Utility-Scale Solar Farms and Agricultural Land Values

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Abstract: Property value models are used to examine how utility-scale, ground-mount solar farms impact nearby agricultural land values. Results indicate that solar farms do not have direct positive or negative spillover effects on nearby agricultural land values. However, results also suggest that solar farm construction may indirectly affect agricultural land values by signaling the land's suitability for future solar development. Specifically, results indicate that proximity of agricultural land to electric transmission lines may be positively valued after a solar farm is constructed nearby.

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1. Introduction

In just over a decade, solar photovoltaic electricity generation in the United States increased 100-fold from 1.2 billion kilowatt hours generated to 114.7 billion kilowatt hours.[1] This high growth is expected to continue as states implement policies that encourage the use of renewables and as the cost of solar generation continues to fall. As of 2022, North Carolina (NC) ranked third in the nation in overall installed solar capacity, behind California and Texas.[2] The total installed ground-mount solar capacity in NC grew from under 10 megawatts (MW) in 2009 to over 5,000 MW by 2020.[3] Ground-mount, utility-scale, solar systems (hereafter referred to as "solar farms") are the primary component of solar capacity in NC, which contrasts with other leading states such as California, Texas, Arizona and New Jersey where residential solar power systems (i.e., roof-top solar panels) are a sizeable portion of the installed solar capacity.

Solar farms are generally placed in rural areas due to their relatively large footprint. For example, the average 5 MW farm in NC occupies approximately 30 acres, exclusive of any buffers or setbacks. The rapid expansion of solar farms in NC and other states has let to conflict as stakeholders in rural counties raise concerns about the loss of farmland to solar development, as well as the potential effects of solar installations on the productivity of the land once the farm is converted back to agricultural service at the end of the solar farm's life (NC Sustainable Energy Association (NCSEA), 2017).[4] In urban and suburban areas, the siting of solar farms has been subject to local resistance, mainly due to perceived negative visual effects from solar installations on surrounding property values. In NC, concerns about negative spillover effects have resulted in local governments either imposing moratoriums on solar farm development or completely banning solar farm development.[5]

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It is well understood that some land uses can negatively affect neighboring property values. Two recent evaluations indicate that solar farms negatively affect nearby residential property values (Abashidze, 2019, Gaur and Lang, 2020).[6] However, we are unaware of research that explores how agricultural land values could be negatively impacted by a nearby solar farm. Solar farms could have negative spillover effects in agricultural land markets if a solar farm negatively impacts the productivity of nearby land or if aesthetic concerns negatively impact the demand for agricultural parcels (Ma and Swinton, 2011). On the other hand, solar farms can be a lucrative land-use choice for property owners in rural areas. Typical lease agreements for solar development in NC guarantee landowners' income greater than $500 per acre for a period of 20 years, which contrasts with average rental rates of farmland in agricultural production of $27 to $102 per-acre, per-year (NCSEA, 2017). Data suggest that solar farms are clustered across space in NC and the same solar developer tends to install solar systems in close proximity to each other. Thus, solar development on one parcel may signal interest in the area and the potential for increased land rents, which could be capitalized into land values. This effect has been demonstrated in other contexts. For example, Haan and Simmler (2018) find that the potential for increased wind farm development significantly increased agricultural land prices in Germany (see also Kirwan, 2009).

We empirically estimate the impacts of utility-scale solar development on nearby agricultural land values using hedonic property value models.[7] A comprehensive database of georeferenced agricultural land sales obtained from Zillow Research is linked to a georeferenced census of solar farm installations in NC.[8,9] North Carolina provides an ideal setting to explore this question given its rich agricultural landscape, numerous solar farms (>450), and the close proximity of solar farms to productive agricultural land.[10]

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To disentangle the potential positive spillover effects of solar development (i.e., option values) from potential negative spillover effects such as impacts on nearby land productivity or visual disamenities, we take advantage of geospatial data on electric transmission infrastructure. Proximity to electric infrastructure is necessary for solar farm siting, and so it is hypothesized that proximity of a parcel to transmissions lines after a solar farm is built could be positively capitalized into land values if solar development nearby signals to markets the potential for higher land rents. Proximity to electric infrastructure is not highly collinear with proximity to a solar development, and so we are able to disentangle solar development option values from solar development visual or other disamenities.

Results indicate that utility-scale solar farms have no direct positive or negative spillover effects on nearby agricultural land values. However, results also suggest that solar farm construction may indirectly affect agricultural land values by creating a signal effect of the land's suitability for future solar development. Specifically, proximity of agricultural land to electric transmission lines is positively valued only after a solar farm is constructed near the agricultural parcel. Although not the focus of this paper, this latter finding is of note since siting of transmission lines also faces significant opposition (Eto, 2016) and our results suggest one instance where proximity to transmission infrastructure may result in pecuniary benefits for landowners.

2. Background

Solar energy capacity in NC grew more than 600-fold in the decade following 2009. This remarkable growth can be attributed to several influences including NC's renewable energy mandating that required electric utilities to produce 12.5 percent of their electricity from

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renewable energy sources by 2021 coupled with generous state and federal financial incentives. From 2006 to 2015, NC also offered a 35 percent state tax credit to solar developers on the cost of each renewable energy project constructed (capped at $2.5 million per project), and federal investment-tax credits increased from 10 percent to 30 percent between 2006 and 2019.[11] In addition, NC implemented requirements for "power purchase agreements" (PPAs) that were generous relative to other states. PPAs mandate that utilities purchase electricity generated by qualifying renewable sources at a fixed price for up to 15 years, reducing price risk for solar developers dramatically. NC allowed PPAs for projects up to 5MW, while most states limit qualifying renewable sources to one-megawatt or less (NC Clean Energy Technology Center, 2017). In addition to generous state and federal incentives, solar panel prices fell by more than 70 percent between 2009 and 2015 (Platzer, 2015).

As of July 2017, there were 451 utility-scale ground-mount solar farms with over one MW electric power capacity installed in NC. Total installed capacity of these 451 farms is 2,900 MW (see Figure 1). To put the scale of these solar installations into context, they occupy 14,864 acres or 0.31 percent of potential cropland in the state. Solar power is expected to expand further and account for five percent of electricity generation in NC by 2030 and will require the use of 0.57 percent of available cropland (NC Clean Energy Technology Center and NC State University, 2019).

[Insert Figure 1 here]

A solar farm's siting process is a complex procedure that can take up to two years and often depends on the scale and location of the project (Kikuma, Rublev, and Tan, 2018). The solar developer must first determine the lease terms with the landowner and obtain an interconnection agreement with an electric utility that includes a PPA specifying the prices paid

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for generation over a period of time. The solar developer must also work with local government ordinances and zoning rules, which often have been revised in consideration of solar growth in the region. Solar ordinances typically include setback requirements that vary by zoning district and are usually more restrictive for residential areas. These ordinances also have standards on the height of solar energy systems, vegetative buffers that could mitigate visual impacts of solar farms, and include decommissioning requirements. Large solar farms are also often required to obtain special use permits that require quasi-judicial hearings, along with the standard construction building and electrical permits, a stormwater permit, and in some instances, an aviation notification. Solar ordinances are heterogeneous across counties and are becoming more stringent over time.[12]

Along with existing solar regulations, proximity to the current electricity infrastructure is an important consideration for solar farm development (Kikuma, Rublev, and Tan, 2018). Solar developers must build and pay for new transmission lines to connect each solar farm to existing high-voltage transmission lines. The construction cost of a new transmission line is estimated to vary from $390,000 per mile for a 138 kV single circuit line (Public Service Commission of Wisconsin, 2011) to $1,343,800 for a 345 kV single circuit line (Western Electricity Coordinating Council, 2014). As such, solar developers prefer siting solar farms as close as feasible to existing high-voltage transmission lines rather than building costly new infrastructure (Brawner et al., 2017 and Kikuma, Rublev, and Tan, 2018).

Other factors that affect solar farm siting processes include land use/land cover (typically land classified as agricultural, vacant, wild, forest, and horticulture are suitable for solar development), slope (typically less than 10 degrees) and aspect (South, south-west, or south-east facing). Parcels located in floodplains, wetlands, and/or protected areas are not considered suitable for solar development (Kikuma, Rublev, and Tan, 2018). We explicitly control for these factors in our empirical strategy.

3. Hypotheses and Data

The expected externality effects of utility-scale solar farms on neighboring agricultural land values follow from a standard hedonic pricing model (Rosen, 1974) as applied to agricultural land markets (Miranowski and Hammes, 1984, Palmquist, 1989, Petrie and Taylor, 2007, Ma and Swinton, 2012, Bishop et al., 2020). In the context of agricultural land markets, the value of land characteristics are derived from their direct or indirect contribution to the net present value of future rents (profits). For example, the marginal value of additional levels of soil quality would be positive since improved soil quality is expected to increase profits directly through increased crop yields and indirectly through reduced production costs (e.g., reduced fertilizer or irrigation costs).

Expectations for the marginal value of proximity to solar farms or transmission lines are not as clear-cut as they are for soil quality. While proximity of an agricultural parcel to either a solar farm or a transmission line is not expected to affect land prices through agricultural production processes, there could be changes in aesthetic views from the land that might be disvalued by farmers (Ma and Swinton, 2011 and 2012). However, proximity to a solar farm may also suggest to buyers that the area is of interest to solar farm developers. This could positively influence prices through an option value to lease the land for future solar development (see Haan and Simmler, 2018, for evidence of this type of effect in the context of wind farms in Germany). Similarly, because cost-minimizing solar developers prefer to locate solar farms as close to transmission lines as feasible, it is hypothesized that proximity to the electricity infrastructure increases the land's option value for solar development.

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We can combine the above insights to hypothesize a set of empirical relationships (Appendix A contains a formal treatment). Consider a parcel of land (parcel "*X*") that is converted to a solar farm in time *T*. We expect that proximity to parcel *X* prior to time *T* will have no effect on agricultural land sales prices. A significant effect of proximity to the future site of a solar farm would indicate selection effects that would bias our estimates. We might see selection effects if land that is chosen for solar development has systematically positive or negative spillover effects on neighboring agricultural land. While it is difficult to imagine what these spillover effects might be, we empirically test for the possibility.

The relationship between sales prices and proximity to parcel *X* after time *T* (after the solar farm is built) is ambiguous. If aesthetics surrounding agricultural land are capitalized into sales prices, and solar farms are considered visually unappealing, we would expect land closer to solar farms to sell for a discount. However, at the same time, solar farm development signals the potential for future solar development on the parcel, which implies a positive external effect.

Lastly, consider the relationship between transmission lines and agricultural land values. Colwell and Sanders (2017) indicate that transmission lines have substantial negative impacts on agricultural land which have direct easements (i.e., for which the transmission line easement crosses part of the land) and several studies reveal negative impacts of nearby transmission lines on residential property values (e.g., Elliott and Wadley, 2002, and Tatos, Glick, and Lunt, 2016). We are unaware of hedonic property value evidence that explores how transmission lines impact nearby farmland values. Absent of any solar development in a region, we hypothesize that transmissions lines would have no effect on nearby agricultural land values or possibly a negative effect due to visual externalities. However, after solar development has occurred near an agricultural parcel, proximity to transmission infrastructure could be positively valued for the reasons stated above.

Data

Three main data sources are used in the empirical analysis. Zillow Research provided geospatially referenced confidential property transactions data that contain transaction prices for agricultural land from 2007-2019, the NC Clean Energy Technology Center provided data on solar farm locations and characteristics, and proprietary GIS on transmission infrastructure in NC was obtained from S&P Global Platts.[13]

The solar farm data include locations of 451 utility-scale ground-mount solar installations in NC that generate at least 1 MW of electric power. By using ArcGIS and satellite imagery in Google Earth and Google Maps, polygons that cover the physical outline of the solar farm panels were created for 428 of the 451 utility-scale solar farms. The remaining 23 solar farms were not yet visible in the latest aerial photography. Based on the GIS-constructed data, a 1 MW solar farm occupies 5.4 acres on average, while a 5 MW solar farm occupies 27.7 acres on average (see Appendix Table A1). These are lower bound estimates of the average land required since these polygons cover only the actual solar panels and do not include the additional land utilized to meet the setback and screening regulation requirements.[14]

In addition, data include information about each solar farm's operation start date as well as their respective capacities, which are summarized in Panel A, Table 1. The first three utility-scale solar farms were built in 2009 and the number of solar farms increased quickly afterwards (see also Figure 1). The size of solar farm installations also increased over time and reached an average size of 12.6 MW by 2017 (Panel A, Table 1). Many solar farms were built (completed)

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in 2015, the year when the NC tax credit program expired. Total installed capacity across 451 solar farms reached 2,895 MW as of August 2017, with the average solar farm generating about 5.4 MW.

To explore solar farm locations relative to the electricity infrastructure, the distance between each solar farm and the nearest transmission line is measured using ArcGIS and is summarized in Panel B, Table 1. The average distance between solar farms and transmission lines is less than one mile and although not reported in Table 1, approximately 90 percent of solar farms are built within two miles of the nearest transmission line. The maximum distance between any solar farm in the sample and a transmission line is 9.9 miles.

[Insert Table 1 here]

Table 2 reports summary statistics for characteristics of the land upon which solar farms are built. Land characteristics were obtained by overlaying solar farm boundaries with the 2006 National Land Cover Data (NLCD) layer, the year just prior to the first solar farm being built.[15] As indicated in Table 2, the average coverage for land that was later converted to a solar farm was 75 percent grass and 20 percent forested. The high percent of grass is not surprising given solar farms are concentrated in the rural counties of eastern NC as shown in Figure 2.

[Insert Table 2 here]

[Insert Figure 2 here]

Transactions data include information on agricultural land sales, sales prices, transaction dates, latitude and longitude of the property, acreage, and the number of buildings present. The sample is restricted to sales that are located within a 5-mile radius from the nearest solar farm because it is not expected that solar farms externalities would be discernable beyond that point.[16] The final sample is restricted to sales greater than 30 acres because, as reported in the previous

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section, more than 70 percent of solar farms are approximately 5 MW or larger in capacity and require no less than 30 acres on average. In addition, agricultural land larger than 30 acres is generally considered production-scale farmland, which is the focus of this research. As a robustness check, models are presented that include sales greater than 10 acres.

After examining the data, 202 sales located in western NC are dropped from the sample because land prices in this mountainous region of the state are likely to be determined by factors outside of agriculture such as tourism or residential development (Blake, 2013, see also Capozza and Hesley, 1989 and 1990, and Nickerson and Zhang, 2014, for a discussion of the role of urban development or its potential on US farmland values). Land classified as "vacant" are included in the analysis because land classification is coded differently across counties. For example, some predominantly agricultural counties (e.g., Nash and Wilson counties) record no sales in agriculture, although visual inspection shows transacted land that is clearly in agricultural production. Vacant land not included in the analysis are those classified as institutional, marsh, swamp, unusable land, conservation, or under construction (nine observations are dropped due to this restriction).

The data are trimmed of unusually low transaction prices because these may not represent arm's length transactions (e.g., transfers between family members or heirs), or are not suitable for agricultural production or solar development (e.g., marsh or swamp land). The data are also trimmed of unusually high transaction prices because they may represent land slated for residential or commercial development. While there is no clear evidence of what constitutes a minimum or maximum price per acre for land expected to stay in agricultural production, Zhang, Lence, and Kuethe (2021) rely on agricultural land sales professionals to determine a price range of $300 to $20,000 per acre for Iowa farmland. Similarly, we consulted a real estate appraisal

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expert in NC who suggested that farmland sales prices typically range between $1,000 and $10,000 per-acre in NC. [17] Thus, our main analysis uses a sample of sales between $1,000 and $10,000 per acre, and in robustness analyses we expand the sample to sales between $300 and $20,000 per acre.

The sample used in our main analysis consists of 1,676 land sales within five miles of 299 solar farms in 60 counties between 2007 and 2019. Table 3 reports summary statistics of the variables used in the analysis. The average price per acre of agricultural land is $3,343 (adjusted to 2019 using the consumer price index). The average size of a parcel sold is 82 acres, and ranges from 30 acres to over 1,300 acres.[18] Although not reported in Table 3, approximately 80 percent of sales are smaller than 100 acres. Appendix Figure A1 shows the distribution of agricultural land sales included in the final sample relative to solar farms.

[Insert Table 3 here]

Location characteristics for each sale were created using the Euclidean distance between the latitude and longitude of a sale to the boundary of the nearest solar farm that has already been constructed at the time of sale or the closest one that is yet to be built. As shown in Table 3, the average distance of a parcel in our sample to the nearest solar farm is 3.1 miles (recall, parcels must be within five miles of a current or future solar farm to be in the sample). Other location characteristics include distance to the nearest transmission line, city boundary, bodies of water, primary and secondary roads, airports, and recreational areas such as parks. The average distance to the nearest transmission line is 1.84 miles (see Table 3). Near zero, or zero distance implies that the land is adjacent to the characteristic, contains the characteristics, or is contained by the characteristic (e.g., distance to a city boundary equals zero if the land is located inside the city boundary).

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The data are further augmented by adding soil quality and land characteristics. Parcels are spatially matched with soil quality data obtained from the US Department of Agriculture's Natural Resources Conservation Service (https://www.nrcs.usda.gov/, last accessed June 2022). Land characteristics are created by spatially matching the latitude and longitude of each agricultural land sale as recorded by Zillow to a parcel boundary map obtained from NC OneMap (https://www.nconemap.gov/pages/parcels, last accessed June 2022). The parcel boundaries are then combined with the NLCD layers for 2006 and 2011 to create the coverage of each parcel in the closest year prior to the sale. As reported in Table 3, the agricultural parcels in our sample tend to be flat with high coverage of grassland (mean = 42%) and forest (mean = 38%). Also, on average, less than ten percent of each parcel is located within a 100-year floodplain or classified as wetland. We note that some sales are observed to have 100 percent of the parcel covered by wetlands. The reason for this could be due to the methodology used to create each agricultural sale's average soil and land cover characteristics. Our calculations include only the parcel that is directly linked to Zillow's latitude/longitude marker for the sale. However, this may be an imprecise characterization of the entirety of the land included in the sale because sales can include more than one legally defined parcel, which is the case for 18 percent of the sample. As such, we test the robustness of results to these covariates by estimating models with and without soil and land characteristics. All results for the key covariates discussed in Section 4 and 5 remain unchanged to inclusion/exclusion of these covariates and to the inclusion/exclusion of the sales that included more than one parcel.

4. Empirical Strategy

First consider a simple hedonic price function that only considers the direct impacts of a solar farm on neighboring agricultural land:

$$\ln\,(price\ per\ acre)_{jtcs} = \alpha + \beta * \ln(dist\_sf)_{jtcs} + \delta * After_{jtcs} + \gamma * \ln(dist\_sf)_{jtcs} * After_{jtcs}$$
$$+X_{jtc} * \theta + Z_{jtc} * \vartheta + \mu_s + \tau_{ct} + \epsilon_{jtcs}\ , \qquad [1]$$

where ln $(price\ per\ acre)_{jtcs}$ denotes the natural log of the per-acre sale price of agricultural parcel *j* that sold in year *t*, located in county *c*, and whose nearest solar farm is denoted by *s*. The term $\ln(dist\_sf)_{jtcs}$ is the natural log of distance between agricultural parcel *j* and its nearest solar farm, *s*, existing or to be constructed during the sample period. The binary variable $After_{jtcs}$ equals one if parcel *j* is sold after the nearest solar farm is built (i.e. year sold > year built). The interaction term, ln $(dist\_sf) * After$, captures any externalities associated with solar farms which are capitalized into property values. The terms X_{jtc} and Z_{jtc} are vectors of land and location characteristics, respectively, that were presented in Table 3. The term μ_s is a solar farm spatial fixed effect that captures any time-invariant, common unmeasured characteristics for all agricultural land sales whose nearest solar farm is *s*. County-by-year fixed effects are denoted by τ_{ct}, which captures any differential change in land values across counties over time that are not attributed to changes in land characteristics. Thus, our model coefficients are identified by the variation in agricultural parcels that occur within a five-mile radius of a particular solar farm (and within a specific county in a specific year).[19] Finally, $\alpha, \beta, \gamma, \delta, \theta$ and ϑ are coefficients to be estimated and ϵ_{jtcs} is the error term, which is clustered at the solar farm level.[20] The coefficient of interest is γ, which indicates whether landowners value/disvalue being in close proximity to a solar farm after its construction.

The model in equation [1] can be expanded to measure the potential option values that may affect sales prices post-construction of a solar farm by including proximity of agricultural sales to transmission lines:

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$$\ln(price\ per\ acre)_{jtcs} = \alpha + \beta * \ln(dist\_sf)_{jtcs} + \delta * \ln(dist\_tl)_{jtc} + \sigma * After_{jtcs}$$
$$+ \gamma * \ln(dist\_sf)_{jtcs} * After_{jtcs} + \varphi * \ln(dist\_tl)_{jtc} * After_{jtcs}$$
$$+ X_{jtc} * \theta + Z_{jtc} * \vartheta + \mu_s + \tau_{tc} + \epsilon_{jtcs}\ , \qquad [2]$$

where $\ln(dist\_tl)_{jtc}$ is the natural log of distance from agricultural parcel *j* that sold in year *t* in county *c* to the nearest transmission line. All other variables are as defined in equation [1]. The coefficient φ indicates whether landowners value being in close proximity to a transmission line after a solar farm is built in the area. The expectation is that once a solar farm is built nearby, landowners will recognize the option value associated with solar farm development and this value will be capitalized into sale prices for parcels located near electricity infrastructure (i.e., we expect $\varphi \leq 0$). The assumption underlying the specification in equation [2] is that that the transmission infrastructure is planned and built independently of where future solar farms might be located. High-voltage transmission infrastructure in eastern NC has largely been in place prior to construction of the first solar farm and new lines can take up to 10 years to build, which is longer than our sample period. Nonetheless, we note that violation of our assumption that transmission lines are not endogenously placed in response to solar farm construction would bias the coefficient estimate for $\ln(dist\_tl) * After$.

5. Results

Table 4 reports key coefficient estimates for equation [2] estimated with the sample including all parcels with 30 or more acres. Columns (1) presents coefficient estimates based on the most restricted sample that includes only sales between $1,000 to $7,000 per acre, and column (4) presents the least restrictive sample that includes all sales between $300 and $10,000 per acre. All models include location and land characteristics described in Table 3 and also include county-by-year and solar-farm fixed effects.[21] Robust standard errors clustered at solar

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farm level are reported in parentheses. Appendix Table A3 reports results where standard errors are clustered at the county level or using Conley standard errors.

As indicated in Table 4, the coefficient estimates for ln*(dist_sf)* are small, highly insignificant, and inconsistently signed across models, which suggests that prior to development of a solar farm, there are no systematic features of the land where a future solar farm will be built that affects neighboring property values. Furthermore, the coefficient estimates for ln*(dist_sf)* x *After* are also inconsistently signed across models and are never statistically significant, indicating that proximity to a solar farm after it is built has no statistically significant effect on agricultural land values.

[Insert Table 4 here]

Coefficient estimates for distance to a transmission line prior to a solar farm being built (*dist_tl*) suggest that transmission lines are potentially a disamenity for agricultural land buyers. The coefficient is always positive, but only statistically significant in models including only parcels that sold for $1,000 or more per acre, suggesting a negative effect for prime farmland. We explore this result further to determine if it is driven by the potential interference with land productivity created by easements when transmission lines cross private agricultural land as suggested by Colwell and Sanders (2017). While our data do not allow us to distinguish precisely when a meaningful easement is present (e.g., when the easement cuts across a field versus an area that would not have been used for crops anyway), we explore this issue by creating a variable, *Easement*, that is equal to one when a transmission line crosses the boundary of the parcel included in the sale and equal to zero otherwise. There are 149 parcels (7.5%) in the largest sample of 1,986 sales for which transmission lines cross the boundary of the parcel

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associated with the sale. Appendix Table A4 reports results that include this variable and are suggestive that the negative externality of transmission lines are primarily driven by easements.[22]

Interestingly, the models also indicate that agricultural lands fully recover any negative values experienced as a result of being near a transmission line after a solar farm is constructed nearby. Specifically, ln*(dist_tl)* x *After* is always negative, statistically significant, and greater in magnitude than the coefficient for ln(*dist_tl*). Wald tests indicate that the sum {ln*(dist_tl)* + ln*(dist_tl)* x *After*} is less than zero for one model and not statistically different than zero for the remaining models. In fact, across all samples and model variations tested, there is never an instance in which proximity to transmission lines is estimated to be a negative externality after a solar farm is constructed within five miles of the parcels in question. Specifically, the direction of the effect is always positive, but rarely statistically significant. [23]

To put these results in perspective, consider a parcel that sells for the mean per-acre price of $3,343 (2019 dollars) and which is located the mean distance from a transmission line (1.84 miles). Results from Table 4, column (3) suggests a statistically significant positive effect of proximity to a transmission line after a solar farm is constructed (Wald test p-value is less than 0.10). This model suggests that after a nearby solar farm is constructed, a parcel would sell for $136 more per acre (4.1% of the mean sales price) if it was located 0.84 miles from a transmission line as compared to 1.84 miles. We find this estimate to be within reason given that locating a solar farm one-mile closer to high-voltage transmission infrastructure can reduce a developer's upfront costs by over $1 million.[24]

We explore the sensitivity of our results to the parcels included in the models. Appendix Table A5 presents key coefficients for models which include agricultural land sales over 10 acres. While land under 30 acres is generally not considered prime agricultural land, we

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nonetheless see qualitatively similar results as presented in Table 4. Namely, proximity to a solar farm has no impact on land values, and after a solar farm is constructed, proximity of a parcel to transmission lines is more highly valued. We note however that the coefficient magnitudes for proximity to a transmission line are smaller than in Table 4, and the coefficients lose statistical significance in the two most restricted samples. This attenuation of the coefficients might be expected if there are transactions costs associated with aggregating smaller parcels to create a footprint large enough for the solar farm.[25]

Table 5 presents models that explore the sensitivity of our results to a variety of sample and specification choices. The models follow the sample and specification for model (2) in Table 4, except where specifically noted. Model (1), (2) and (3) in Table 5 trim the sample in various ways to exclude transactions that may not be for production agriculture (i.e., the land is purchased to be developed as commercial or residential), while models (4) and (5) consider the potential influence of particularly large parcels (>1,000 acres) and particularly large solar farms (>5 MW).[26] Model (6) and (7) presented in Panel B expand the sample to include parcels within seven miles of a solar farm and whose sales prices range from $300 to $20,000 per acre, respectively. Models (8), (9) and (10) explore sensitivity to specification choice. Model (8) excludes transmission line proximity from the model and model (9) excludes land cover characteristics that are likely to suffer from measurement error as discussed earlier. Finally, model (10) recodes the variable *After* to be equal to one in the year prior to a solar farm being completed, and each year thereafter (see equation [1] for the definition of *After*), thus allowing the construction phase of a solar farm to also impact surrounding land values.

Across models in Table 5, it is apparent that proximity to a solar farm does not have a statistically significant effect on nearby agricultural land values. Overall, the results with respect to proximity to a transmission line are largely consistent with the results reported in Table 4. Namely, if transmission lines are found to have negative spillover effects, the construction of a nearby solar farm eliminates this negative influence.

[Insert Table 5 here]

Although not reported for succinctness, each model presented in Table 5 is estimated on samples that match Table 4, columns 1, 3 and 4, and results remain unchanged. Also, we estimate log-linear models duplicating the models presented in Table 4 and results remain unchanged: proximity to a solar farm, before or after its construction, is never statistically significant, and proximity to a transmission line is positively valued after construction of a nearby solar farm and is statistically significant at the 10% level in two of the four models. Finally, we estimate models in which linear measures of distance to a solar farm or transmission line is replaced with distance categories. We create five categories that capture proximity of a parcel to a solar farm or transmission line: (adjacent, 0.5], (0.5-1.0], (1.0-1.5], (1.5-2.0], and >2.0 miles. Models again support our main conclusions that proximity to a solar farm does not affect nearby agricultural land values, but proximity to a transmission line (closer than two miles) is positively valued after a solar farm is built nearby.

6. Conclusions

The fast-paced growth of ground-level, utility-scale solar installations in some regions of the U.S. have led to conflict within communities about land-use choices, especially in rural areas where some stakeholders have expressed concerns about the loss of farmland and the potential negative impacts of solar farms on neighboring properties. We provide quantitative evidence for these debates by examining whether solar farm construction impacts neighboring land values. If

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there are negative (or positive) effects of solar farms on neighbors, we should see those values reflected in agricultural land markets.

Agricultural land sales surrounding 451 solar farms in North Carolina are examined and across many samples and empirical specifications, we find no direct negative or positive spillover effect of a solar farm construction on nearby agricultural land values. Although we find no direct effects of solar farms on nearby agricultural land values, we do find evidence that suggests construction of a solar farm may create a positive option-value for landowners that is capitalized into land prices. Specifically, after construction of a nearby solar farm, we find that agricultural land that is also located near transmission infrastructure could increase in value. This latter result is also of note given the difficulty in siting transmission lines. Our results suggest one instance where proximity to transmission infrastructure may result in pecuniary benefits for landowners.

Although our results consistently indicate that solar farms do not directly impact nearby agricultural property values, we also note that our results only apply within the context of our study. We cannot inform debates around longer-term effects of solar development on agricultural land values (longer than 10 years), or effects that could occur if greater penetration of solar development is observed as compared to our sample. For example, concerns have been expressed that as solar displaces traditional agricultural production in a region, local supply chains could suffer and lead to a negative cycle in which more farmers exit the industry and supply chains further weaken. This type of general equilibrium effect would require significantly more solar penetration than already observed in North Carolina and thus we cannot empirically evaluate these concerns.

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Table 1. Solar farm summary statistics.[a]

Panel A. Solar farm summary statistics by year of construction

Year	# of Facilities Built Each Year	Total New Capacity (MW)	Mean New Capacity (MW)	Std. Dev.	Min Capacity	Max Capacity
2009	3	9.5	3.2	3.6	1	7.3
2010	5	14.4	2.9	4.0	1	10
2011	9	21.8	2.4	1.9	1	5
2012	29	125.1	4.3	3.7	1	20
2013	49	231.2	4.7	3.4	1	20
2014	86	402.8	4.7	2.9	1	20
2015	145	968.3	6.7	9.6	1.5	80
2016	89	668.9	7.5	12.0	1.2	78.5
2017	36	452.9	12.6	18.2	1.9	78.7
Total	451	2,895	5.4	6.6	1.0	80.0

Panel B. Distance (miles) between a solar farm and the nearest transmission line by year of construction

Year	# of Facilities Built Each Year	Mean Distance to a Transmission Line	SD	Min[b]	Max
2009	3	0.17	0.21	0.01	0.47
2010	5	0.40	0.22	0.04	0.74
2011	9	0.91	1.22	0.01	3.89
2012	29	0.79	1.11	0	4.45
2013	49	0.91	1.33	0	5.54
2014	86	0.94	1.22	0	5.28
2015	145	0.87	1.31	0	9.90
2016	89	0.61	0.64	0	2.41
2017	36	0.74	1.03	0	3.26
Total	451	0.70	0.92	0	9.90

[a] The last solar farm in the sample was built in August 2017.

[b] A minimum distance to the nearest transmission line of zero indicates that the solar farm boundaries are adjacent to the nearest transmission line.

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Table 2. Characteristics of land upon which solar farms are eventually built.[a]

Land Characteristics in 2006	Mean	Std. Dev.	Min	Max
Water (%)	<0.01	0.0029	0	0.06
Open Space development (%)[b]	3.54	9.34	0	89.40
Low Intensity development (%)[c]	0.62	3.23	0	36.80
Medium Intensity development (%)[d]	0.17	2.30	0	46.59
High Intensity development (%)	<0.01	0.041	0	0.84
Barren (%)	0.17	1.33	0	18.35
Forest (%)	19.93	31.21	0	100
Grass (%)	74.74	32.45	0	100
Wetland (%)[e]	0.82	3.50	0	35.99

[a] The NLCD layer for 2006 is used to construct land characteristics for parcels prior to the installation of a solar farm.

[b] Open space development is a mixture of constructed materials and vegetation, where impervious surface accounts for less than 20 percent of total cover.

[c] Low intensity development contains up to 49 percent impervious surface. Five parcels had more than 10 percent of low intensity development prior to solar farm construction. These observations also had some parking lot coverage prior to solar farm development.

[d] Medium intensity development is defined by the NLCD as a mix of constructed materials and vegetation that contains up to 79 percent impervious surface. There is only one observation with more than six percent of medium intensity development prior to solar farm construction and visual inspection from Google Earth 2006 imagery indicates this parcel had a large parking lot on the land prior to development.

[e] The NLCD defines wetlands as areas where more than 20 percent of vegetative cover is either forest or shrubland and is periodically soaked with water. Eight parcels had more than 10 percent wetland coverage prior to solar farm construction. Visual inspection from Google earth imagery did not indicate any water coverage on the parcels.

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Table 3. Agricultural land sales summary statistics (N=1,676 sales).[a]

	Unit	Mean	Std. dev.	Min	Max
Transaction Information[b]					
Sales Price (2019 dollars)	Dollars	227,143	271,598	27,118	5,301,988
Price per acre (2019 dollars)	Dollars	3,343	1,977	1,000	9,988
Total acres	acres	82	88	30	1,394
Buildings	Number	0.06	0.25	0	2
Location Characteristics[c]					
Distance to nearest solar farm	mile	3.10	1.28	0.04	5.00
Distance to nearest transmission line	mile	1.84	1.64	<0.001	11.23
Distance to nearest river	mile	0.27	0.19	<0.001	1.30
Distance to nearest lake	mile	1.61	1.41	0	9.63
Distance to nearest primary road	mile	1.12	0.95	<0.001	5.56
Distance to nearest secondary road	mile	0.18	0.19	<0.001	1.71
Distance to nearest city boundary	mile	2.50	2.16	0	13.72
Distance to nearest recreational land	mile	9.79	5.83	0	36.18
Distance to nearest airport	mile	26.63	15.24	0.53	94.81
Soil Characteristics and Land Cover[c]					
Well drained	binary	0.67	0.47	0	1
Best soil	binary	0.88	0.33	0	1
Soil loss tolerance factor (T factor)	Tons	4.5	1.0	1	5
Representative slope	degrees	4.8	4.1	0.7	35
Water (% of parcel coverage)	%	0.43	0.03	0	1
Wetland (% of parcel coverage)	%	9.82	0.18	0	1
Developed (% of parcel coverage)	%	7.46	0.15	0	1
Grassland (% of parcel coverage)	%	42.01	0.31	0	1
Forest (% of parcel coverage)	%	37.97	0.32	0	1
Barren (% of parcel coverage)	%	0.17	0.02	0	1
% of parcel within 100 year flood plain	%	6.16	0.17	0	1

[a] The sample upon which the summary statistics are calculated include 1,676 land sales between 2007 and 2019 around 299 solar farms built between 2009 and 2017.

[b] Source: Zillow Research (2019), Zillow Transaction and Assessment Dataset (ZTRAX).

[c] Authors calculations based on sources for parcel boundaries (https://www.nconemap.gov/pages/parcels), land characteristics (https://www.mrlc.gov/), and soil quality (https://www.nrcs.usda.gov/).

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Table 4. Select coefficient estimates for agricultural land sales over 30 acres.[a]

	Sample Includes:			
	Sale prices from \$1,000 to \$7,000 per acre	**Sale prices from \$1,000 to \$10,000 per acre**	**Sale prices from \$300 to \$7,000 per acre**	**Sale prices from \$300 to \$10,000 per acre**
	(1)	**(2)**	**(3)**	**(4)**
ln *(dist_sf)*	-0.003	0.008	-0.042	-0.022
	(0.047)	(0.051)	(0.055)	(0.058)
After	0.158	0.164	-0.050	-0.065
	(0.159)	(0.182)	(0.183)	(0.195)
ln *(dist_sf)* x *After*	-0.007	-0.011	0.056	0.066
	(0.069)	(0.071)	(0.088)	(0.089)
ln *(dist_tl)*	0.043*	0.044*	0.024	0.037
	(0.023)	(0.023)	(0.029)	(0.029)
ln *(dist_tl)* x *After*	-0.084**	-0.073**	-0.099*	-0.099**
	(0.036)	(0.036)	(0.050)	(0.048)
Adjusted R2	0.185	0.238	0.125	0.167
Observations	1,555	1,676	1,865	1,986
Wald test[b]	1.662	0.900	3.378	2.527
P-value	(0.198)	(0.343)	(0.067)	(0.113)

[a] The dependent variable is the natural log of sales price per acre. Agricultural land that sold between 2007 and 2019 and which are within 5 miles of the nearest solar farm are included in the sample. All models include all spatial and land characteristics as described in Table 3, as well as county-by-year fixed effects and solar farm fixed effects. Robust standard errors clustered at solar farm level are in parentheses, and *** p<0.01, ** p<0.05, and * p<0.1.
[b] Wald test is for ln *(dist_tl)* + ln *(dist_tl)* x *After* = 0, and the corresponding p-value is in the next row.

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Table 5. Robustness analysis: select coefficient estimates for agricultural land sales.[a]

Panel A: Sample Robustness[b]					
	Excluding Residential Vacant (1)	**Excluding Urban Counties (2)**	**Only parcels recorded as agricultural (3)**	**Only Parcels <1,000 acres (4)**	**Only Solar farms <5MW (5)**
ln *(dist_sf)*	0.024	-0.002	0.054	0.010	-0.017
	(0.066)	(0.055)	(0.103)	(0.051)	(0.058)
After	0.131	0.124	0.272	0.168	0.161
	(0.191)	(0.203)	(0.287)	(0.182)	(0.202)
ln *(dist_sf)* x *After*	0.013	-0.002	-0.047	-0.015	0.020
	(0.088)	(0.082)	(0.144)	(0.070)	(0.083)
ln *(dist_tl)*	0.029	0.055**	0.060*	0.044*	0.046*
	(0.025)	(0.026)	(0.036)	(0.023)	(0.026)
ln *(dist_tl)* x *After*	-0.053	-0.077*	-0.109**	-0.073**	-0.081**
	(0.041)	(0.043)	(0.054)	(0.036)	(0.040)
Adjusted R2	0.251	0.240	0.331	0.238	0.238
Observations	1,380	1,435	597	1,674	1,444
Wald test[c]	0.525	0.376	1.192	0.860	1.115
P-value	(0.469)	(0.540)	(0.277)	(0.355)	(0.292)
Panel B: Sample and Specification Robustness[c]					
	Parcels up to 7 miles from a solar farm (6)	**Sales prices from \$300 to \$20,000/acre (7)**	**Excluding transmission lines (8)**	**Excluding land characteristics (9)**	***After* = 1 one-year prior to SF build (10)**
ln *(dist_sf)*	0.008	-0.002	0.028	0.003	0.031
	(0.042)	(0.057)	(0.050)	(0.051)	(0.059)
After	0.211*	-0.191	0.204	0.158	0.038
	(0.113)	(0.187)	(0.177)	(0.186)	(0.129)
ln *(dist_sf)* x *After*	-0.046	0.080	-0.044	-0.005	-0.051
	(0.059)	(0.091)	(0.070)	(0.070)	(0.071)
ln *(dist_tl)*	0.006	0.030	--	0.042*	0.039
	(0.019)	(0.029)		(0.023)	(0.026)
ln *(dist_tl)* x *After*	-0.022	-0.088*	--	-0.075**	-0.044
	(0.029)	(0.047)		(0.036)	(0.036)
Adjusted R2	0.212	0.238	0.234	0.241	0.235
Observations	2,277	2,102	1,676	1,676	1,676
Wald test	0.394	2.382	--	1.178	0.046
P-value	(0.531)	(0.124)	--	(0.279)	(0.831)

[a] The dependent variable is the natural log of sales price per acre. All models follow the specification and sample in Table 4, model (2), with variations as noted in the column header and footnotes b and c. Robust standard errors clustered at solar farm level are in parentheses, and *** p<0.01, ** p<0.05, and * p<0.1

[b] Model (1) excludes vacant land that is classified as residential. Model (2) excludes counties coded as "urban" (see notes to Figure 2). Model (3) includes only sales coded as "Agricultural" by county tax assessor offices (thus, excluding "Vacant" land). Model (4) excludes sales larger than 1,000 acres and Model (5) includes only sales located around solar farms with 5MW or smaller capacity.

[c] Model (6) includes parcels located seven miles of a solar farm (existing or yet to be constructed). Model (7) expands the sample to include sales with prices up to \$20,000 per acre. Model (8) reports coefficient estimates for equation [1] and thus excludes distance to a transmission line from the analysis. Model (9) excludes soil and land cover characteristics from the model. Model (10) recodes *After* = 1 (see equation [1] for a definition) one year prior to a solar farm being completed and each year after.

[c] Wald test for ln*(dist_tl)* + ln*(dist_tl)* x *After* = 0, and the corresponding p-value is in the next row.

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Figure 1. Number of solar farms and cumulative installed capacity by years.

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Figure 2. Distribution of solar farms across North Carolina, by installed MW.

Notes: Counties with density that exceeds 750 people per square mile are classified as urban, counties with density between 250 – 750 people per square mile are sub-urban, and counties with density less than 250 people per square mile are defined as rural (https://www.ncruralcenter.org/about-us/).

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FOOTNOTES

[1] U.S. Energy Information Administration, https://www.eia.gov/energyexplained/electricity/electricity-in-the-us-generation-capacity-and-sales.php, last accessed June 2022.

[2] U.S. Energy Information Administration, https://www.eia.gov/todayinenergy/detail.php?id=47636, last accessed June 2022.

[3] U.S. Energy Information Administration, https://www.eia.gov/state/analysis.php?sid=NC#37, last accessed June 2022.

[4] Examples of conflict between solar development and agricultural communities are seen in many states including Connecticut (https://ctmirror.org/2017/02/21/new-farmland-harvest-solar-energy-creating-political-sparks/), Maryland (https://www.baltimoresun.com/maryland/bs-md-renewable-energy-conflict-20161015-story.html), New Jersey (https://www.njspotlight.com/2020/08/utility-scale-solar-agricultural-land-state-clean-energy-goals-ratepayer-costs/), North Carolina (https://www.carolinajournal.com/news-article/rural-solar-developments-pit-neighbor-against-neighbor/), Oregon (https://www.opb.org/news/article/solar-development-farmland-oregon-ban/), and Virginia (https://www.npr.org/2019/03/25/706546214/a-battle-is-raging-over-the-largest-solar-farm-east-of-the-rockies). All sites last accessed June 2022.

[5] By 2020, moratoriums on solar development had been implemented in at least seven NC counties, and one township had banned solar farms within its jurisdiction.

[6] In contrast to the negative spillover of being located near a solar farm, several studies have shown that equipping a home with rooftop solar panels can increase the value of the home with an installation (Qiu, Wang, and Want, 2017, Hoen et al. 2017, Dastrup et al. 2012, Adomatis and Hoen, 2016, and Wee, 2016). Gaur et al. (2022) conduct a choice experiment survey and find that land use prior to solar development is an important factor shaping respondents' preferences. Specifically, respondents are willing to pay between \$15 to \$19 per month if a fully visible solar farm is constructed on brownfields or commercial lands, and need to be compensated between \$13 and \$49 per month if the solar farm is sited on farmlands or forest lands..

[7] A related empirical question is whether land with a solar farm already installed sells for more than nearby land without a solar farm. Unfortunately, our data do not allow us to explore this question as we observe only three sales for land after a solar farm is installed. We note, however, that these three transactions sold for double the mean price-per-acre observed for our full sample of agricultural sales.

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

[9] We thank the NC Clean Energy Technology Center at North Carolina State University for providing georeferenced data on ground-mount solar farms in North Carolina.

[10] In California and Arizona, most of the large, ground-level solar systems are installed in desert areas, thus providing less potential to examine externality effects of the solar farms on agricultural (or residential) land values.

[11] The federal investment-tax credit declined to 26 percent in 2020, 22 percent in 2021, and to ten percent thereafter.

[12] For additional details on solar farm siting processes, see the *2013 Template Solar Energy Development Ordinance* prepared by NCSEA and NC Clean Energy Technology Center, available at https://nccleantech.ncsu.edu/wp-content/uploads/2018/06/NC-Template-Solar-Ordinance.pdf, last accessed August 2022.

[13] Data on electric infrastructure included transmission lines and substations are proprietary and were obtained from S&P Global Platts (https://www.spglobal.com/platts/en/products-services/electric-power/north-american-electric-transmission-system-map).

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[14] Kikuma, Rublev, and Tan (2018), NCSEA (2017), NCSEA and NC Department of Agriculture and Consumer Service (2016) also suggest similar acreage is needed for one and five MW solar farms.

[15] The NLCD is available every five years since 2001 (https://www.usgs.gov/centers/eros/science/national-land-cover-database).

[16] We also estimate models including sales located within a 7-mile radius from the nearest solar farm. Results remain qualitatively unchanged and are discussed further in Section 5.

[17] We thank Rich Kirkland for his valuable insights regarding agriculture land values in NC.

[18] Appendix Table A2 reports summary statistics for the largest sample that includes sales between $300 and $20,000 per acre around 309 solar farms.

[19] For a discussion of spatial fixed effects in hedonic models, see Kuminoff, Parmeter, and Pope (2010).

[20] We also estimate each model with standard errors clustered at the county-level or using Conley standard errors (Hsiang, 2010) and report these in Appendix Table A3. Hypothesis tests and overall conclusions remain the same.

[21] The full set of covariates are reported in Appendix Table A2, excluding the solar-farm fixed effects and the county-by-year fixed effects. Briefly, coefficient estimates in Table A2 indicate that larger parcels sell for lower prices per acre, on average. This inverse relationship between price per acre of agricultural land and parcel size is consistent with the findings of Miller (2006), Ma and Swinton (2012), and Brorsen, Doye, and Neal (2015). Results also indicate that parcels with greater water coverage and closer proximity to a city boundary are associated with higher prices per acre. Proximity to a secondary road has a negative influence on agricultural land that is very close to the road (less than one-half mile), but a positive effect on prices for distances greater than one-half mile. Other variables are not statistically distinguishable from zero.

[22] Note, our sales data only contains a single latitude-longitude marker per sale. To obtain parcel boundaries, we map these markers to the NC OneMap GIS (see Section 3). However, 18 percent of our sales included more than parcel (whose boundaries we do not have), making it difficult to determine the relationship between transmission lines and the entirety of the acreage purchased. Results are nearly identical to those presented in Appendix Table A4 when we drop sales with one more than parcel.

[23] The coefficient estimates remain qualitatively unchanged when restricting the sample to agricultural land sales within five miles of only a single solar farm (Haninger, Ma and Timmins, 2017).

[24] Solar developers must build transmission lines to connect the solar farm to high-voltage transmission lines. These construction costs are estimated to vary between $400,000 per mile for a 138 kV single circuit line to well over $1 million per mile for a 345 kV single circuit line (Public Service Commission of Wisconsin, 2011, Western Electricity Coordinating Council, 2014). We note that there is the possibility of transmission line "congestion" that could dimmish the ability to develop new solar farms in a particular location. Our models estimate the average effect of the value of proximity to a transmission line, which would be inclusive of this congestion effect when present and understood by the market. If market participants are uninformed, then the average value of proximity to transmission lines after a nearby solar farm is built (i.e., the coefficient on $ln(dist\_tl) \times After$) is inflated relative to a fully informed market. See Pope (2008) for a discussion on the effects of buyer information in hedonic property models.

[25] Transactions costs could include negotiating and contracting with multiple landowners or removing trees and natural areas that may exist at parcel boundaries. An apparent preference for single-parcel installations is evidenced by the fact that 81 percent of solar farms in the sample are built on a single parcel (and 96 percent are constructed on one or two parcels).

[26] Models were also estimated including only parcels less than 200 acres and less than 80 acres (approximately the 95^{th} and 75^{th} percentile in the sample, respectively). Results remain qualitatively unchanged: solar farms do not affect nearby property values after their construction, except that land that is also close to transmission lines experiences a positive influence on price after the construction of a nearby solar farm.

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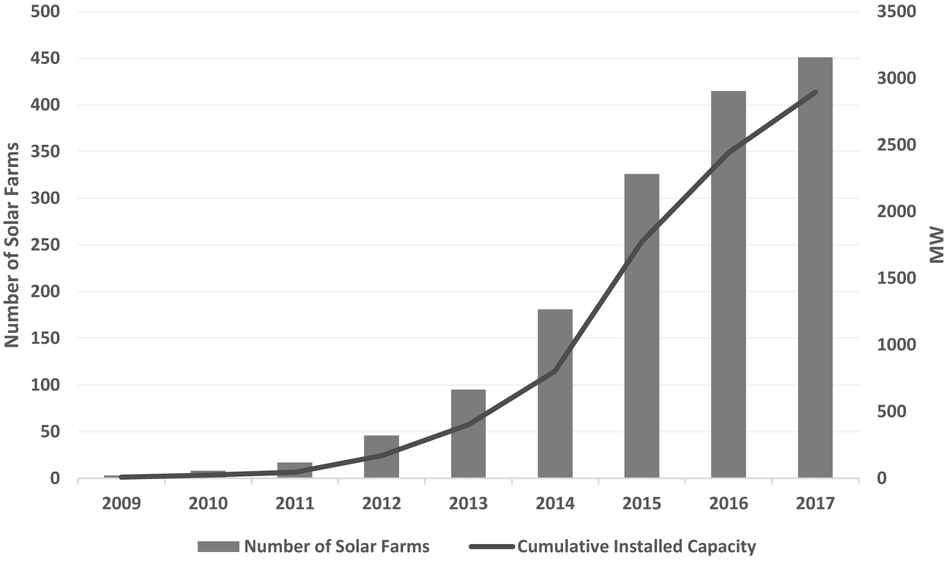
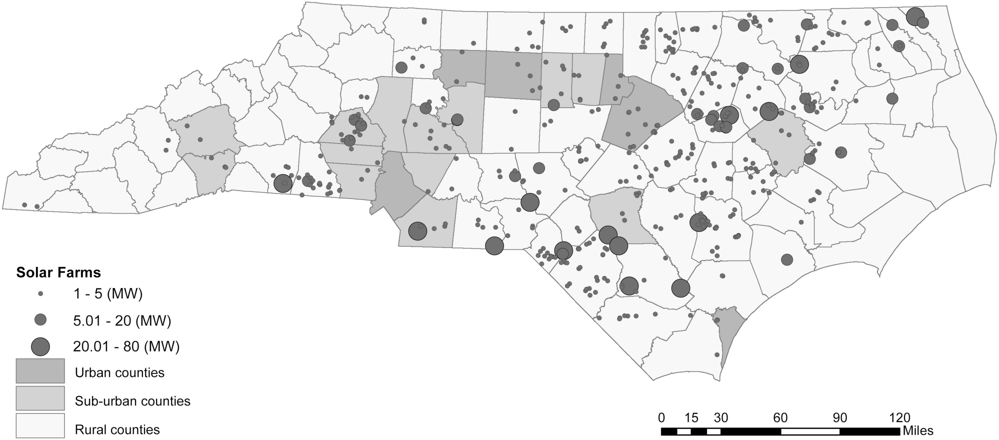


Number of Solar Farms
MW
0
50
100
150
200
250
300
350
400
450
500
0
500
1000
1500
2000
2500
3000
3500
2009
2010
2011
2012
2013
2014
2015
2016
2017
Number of Solar Farms
Cumulative Installed Capacity

Downl


Solar Farms
1 - 5 (MW)
5.01 - 20 (MW)
20.01 - 80 (MW)
Urban counties
Sub-urban counties
Rural counties
0 15 30 60 90 120
Miles