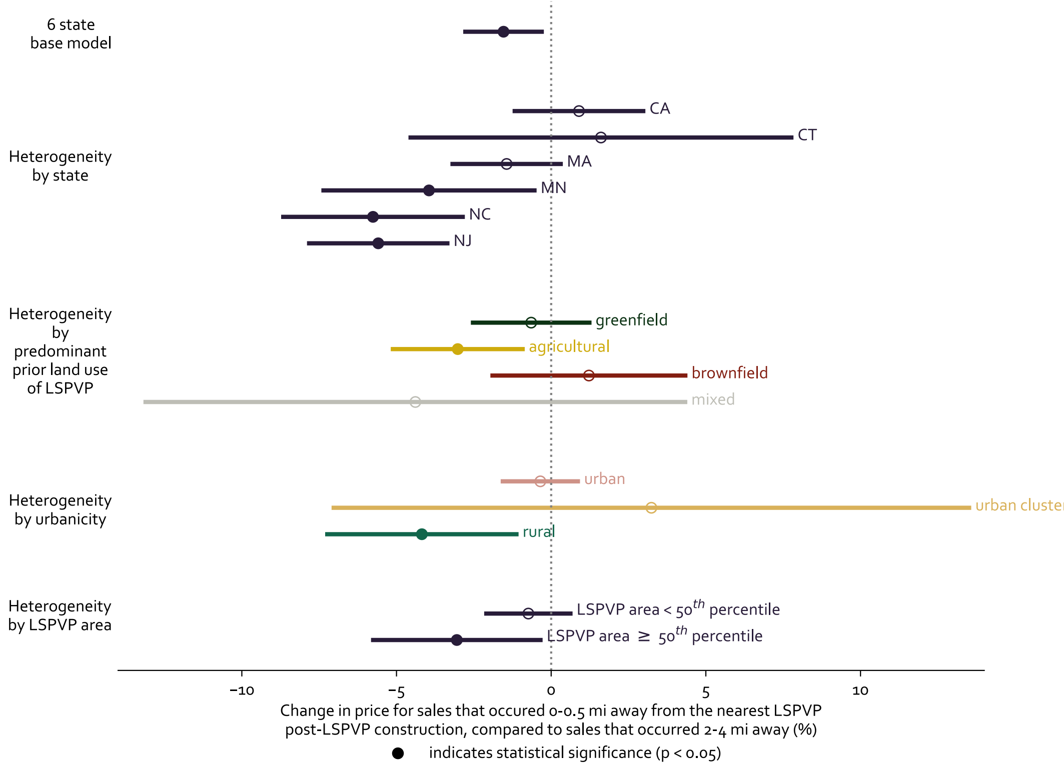

Fig. 8. Results from base model as well as each heterogeneity analysis, showing average effect of LSPVP construction and proximity for homes 0–0.5 mi away from nearest LSPVP. Range of change in price represents the 95th percent confidence interval.

Table 5
Effect of LSPVP construction and proximity on home prices in individual states, using base model specification. Standard errors are clustered at the project cohort level and are in parentheses. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1

Dependent variable: the logarithm of house prices	CA	CT	MA	MN	NC	NJ
Distance between home and LSPVP: [0 mi, 0.5 mi)	0.00899 (0.0106)	0.0161 (0.0314)	−0.0144 (0.00892)	−0.0395** (0.0174)	−0.0576*** (0.0148)	−0.0559*** (0.0114)
Distance between home and LSPVP: [0.5 mi, 1 mi)	0.000849 (0.00696)	0.0234 (0.0150)	−0.00933** (0.00469)	−0.0209** (0.00932)	−0.0473*** (0.0118)	−0.0135* (0.00698)
Distance between home and LSPVP: [1 mi, 2 mi)	0.00296 (0.00384)	0.0186** (0.00786)	−0.00190 (0.00319)	−0.0108* (0.00625)	−0.0117** (0.00570)	−0.00487 (0.00331)
Observations	931,735	34,135	291,403	74,905	203,005	297,677
R^2	0.881	0.774	0.777	0.708	0.735	0.751

Table 6
Average effect of LSPVP construction and proximity on home prices by predominant prior land use of nearest LSPVP to home, using base model specification. Standard errors are clustered at the project cohort level and are in parentheses. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1

Dependent variable: the logarithm of house prices	Greenfield	Agricultural	Brownfield	Mixed
Distance between home and LSPVP: [0 mi, 0.5 mi)	−0.00646 (0.00960)	−0.0302*** (0.0107)	0.0122 (0.0159)	−0.0439 (0.0445)
Distance between home and LSPVP: [0.5 mi, 1 mi)	−0.000991 (0.00480)	−0.0202*** (0.00629)	−0.00909 (0.0170)	−0.00679 (0.0342)
Distance between home and LSPVP: [1 mi, 2 mi)	0.000836 (0.00248)	−0.00408 (0.00498)	−0.00483 (0.00739)	−0.000377 (0.0191)
Observations	1,074,492	577,769	147,951	12,987
R^2	0.843	0.833	0.860	0.828

Table 7
Average effect of LSPVP construction and proximity on home prices by home urban, urban cluster, or rural designation, using base model specification. Standard errors are clustered at the project cohort level and are in parentheses. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1

Dependent variable: the logarithm of house prices	Rural	Urban cluster	Urban
Distance between home and LSPVP: [0 mi, 0.5 mi)	−0.0418*** (0.0156)	0.0324 (0.0524)	−0.00350 (0.00619)
Distance between home and LSPVP: [0.5 mi, 1 mi)	−0.0201* (0.0119)	0.0221 (0.0316)	−0.00342 (0.00437)
Distance between home and LSPVP: [1 mi, 2 mi)	0.00775 (0.00613)	−0.00597 (0.00896)	0.00137 (0.00222)
Observations	151,792	79,279	1,592,715
R^2	0.803	0.785	0.845

Table 8
Average effect of LSPVP construction and proximity on home prices by area of LSPVP, using base model specification. Standard errors are clustered at the project cohort level and are in parentheses. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1

Dependent variable: the logarithm of house prices	**LSPVP area < 50th percentile of area (75,138 m^2)**	**LSPVP area ≥ 50th percentile of area (75,138 m^2)**
Distance between home and LSPVP: [0 mi, 0.5 mi)	−0.00737 (0.00694)	−0.0305** (0.0138)
Distance between home and LSPVP: [0.5 mi, 1 mi)	−0.00483 (0.00521)	−0.0166** (0.00684)
Distance between home and LSPVP: [1 mi, 2 mi)	0.00225 (0.00287)	−0.00841** (0.00344)
Observations	1,291,762	537,189
R^2	0.841	0.833

Table 7, which shows that statistically significant effects were only observed for homes located in rural areas. Finally, in Table 8 we examine potential heterogeneity in property value impacts by the size of a LSPVP project. Specifically, we split the sample based on LSPVP areas and estimate separate models for homes located near LSPVPs that are above or below the median LSPVP area in our sample. Adverse effects are only observed for LSPVPs with an area larger than the median area of all unique LSPVPs in our sample[10].

5. Discussion

In this paper, we add to the growing body of research on the impact of LSPVPs on residential home values. By assembling an analysis dataset consisting of transaction data, an original dataset of LSPVP footprints, a suite of environmental amenities and dis-amenities, urbanicity classifications, and historic land cover data, we answer two related research questions.

First, we ask: what effect, if any, do LSPVPs have on residential home prices? Across the six states in the study area, we observe that homes within 0–0.5 mi of an LSPVP that transact after a LSPVP is constructed decline in sale price by an average of 1.5% compared to homes 2–4 mi away. At closer distances of 0–0.25 mi, the average decline in property values is 2.3%. This effect fades at further distances from a LSPVP; we observe a small adverse effect for homes 0.5–1 mi away of 0.8%, and no evidence of an effect at distances beyond 1 mi. Our estimates are robust to choices of time FEs and we control for other landscape characteristics that could impact property values. Our results are consistent with some prior literature (Dröes and Koster, 2021; Gaur and Lang, 2020) that find an overall adverse impact of LSPVP construction on property values.

Second, we ask: does the effect of LSPVPs on home prices differ based on the state, the prior land use on which a LSPVP is located, the size of the LSPVP, or the urbanicity of a home? When looking at individual states in our sample, we observe no effect on sales prices in CA, CT, and MA, but find sale price reductions for homes 0–0.5 mi away from a LSPVP of 4%, 5.8%, and 5.6% in MN, NC, and NJ, respectively. In those states where we do observe sale price reductions, the effect fades as distances from an LSPVP increases, as with the full 6 state model. When separating transactions by the prior land use and the area of the LSPVP to which they are closest, as well as by the urbanicity of the home, we observe statistically significant effects only for transactions near LSPVPs sited on previously agricultural land, transactions in rural areas, and transactions near larger LSPVPs by area. We observe decreases of 3%, 4.2%, and 3.1% for homes within 0–0.5 mi of LSPVPs on previously agricultural land, in rural areas, or near large LSPVPs, respectively, compared to homes 2–4 mi away. In all three cases, these effects fade with distance from a LSPVP. We observe no statistically significant effect of LSPVP construction and proximity on home prices in other categories for land use (greenfield, brownfield, or mixed land use sites), urbanicity (urban or urban cluster regions), or LSPVP area (where areas fall below the median LSPVP area in our dataset). Looking at the heterogeneity results by land use and urbanicity may help us understand the heterogeneity we observe by state: the states where we observe no statistically significant difference in sales price (in CA, CT, and MA) are also the states with lower proportions of LSPVP development on agricultural land (Fig. 3). CA additionally has very few transactions in rural areas (Fig. 4).

Our heterogeneity analyses show that the property value impacts of LSPVP development are highly contextual, and reinforce scholarly arguments that research on public support for solar energy should consider both project scale and proposed locations (Nilson and Stedman, 2022). Specifically, our results point to the importance of understanding the perceptions, economic impacts, and social dynamics of larger solar developments, rural developments, and developments built on previously agricultural land. Broader social science scholarship can contextualize these results: for instance, researchers have theorized that the siting of renewable energy in rural areas can counter personal, cultural, and political representations and understandings of rural landscapes (Batel et al., 2015). Our observed heterogeneity may reflect how large, agricultural, or rural developments potentially conflict more directly with those representations than smaller, non-agricultural, or urban developments. Furthermore, our results with respect to land use connect to an emerging literature on the co-location of solar and agriculture: surveys show that residents in agricultural communities are more likely to support solar development that integrates agricultural production (Pascaris et al., 2022), though scholarly reviews note that our understanding of perceptions of solar-agricultural systems remains limited (Mamun et al., 2022).

6. Limitations and future work

A key limitation of our research approach is that we consider only one aspect of the economic impacts of LSPVPs: property values. The impacts of local energy development are also shaped by local tax revenue and employment impacts, which have consistently been found to result in positive benefits (Brunner et al., 2021; Brunner and Schwegman, 2022a, 2022b), as well as by LSPVP ownership structures. This implies that homeowners can and do capitalize the positive impacts of renewable energy into home prices. Because this analysis compared home prices between homes around the same projects, any differences in value as compared to homes not near any LSPVP, and thus not subject to local tax or employment impacts, would have remained undiscovered. Furthermore, to the extent that property value changes reflect the revealed preferences of residents, they only reflect the preferences of the subset of residents who are homeowners. Where homeownership rates are lower – largely in urban areas, but in an increasing portion of rural areas as well (Pendall et al., 2016) – property value changes may not reflect the preferences of neighbors to the extent that they do where homeownership rates are higher. Considering these varied economic impacts would necessitate methodologies and data collection beyond the hedonic DiD analysis used in this paper.

These limitations suggest two major avenues for future work. First, more research attention is needed on the economic impacts of LSPVPs, broadly understood to encompass dimensions such as tax revenue, ownership structures, or employment. Added research on the local economic impacts of LSPVPs can position our findings on the average

[10] We also tested the base model for two additional samples: homes near very large LSPVPs (areas greater than the 75th percentile of areas of unique LSPVPs in our sample) and near very small LSPVPs (areas below the 25th percentile of areas of unique LSPVPs in our sample). For both subsets of our data, we found no statistically significant results with p < 0.1.

adverse impact of LSPVP development on home prices in a broader context of economic benefits and burdens due to LSPVP development. Second, more research is needed to understand the heterogeneity that we observe with respect to larger, agricultural, and rural LSPVPs. Here, surveys, qualitative research, mixed-methods, and case study-based approaches may indicate how neighbors of LSPVPs engage differently with their nearby solar installation based on its size, land use, or the urbanicity of their home.

7. Conclusion and policy implications

This paper provides some of the first comprehensive evidence on the impact of LSPVPs on residential home values. Specifically, we ask: (1) what effect, if any, do LSPVPs have on residential home prices and (2) does the effect of LSPVPs on home prices differ based on the prior land use on which an LSPVP is located, the size of the LSPVP, or the urbanicity of a home? In our six-state study area (CA, CT, MA, MN, NC, NJ), we find that homes within 0.5 mi of LSPVP experience an average home price reduction of 1.5% compared to homes 2–4 mi away; statistically significant effects are not measurable over 1 mi from a LSPVP. These effects are only measurable in certain states (MN, NC, and NJ), for LSPVPs constructed on agricultural land, for larger LSPVPs, and for rural homes.

Our study extends the existing literature in three ways. First, we consider a larger sample, both in terms of transactions and LSPVPs, than prior studies. Our six-state study area encompasses 53% of the total MW nameplate capacity of PV generators in the U.S., and our analysis included evidence from over 1,500 LSPVPs and over 1.8 million home transactions. The scope of our dataset allows us to provide average impact estimates for a much larger set of LSPVP projects within the United States. Second, to our knowledge, our study is the first study on LSPVP property values impacts to use a dataset of LSPVP footprints (as opposed to point locations or approximations of LSPVP area using circular buffers). By constructing and using footprint data, we can more precisely assess the land area and prior land use of LSPVPs, as well as reduce measurement error when calculating distances between homes and a LSPVP. Finally, we employ a stacked DiD specification with bin-by-project cohort FEs, which not only advances the methodology used for this type of analysis but also addresses recent concerns over DiD specifications that rely on staggered timing of treatment.

Our findings have two main policy implications. First, they point to the need for policy and development measures to ameliorate possible negative impacts of LSPVP development in some contexts. Our results suggest that there are adverse property value impacts of LSPVP construction for homes very close to a LSPVP and those predominantly in rural agricultural settings around larger projects. But we find that most impacts fade at distances greater than 1 mile from a LSPVP. In some cases – for homes near large LSPVPs, and in the states of MN and NC – negative effects persist at distances greater than 1 mile but are smaller than they are at nearer distances to a LSPVP. These results suggest that care should be taken in siting LSPVPs near homes in some contexts. Developers or policymakers considering siting LSPVPs very close to homes have several tools to employ, such as compensation schemes with neighbors and landscape measures like vegetative screening.

Second, the heterogeneity analyses reveal the importance of place and project-specific assessments of LSPVP development practices. Although we find adverse impacts of LSPVP construction on property values overall, we notably find no evidence of impacts in three states in our study area – including in CA, which alone accounts for over half of the transactions in our dataset. On the other hand, we do see evidence of adverse property value impacts of LSPVPs in the other three states in our dataset – including in MN, despite MN having arguably the most restrictive state-wide laws on LSPVP development in high-value agricultural areas of the states in our study area (Bergan, 2021). While our sample for individual states was too small to conclusively explore heterogeneity within states, our overall heterogeneity analysis suggests that adverse impacts of LSPVP development are present specifically in rural areas, where LSPVP displaces agricultural land uses, and where LSPVP installations are larger. For policy-makers, this heterogeneity may point to the importance of carefully considering siting strategies for rural, large, or agricultural installations – for instance, by exploring ways to co-locate agricultural land uses and solar development. However, this heterogeneity does not mean that economic impacts are negligible where property value impacts were insignificant (CA, CT, MN, as well as urban, non-agricultural, and smaller developments): as discussed in section 6, many economic impacts remain undiscovered by our methodology, some of which might increase home values, and future policy-relevant research is needed to understand the economic impacts of LSPVPs, broadly construed.

By combining a novel dataset of LSPVP footprints with home transaction data, our analysis provides comprehensive evidence that LSPVPs have an average adverse effect on home prices, but notably shows that these impacts are not uniform across geographies, land uses, or LSPVP size. In doing so, we contribute to the emerging literature on the economic impacts of LSPVPs and point to important avenues for future policy discussions and research.

CRediT authorship contribution statement

Salma Elmallah: Conceptualization, Methodology, Formal analysis, Data curation, Writing. **Ben Hoen:** Conceptualization, Methodology, Formal analysis, Writing, Project administration, Supervision, Funding acquisition. **K. Sydny Fujita:** Methodology, Formal analysis, Data curation, Writing. **Dana Robson:** Data curation, Writing. **Eric Brunner:** Conceptualization, Methodology, Formal analysis, Writing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Datasets related to this article that can be shared can be found at https://zenodo.org/record/7415662.

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Appendix

Table A.1
Retention criteria for transactions

Condition for retention	Rationale
Coordinate values are populated	Coordinates are needed to obtain distances between homes and LSPVP, amenities, and dis-amenities
Land area, year built, and home square footage are populated	Land area, year built, and home square footage are essential property characteristics to control for in analysis
Coordinates appear 20 times or less	Repeated, identical coordinates for multiple properties may indicate data quality issue
Property type is residential (including single family residence, condominium, duplex, apartment)	Analysis only considers homes (i.e. residential properties) sold in arms length transactions after the year 2000
Transaction is categorized as arms length	
Year of sale between 2000 and 2021	
Sale amount is greater than $5000 or the 1st percentile of sale price (whichever value is higher) and less than the 99th percentile of sale amount values within a given state	Removing outliers from analysis
Sale amount per unit area of living space is greater than the 1st percentile and less than the 99th percentile of sale amount per unit area of living space values within a given state	
Land area is greater than the 1st percentile and less than the 99th percentile of land area values within a given state	
Property was built before 2020, and after the 1st percentile of values for year built within a given state	
Sale amount is greater than the mortgage amount, or mortgage amount is missing	Any other relationship (between sale amount & mortgage amount, land area & living space area, sale year & year built, set of variables representing land area) may indicate data quality issues
Land area is greater than living space area	
Age of property (sale year minus year built) is non-negative	
Both variables representing land area converge within 0.01 acres	
Deed is not categorized as foreclosure	Sale amount in a foreclosure may not accurately represent the value of a home
Sale occurred over one year after last recorded sale for that property	Removes potentially "flipped" homes, or homes that undergo a rapid renovation and are re-sold, from dataset; for those homes, characteristics in CoreLogic dataset may not be representative of characteristics after renovation
Property address was not determined from mail	Address determined from mail may reflect the address of an absentee owner, not of the physical property location

Table A.2
Amenity and dis-amenity data sources

Amenity/dis-amenity	Data source	Data description	Reference
Aviation noise Road noise	U.S. Department of Transportation	Raster representing approximate average noise energy due to transportation noise sources over a 24-h period at the receptor locations where noise is computed, expressed in decibels (dB)	U.S. Department of Transportation (2020)
Flood zones	U.S. Federal Emergency Management Agency	Categorizes areas by likelihood of flood, ranging from minimal risk to 26% chance of flooding over the life of a 30-year mortgage	Federal Emergency Management Agency (2021)
Municipal, industrial, and transfer landfills	U.S. Department of Homeland Security	Provides locations of active permitted municipal solid waste facilities and construction and demolition debris facilities.	Department of Homeland Security (2020)
State and national parks	Esri	Provides boundaries of parks and forests in the United States at the national, state, regional, and local level	Esri (2021)
Nuclear power generation facilities	National Institute of Health	Provides locations of U.S. commercial nuclear power plants	Hochstein and Szczur (2006)
Coal power generation facilities	U.S. Environmental Protection Agency	Facility data (as of 2017) where primary or secondary fuel type is coal-related (e.g., Coal, Coal Refuse, and Petroleum Coke).	U.S. Environmental Protection Agency (2021)
Coastline	ABB Group	Locations of U.S. coastline, including bays, river outlets, and Great Lakes	ABB Group (2020)
Lakes		Locations of U.S. lakes, represented as polygons	
High-voltage lines		Transmission and distribution lines with a voltage of 100 V or greater, represented as polylines	

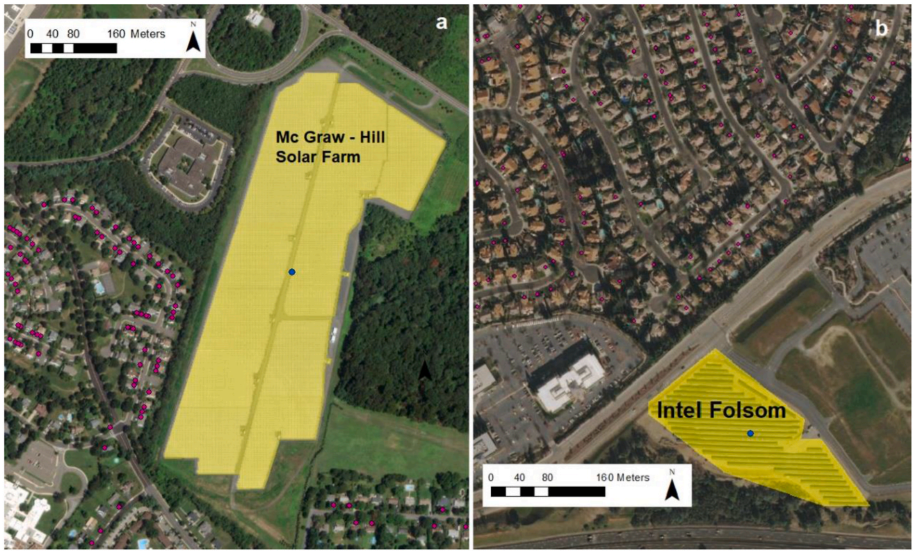

Fig. A.1. Satellite imagery showing examples of LSPVP centroids (blue dots) and polygons (yellow shaded areas) near homes including homes that transacted during our study period (pink dots): (a) McGraw-Hill Solar Farm, NJ and (b) Intel Folsom, CA

Table A.3
Summary of dependent variables and property characteristics, CA

Variable	Description	Mean	Std. dev.	Min.	Med.	Max.
Sp	Sale price ($)	$457,797.53	$403,489.03	$35,500.00	$350,000.00	$3,998,000.00
Lsp	log of sale price	12.75	0.75	10.48	12.77	15.2
Lsf	Living area (ft^2)	1868.69	1026.22	102	1654.00	98,694.00
Acres	Land area (acres)	0.336	0.7	0.018	0.165	7.231
Age	Age of home at time of sale (years)	36.94	24.79	0	34	112
Agesq	Age of home at time of sale, squared (years^2)	1979.42	2233.94	0	1156.00	12,544.00
Salesqtr	Quarter of sale	2.23	0.88	1	2	4
Salesyr	Year of sale	2014	3	2003	2015	2020

Table A.4
Summary of dependent variables and property characteristics, CT

Variable	Description	Mean	Std. dev.	Min.	Med.	Max.
Sp	Sale price ($)	$283,251.18	$184,202.97	$36,000.00	$239,900.00	$1,640,000.00
Lsp	log of sale price	12.4	0.56	10.49	12.39	14.31
Lsf	Living area (ft^2)	1916.21	951.46	196	1669.00	35,170.00
Acres	Land area (acres)	0.818	1.114	0.07	0.41	9.51
Age	Age of home at time of sale (years)	59.74	33.65	0	58	212
Agesq	Age of home at time of sale, squared (years^2)	4700.55	5311.95	0	3364.00	44,944.00
Salesqtr	Quarter of sale	2.32	0.83	1	2	4
Salesyr	Year of sale	2017	2	2011	2018	2020

Table A.5
Summary of dependent variables and property characteristics, MA

Variable	Description	Mean	Std. dev.	Min.	Med.	Max.
Sp	Sale price ($)	$428,122.04	$284,039.71	$5100.00	$360,000.00	$2,199,000.00
Lsp	log of sale price	12.78	0.63	8.54	12.79	14.6
Lsf	Living area (ft^2)	2019.36	961.96	173	1802.00	35,721.00
Acres	Land area (acres)	0.584	0.764	0.03	0.315	6.6
Age	Age of home at time of sale (years)	62.74	38.25	0	58	209
Agesq	Age of home at time of sale, squared (years^2)	5399.73	5906.47	0	3364.00	43,681.00
Salesqtr	Quarter of sale	2.35	0.84	1	2	4
Salesyr	Year of sale	2015	3	2005	2016	2020

Table A.6
Summary of dependent variables and property characteristics, MN

Variable	Description	Mean	Std. dev.	Min.	Med.	Max.
Sp	Sale price ($)	$274,027.53	$152,774.95	$5500.00	$240,000.00	$1,299,000.00
Lsp	log of sale price	12.38	0.56	8.61	12.39	14.08
Lsf	Living area (ft^2)	1956.58	978.6	155	1740.50	42,840.00
Acres	Land area (acres)	0.612	1.316	0.02	0.26	11.87
Age	Age of home at time of sale (years)	42.03	31.21	0	35	134
Agesq	Age of home at time of sale, squared (years^2)	2739.86	3587.53	0	1225.00	17,956.00
Salesqtr	Quarter of sale	2.31	0.82	1	2	4
Salesyr	Year of sale	2016	2	2010	2016	2020

Table A.7
Summary of dependent variables and property characteristics, NC

Variable	Description	Mean	Std. dev.	Min.	Med.	Max.
Sp	Sale price ($)	$233,970.66	$169,170.45	$5050.00	$194,000.00	$1,499,500.00
Lsp	log of sale price	12.12	0.75	8.53	12.18	14.22
Lsf	Living area (ft^2)	2091.02	1110.70	150	1852.00	120,215.00
Acres	Land area (acres)	0.788	1.437	0.021	0.36	14.14
Age	Age of home at time of sale (years)	29.48	24.08	0	22	114
Agesq	Age of home at time of sale, squared (years^2)	1448.56	2083.56	0	484	12,996.00
Salesqtr	Quarter of sale	2.26	0.86	1	2	4
Salesyr	Year of sale	2016	3	2004	2016	2020

Table A.8
Summary of dependent variables and property characteristics, NJ

Variable	Description	Mean	Std. dev.	Min.	Med.	Max.
Sp	Sale price ($)	$390,953.28	$243,373.52	$5143.00	$340,000.00	$1,599,999.00
Lsp	log of sale price	12.68	0.66	8.55	12.74	14.29
Lsf	Living area (ft^2)	1959.42	868.99	160	1786.00	19,176.00
Acres	Land area (acres)	0.393	0.656	0.006	0.185	6.167
Age	Age of home at time of sale (years)	56.92	30.02	0	57	139
Agesq	Age of home at time of sale, squared (years^2)	4140.35	3664.38	0	3249.00	19,321.00
Salesqtr	Quarter of sale	2.31	0.86	1	2	4
Salesyr	Year of sale	2014	4	2004	2014	2020

Table A.9
Categorical variables representing property characteristics (* = omitted category in regressions)

Variable	Category
Fullbaths	Number of full bathrooms missing*
	1 full bathroom
	2 full bathrooms
	3 full bathrooms
	4 full bathrooms
	$\geq$ 5 full bathrooms
Actype	Air conditioning code missing*
	Central AC
	AC type unknown
	Refrigeration AC
	Separate AC system
	No AC
	Evaporative AC
	All other types of AC
Constrtype	Construction type missing*
	Wood construction type
	Frame construction type
	Wood metal/frame construction type
	All other construction types
Heattype	Heating type missing*
	Central heat
	Forced air
	Unknown heating type
	Forced hot water

(*continued on next page*)

Table A.9 (*continued*)

Variable	Category
	Heat pump
	Hot air
	Floor/wall furnace
	No heat
	Steam
	All other heating types
Extwalltype	Exterior wall type missing*
	Stucco
	Frame
	Vinyl
	Aluminum/vinyl
	Wood siding/shingle
	Brick
	Aluminum siding
	Wood siding
	Wood
	All other wall codes
Fireplace	No fireplace indicated*
	Fireplace present
Garagecode	Garage type missing*
	Undefined garage type
	Attached
	Attached frame
	Undefined type – 2 car
	Detached
	Finished
	Basement
	Carport
	Undefined type – 1 car
	Frame
	Attached finished
	Attached garage/carport
	All other garage codes
Stories	Number of stories missing*
	0 to 1 stories
	1 to 2 stories
	2 to 3 stories
	>3 stories
View	View category missing*
	Average view
	All other view categories
newconstruction	New construction not indicated*
	New construction

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