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# Spatial patterns of solar photovoltaic system adoption: The influence of neighbors and the built environment[‡]

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## Abstract

The diffusion of new technologies is often mediated by spatial and socioeconomic factors. This article empirically examines the diffusion of an important renewable energy technology: residential solar photovoltaic (PV) systems. Using detailed data on PV installations in Connecticut, we identify the spatial patterns of diffusion, which indicate considerable clustering of adoptions. This clustering does not simply follow the spatial distribution of income or population. We find that smaller centers contribute to adoption more than larger urban areas, in a wave-like centrifugal pattern. Our empirical estimation demonstrates a strong relationship between adoption and the number of nearby previously installed systems as well as built environment and policy variables. The effect of nearby systems diminishes with distance and time, suggesting a spatial neighbor effect conveyed through social interaction and visibility. These results disentangle the process of diffusion of PV systems and provide guidance to stakeholders in the solar market.

**Keywords:** Peer effects, neighbor effects, renewable energy, technology diffusion
**JEL classifications:** R11, R12, Q42, O33
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## 1. Introduction

Economists and geographers have long been interested in the factors governing the patterns of diffusion of new technologies. Since the work of Hägerstrand (1952) and Rogers (1962), many authors have explored the characteristics of technology diffusion and the role of policies, economic factors and social interactions in influencing the waves of diffusion seen for many new products (Bass, 1969; Brown, 1981; Webber, 2006). Understanding the patterns of diffusion—and particularly spatial patterns—is important not only from a scholarly perspective, but also from a policy and marketing

‡ This article is a chapter in Marcello Graziano's dissertation at the University of Connecticut.

perspective. This is especially true when examining the diffusion of technologies with both private and public good characteristics, such as renewable energy technologies.

This article examines the spatial pattern of adoption of an increasingly important renewable energy technology: residential rooftop solar photovoltaic systems (henceforth 'PV systems'). Our study area is the state of Connecticut (CT), which has actively used state policy to promote PV system adoption. We explore the patterns of diffusion using geostatistical approaches, finding that diffusion of PV systems in CT tends to emanate from smaller and midsized population centers in a wave-like centrifugal pattern. To explain the factors underlying these patterns of adoption, we perform a panel data analysis of the effects of nearby previous adoptions, built environment and demographic, socioeconomic and political affiliation variables on PV system adoptions. We develop a novel set of spatiotemporal variables that both capture recent nearby adoptions and retain the ability to control for unobserved heterogeneity at the Census block group level. We find clear evidence of spatial neighbor effects (often known as 'peer effects') from recent nearby adoptions that diminish over time and space. For example, our results indicate that adding one more installation within 0.5 miles of adopting households in the year prior to the adoption increases the number of installations in a block group by 0.44 PV systems on average. We also develop a new panel dataset of demographics and built environment variables that allows for a detailed examination of other contextual factors of adoption. Our results indicate that built environment variables, such as housing density and the share of renter-occupied dwellings, are even more important factors influencing adoption than household income or political affiliation in CT.

Several recent studies have explored the diffusion of PV systems in different contexts. McEachern and Hanson (2008) study the adoption process of PV systems across 120 villages in Sri Lanka and find that PV system adoption is driven by expectations of whether the government will connect the villages to the electricity grid, as well as tolerance for non-conformist behavior in the villages. Such findings suggest the possibility of social interactions influencing the decision to adopt a PV system, in line with a large literature on spatial knowledge spillovers in the form of neighbor or peer effects (Glaeser et al., 1992; Foster and Rosenzweig, 1995; Bayer et al., 2009; Conley and Udry, 2010; Towe and Chad, 2013).

Bollinger and Gillingham (2012) are the first to demonstrate an effect of previous nearby adoptions on PV system adoption. Specifically, Bollinger and Gillingham use a large dataset of PV system adoptions in California to show that one additional previous installation in a zip code increases the probability of a new adoption in that zip code by 0.78%. Bollinger and Gillingham find evidence of even stronger neighbor effects at the street level within a zip code and use a quasi-experiment to verify their results. Richter (2013) uses a similar empirical strategy to find small, but statistically significant, neighbor effects in PV system adoption at the postcode district level in the United Kingdom. Both studies artificially constrain such effects along postal boundaries, potentially risking spatial measurement error. Our analysis avoids such artificial boundaries to provide a more precise understanding of how neighbor effects dissipate over space. At the same time, we are also the first to demonstrate how such effects dissipate as the time between adoptions increases. Moreover, these previous studies do not explore the spatial patterns of diffusion PV systems, which may provide insight into future technology diffusion.

Rode and Weber (2013) use spatial bands around grid points to reduce the possible measurement error bias from artificial borders. Using an epidemic diffusion model, they estimate localized imitative adoption behavior in Germany that diminishes over space. Their approach uses over 550,000 observations coded around a grid of points 4–20 km apart covering Germany. Müller and Rode (2013) focus on a single city in Germany, Wiesbaden, and use the actual physical distance between new adoptions in a binary panel logit model. Müller and Rode also find a clear statistically significant relationship between previous nearby adoptions that diminish with distance.[1] Neither Rode and Weber (2013) nor Müller and Rode (2013) explore the spatial patterns of diffusion or other factors that may influence PV system adoption.

All studies attempting to identify a spatial neighbor or peer effect must argue that they overcome the classic identification challenges of identifying peer effects: homophily, correlated unobservables and simultaneity (Brock and Durlauf, 2001; Manski, 1993; Moffit, 2001; Soetevent, 2006). Homophily, or self-selection of peers, could bias an estimate of a spatial peer effect upward if neighbors with similar views and interests move to the same neighborhoods. In this case, the coefficient on the previous nearby installations would simply capture common preferences. Correlated unobservables, such as localized marketing campaigns, would also clearly pose an endogeneity concern. Finally, simultaneity or 'reflection' could also bias estimates to the extent that one is affected by their peers just as their peers affect them.[2]

Hartmann et al. (2008) discuss approaches to address each of these identification issues, including the fixed effects and quasi-experimental approaches taken in some studies, such as Bollinger and Gillingham (2012). In this study, we address the possibility of homophily with a rich set of fixed effects at the Census block group level. To control for the possibility of time-varying correlated unobservables, we include block group-semester fixed effects. Finally, simultaneity is not a concern for our estimation of spatial neighbor effects because we use previously installed PV systems. Our fixed effects strategy also addresses potential confounders for the other factors we examine that may influence the adoption of PV systems. Our empirical strategy combined with our new spatiotemporal variables provides new insight into the spatial and temporal nature of solar PV neighbor effects, as well as other factors that mediate the diffusion of solar PV.

The remainder of the article is organized as follows. In Section 2, we provide institutional background on the solar PV system market in our area of study, CT. In Section 3 we present our data sources and summarize our detailed dataset of PV systems in CT. Section 4 analyzes the spatial patterns of diffusion of PV systems using geostatistical approaches. In Section 5 we describe our approach to empirical estimation, including the development of our spatiotemporal variables, our empirical model and our identification strategy. Section 6 presents our empirical results, showing the primary factors that have influenced diffusion of solar PV in CT, such as spatial neighbor effects and area geography. Finally, Section 7 concludes with a discussion of our findings and policy implications.

1 Rai and Robinson (2013) provide further evidence suggestive of neighbor effects with survey data of PV adopters in Austin, Texas. Of the 28% of the 365 respondents who were not the first in their neighborhood to install, the vast majority expressed that their neighbors provided useful information for their decision.

2 See Bollinger and Gillingham (2012) for a mathematical exposition of each of these issues.

## 2. Background on solar policy in CT

The state of CT is a valuable study area for the diffusion of PV systems. Despite less solar insolation when compared with more southerly states, CT is surprisingly well suited for solar, with high electricity prices, a relatively dispersed population with many suitable rooftops and few other renewable energy resources (EIA, 2013; REMI, 2007). Moreover, the CT state government has been very supportive of solar PV technology, with several ambitious state programs. At the utility level, electric suppliers and distribution companies in CT are mandated to meet a Renewable Portfolio Standard (RPS) that requires 23% of electricity to be generated by renewable energy sources by 2020. Furthermore, CT Public Act 11-80 of 2011 requires the CT Clean Energy Finance and Investment Authority (CEFIA) to develop programs leading to at least 30 MW of new residential solar PV by 31 December 2022. This solar energy can be used in support of the utility RPS requirement, leading to more utility support for PV systems than in other states (DSIRE, 2013).

The CEFIA programs involve state incentives, which started at $5/W in 2005 and are currently $1.25/W for resident-owned systems up to 5 kW (there is a similar incentive scheme for third-party owned systems), as well as a series of community-based programs to promote PV systems (Cadmus Group, 2014).[3] These programs, begun in 2012, designate 'Solarize' towns that choose a preferred installer, receive a group buy that lowers the price with more installations and receive an intensive grassroots campaign with information sessions and local advertising. The first phase of the program involved four towns, subsequently expanded to five by March 2013. As of February 2014, the program involves 30 participating towns out of the 169 across the state, and has been quite successful in increasing the number of installations in these towns (Solarize CT, 2013).[4]

## 3. Data

To study the drivers and the spatial patterns of PV systems adoption in CT, we rely on several sources, as described in this section.

### 3.1. PV system adoptions

CEFIA collects and maintains a database with detailed technical and financial characteristics of all residential PV systems adopted in state that received an incentive since the end of 2004. The database, updated monthly, contains detailed PV system characteristics for nearly all installations in CT.[5] Two variables are particularly

3 As of 6 January 2014, the Residential Solar Investment Program incentive for system above 5 kW is $0.75/W, up to 10 kW. Performance-based incentives are also available and as of 6 January 2014 are set at $0.18 kW/h. Third party-owned systems make up ~20% of our sample, and their incentives have changed over time in parallel to resident-owned systems.

4 The Phase I Towns are Durham, Fairfield, Portland and Westport. The Phase II Towns are Bridgeport, Canton, Coventry and Mansfield/Windham. The current towns (as of February 2014) are Ashford, Chaplin, Hampton, Pomfret, Cheshire, Columbia, Lebanon, Easton, Redding, Trumbull, Enfield, Glastonbury, Greenwich, Hamden, Manchester, Newtown, Roxbury, Washington, Stafford, West Hartford and West Haven. Some towns participate as a joint effort.

5 Our understanding is that the only PV systems not in the CEFIA database are those in the small municipal utility regions (e.g. Wallingford, Norwich and Bozrah). We expect that these are few.

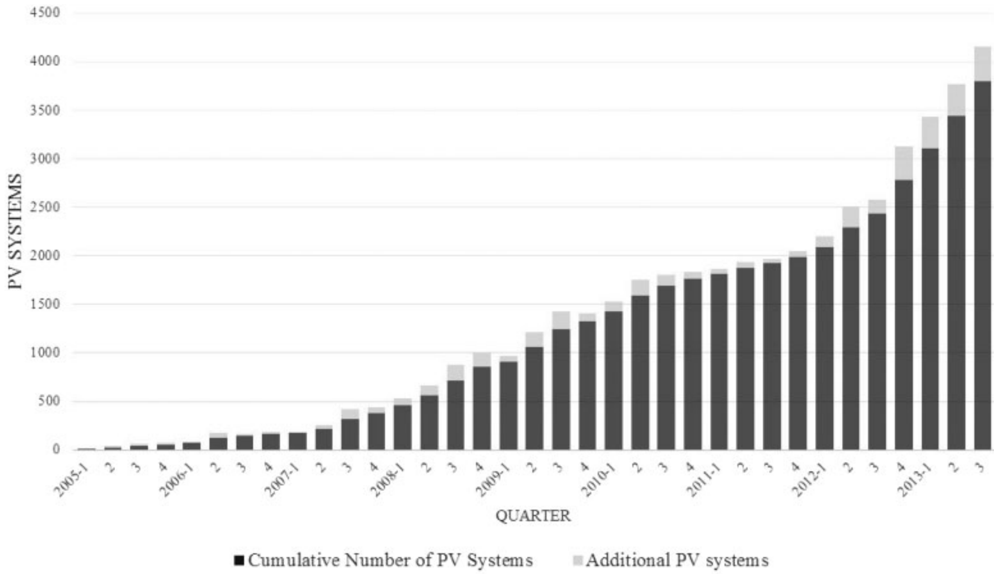


**Figure 1.** Total and additional adoptions PV systems in CT over time.

important for this study: the application date and the address. Using the address information, we successfully geocoded 3833 PV systems that were installed in CT from 2005 through the end of September 2013 at the Census block group level, out of the 3843 installations in the database.

Despite a slight reduction in new systems in 2011, CT residents have steadily adopted an increasing number of residential PV systems each quarter, as shown in Figure 1. In the last four quarters for which data are available, adoptions averaged 340 per quarter, or 11.7% increase from quarter to quarter. We will explore the spatial patterns of this technology diffusion in Section 4.

### 3.2. Demographic, socioeconomic and voting data

We focus our analysis on the Census block group level, which is the most disaggregated level available for which key variables, such as median household income, are available. There are 2585 block groups in CT. We drop ocean block groups, and those including only university campuses or prisons, such as Yale University in New Haven and the prison block groups in Somers. We retained 2574 (99.6%) of the block groups. In Table 1, we summarize the descriptive statistics for each variable in our dataset.

We use socioeconomic and demographic data from several waves of the US Census. We use the 2000 and 2010 US Decennial Census as well as the 2005–2009, 2006–2010 and 2007–2011 waves of the American Community Survey (ACS) (US Census Bureau, 2013). Since Census boundaries changed after the 2005–2009 ACS, we convert the 2000 Census and 2005–2009 ACS to the 2010 Census boundaries. For this conversion, we calculate the share of land assigned and lost to and from each block group and then take a weighted average of the variables in the 2000 boundaries based on land area. Once all of the Census data are based on 2010 boundaries, we use a quadratic regression to interpolate values for the unobserved years, providing a panel of socioeconomic and

**Table 1.** Summary statistics

| Variables | Mean | SD | Min | Max | Source |
|---|---|---|---|---|---|
| Count of new PV systems by block group and quarter | 0.04 | 0.27 | 0 | 18 | CEFIA (2013) |
| Installed base | 0.48 | 1.24 | 0 | 39 | CEFIA (2013) |
| Average neighboring installations, 0.5 miles, 6 months | 0.005 | 0.08 | 0 | 5 | Calculated |
| Average neighboring installations, 0.5–1 mile, 6 months | 0.006 | 0.09 | 0 | 6 | Calculated |
| Additional number of new installations, 1–4 miles, 6 months | 0.05 | 0.57 | 0 | 58 | Calculated |
| Average neighboring installations, 0.5 miles, 12 months | 0.009 | 0.17 | 0 | 16 | Calculated |
| Average neighboring installations, 0.5–mile, 12 months | 0.008 | 0.16 | 0 | 14 | Calculated |
| Average neighboring installations, 1–4 miles, 12 months | 0.067 | 0.88 | 0 | 72 | Calculated |
| Number of housing units (1,000 s) | 0.61 | 0.37 | 0.01 | 13.38 | US Census |
| Housing density (0.001 s) | 0.79 | 1.30 | >0.01 | 28.91 | Calculated |
| Renter-occupied houses (%) | 32.03 | 27.82 | 0 | 100 | US Census |
| Median household income (tens of thousands of 2013 dollars) | 7.89 | 4.71 | 0.15 | 76.86 | US Census |
| Population who are white (%) | 77.38 | 23.45 | 0 | 100 | US Census |
| Population who are black (%) | 10.70 | 16.86 | 0 | 100 | US Census |
| Population who are Asians (%) | 4.34 | 5.79 | 0 | 73.12 | US Census |
| Median age | 40.41 | 8.50 | 11.10 | 80 | US Census |
| Median age in highest 5% | 0.10 | 0.30 | 0 | 1 | US Census |
| Democrats (%) | 37.70 | 13.73 | 0 | 75.23 | CT SOTS |
| Population in minor parties (%) | 0.53 | 0.56 | 0 | 7.06 | CT SOTS |
| Electricity cost (Cent/kWh) | 18.39 | 1.40 | 16.28 | 20.46 | EIA (2013) |
| Unemployment (%) | 7.04 | 1.99 | 4.4 | 9.9 | FRED (2013) |
| Solarize CT | 0.005 | 0.07 | 0 | 1 | CEFIA (2013) |

*Note:* All variables have 90,090 observations, where the observation is a block group-year-quarter.

demographic data.[6] The Census data also include built environment variables such as housing density, the number of houses and the share of renters. We also add the quarterly average unemployment rate (not varying over block groups), which controls for the general health of the economy (FRED, 2013). In addition, we bring in the statewide annual electricity price average from the preceding year to account for changes in electricity prices, which may affect the attractiveness of PV systems (EIA, 2013).

We also use voter registration data provided by the Connecticut Secretary of State (SOTS). These data are collected on the last week of October of every year (CT SOTS, 2013). They include both active and inactive registered voters for each of the major political parties, as well as total voter registration. Unfortunately, SOTS data only provide aggregate data on 'minor party' registration, so we are unable to separately identify enrollment in green and environmental parties from enrollment in other minor parties, such as the libertarian party. Using an analogous methodology to our approach for the Census data, we develop an estimate for block group-level political affiliation from the precinct-level data provided.

6 We use the mid-point of each ACS to provide values for 2007, 2008 and 2009. We carefully checked the interpolation and when it led to unrealistically low or high values, we cut off the values at 18 years for a minimum median age and 70 years for a maximum median age, and we cut all probabilities at 0 and 100.

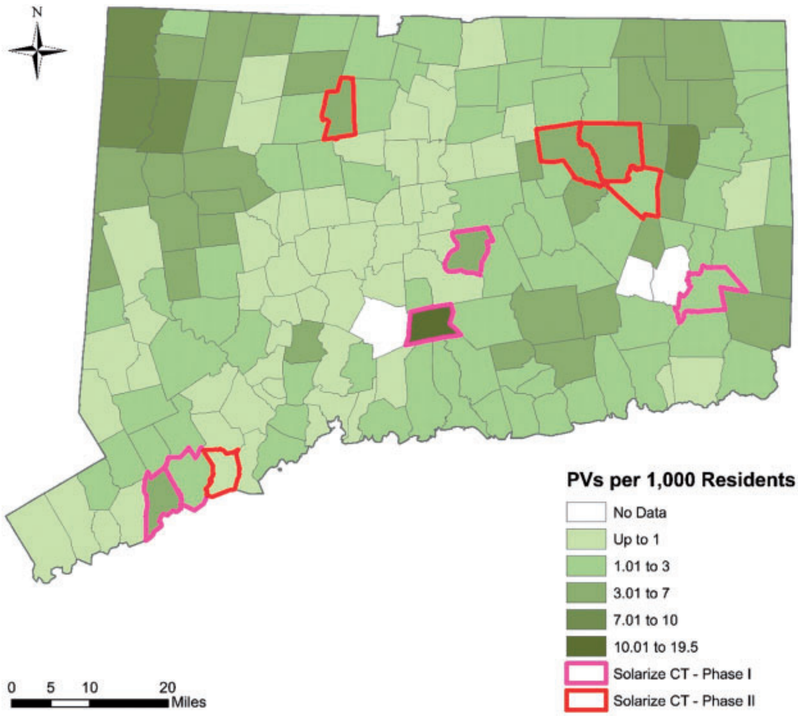


**Figure 2.** PV system density and Phases I and II Solarize CT towns in 2013.

We calculate housing density by dividing population by land area. The land area field used is 'ALAND' in shapefiles available from the Map and Geographic Information Center (MAGIC) at the University of Connecticut (MAGIC, 2013). 'ALAND' is not the ideal field, for there may be land uses that should not be included (e.g. wetlands and forest), and it misses local differences in types of housing units. However, it captures the broader differences in housing across block groups quite well, with higher housing density in center cities and decreasing housing density further out.

### 3.3. Spatial data

To examine the factors influencing patterns of diffusion of PV systems, we combine spatial data (GIS layers and map data) with the adoption data contained in the CEFIA Solar database. Our sources for the spatial data are the CT Department of Energy and Environmental Protection (DEEP, 2013) and the University of Connecticut MAGIC data holdings mentioned earlier.

## 4. Spatial patterns of PV system diffusion

### 4.1. Adoption rates across towns in CT

The diffusion of PV systems displays surprising spatial patterns across CT. Figure 2 shows the density of PV systems at the town level as of September

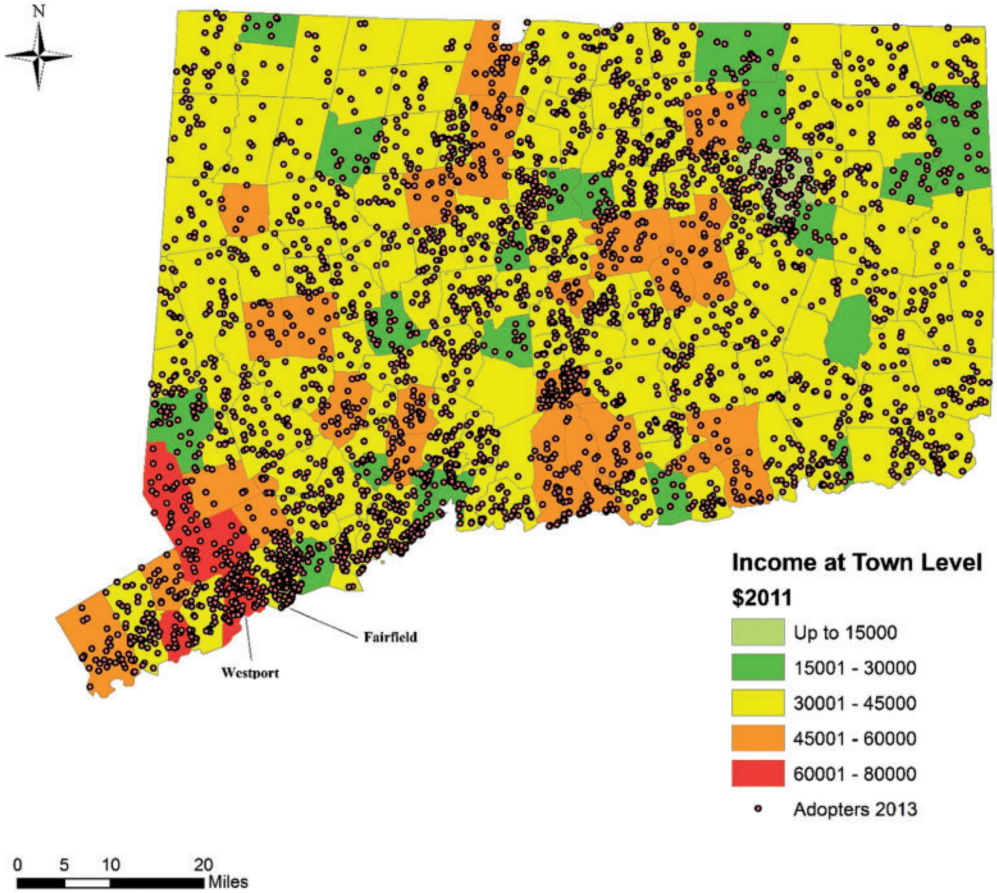


**Figure 3.** PV systems and median household income in CT in 2013.

2013.[7] The two upper corners of the state show higher per-capita density, with northwestern CT recording among the highest values. These towns are mostly rural or semi-rural communities, with a strong presence of vacation homes for residents of the New York and the Greater Boston areas. In the southern-central part of the state, the town of Durham (a Phase I Solarize town) shows among the highest rate of adoption in the state.

A knowledgeable CT resident will quickly observe that PV system adoption does not entirely follow patterns of income in CT. For example, the southwestern corner of the state hosts some of the wealthiest municipalities in the USA, yet displays a lower rate of adoption than the much less wealthy towns in southeastern CT. This can be seen clearly in Figure 3.

7 As mentioned above, Norwich, Bozrah and Wallingford are served by municipal utility companies and do not participate in the CEFIA incentive program. Thus, these towns have no data.

### 4.2. Hot spots and cold spots in PV system diffusion

Looking at adoption rates by town provides insight, but aggregating results at the town level imposes artificial boundaries, reducing the effects of agglomerations at the edges of towns, which may be particularly problematic for smaller and more densely populated towns. For a clearer picture of the location of agglomeration clusters of PV systems, we use two well-known spatial techniques: Optimized Getis-Ord method (OGO) and Anselin's cluster and outlier analysis (COA) (Anselin, 1995; Getis and Ord, 1992; Ord and Getis, 1995). These approaches have been applied to many fields, from epidemiology (Robinson, 2000) to land use change and sustainability (Su et al., 2011). By identifying agglomeration clusters and mapping them against other spatial factors, these approaches provide guidance on the underlying factors influencing adoption.

We run these techniques using ESRI's ArcMap 10.2. Both require aggregated data to achieve variability within the adoption values. Our scale is the block group level; thus, we use the geographic center (centroid) of each block group as the point of reference. For COA, we use a 10-mile threshold and an inverse distance spatial relationship. OGO chooses the threshold to optimize the balance between statistical significance and observation size and thus is self-selected by ArcGIS. Of course, these methodologies are sensitive to the input parameters, so we test each with different thresholds, starting at 1-mile radius around each block group centroid, up to the cutoff distance of 10 miles. We find little difference in the results. In fact, using COA, results did not change appreciably even using the maximum distance in the study area as the threshold.

Figure 4 presents the results of the spatial analysis. For reference, Figure 4(A) shows the housing density in CT by Census block group and the geocoded PV systems; Figure 4(B) presents the results from the OGO approach; and Figure 4(C) shows the results from the COA approach. Hartford is highlighted as a reference town across the maps.

The results are consistent across the three methodologies: there is clustering of hot spots in the northeastern, central-eastern and southeastern parts of CT. In addition, there is a hotspot in Fairfield County in southwestern CT. There is a clustering of cold spots through the middle of the state, which corresponds with the most densely populated urban areas, which includes urban areas such as New Haven, Bridgeport, Meriden and Waterbury. Interestingly, there also appears to be a cold spot in some of the wealthiest areas of CT in the southeast, which includes towns such as Greenwich and Stamford. These initial results do not mean that income plays no role in the adoption process. Rather, it suggests that policies aimed solely at lowering the cost of PV systems are not enough to speed the adoption of PV systems. These maps greatly enrich our view of the diffusion of PV systems and underscore the complex relationships between housing density and income, and the rate of PV system adoption.

### 4.3. Spatial patterns of diffusion over time

The diffusion of any new technology is a dynamic process, which often exhibits a characteristic spatial pattern over time. For example, classic diffusion models often show that new technologies are adopted in a centrifugal, wave-like pattern, starting from larger population centers (Hägerstrand, 1952; Brown, 1981).

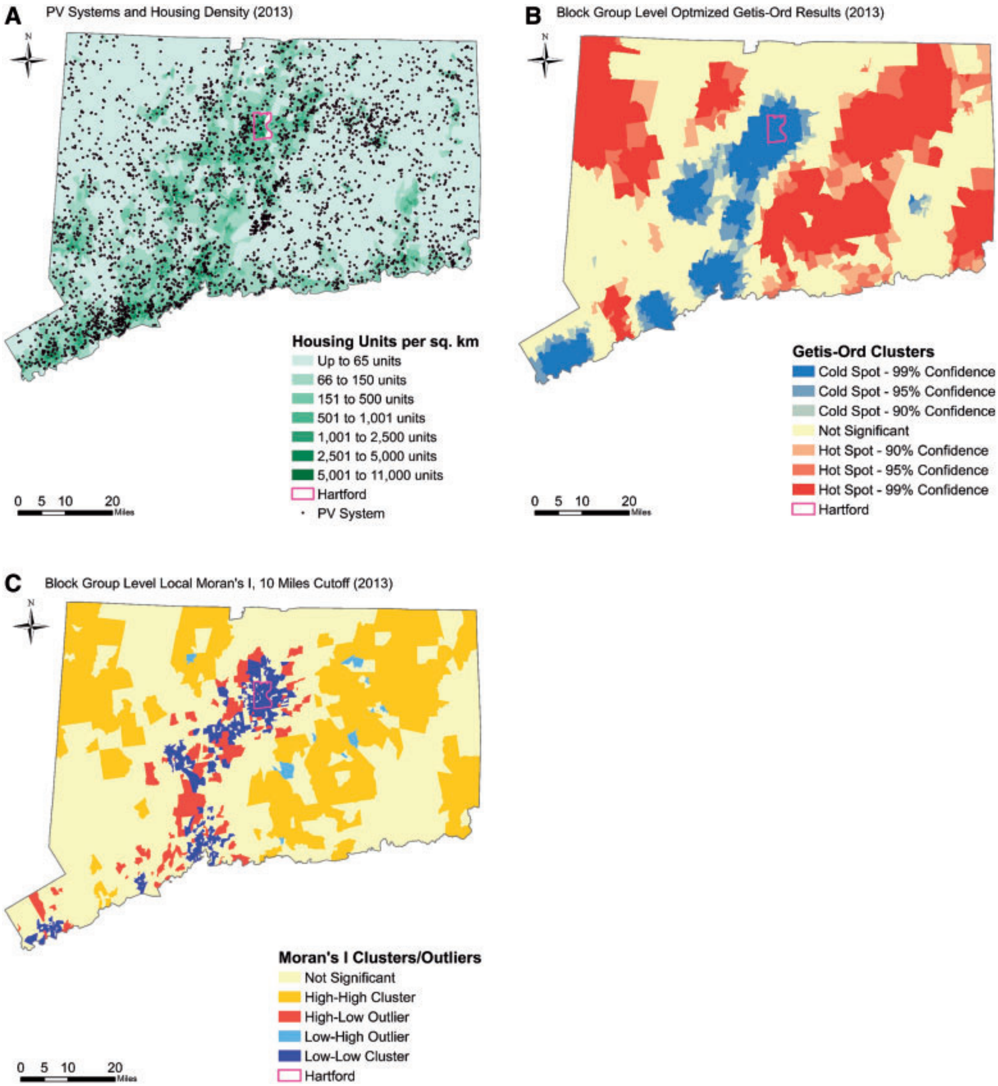


**Figure 4.** Spatial distribution of PV system hot spots and cold spots using different approaches. (**A**) PV systems and housing density. (**B**) Optimized Getis-Ord (OGO). (**C**) Local Moran's I (COA) results.

To examine the pattern of diffusion over time and space, we use a methodology called fishnetting (Mitchell, 2005). In our context, fishnetting divides CT into cells of a specified size and then highlights the cells based on the number of adoptions in the cell. This approach is particularly useful for visualizing diffusion patterns because it disaggregates the process into a smaller scale than town or block group.

We specify the size of each cell in the fishnet as 1.5 km, a length small enough to effectively disaggregate our block-group level data, but large enough to capture more than one adoption in each cell. Figure 5 illustrates our fishnetting analysis for adoption

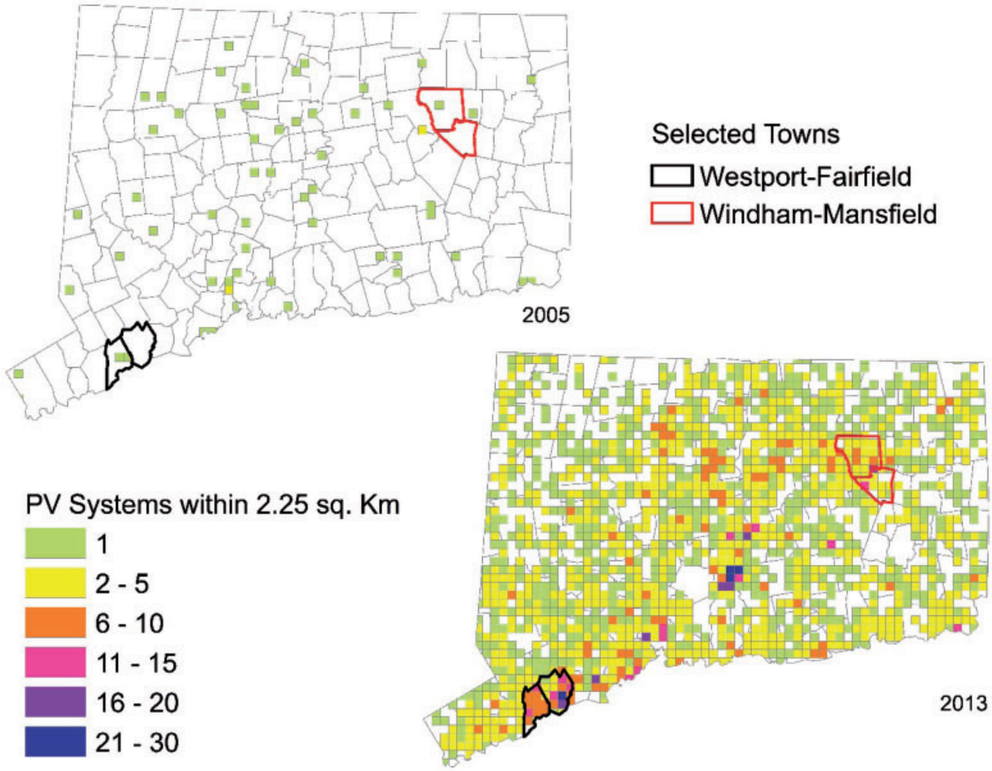


**Figure 5.** Fishnetting reveals the patterns of adoption of PV systems between 2005 and 2013.

at the end of 2005 and at the end of our dataset in 2013. Each colored cell displays the actual number of installations within 2.25 $km^2$.

In Figure 5, we highlight two areas: Westport-Fairfield (black outline) and Windham-Mansfield (red/grey outline). In Westport-Fairfield, we see a case of town that already had PV system adoptions in 2005, and these adoptions multiplied substantially by the beginning of 2013. In contrast, Windham-Mansfield had no adoptions in 2005 and had very few adoptions in neighboring cities. Yet, with the Phase II Solarize program providing a major boost, the two towns now have a very high density of PV systems, with up to 24 adoptions in 4.5 square miles. These examples highlight the factors that influence the dynamics of the diffusion process in CT: areas 'seeded' with installations early on appear to have an increasing density of adoption, while at the same time programs like Solarize can dramatically increase the number of PV systems in a locality in a short time.

The fishnetting approach is also well suited for testing the hypothesis that the diffusion of PV systems follows the typical pattern of diffusion from larger population centers. To examine the spatial relationship between population and PV system adoption, we map the town population along with the fishnet of PV system adoptions for 2005, 2008 and 2013 in Figure 6.

If the adoption process of PV systems followed the classic literature in exhibiting a wave-like centrifugal pattern based in the largest towns, we would expect to see initial

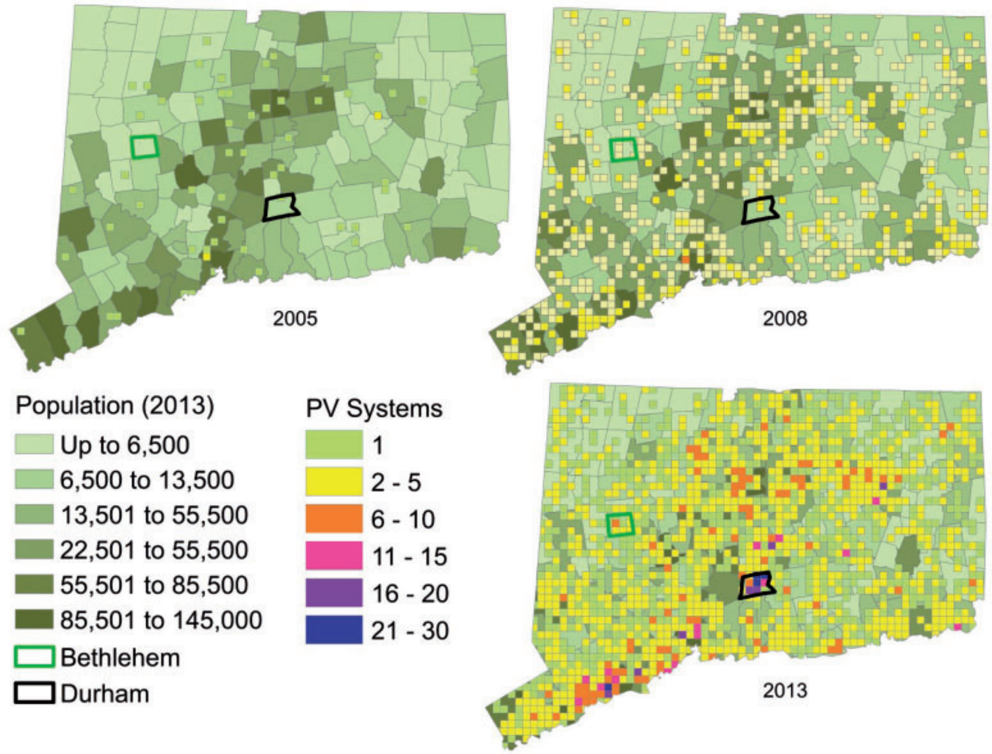


**Figure 6.** The spatial pattern of adoption does not simply follow the population distribution; even at early stages of adoption solar PV systems diffuse from small- and medium-sized centers.

concentrations within the largest towns in the state, with adoptions multiplying within these areas and diffusing to the smaller towns over time. Of course, not all technologies are the same, and PV systems may well display a different pattern of diffusion.

We find that PV systems diffuse not only from the largest centers, but also from many midsized and smaller towns. For example, consider Durham, in south-central CT, with a population of 7388, which is about one-third of the state mean of 21,300 residents per town. Durham hosted one of the very first PV systems, and, as of September 2013, it has the highest number of PV systems in the state (143), thanks, in part, to the Solarize CT program. In fact, the Solarize CT program appears to strengthen the role of midsized centers, building on the clustering that began before the program.

We also find that new agglomeration centers appear over time in areas that did not have installations in 2005. For example, the town of Bethlehem (population 3607) had neither a single PV system in 2005 nor a neighboring town with one. By the end of 2008, the town still had very few adoptions. By 2013 it had 23 PV systems. Interestingly, it appears that other towns around Bethlehem followed suit, with increasing number of PV systems, perhaps indicative of a centrifugal pattern of diffusion.

Why might we see midsized and smaller towns acting as centers for diffusion of PV systems, in contrast to the classic results? The combination of the technical characteristics of PV systems along with the built environment and institutional setting in CT provides likely explanations. Most directly, PV systems are most suitable for single-family housing, due to the larger roof space and lack of split incentives that multifamily dwellings must contend with. Many of the single-family homes in CT that are well suited for PV systems are in smaller communities.

In addition, local permitting regulations and fees have an important influence on the speed and difficulty of installing a PV system. A new pro-solar local administration can expedite the process of installing a PV system and provide an example for neighboring towns. This could quickly change a town from a town with few adoptions to source of diffusion waves. The Solarize program has the potential to do the same.

These results, while deviating from the classic models of diffusion, make sense and may apply in other contexts as well. Of course, a different set of regulatory, socioeconomic and technological characteristics would likely create a very different pattern. The results in McEachern and Hanson (2008), indicating a wave-like pattern emanating from peripheral villages with limited connection to the central grid, are a case in point. In the next section, we turn to an empirical model designed to explore the factors that underlie the spatial diffusion patterns observed here.

## 5. Empirical approach

### 5.1. Creation of the spatiotemporal neighbor variables

One major factor that may mediate the diffusion of solar PV is the presence of spatial neighbor effects. At the heart of our empirical approach is our methodology for creating spatiotemporal variables to capture the influence of previous neighboring installations on adoption.

For each PV system application in the database, we record how many PV systems had previously been completed within a 0.5-, 1- and 4-mile radius of the installation. We make the calculation recording the number of installations within each radius in the 6 months prior to the installation, 12 months prior, 24 months prior and since 2005 (there were very few installations prior to 2005 in CT). We also remove other installations with applications occurring within 120 days prior to each observation $k$. This entirely avoids the simultaneity, or reflection, problem discussed in Section 1 and greatly reduces the likelihood that the decision to install is made before some of the other neighbors chose to install.[8]

In other words, for each PV system $k$, we counted the number of neighboring installations $j$, such that:

$$d_{k,j} \leq D,$$

$$t_k - t_j \leq T \ or \ t_k \geq t_j,$$

and

$$t_k - t_j > W$$

where $d_{k,j}$ is the Euclidean distance (in feet) between PV systems $k$ and $j$, $D$ is the distance specification (2640, 5280 or 21120 feet), $t_k$ is the application date of PV system

8 We choose 120 days as a conservative assumption, but it turns out that our results are very robust to this assumption. Using a 30-day window, or even no window, does not appreciably change the results.

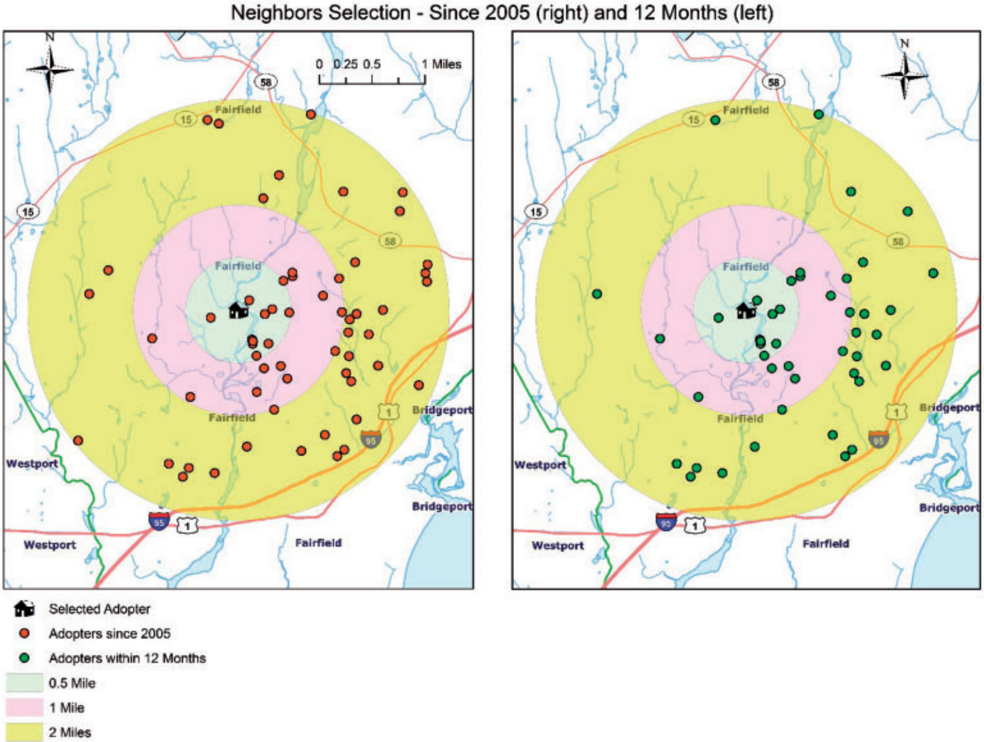


**Figure 7.** Selection of all neighbors since 2005 (left) and in previous 12 months (right).

$k$, $t_j$ is the application date of PV system $j$, $T$ is the temporal lag (e.g. 6 months) and $W$ is the time window of installations assumed to be simultaneously decided (e.g. 120 days).

To more precisely examine the effect at each distance, we subtract the inner distances from the outer radii, to see an effect within 0.5 miles, from 0.5 to 1 mile and from 1 mile to 4 miles. This approach is a multiple-ring buffer method, where the buffers are both spatial and temporal, as shown graphically in Figure 7.

These spatiotemporal counts of nearby PV systems capture the relevant previous installations that we hypothesize will influence the household decision to adopt a PV system. We finally convert these variables to the block-group level by calculating the mean of the spatiotemporal count in that block group for each of the radii and period. This provides a useful measure of the average number of neighbors that are influencing new adopters in a block group. Since the variable is at the block-group level, it can be matched with our Census data to allow for a panel data analysis. We call these block-group level variables our 'spatiotemporal neighbor' variables.

This approach has significant advantages over the previous approaches to quantifying spatial neighbor effects. For example, Bollinger and Gillingham (2012) use variables for the cumulative number of installations in a zip code, which they call the 'installed base', as well as the cumulative number of installations on a street in a zip code. Estimates based on the zip code may be subject to a measurement error bias, analogous to the well-known areal bias (e.g. Openshaw, 1984), for there is a clear bias for households on the edge of zip codes. Moreover, zip codes are much larger than block groups.

Müller and Rode (2013) avoid this potential measurement error bias by examining the distance between 286 geocoded buildings with PV systems in Wiesbaden, Germany. Despite the small sample, this is an improvement over a zip code-level or street-level analysis. However, from a spatial perspective, several possible errors were introduced: issues with geocoding led to 149 of the PV systems assigned to proximate buildings and 38 PV systems that were second or third systems on these buildings were allocated to nearby buildings rather than assigned to the building they were on. From an econometric perspective, a reader may also be concerned that no effort was taken to address the classic issues in identifying peer effects discussed in the Section 1. We feel that our approach is a useful compromise that allows for a block group panel data analysis to address peer effect identification concerns, while at the same time leveraging careful spatial analysis to reduce spatial measurement error.

### 5.2. Model of demand for PV systems

To examine the factors that influence residential PV system adoption, we model the demand for residential PV systems in a block group $i$ and at time $t$ as a function of a variety of socioeconomic, demographic, political affiliation, built environment, policy and installed base variables. Our specification can be parsimoniously written as follows:

$$PVcount_{i,t} = \alpha + \boldsymbol{N}_{\mathbf{i},t}\,\beta + \boldsymbol{B}_{i,t}\,\gamma + \boldsymbol{D}_{i,t}\,\theta + \pi\,S_{i,t} + \mu_i + \phi_t + \varepsilon_{i,t}$$

where $PVcount_{i,t}$ is the number of new PV system adoptions in block group $i$ at time $t$; $\boldsymbol{N}_{i,t}$ is a vector of the spatiotemporal neighbor variables described earlier (we run separate regressions for 12 months prior and 24 months prior); $\boldsymbol{B}_{i,t}$ is a vector of built environment variables; $\boldsymbol{D}_{i,t}$ is a vector of socioeconomic, demographic and political affiliation variables; $S_{i,t}$ is an indicator variable for whether or not a block group is part of a Solarize CT campaign at time $t$; $\mu_i$ is block group fixed effect; $\phi_t$ is time dummy variable; and $\varepsilon_{i,t}$ is a mean-zero error term.[9] In one of our specifications, we consider the number of new adoptions in a year-quarter (i.e. 2005Q1), so $t$ is the year-quarter. In addition, we also examine a specification with block group-semester fixed effects (the two semesters are defined as the January through June and July through December). In this specification, $\mu_i$ and $\phi_t$ would be combined into a single interaction fixed effect.

Vector $\boldsymbol{D}_{i,t}$ contains variables for the average quarterly unemployment to capture overall economic conditions, the electricity price (largely constant within utility region over time), median age, a dummy for the median age being in the oldest 5% of our sample to capture concentrations of elderly, percentage of population who are white, percentage of the population who are black, percentage of the population who are Asian, median household income, percentage of registered voters who are democrats and percentage of voters who are registered to minority parties (e.g. the Green Party or Libertarian Party). These variables are important controls and are also useful to interpret. For example, the political affiliation variables help us understand the effects

9 We use a fixed effects approach, as a Hausman test results allow us to reject the orthogonality assumption of the random effects model at 99% confidence level.

of environmental values on the adoption of PV systems, for democrats consistently tend to vote in favor of RPS regulations (Coley and Hess, 2012).

The vector of built environment variables $\boldsymbol{B}_{i,t}$ includes the housing density, the number of houses and the share of renters. These variables control for differences in the number of households available to install PV systems. Finally, our block group fixed effects and time dummies are critical for controlling for unobserved heterogeneity at the block group level and over time. For example, block group fixed effects control for any non-time-varying block group-specific unobservables, such as a solar installer being headquartered in that location. Time dummies help control for broader trends in increased adoption over time due to lower prices and increased awareness of PV systems. Furthermore, our results with block group-semester fixed effects address the possibility that there are localized trends that work at the sub-yearly level that could confound our estimate of the peer effect. For instance, if a new solar installer moved into a block group, we might see a surge of adoptions in a localized area.

### 5.3. Estimation and identification

We estimate this model first using a linear fixed effects approach and then using a negative binomial approach as a robustness check. The negative binomial model is a common approach for use with count data when the mean of the count variable does not equal the variance, but it involves additional structural assumptions about the relationship (e.g. Cameron and Trivedi, 1998). We also examine the results of a Poisson model as an additional check.

Our approach follows the logic in Bollinger and Gillingham (2012) and discussed in Hartmann et al. (2008) by using a flexible set of fixed effects to identify spatial peer effects. Block group fixed effects clearly control for endogenous group formation leading to self-selection of peers (homophily). Simultaneity, whereby one household influences others at the same time that they are influenced by others, is addressed by the temporal lag between when the household decision to adopt is made and when others have adopted. Specifically, we create our spatiotemporal installed base variables in such a way that we are focusing on the effect of *previous* installations on the decision to adopt. Finally, we flexibly control for correlated unobservables, such as time-varying marketing campaigns or the opening up of a new headquarters by an installer, with block group-semester fixed effects. These approaches follow the state-of-the-art in the literature in identifying peer effects in the absence of a quasi-experiment and at the same time address possible identification concerns regarding the coefficients on the other covariates of interest.

For our primary empirical strategy to identify the neighbor effect coefficients, we must assume that there is not a continuous time trend of growth of PV system that could lead to a spurious correlation between the spatiotemporal variables and adoptions. To assuage this concern, we also estimate the model with a set of year-specific time trends. Our identification also rests on the assumption that the fixed effects demeaning transformation does not lead to endogeneity due to shocks previous to adoption entering both the spatiotemporal variables and the error (see Narayanan and Nair, 2013 and Bollinger and Gillingham, 2012, for a mathematical treatment of this potential issue). A first-differencing approach avoids this concern, and thus we examine the results of a first-difference estimator as well.

# 6. Results

## 6.1. Primary results

We are particularly interested in the vector of parameters $\beta$, which tells us the extent to which spatial neighbor effects influence the decision to adopt PV systems. In addition, we are also interested in many of the other coefficients to help us better understand the influence of different built environment, socioeconomic, political affiliation and demographic factors on the decision to adopt.

In Table 2, we present our primary results using the spatiotemporal variable that includes installations from the previous 6 months. Column 1 presents OLS results with year-quarter dummy variables to control for changing trends in the PV system market, but no block group fixed effects. Column 2 adds block group fixed effects to also control for unobserved heterogeneity at the block group level. Column 3 presents results with block group fixed effects, yearly dummy variables and a linear time trend interacted with each yearly dummy variable to address the possibility of an underlying continuous trend that is correlated with our spatiotemporal variables. Finally, column 4 presents our preferred results, which include block group-year-semester fixed effects to flexibly address possible time-varying correlated unobservables.

Looking across specifications, our results show robust evidence suggestive of a spatial neighbor effect. Regardless of whether we include block group fixed effects, block group-year-semester fixed effects or time trends, our spatiotemporal variables are positive, statistically significant and of a similar magnitude. This finding demonstrates that the mean number of installations surrounding households increases the number of adoptions in that block group. For example, in column 4, the coefficient on the number of neighbors within 0.5 miles indicates that one additional nearby installation within 0.5 miles in the previous 6 months increases the number of installations in the block group per quarter by 0.44 PV systems on average. At the average number of block groups in a town (15), this implies 26.4 additional PV systems per town due to the spatial neighbor effect.

Furthermore, the change in the results with distance is intuitive. The coefficients are generally smaller when we consider installations that are further away, such as between 0.5 and 1 mile, and between 1 and 4 miles. These results are consistent with Bollinger and Gillingham (2012), who find evidence of a stronger effect of neighboring installations at the street level than at the zip code level.

In contrast to Rode and Weber (2013), and Müller and Rode (2013), the spatial peer effect does not appear to fade after 1 or 1.2 km. While the magnitude of the coefficient decreases with distance, it is still highly statistically and economically significant in the 1–4 mile range.[10] This result may be explained in part by a difference in area geography. Wiesbaden, the city studied by Müller and Rode (2013), is an urban area with a population density almost double the population density in CT (CIA, 2013; Statistik Hessen, 2013). Moreover, the transportation system and physical mobility is quite different: CT has 0.86 vehicles per capita, whereas Wiesbaden has only 0.52 (DOE, 2013; World Bank, 2013). We might expect spatial peer effects to be weaker, but to

10 We also performed specifications with a 1–2 and 2–4 mile range, which show a similar pattern, but with less statistical significance.

**Table 2.** Primary specifications including previous 6 months of installations

| | Year-quarter dummies (1) | BG FE and year-quarter dummies (2) | BG FE and time trends (3) | BG-year-semester FE (4) |
|---|---|---|---|---|
| Average neighbors within 0.5 miles | 0.51*** | 0.49*** | 0.49*** | 0.44*** |
| | (0.0110) | (0.0996) | (0.0996) | (0.1000) |
| Average neighbors 0.5–1 mile | 0.38*** | 0.38*** | 0.38*** | 0.39*** |
| | (0.0106) | (0.0828) | (0.0828) | (0.0832) |
| Average neighbors 1–4 miles | 0.11*** | 0.11*** | 0.11*** | 0.12*** |
| | (0.0016) | (0.0227) | (0.0227) | (0.0224) |
| Number of housing units (1000 s) | 0.032*** | 0.014** | 0.014** | 0.0017 |
| | (0.0024) | (0.0065) | (0.0065) | (0.0310 |
| Housing density (0.001 s) | 0.0066*** | 0.0091*** | 0.0091*** | 0.0014 |
| | (0.0008) | (0.0016) | (0.0016) | (0.0097) |
| Renter-occupied houses (%) | 0.00029*** | 0.00045*** | 0.00045*** | 0.00011 |
| | (0.0000) | (0.0001) | (0.0001) | (0.0004) |
| Median household income ($10,000) | 0.00048** | 0.00058 | 0.00058 | 0.0038 |
| | (0.0002) | (0.0005) | (0.0005) | (0.0047) |
| Population who are white (%) | 0.00025** | 0.00019* | 0.00019* | 0.00014 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0004) |
| Population who are black (%) | 0.000035 | 0.00024* | 0.00024* | 0.00024 |
| | (0.0001) | (0.0001) | (0.0001) | (0.0004) |
| Population who are Asians | 0.00067*** | 0.00022 | 0.00022 | 0.00075 |
| | (0.0002) | (0.0003) | (0.0003) | (0.0008) |
| Median age | 0.00023 | 0.00014 | 0.00014 | 0.00096 |
| | (0.0001) | (0.0002) | (0.0002) | (0.0008) |
| Median age in highest 5% | 0.0074** | 0.0081 | 0.0081 | 0.014 |
| | (0.0034) | (0.0051) | (0.0051) | (0.0137) |
| Democrats (%) | 0.000056 | 0.000061 | 0.000061 | 0.00031 |
| | (0.0001) | (0.0003) | (0.0003) | (0.0012) |
| Population in minor parties (%) | 0.0017 | 0.0046 | 0.0046 | 0.0096 |
| | (0.0016) | (0.0029) | (0.0029) | (0.0090) |
| Electricity cost (Cent/kWh) | 0.0028 | 0.0030*** | 0.0036*** | 0.00072 |
| | (0.0017) | (0.0009) | (0.0009) | (0.0014) |
| Unemployment (%) | 0.00071 | 0.00092 | 0.000097 | 0.00027 |
| | (0.0011) | (0.0007) | (0.0009) | (0.0019) |
| Solarize CT | 0.80*** | 0.77*** | 0.77*** | 0.87*** |
| | (0.0114) | (0.1127) | (0.1127) | (0.2001) |
| Constant | 0.073** | 0.058*** | 0.064*** | 0.0039 |
| | (0.0336) | (0.0209) | (0.0183) | (0.0681) |
| $R^2$ | 0.25 | 0.24 | 0.24 | 0.19 |
| Observations | 90,090 | 90,090 | 90,090 | 90,090 |

*Notes:* Dependent variable is the number of installations in a block group (BG) in a year-quarter. An observation is a BG-year-quarter. Standard errors clustered on BG in parentheses.
* denotes $P<0.10$, $^{**}P<0.05$ and $^{***}P<0.010$.

extend over a larger area, when potential adopters tend to move further to pursue their normal social interactions.

Our results also highlight the important role of our built environment variables. Consistent with our geospatial analysis, housing density appears to decrease adoption.

Similarly, the share of renters decreases adoption. These results are consistent with the presence of split incentive problems in multifamily and renter-occupied dwellings (Bronin, 2012; Gillingham et al., 2012; Gillingham and Sweeney, 2012). In owner-occupied multifamily dwellings, it may not be possible to prevent free-ridership and recoup the costs of the installation. Similarly, when the landlord pays for electricity in a rental arrangement, the landlord may not be able to contract with the renter to pay for the cost of the installation. Even when the renter pays for electricity, there may still be barriers: the renter may not have permission to install a PV system and may not plan on staying in the dwelling long enough to make a PV system pay off.

Our results are less statistically significant when it comes to most other socio-economic and demographic variables. There is weak evidence that higher median household income increases adoption, which may not be surprising, given the complicated spatial relationship shown in Section 4 between income and PV system adoption. The racial variables are largely not statistically significant, with only weak evidence of more adoption when there is a higher percentage of whites in the block group. The political affiliation variables and the unemployment rate are not statistically significant.

The electricity price is positive and highly statistically significant in columns 2 and 3, and positive in the remaining columns. The result in column 2 can be interpreted as indicating that a \$1 increase in the electricity cost increases the number of adoptions in a block group and a year-quarter by 0.3 additional installations. The Solarize campaign dummy variable has a highly statistically significant and positive effect on adoptions. The result in column 4 suggests that the presence of a Solarize program in a block group leads to 0.87 additional installations in that block group per year-quarter.

To summarize, we find strong evidence of localized spatial neighbor effects and built environment variables influencing the adoption of PV systems and much weaker evidence of other socioeconomic, demographic and political affiliation variables influencing adoption. This result may seem surprising, but in light of the spatial patterns seen in Section 4, it makes a great deal of sense.

### 6.2. Diminishing effects over time

While the previous literature has shown that neighbor effects may decrease over calendar time with the diffusion of solar PV (Richter, 2013), and as the installed base increases (Bollinger and Gillingham, 2012), we hypothesize that the neighbor effect may also diminish for each installation as more time passes since the previous installations occur.[11] Table 3 demonstrates this diminishing neighbor effect over time since prior installations. All columns contain block group-year-semester fixed effects, just as in our preferred specification in Table 2. Column 1 repeats column 4 in Table 1 for reference. Column 2 extends the spatiotemporal variables to include previous installations up to 12 months prior. Column 3 extends these variables further to include all previous installations since 2005, when the CT market really began. Column 4 includes the classic installed base variable for comparison with the results in Bollinger and Gillingham.

11 Consistent with Richter (2013), we also run specifications over time and find that the neighbor effects change over time. In our context, they approximately double when going from the 2005–2011 period to the 2012–2013 period.

**Table 3.** Diminishing neighbor effects with time prior to installation

| | Block group-year-semester FE | | | |
|---|---|---|---|---|
| | 6 Months (1) | 12 Months (2) | Since 2005 (3) | Installed base (4) |
| Average neighbors within 0.5 miles | 0.44*** | 0.22** | 0.040** | |
| | (0.1000) | (0.1048) | (0.0164) | |
| Average neighbors 0.5–1 mile | 0.39*** | 0.051 | 0.023* | |
| | (0.0832) | (0.0752) | (0.0136) | |
| Average neighbors 1–4 miles | 0.12*** | 0.081*** | 0.031*** | |
| | (0.0224) | (0.0140) | (0.0019) | |
| Installed base | | | | 0.27*** |
| | | | | (0.0279) |
| Number of housing units (1000 s) | 0.0015 | 0.0069 | 0.0097 | 0.24*** |
| | (0.0311) | (0.0317) | (0.0259) | (0.0617) |
| Housing density (0.001 s) | 0.0014 | 0.0045 | 0.010 | 0.076*** |
| | (0.0097) | (0.0080) | (0.0093) | (0.0151) |
| Renter-occupied houses (%) | 0.00011 | 0.000018 | 0.00033 | 0.00082 |
| | (0.0004) | (0.0004) | (0.0004) | (0.0005) |
| Median household income ($10,000) | 0.0038 | 0.00082 | 0.0027 | 0.0063 |
| | (0.0047) | (0.0042) | (0.0037) | (0.0057) |
| Median age | 0.00097 | 0.00051 | 0.00094 | 0.00098 |
| | (0.0008) | (0.0008) | (0.0007) | (0.0012) |
| Median age in highest 5% | 0.014 | 0.0045 | 0.0082 | 0.024 |
| | (0.0137) | (0.0143) | (0.0112) | (0.0258) |
| Electricity cost (Cent/kWh) | 0.00017 | 0.00045 | 0.00058 | 0.0071 |
| | (0.0014) | (0.0015) | (0.0013) | (0.0019) |
| Unemployment (%) | 0.00021 | 0.0040** | 0.0023 | 0.015*** |
| | (0.0018) | (0.0019) | (0.0017) | (0.0035) |
| Solarize CT | 0.87*** | 0.21 | 0.40*** | 0.63*** |
| | (0.2002) | (0.2350) | (0.1934) | (0.1053) |
| Constant | 0.0052 | -0.072 | 0.045 | 0.045 |
| | (0.0675) | (0.0705) | (0.0554) | (0.0554) |
| Race variables | X | X | X | X |
| Political affiliation | X | X | X | X |
| $R^2$ | 0.19 | 0.19 | 0.34 | 0.34 |
| Observations | 90,090 | 90,090 | 90,090 | 90,090 |

*Notes:* Dependent variable is the number of installations in a block group (BG) in a year-quarter. An observation is a BG-year-quarter. Standard errors clustered on BG in parentheses.
* denotes $P<0.10$, ** $P<0.05$ and *** $P<0.010$.

The results in columns 1–3 provide strong evidence that the spatial neighbor effects diminish over time since an installation occurs. This is intuitive and suggests that previous installations have less of an effect on increasing the likelihood of new installations as time goes on. After a year or two, households are likely to already be aware of previous installations, and thus would be less affected by them. The results in column 4 indicate a highly statistically significant and positive installed base effect, indicating that one additional installation in the installed base increases adoptions in a block group by 0.27 in that quarter. This is a roughly comparable effect to the effect shown in our spatiotemporal variables, but appears to be an average of the effect over space and time. A major contribution of this article is that it allows for a much more detailed view of the levels at which neighbor effects work.

### 6.2. Further robustness checks

We perform several robustness checks on our primary results in Table 2, such as varying the spatial distance and time frame of our spatiotemporal variables and exploring additional fixed effects specifications. We do not report these results here for they are entirely consistent with the results in Table 2. However, we do report two interesting robustness checks in Table 4. Column 1 shows the results where we control for block group unobserved heterogeneity using first-difference results rather than the fixed effects transformation. These results also include year-quarter fixed effects. Column 2 presents the results of a negative binomial estimation with year dummy variables (the model did not converge with year-quarter dummy variables or with block group fixed effects). Both use spatiotemporal variables that include installations over the previous 6 months to be at least somewhat comparable with the results in Table 2.

The first-difference results are very reassuring. The coefficients on the spatiotemporal variables are very similar to those in Table 2 and are nearly identical for the average neighbors adopting between a 0.5–1 mile and 1–4 miles. The first-difference estimation results suggest coefficients that are slightly smaller for the average neighbors adopting within 0.5 mile, but still quite similar to those in Table 2.

As mentioned in Section 5, the nonlinear negative binomial model is a common approach to use with count data for the dependent variable. It adds a structural assumption, but this structure may make sense if adoptions occur according to a negative binomial distribution. The negative binomial model is preferred to the other common nonlinear model used for count data, the Poisson model, when the mean of the count variable is not equal to the variance, for a characteristic of the Poisson distribution is that the mean is equal to the variance.

In our data, the mean of our PV count variable is 0.04 and the variance is 0.07. This suggests that a negative binomial model is preferable to a Poisson distribution. The negative binomial results are larger than those in our preferred linear specification, but tell the same overall story. These results can be viewed as confirmatory of our previous results, which we view as our preferred results due to the ability to include additional fixed effects as controls for unobserved heterogeneity.[12]

## 7. Conclusions

This article studies the primary drivers influencing the diffusion of solar PV systems across time and space. We use detailed data on PV systems in CT, along with built environment, socioeconomic, demographic and political affiliation data, to highlight the key drivers through both a geospatial analysis and a panel data econometric analysis.

12 Results from a Poisson model with block group fixed effects did converge, and also provided comparable results, but with very weak statistical significance for nearly all coefficients, including the spatiotemporal ones.

**Table 4.** Further robustness checks

| | First-differences (1) | Negative binomial (2) |
|---|---|---|
| Average neighbors within 0.5 miles | 0.37*** | 1.11*** |
| | (0.0806) | (0.2052) |
| Average neighbors 0.5–1 mile | 0.33*** | 0.97*** |
| | (0.0757) | (0.1706) |
| Average neighbors 1–4 miles | 0.12*** | 1.04*** |
| | (0.0222) | (0.0499) |
| Number of housing units (1000 s) | 0.0015 | 0.67*** |
| | (0.00194) | (0.0522) |
| Housing density (0.001 s) | 0.0015 | 0.73*** |
| | (0.0037) | (0.1507) |
| Renter-occupied houses (%) | 0.00031 | 0.0099*** |
| | (0.0002) | (0.0015) |
| Median household income ($10,000) | 0.0017 | 0.0034** |
| | (0.0019) | (0.0037) |
| Electricity cost (Cent/kWh) | 0.0011 | 1.32*** |
| | (0.0009) | (0.1166) |
| Unemployment (%) | 0.0097*** | 0.075* |
| | (0.0014) | (0.0424) |
| Solarize CT | 0.34*** | 1.39*** |
| | (0.0609) | (0.1453) |
| Constant | 0.0050*** | 29.1*** |
| | (0.0005) | (1.9328) |
| Race variables | X | X |
| Age variables | X | X |
| Political affiliation | X | X |
| Block group effects | X | |
| Year-quarter dummies | X | |
| Year dummies | | X |
| $R^2$ | 0.19 | |
| Observations | 84,942 | 90,090 |

*Notes:* Dependent variable is the number of installations in a block group (BG) in a year-quarter. An observation is a BG-year-quarter. The spatiotemporal variables include installations from the previous 6 months. Standard errors clustered on BG in parentheses.
* denotes $P<0.10$, $^{**}P<0.05$ and $^{***}P<0.010$.

Our geospatial analysis reveals that the pattern of PV system diffusion does not simply follow patterns of housing density or income. The patterns we find indicate that small and midsized centers of housing density are just as important—if not more important—than larger centers as the main players for the diffusion of PV systems. We speculate that this pattern in CT is a result of the state's jurisdictional and socioeconomic fragmentation, current regulations affecting adoption in multifamily buildings and the Solarize community-based programs.

Our panel data analysis develops a new set of spatiotemporal variables that we have not previously seen in the literature. These variables allow us to more carefully model the spatial and temporal aspects of the influence of neighboring installations on the decision to install, while still retaining a panel data structure that allows us to address the primary confounders of any peer effects or neighbor effects analysis: homophily, correlated unobservables and simultaneity. We consider the refined scale of our analysis as an important contribution.

We find evidence that the primary determinants of the patterns of diffusion of PV systems in CT are spatial neighbor effects and built environment variables. The electricity price and existence of a Solarize program also play a major role in influencing adoption. Our results indicate that there are important spatial neighbor effects: adding one more adoption in the previous 6 months increases the number of PV system adoptions in a block group per year-quarter within 0.5 miles of the system by 0.44 systems on average. Over a year, this is roughly 26.4 additional systems per town when taken at the average number of block groups in a town.

These empirical findings are consistent with the theoretical work by Brock and Durlauf (2010) in showing how social interactions may lead to a different timing of adoptions than can be explained by private characteristics. Of course, it is important to interpret these results keeping in mind that CT is in the early stage of adoption of PV systems, so the neighbor effect is influencing the early, exponential stage of a classic 'S-shaped' diffusion curve (Rogers, 1962). Applying these estimates to later stages in the diffusion process would certainly be problematic. Eventually, nearly all rooftops suitable for PV systems will have already been adopted, and block groups in CT will become saturated.

Our built environment empirical results align with our spatial analysis. We find that adoptions are decreasing in housing density and the share of renter-occupied dwellings, corresponding to our finding that large centers are less important for the diffusion of the new technology. We view these results as consistent with the possibility of split incentives in multifamily and rental properties (Bronin, 2012; Gillingham and Sweeney, 2012).

Besides providing fresh evidence on the nature of the diffusion process of an important renewable energy technology, our results also have several policy and marketing implications for CT and comparable settings. The demonstrated importance of spatial neighbor effects is undoubtedly useful for PV system marketers and policymakers interested in promoting PV systems, for it suggests carefully considering measures to leverage such spatial neighbor effects. Indeed, the community-based Solarize programs are designed to foster social interactions about solar PV systems and have thus far appeared in our data to be quite successful in increasing PV system adoption. Our results showing the pattern of adoption of PV systems are also relevant to policymakers, for they underscore Bronin's finding that split incentives are quite important in hindering the adoption in many more populated communities in CT. Policies reducing regulatory barriers for 'shared solar' or 'community-based solar' may allow for greater penetration of PV systems in more densely populated and less wealthy communities.

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