Spatial peer effects in urban areas: A case study from Hartford Capital region, Connecticut.

By

Marcello Graziano*[1]

Maurizio Fiaschetti**

Carol Atkinson-Palombo***

* *Assistant Professor*, Department of Geography & Institute for Great Lakes Research, Central Michigan University, Dow Science Complex 280, Mt. Pleasant, MI 48858, USA. Email: grazi1m@cmich.edu, P: +1-989-774-1627.

** *Lecturer*, School of Finance and Management, SOAS, University of London.

*** *Associate Professor*, Department of Geography, University of Connecticut.

Building upon recent literature, we combine a novel spatiotemporal variable with spatial methods to investigate and quantify the influence of the built environment and jurisdictional boundaries on spatial peer-effects (SPEs) in inner-city areas. We focus on the Hartford Capital region, using detailed data at block-group and PV system levels for the years 2005-2013. This region is part of a state, Connecticut, actively engaged in supporting PV system at residential level. Adoption of PV systems varies substantially, and state policies are mediated by town-level regulations. We initially employ typology analysis to investigate the heterogeneity of the block groups with higher adoption rates. We then use panel FE and spatial estimations to determine the existence of spill-overs of SPEs beyond town boundaries. Our estimations suggest that new PV systems have a more limited spatiotemporal influence in inner-cities. We identify spatial spill-overs from neighboring block groups even between towns, suggesting that SPEs transcend municipal barriers. We do not find significant results for built-environment, although we identify several data limitations. Our results suggest that centralized, non-voluntary support policies may have larger effects if implemented beyond town-level, and that SPEs change their determination power depending on the underlying built environment.

[1] **Contact Author.**

1. Introduction & Objectives

Like many other experiential goods with high upfront capital costs [1], the diffusion of residential solar photovoltaic (PV) systems can be decisively driven by information flows between peers [2,3,4, 5,6] and through social networks [7], particularly in young markets [8]. As the price of PV systems continues to fall, information-based drivers, and the role of non-monetary barriers may become more important in encouraging households to transition towards this low-carbon option [9,10]. Recent literature has attempted to identify non-monetary drivers influencing the diffusion of PV systems, often finding that spatial peer effects have a positive influence (see e.g. [5,3,11,12]. Similar results have been found even when treated as spill-overs between regions, that is, when neighboring regions do influence each other throughout the adoption process [13,14,15]. As Mills et al. [16] correctly pointed out, researchers and policymakers need to improve their understanding of non-monetary adoption factors in order to better incorporate solar systems in to utility planning, thus focusing on potential policy shortfalls in supporting the adoption of PV for late-comers.

As an extension of prior research, this work has four main objectives: *i)* to typify the profile of average adopters across different urban areas using secondary data ; *ii) to* investigate the existence and influence of spatial peer effects (SPEs) within an urban area characterized by strict jurisdictional (town) boundaries determining differences in local policies; *iii)* to understand the role of spatial barriers in influencing diffusion; and *iv*) to improve the models available for investigating the existence of SPEs, by combining a previously spatiotemporal peer-effect variable as developed by Graziano and Gillingham [3], with spatial models as previously used in the context of peer-effects by Dharshing [15[15], and following the methodological considerations of LeSage [17]. The introduction of spatial techniques based on Dharshing

[15[15], mixed with a previously tested SPEs variable, provides a new, more robust insight in to the dynamics of SPEs across a diverse urban spatial setting, thus highlighting the role of space-time in the diffusion of innovation. To achieve our objectives, we focus on block-group level data from four towns within the Greater Hartford area in Connecticut, a state that has implemented several monetary and informational policies to support PV system adoption at the residential level.

1.1 Relevant Works

Our analysis builds upon the works of Bollinger and Gillingham [6], Graziano and Gillingham [3], Bronin [18], and, partly, Dharshing [15[15]. In their analysis of the diffusion of PV systems in California, [6] identified and quantified the presence of SPEs using zip-code level data, as well as an alternative mean to the installed-base level, which was previously used in literature. Focusing on Connecticut, and conducting their analysis as block group level, [3] built upon Bollinger and Gillingham's intuition about SPEs, focusing on the spatial and temporal degree of influence of these effects, developing a spatiotemporal band of proximity built off of different Euclidean distances of proximity (0.5, 1 and 4 miles), and testing it for different time lengths since the neighboring installations occurred (30 days to 24 months). The authors not only confirmed the presence of SPEs, but found that their effects decayed as time passed and distance increased, virtually fading beyond 4 miles. Further, the authors linked these results to suggest that the spatiotemporal influence of these effects may vary depending on the underlying social and built environment (e.g. use of personal vehicles), differently [11,21], which instead interpreted their similar results as the existence of a cut-off distance beyond which SPEs would rapidly disappear. Focusing on the relationship between built environment and the laws regulating the operation of diffused renewable energy technologies, [18] found that the adoption of these technologies could have been hampered in urban-city areas in Connecticut, thus suggesting that support policies for adoption need to be paired with operational regulations for operating these technologies within multiple built landscapes. Finally, [15] has applied spatial regressive and error models for investigating the factors influencing the diffusion of PV systems in Germany, finding that connected, although not necessarily neighboring, areas influence each other's adoptions.

2. Study Area

Despite being quite wealthy on aggregate, CT has widespread income inequality and poverty [20]. These differences within the state are intertwined with a highly fragmented jurisdictional landscape. A state-wide program subsidizes PV system adoption, and, upon request from towns, community programs such as Solarize CT [3]. In recent years, the residential PV program has been extended to include multi-family buildings (> 5 owners, see [21]), although sub metering is not allowed [18].

Each of the 169 towns retains wide powers in several regulatory matters, including some affecting directly residential PV systems [3]. For example towns may restrict the adoption of roof-top solar systems on certain buildings depending on their age, or the zoning (e.g. historic neighborhood), thus influencing the possibility of adoption, and creating a varied jurisdictional and socioeconomic landscape.

PV systems in CT have reached grid-parity as of 2014 meaning that the cost of electricity is at least the same as the price of electricity purchased from the grid [22], mostly thanks to the high electricity prices in the state and the generous state incentives. The incentive programs are managed at state-level, with incentive amounts and types (e.g. tax-break, cash-back, etc.) set equal for the state as a whole. Among these incentives, homeowners primarily have access to the

Residential Solar Investment Program (RSIP). RSIP can be used for either accessing a PV-lease program, or a feed-in-tariff based on consumption, and funded through the Smart E-Loan program, a zero-interest program available state-wide [23]. Overall, the state is considered as a solar 'friendly' state by market watch groups, featuring in the top-10 PV states in 2018 [24,25], and featuring among the highest states for PV system count, capacity installed, and in the lower half for PV system cost [23].

Our analysis focuses on four towns in the central area of Connecticut: Hartford, the state capital, East Hartford, Glastonbury, and Manchester. All these towns are relatively old by standards in the USA, some having being incorporated as early as the 16th century. The towns form an interrelated space within the Hartford Metropolitan Statistical Area, and have strong economic ties. Nevertheless, each town is administered independently, and, even though they all enjoy the same statewide incentives, they regulate the processes through which PV systems can be licensed. Further, these towns are part of one of the most income and minority segregated regions in the country [26].

Residents of smaller towns usually live in single-family houses, whereas those of larger, and older, core-municipalities such as Hartford live in multi-family buildings. Due to the statewide prohibition of sub-metering and the lack of split-incentives (between landlord and renter of among occupants of multi-family buildings) to encourage adoption in these areas, diffusion of PV systems might be difficult even when access to the financial resources is not an issue [18]. On aggregate, the state has seen a surge of PV systems adoption in recent years. As of September 2013, 3,843 residents have adopted rooftop PV systems, equating to an increase of 36.5% from December 2012 [27]. Within this context, our study area offers a wide range of socioeconomic conditions. Figure 1 shows the extent and location of our four towns and the median household income for each town.

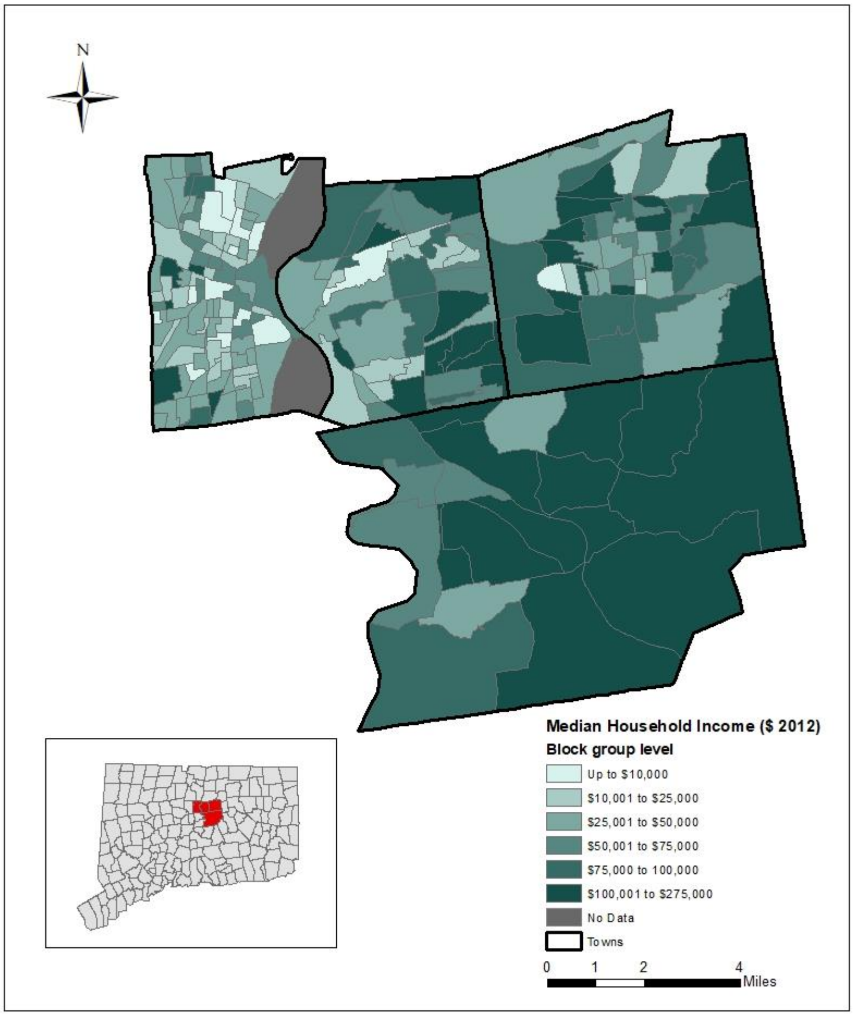


Figure 1 – Study Area with Median Household Income at town level, 2012

The four towns play different roles within the Connecticut's economy. Hartford, the capital, hosts several governmental buildings and it is one of the major international centers for insurance companies. East Hartford still hosts few large manufacturing plants. Both these towns have problems related to poverty and crime. Manchester hosts one of the largest shopping areas in the state. Finally, Glastonbury has recently developed as a wealthier, suburban community, although it still has several plots of farmland. Overall, the towns extend for about 300 sq. km of land and are home to 268,000 people, or 7.5% of the state population. None of these towns was part of the CT Solarize program during the period analyzed.

2.1 Data Sources

We conduct our analysis at the (Census) block group level, selecting data at this scale when possible. Table 1 provides an overview of the sources used.

Table 1. Summary Statistics and Sources[2]

Variable	Mean	Std. Dev.	Min	Max	Source
Number of new Adoptions	0.05	0.22	0.00	1.00	[27]
Cumulative Installed Base	0.16	0.54	0.00	7.00	[27]
Average Neighbours within 0.5 Mile (6 months)	0.01	0.11	0.00	3.00	Calculated from [27]
Average Neighbours within 0.5 Mile (12 months)	0.02	0.29	0.00	16.00	Calculated from [27]
Average Neighbours within 1 Mile (6 months)	0.01	0.18	0.00	5.50	Calculated from [27]
Average Neighbours within 1 Mile (12 months)	0.03	0.53	0.00	30.00	Calculated from [27]
Average Neighbours within 1.5 Mile (6 months)	0.01	0.08	0.00	2.50	Calculated from [27]
Average Neighbours within 1.5 Mile (12 months)	0.01	0.26	0.00	14.00	Calculated from [27]
Average Neighbours within 4 Miles (6 months)	0.05	0.61	0.00	19.00	Calculated from [27]
Average Neighbours within 4 Miles (12 months)	0.10	1.74	0.00	102.00	Calculated from [27]
Number of Housing Units (000s)	0.62	0.40	0.05	3.65	U.S Census
% of Rent-occupied Houses	51.32	33.76	0.00	100.00	U.S Census
% of Houses >5 bedrooms	3.49	6.29	0.00	65.86	U.S Census
Gross Housing Density	1561.32	2230.40	9.50	28908.94	U.S Census
Number of Housing Units (000s)	0.62	0.40	0.05	3.65	U.S Census
Median Household Income ($10,000)	5.47	3.62	0.15	25.57	U.S Census
Dow Jones Level (1,000)	11.66	1.59	8.89	14.87	U.S Census
% pop who are white	52.07	28.75	0.00	100.00	U.S Census
% pop who are black	25.82	25.14	0.00	100.00	U.S Census
% pop who are Asians	5.41	8.00	0.00	73.12	U.S Census
Median Age	36.62	9.42	11.61	80.00	U.S Census

[2] Values based on [7] and interpolated from the U.S. Census 10-year Census 2000 and 2010, and ACS 5-year averages for the years starting in 2008.

% Registered to minority parties	0.42	0.46	0.00	2.82	[28]
% Registered to the Democratic Party	53.44	16.36	21.80	75.23	[28]
		Built Environment			
Net Housing Density	886.49	523.23	0.00	2753.67	Calculated
Share of Single-Family Houses	55.67	35.12	0	100.25	Calculated

We employ a data subset from [3], selecting the block groups belonging to Hartford, East Hartford, Glastonbury and Manchester. These data are the result of interpolated values from actual observation points derived from the Census 2000 and 2010 and the American Community Surveys (ACS) – 5-year averages from 2005 to 2011. The time period covered is January 2005 through September 2013. In the interpolation process, [3] accounted for the changes in block group boundaries using the newer boundaries assigned by the U.S. Census after 2008. The interpolation process was necessary to obtain a continuous dataset within the period of interest.

PV systems location and date of application to the Connecticut Energy Financial and Investment Authority (CEFIA)[3] incentive program come from the CEFIA Solar Database [27]. The dataset contains several information about adopters, including addresses and the day-month-year of installations. The dataset records each residential installation since 2004. Because of the methodology used (i.e. with lagged values), we dropped the (few) observations available for the first year. Overall, the period considered runs from January 2005 and September 2013, equal to 35 quarters. To understand the role of spatial peer effects, we build upon the work of [3], introducing the spatiotemporal variable developed by the two authors. This variable aggregates at block group level the number of PV installations within 6 and 12 months from each actual PV system location at various spatial distances starting 0.5 miles. The advantages of using the framework and the spatiotemporal variable developed by [3] are multiple. Their approach

[3] As of 2016, the new name of the agency is Connecticut Green Bank.

overcomes the issues related with homophily, correlated unobservables, and simultaneity. Furthermore, the spatiotemporal band *per se* allows us to reduce the effects of aggregating data at specific areal units, as it is calculated starting from each observation.

Compared to [3], we allow the search model to account for installations in towns outside the study area. Further, we adjust our specifications to account for the different total extent of our study area, as explained in the model specifications. Combining the proximity variable developed by [3] with the spatial models utilized by [15], we further improve our estimations, accounting for spatial effects and the influence of neighboring areal units.

2.2 Spatial Data and Parcels Data Collection

The majority of the spatial and boundary data employed assess the role of peer effect and for display purposes come from the University of Connecticut Map and Geographic Information Center [29]. For understanding the role of the housing composition, we use parcel data created by each town. We calculate the net housing density, the density of parcels where adoption of residential PV systems can actually occur.

This density is expressed as:

$$NetHouseDens = \frac{\#\ of\ Residential\ Parcels}{Total\ area\ of\ Housing\ Parcels\ (sq.km)}$$

Many of the parcels within these four towns have been developed pre-1970, and dwellings tend to occupy almost the entirety of each parcel, with little space for yards. Because of the data limitation, we adopt a gross housing density in our panel models. This can be written as:

$$GrossHouseDens = \frac{\#\ of\ Housing\ Units}{Total\ land\ area\ in\ block\ group}$$

A third measure controlling for the urban setting is the share of single-family houses within each block group. We define this variable as follows:

$$ShSingleFam = \frac{\#\ of\ Single\ family\ Parcels}{\#\ of\ Residential\ Parcels}$$

The study does not include a single source for the parcels data. Indeed, Connecticut does not have a statewide or a region-wide depository of such data. Each of the 169 towns is responsible for collecting, storing and sharing its own parcel data, without standardization across municipalities, and none has multiple years of parcel data to use as a comparison. As a result, we are forced to introduce these variables into an OLS model.

3. Methods: Typology Analysis and Modelling Strategies

Following the suggestion that underlying human and physical geographies influence peer effects and diffusion [3][3], and giving the data limitations presented above, to capture the differences of users within the study area, we use three methodologies, two of which are presented in this section. First, we employ hierarchical clustering to assess the number of block group clusters within each town, and the major drivers behind this clusterization [30, 31, 32]. Through hierarchical cluster analysis, we produce a unique set of nested categories by sequentially pairing variables. Then select that pair (or cluster and variable) producing the highest average inter-correlation within the trial cluster, and deem it to be the new cluster [30, 30]. Following this first analysis, we proceed with a spatial inference of the distribution of adopters in relation to spatial barriers. We display the results of hierarchical clustering in dendograms (appendix A). From this analysis, we infer that the optimal number of clusters is four, with income being the major element determining the dataset partition. In the following section, we will use these results to create and compare adopters' profiles across the four towns.

Figure 2a provides an overview of the number of PV systems within each block group across the study area. In Figure 2a, we show the four towns, highlighting the residential parcels in 2013 over all other town parcels. It appears quite clear that the four towns differ in terms of PV system diffusion, and of residential distribution within their boundaries.

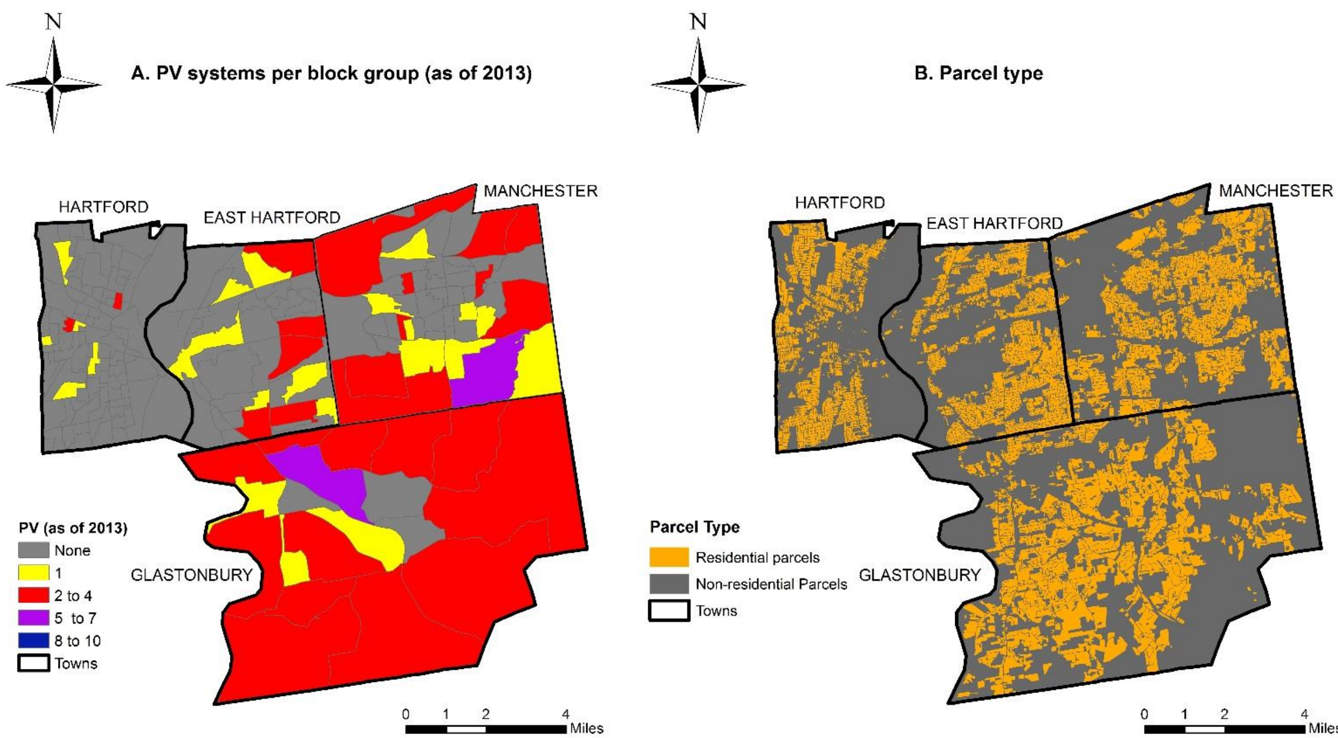


Figure 2 – A. Number of residential PV system adopters (as of October 1, 2013) within Hartford, West Hartford, East Hartford, Glastonbury, and Manchester (Connecticut). **B.** Spatial barriers and residential parcels in Hartford, West Hartford, East Hartford, Glastonbury, and Manchester (Connecticut), composite of last available years.

Overall, the towns have several spatial gaps in their residential patterns. For example, parks and green spaces can be easily accessed and can provide places of aggregation for people, but also operate as 'disaggreagators' in terms of social interaction with the built environment [33]. Effectively, spatial peer effects appear to be concentrated within neighborhoods, depending on the layout of each town. Consequently, programs partly based on community incentives will have to target several neighborhoods within each town, rather than treating these towns as uniform entities, building business models capable of fulfilling utility needs [34,33], and leveraging further on social networks [34].

3.1 Modelling Strategy 1: Panel and OLS to identify SPEs and the Role of Spatial Barriers

The analysis of block groups' characteristics provided us with two main results. First, we identify the general profile of PV adopters, or, more precisely, the profile of an adopter's block group. Second, we establish that this profile changes across towns, and, given the jurisdictional and socioeconomic fragmentation, current statewide policies not capable of capturing these local nuances may result in an overall lower efficiency or bias towards specific regions. Building on [3] and [6] we use panel fixed-effect[4] and OLS models to identify the drivers of PV diffusion, and the role of the built-in environment.

Starting from the panel data analysis, our specification can be parsimoniously stated as follows:

$$PVcount_{i,t} = \alpha + \boldsymbol{N}_{i,t}\,\beta + \boldsymbol{B}_{i,t}\,\gamma + \boldsymbol{D}_{i,t}\,\theta + \mu_i + \psi_t + \varepsilon_{i,t} \qquad (EQ : 1)$$

where $PVcount_{i,t}$ is the number of new adoptions in block group i at time t; $\boldsymbol{N}_{i,t}$ is the vector of spatiotemporal variables built by [3] and $\boldsymbol{B}_{i,t}$ is the vector of built environment variables. $\boldsymbol{D}_{i,t}$ is a vector of socioeconomic and demographic variables also containing controls for median income, racial and age profile for each block group similar to those of [3][3], and commonly used in previous works. We further add a dummy variable, *Income100k*, to control for those block groups with median household income greater than $100,000 to investigate if there is

[4] 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.

a break-point above which adoption is more likely. ψ_t is a time dummy variable; and $\varepsilon_{i,t}$ is a zero-mean error term.

In line with previous research [2,3,37] we use a series of fixed-effects (FE) to assess the drivers of the PV adoption. In particular, we are interested in two sets of FEs: those addressing personal characteristics of the decision maker (e.g. age and ethnic group) and those addressing the spatial peer effects. With respect to the latter we define a set of proxy as the number of new adoptions respectively within 0.5, 1, 1.5 and 4 miles from each block-group center, and excluding adoptions occurring in the same quarter to account for simultaneity. These proxy variables allow us to investigate the role of geography in generating spatial spillovers which we specifically address with the spatial analysis. The values of the spatiotemporal variable are then aggregated and averaged at block group level. Given the physical nature of the spatial interactions, our analysis can easily overcome the major issues raised in [38] such as those regarding identification, computational matters, measurement errors, misspecification and the presence of endogenous networks (i.e. unobserved features of the decision makers influencing their behavior). Conversely, spatial effects can still suffer from a time and context dependence and this is why we also add the time dimension defining a set of SPEs for two time periods: six months and twelve months, as suggested by [3].

The limited number of observations makes town-level partition of little use; therefore, we focus on the study area as a whole, at the U.S. Census block-group level.

Due to the availability of more granular (parcel) data describing the built environment for the year 2013 only we further proceed with a set of cross-sectional models. We specify three OLS regressions adopting the same specification we use for panel data as (EQ.:1). Time variable is fixed to 2013 and the vector $\boldsymbol{B}_{i,t}$ is changed according to the more granular information available. In panel data, $\boldsymbol{B}_{i,t}$ includes the 'Gross Housing Density', presented above, to control for housing densities and, to a certain extent, housing type. In cross section, we replace this control with the 'Net Housing Density'. Further, we introduce the share of single-family parcels to control for housing type. As a whole, these variables investigate the relationship between the built environment and current regulations on sub-metering and split incentives would increase adoption of PV systems, as suggested by Bronin [18]. Because of the effect of town policies on PV adoptions, we cluster standard errors in both panel data and cross section analysis at a city level.

3.2 Modelling Strategy 2: Introducing Spatial Models and Cross-Jurisdictional SPEs spill-overs

The importance of spatial aggregations of PV systems, quite evident from Figure 1, and Moran's I test performed in ArcMap (at the block group level) reporting the existence of non-random clustering[5], suggest further work is needed. In order to address the issue of spatial spillovers, we use the standard empirical methods of spatial econometrics as suggested by the literature (e.g. [15]). Given the nature and scope of our analysis, we adopt a Spatial Autoregression Model (SAR) as our best specification. Following [17], SAR is among the most suitable specifications to address local spillover effects without postulating a spatial autocorrelation of the error term (see [36] for further references about alternative specifications) and it is a special case of the more general Spatial Durbin model (SDM). The general specification for the SDM is the following:

$$y = \rho W y + \alpha i_n + X\beta + WX\beta_2 + \varepsilon \qquad \textit{(EQ : 2)}$$

[5] P-value: 0.00069, Z-value: 3.39.

Where W is the matrix of spatial lags, αi_n and ε error terms and X the matrix of characteristics of the regions. The model collapses to a SAR when $\beta_2 = 0$, thus allowing a major focus on the autoregressive nature of the dependent variable. SDM (and SAR, as its special case) is particularly useful when there is a reason to assume (and test) that the dependent variable shows a path dependence, thus focusing on this specific type of spillover effects neglecting the spatial effects of the other characteristics of the regions. Given the nature and scope of our analysis, focused on local spillovers, and the problems highlighted by [17] in estimating the other specifications, we consider SAR model the best option to capture the underlying dynamics of the PV adoption. Therefore, our specification can be parsimoniously stated as: :

$$PVcount_{i,t} = \rho W\, PVcount_{i,t} + N_{i,t}\,\beta + a_i + \gamma_i + \varepsilon_t \qquad (EQ : 3)$$

where $\boldsymbol{\rho}$ is the spatial coefficient, W is a queen matrix of spatial lags, $\boldsymbol{N_{i,t}}$ a reduced vector of regressors, a_i the individual fixed effect, $\boldsymbol{\gamma_i}$ the time effect and $\boldsymbol{\varepsilon_t}$ the error term. In terms of weight matrix, in line with the objective of this section, we chose a contiguity (rather than a distance) approach. Following the most recent and advanced techniques we developed a queen contiguity matrix which defines as 'neighbors' those regions sharing an edge of a node, thus accounting for those block groups with common boundaries. This approach is consistent with [15] and the queen weight matrix has proven to generate at least as many links as the alternative ones. Moreover, given the explicit focus on jurisdictional boundaries between neighboring block groups, the choice of a queen weight matrix seems to suit best the coexistence of administrative and geographical interactions.

As a robustness check, together with our benchmark model (SAR) we chose to run a Spatial Error model and a Spatial Autocorrelation model (SAC, see Appendix). Our main hypothesis is that when it comes to choose whether or not to adopt a PV, the contiguity with a block group with at least one PV system has a positive effect in enhancing the propensity to follow through.

4. Results

4.1 Profiling Adopters: Social Status and Built Environment

Following the hierarchical clustering results, we employ two scales for comparing the profile of adopters. First, we focus on the characteristics, both socioeconomic and related to the built environment, of the block groups within these towns. Second, we seek to understand whether or not these characteristics are common across the study area. Table 2 presents summarizes the profile of the adopters for each town and the one for the region as a whole.

Table 2. Adopters' Profile, Towns and Study Area

Characteristic	**East Hartford**	**Glastonbury**	**Hartford**	**Manchester**	**Study Area**
Income	High income	Middle income	Middle-lower income	High income	High income
Race	White	Diverse	White	Diverse	White
Home Ownership	Homeowner	Homeowner	Homeowner	Non-homeowner	Homeowner
House Size	Large houses	Smaller houses	Large houses	Large houses	Large houses
Housing Age	Recent houses	Old houses	Recent houses	Old houses	Recent houses
Residents Age	Relatively old	Relatively young	Relatively old	Relatively old	Relatively old
Housing Density	In sparsely populated neighborhood	In sparsely populated neighborhood	In densely populated neighborhood	In sparsely populated neighborhood	In sparsely populated neighborhood
Housing Type	Single family	Single family	Mixed	Single family	Single Family

Note: "Recent houses" are built post 2000; "Old houses" are built pre-1900. Large houses have more than 5bedrooms.

The description of the average adopter within the study reads like the following: "a high-income, white home-owner, around 45 years of age living in a newly built, large house in the outskirt of the towns". For each of these characteristics we can find an exception when looking at the profiles in Table 2. In particular, income and race appear to vary across the towns. In Table 3, we present the same data in a different way: each characteristic is compared to the average for the study area. In brackets the actual value is displayed together with ranking within each town expressed in roman numbers or category-score such as highest/youngest and the like.

Table 3. Adopters' Characteristics – Relative Rankings

Characteristic*	**East Hartford**	**Glastonbury**	**Hartford**	**Manchester**
Overall Adoption (PV Rate)	Higher (0.0026)	Highest (3.79)	Lowest (0.004)	Higher (0.028)
Income (Mean)	Average ($110,000; II)	Highest ($110,000; III)	Lowest ($36,000; III)	Higher ($245,000; I)
Diversity (% white)	Diverse (60%; I)	Uniform (79%, III)	Diverse (35%; I)	Moderately Uniform (61%; IV)
Home Ownership (% owners)	Higher (78%, I)	Highest (80%, I)	Lowest (32%; III)	Higher (98%; I)
House Size (% homes > 5 bedrooms)	Lowest (22%; I)	Highest (2%, IV)	Average (5%, II)	Lower (12%; I)
Housing Age (max)	Relatively old (1950; II recent)	Relatively recent (1970; oldest)	Most Recent (1976, II recent)	Oldest (1860; oldest)
Residents Age (median age)	Average (45; oldest)	Highest (46; II youngest)	Lowest (37; II youngest)	Lower (47; oldest)
Housing Density (max residential/sq.km)	Below average (636; II lowest)	Lowest (258; lowest)	Highest (2325, highest)	Lower (354; lowest)
Housing Type (% single family houses)	Single Family (91%; lowest)	Single Family (81%, II lowest)	Mixed (40%; II highest)	Mixed-Single Family (97%; Highest)

*Notes: Description is relative to whole area. Level and ranking of highest adopting group are shown in parentheses.

Towns show differences in the profile and distribution of PV systems. Overall, the rate of adoption[6] (PV rate) is far higher in Glastonbury than in all other towns. However, most of these installations are contained within one block group, which displays a value several times higher than the average for the whole region. The consequence of this difference is that while in Glastonbury adoption appears more advanced, East Hartford is at a different stage of PV systems penetration. Income is another characteristic changing its relative value across the towns. Although levels above $100,000 are displayed in three of the towns, adopters in Hartford appear to reside in medium-low income areas. Further, the same income level places adopters at

[6] PV systems installed as of September 2013/Residential Parcels in 2013.

different levels within each town. In Glastonbury, the same top-income level of East Hartford belongs only to the second highest income brackets, whereas in Manchester, the top earners make twice as much as East Hartford. Overall, a household income of around $100,000 is expected to characterize the block groups where adopters reside. Additional differences are evident in the racial profile of adopters. In Glastonbury, the adopters tend to be described as residents of diverse neighborhood. In Hartford, the larger number of adopters is in areas with the highest percentage of white people. However, the 'diverse' neighborhood in Glastonbury has twice the share of white people than the one in Hartford. These results are in line with those of [18] and of [3], as support policies in Connecticut over this period were used mainly in single-family, owner-occupied areas.

Finally, the socioeconomic profile of adopters across these towns appears to be quite different from the overall profile across the study area, although partly in line with the findings of [11]. However, with the partial exception of the capital, the area geography characterizing the presence of adopters is consistent with the findings of [3].

4.2 Empirical Analysis: Panel and Cross-section Models

Looking at EQ.: (1) of the panel approach in the present work, we are interested in: (i) **the parameter $\boldsymbol{\beta}$**, which controls for spatial peer effects; (ii) **the parameter $\boldsymbol{\gamma}$**, which would link the effect of current polices with area geography and the adopter's profile (as the coefficient of the built-in environment); and (iii) **the parameter $\boldsymbol{\theta}$** associated with *Income100k*, that is, a measure of higher income earners. Table 4 presents the results of our econometric analysis where Column (1) shows the outcome of the benchmark specification in which there is no proxy for SPEs, but rather the cumulative number of adoption is used. Column (2) addresses the role of new adoptions in the previous 6 months within a range of 0.5 miles and Column (3) broadens the time frame to 12 months. We use the installed-base because as this is the more common control in works on PV diffusion (e.g. [19]), and provides a comparison with the other spatiotemporal estimates.

Table 4. Panel Specifications

	Cumulative Base, Block FE (1)	0.5 mile, 6 Months, Block FE (2)	0.5 mile, 12 Months, Block FE (3)
Installed base	0.716*** (0.154)		
Spatial Peer Effect		4.125** (1.221)	1.082** (0.241)
Median Household Income	-0.015 (0.013)	-0.015 (0.011)	-0.021** (0.009)
Median Age of the Population	0.000 (0.002)	0.006* (0.003)	-0.005* (0.003)
Number of Housing Units	0.098 (0.074)	0.163* (0.092)	-0.152* (0.087)
Share of Houses with more than 5 bedrooms	-0.006* (0.004)	-0.004 (0.003)	-0.002 (0.003)
Share of Black Resident	-0.000 (0.001)	-0.002 (0.001)	-0.002* (0.001)
If income >$100,000	-0.007 (0.091)	-0.051 (0.129)	-0.043 (0.129)
Minority* Proximity (0.5 miles)	-0.083 (0.059)	-0.161** (0.035)	-0.072 (0.040)
Minority*Proximity (1.0 miles)	0.150** (0.060)	0.139 (0.065)	0.140* (0.052)
Minority* Proximity (4 miles)	0.012 (0.015)	0.012 (0.015)	0.014 (0.014)
Median HH Income * Proximity (0.5 miles)	0.141 (0.103)	-0.127 (0.113)	0.120* (0.040)
Median HH Income * Proximity (1.0 miles)	-0.128* (0.074)	-0.038 (0.066)	-0.135** (0.034)
Median HH Income * Proximity (4 miles)	0.072** (0.034)	0.083* (0.034)	0.077* (0.029)
Built Environment	Y	Y	Y
Socio-Demographics	Y	Y	Y

Political Affiliation	Y	Y	Y
Quarter dummies	Y	Y	Y
Constant	-0.302 (0.239)	-0.317 (0.506)	-0.141 (0.481)
R-squared	0.450	0.419	0.481
Observations	7,175	7,175	7,175

*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.*

Our estimations (columns (2) and (3)) suggest a positive value for the coefficient β, i.e. the existence of positive SPES at a block level. Comparing the estimations (2) and (3) the peer effect is proven to be stronger in the shorter spatial range and rapidly diminishing as time passes[7].

In our results, the medium range, 1 mile, is the distance at which the interaction effects of the adopters' personal characteristics displays the highest influence on neighborhood's choices. Interestingly, the median household income exerts a statistically significant effect on the adoption, even though limited to the short range. This is consistent with the previous literature signaling a weak relationship between PV adoptions and environmental concerns [3, 13,39]. The result is further confirmed by the significant negative effect of the share of houses with more than 5 bedrooms, usually associated with larger and more expensive dwellings. Even though personal and contextual factor, in fact, are weakly statistically significant when taken individually, their effect becomes stronger when interacting with a proximity variable. As shown in table 4, being part of a non-white race minority generally increases the effect of proximity (except for the short distance, i.e. 0.5 miles, where it seems to reduce it. We interpret this result as smoothing the already strong effect of 4.125 registered at this level). Similarly, the median

[7] We performed several additional runs, including quarter-level specifications and town-year FE. Results are available upon request.

household income seems to generally boost the proximity effect in the short and long ranges (0.5 and 4 miles), and it curbs it in medium range (1 mile). Our interpretation is the following: income plays a role in driving the spatial peer effects of PVs adoption and it has two distance-related dimensions. In the short range (0.5 miles) it may capture a 'Keeping up with the Joneses' effect, whereas in the long haul (4 miles) it displays a more standard income effect, though spatially mediated (it is an interaction effect not a purely income one). Where neither of the two effects are in place, i.e. in the medium range of 1 mile, it negatively affects the choice of adopting PVs, even though it is not statistically significant.

These results highlight the sensitivity of spatial peer effects to the underlying human-urban geography of the study area. In densely populated, although fragmented, urbanized areas, spatial and social interaction require shorter distances than in suburban towns, showing consistency with previous works (e.g. [6]). Additionally, the built environment of urban areas is more complex, and new installations possibly become easily part of what agents perceive as 'familiar', and influenced by the layout of the built environment [33]. The results from the variables on the built environment are less conclusive. In our panel models, none of the variables controlling for housing density or tenure are significant. Of all other socioeconomic and demographic controls, specifications (2) and (3) are consistent with the negative impact associated with higher share of self-defined black residents. This result needs to be interpreted in light of the disproportionate number of low-income, non-white population in Connecticut [20], and in the USA [40]. Finally, median household income and the control for income above $100,000 are not significant, as well as the indicator for the Dow Jones Industrial Average. This last result is particularly important since this variable has the advantage of capturing the global influence the economic cycle exerts over the adoption decision, which seems not to influence the adoption of PVs. Finally, it is important to focus on the time dynamics of peer effect. Comparing results in columns (2) and (3) it is evident how the pure peer effect remains positive and statistically significant, but decreases hugely through time from 4.125 (6 months) to 1.082 (12 months), once again signaling that the PV installation becomes part of the potential adopters' surroundings as time passes. This result is consistent with that of [3], although it is interesting, for the effect is far bigger in size, but not in extent (results using SPEs above 1 mile are non-significant), thus confirming that changes in the underlying area geography (including the location on the adoption curve) change the relative influence of SPEs. Because of collinearity issues, we are forced to introduce our refined density and housing typology in cross section specifications. Table 5 shows the results of the cross section analysis where Column (1) provides the outcome of the benchmark OLS with the installed and no proxy for SPEs, Column (2) tests the significance of new adoptions in the previous 6 months within a 0.5 miles range and Column (3) extends this time frame to 12 months.

Table 5. OLS specifications

	Installed Base (1)	0.5 mile, 6 Months, Block FE (2)	0.5 mile, 12 Months, Block FE (3)
Installed base	0.4425*** (0.0348)		
Spatial Peer Effect		6.8583*** (0.8446)	0.4057** (0.0837)
Number of Housing Units (1,000s)	-0.0600 (0.0934)	-0.0043 (0.0622)	-0.0265 (0.04449)
If income >$100,000	-0.1105 (0.3056)	0.2059 (0.4952)	0.4839 (0.2990)
% of Renter-occupied Houses	0.0016 (0.0016)	-0.0038** (0.0011)	-0.0035** (0.0008)
% of Single-family parcels	0.0015 (0.0021)	0.0002 (0.0016)	-0.0004 (0.0008)
Net Housing Density (# residential parcels/sq.km of residential parcels)	0.0004 (0.0002)	0.0001 (0.0001)	0.0001** (0.0000)

Socio-Demographics Controls	Y	Y	Y
Built Environment	Y	Y	Y
Socio-Demographics	Y	Y	Y
Political Affiliation	Y	Y	Y
Constant	-1.525 (0.653)	-0.897* (0.290)	-0.553* (0.192)
R-squared	0.2872	0.2046	0.4988
Observations	205	205	205

*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 in parentheses. * denotes p<0.10, ** p<0.05, and *** p<0.010.*

The cross section specifications confirm the existence of spatial peer effects at 0.5 miles and in general few variables are statistically significant parameters. This is relatively disappointing, but the very low numbers of non-zero values in the count variable may have contributed to this outcome, in spite of the zero-inflated values. We find that the share of rented-occupied houses affects negatively the adoption. Our interpretation is that the high average estate values may increase the share of rent-occupied houses and the renters have a lower incentive to adopt PVs. On the other hand, net housing density has a weak positive effect, confirming our assumption that also spatial gaps, at least in a cross section framework, play a role in driving the choice of adopting PVs.

4.3 Empirical Analysis: Spatial Insights

Table 6 shows the results for our SEM, SAR, and SAC models. Both SEM and SAR assess a positive and statistically significant effect of the neighborhood in both the variable summing the 6-month average of the neighborhood adoption within 0.5 miles and the specific spatial coefficient peculiar to each model, i.e. *lambda* and *rho*, indicating an improvement from the panel specifications.

Table 6. Spatial regression models

	SEM (1)	SAR (2)	SAC (3)
Average Neighbors within 0.5 Miles (6 months Average)	0.57424*** (0.07432)	0.57522*** (0.07460)	0.57764*** (0.07804)
% of Renter-occupied houses	-0.00025 (0.00021)	-0.00026 (0.00021)	-0.00022** (0.00011)
Built environment Controls	Y	Y	Y
Socio Demographic Controls	Y	Y	Y
Race Controls	Y	Y	Y
Political Affiliation	Y	Y	Y
Lambda	0.05146** (0.02022)	N/A	-0.06670 (0.14950)
Rho	N/A	0.06106*** (0.00770)	0.14215 (0.11921)
Variance	0.01153* (0.00648)	0.01152* (0.00647)	0.01197* (0.00651)
R-squared	0.26060	0.26056	0.27338
Observations	7,175	7,175	7,175

*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 in parentheses. * denotes p<0.10, ** p<0.05, and *** p<0.010.*

Interestingly enough, the spatial dimension seems to be the only significant driver of the choice, something which is consistent with our general econometric results in Section 5 where we found a general significance of the geographical variables, both individually and interacting with other controls such as minority and median income.

To better understand the nature and dynamics of the spatial spillovers we provide a decomposition of their direct and indirect effects, building upon the procedure suggested by [41].. Table 7 shows the direct and indirect effect, that is, the effect exercised from within the block group (direct), and the one from neighboring (contiguous) block groups.

Table 7. Spatial decomposition of SAR model

	SAR Model

Main	
Average Neighbours within 0.5 Miles (6 months Av.)	0.57899*** (0.07591)
Spatial Effects	
Rho	0.06147*** (0.00988)
Variance	0.01159*
σ^2	(0.00654)
Direct	
Average Neighbours within 0.5 Miles (6 months Av.)	0.28987*** (0.06139)
Indirect	
Average Neighbours within 0.5 Miles (6 months Av.)	0.03798*** (0.00804)
Total	
0.5 miles, 6 months	0.61618*** (0.06885)
R-squared	0.27042
Observations	7,175

*Note: New installation in block group/quarter as d.v. See full table in Appendix. * p<0.10, ** p<0.05, *** p<0.010*

As shown by Table 7 the spatial effect of adopting a PV is not limited to the block. Even though the direct effect represents by far the principal component of the spatial driver also spillovers play a role. As expected, we found an indirect effect statistically significant and positive thus confirming that the adoption of PVs generates neighborhood effects which should be accounted for together with the other geographical dimensions of the problem.

5. Conclusions and Future Research: *defining the right policies, choosing the right scale.*

We investigated different drivers and profiles associated with PV systems adopters in four Connecticut towns. Comparing the results of the town and area profiles with those of the econometric models, we find that the role of income and the built environment are greatly reduced in the latter, possibly because of the way income has become dissociated from wealth (see e.g. [42]). The differences in the adopters' neighborhood profiles among the towns, and between each town and the study area as a whole, suggests that policies promoting the adoption of PV systems should expand their degree of flexibility to account for multi-family housing units, possibly through solar cooperatives or community organizations, which have been found to promote the diffusion of PV systems [7]. In addition, towns with large spatial gaps between residential areas, group-based programs like Solarize CT should be replicated within each neighborhood, rather than at town level, thus aggregating adopters from within the same spatial region. Spatial peer effects last for a shorter time and within a lower distance in urban environments than what was previously found for Connecticut as a whole, suggesting that PV systems are absorbed faster within urban environments than in suburban areas [3]. Besides confirming the spatial peer effect within 0.5 miles, our spatial models show that the within-block group effects are stronger than those from neighboring block groups. The results related to SPEs result was expected, for other specifications with larger spatial buffers show decreasing influence. However, it also suggests that, even in a state jurisdictional boundaries (i.e. with towns with strong regulatory powers influencing PV adoption) such as Connecticut, spatial peer effect can be used as way to accelerate the adoption of PV systems across town boundaries, at least at the early stages. As the SPE fades, other variables come in to play to influence adoption, mainly in relation to race and age, which, once again, drive back to an issue of income measurement. Finally, one interesting result is the lack of influence of the controls for the general state of the economy (in our specification by the Dow Jones Annual Average Index), or of any other control used (Consumer Confidence Index; unemployment rate), which suggest a strong, yet independent resilience of PV diffusion in relation to the macroeconomic fluctuations of the general economy. Potentially, this result strengthens the indication that subsidies can hedge against more than other shortcomings, as suggested by [43].

Comparing our findings with those of other studies on spatial peer effects and socioeconomic profile of PV adopters (e.g. [15]), we persistently find differences related to the urban geography, the jurisdictional fragmentation, and socioeconomic levels, affecting the dynamic of diffusion. To account for these local characteristics we are not suggesting a return to a strong regionalism, where no region is similar to another, and generalizations are impossible to be made [44]. For instance, several works have found sets of socioeconomic demographic and spatial elements that encourage or reduce adoption of PV and other energy systems across various countries (e.g. [2,12,21]). We argue that the interaction among these elements does not always follow the same patterns because mediated by institutional and social factors [45,20]. In the case of PV systems in CT, recent efforts are being made to target more densely populated areas, multi-family buildings, and lower-income areas, and proposals exist to introduce legislation on solar community gardens and other share-ownership initiatives [46]. We see these policies as correct in their effort to expand the base of adopters, overcoming the distortions generated by interaction of policies and the human geography of adoption, and they can further ease concerns about financing and maintenance, which are determining factors in the mode of adoption, especially as the market matures [47].

Finally, our methodologies provide a better understanding of profile adopters and adoption patterns within areas at the bottom of their adoption curve [16]. These results are important for making it easier for utilities and policymakers to address potential needs within the power grid system, especially as community solar is bound to expand further, and social interactions increase in importance [34] for successfully transitioning towards a low-carbon electricity generation.

Acknowledgments

This work has been partly supported by the MERIKA (merikafp7.eu) project funded by the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 315925, the U.S. Department of Energy Sunshot Program, and the Connecticut Center for Economic Analysis. The authors would like to thank Dr. Kenneth T. Gillingham (Yale University), Professor Dean Hanink (University of Connecticut), and Professor Fred V. Carstensen (University of Connecticut) for their feedback and support during the development of our models. The authors further thank GIS offices for the towns of Hartford, East Hartford and Manchester for assisting on the data collection process, along with Professor John Glascock (University of Connecticut) for supporting us during the data gathering process, and Mike Howser (University of Connecticut - MAGIC), for his continuous help in dealing with U.S. Census datasets. Finally, we thank Dr. Matt Liesch (CMU) for helping us improving the verbiage on such a short notice. Dr. Graziano expresses his appreciation to the late Professor Laurence Mee, whose inspiration as a scholar and brilliance as a person still inspire his work. This work is dedicated to his memory.

References

[1] Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy*, 78(2): 311-329.

[2] Bollinger, B., Gillingham, K. (2012) Peer Effects in the Diffusion of Solar Photovoltaic Panels. *Marketing Science,* 31(6): 900-912.

[3] Graziano M., Gillingham K. (2015). Spatial Patterns of Solar Photovoltaic System Adoption: The Influence of Neighbors and the Built Environment. *Journal of Economic Geography*, 15(4): 815-839.

[4] Rai V., Robinson S.A. (2013). Effective information channels for reducing costs of environmentally-friendly technologies: evidence from residential PV markets. *Environmental Research Letters*, 8(1): 14022-14044.

[5] Palm, A. (2017). Peer effects in residential solar photovoltaics adoption—A mixed methods study of Swedish users. *Energy Research & Social Science*, 26:1-10.

[6] Wolske, K. S., Stern, P. C., & Dietz, T. (2017). Explaining interest in adopting residential solar photovoltaic systems in the United States: Toward an integration of behavioral theories." *Energy Research & Social Science*, 25: 134-151.

[7] Noll D., Dawes C., Rai V. (2014). Solar Community Organizations and active peer effects in the adoption of residential PV. *Energy Policy*, 67: 330-343.

[8] Reeves, D. C., Rai, V., & Margolis, R. (2017). Evolution of consumer information preferences with market maturity in solar PV adoption. *Environmental Research Letters*, 12(7): 074011.

[9] Gillingham, K., Sweeney, J. (2012) Barriers to the Implementation of Low Carbon Technologies. *Climate Change Economics*, 3(4): 1-25.

[10] Zhang, X., Shan, L., Chan, S.Y. (2012). The diffusion of solar energy use in HK: What are the barriers*? Energy Policy,* 41: 241-249.

[11] Müller, S., Rode, J. (2013) The Adoption of Photovoltaic Systems in Wiesbaden, Germany. *Economics of Innovation and New Technology,* 22(5): 519-535.

[12] Palm, A. (2016). Local factors driving the diffusion of solar photovoltaics in Sweden: A case study of five municipalities in an early market. *Energy Research & Social Science*, 14: 1-12.

[13] Balta-Ozkan, N., Yildirim, J., & Connor, P. M. (2015). Regional distribution of photovoltaic deployment in the UK and its determinants: a spatial econometric approach. *Energy Economics, 51*, 417-429.

[14] Schaffer, A. J., & Brun, S. (2015). Beyond the sun—Socioeconomic drivers of the adoption of small-scale photovoltaic installations in Germany. *Energy Research & Social Science*, 10, 220-227.

[15] Dharshing, S. (2017). Household dynamics of technology adoption: A spatial econometric analysis of residential solar photovoltaic (PV) systems in Germany. *Energy research & Social Science*, 23:113-124.
[16] Mills, A., Barbose, G., Seel, J., Chanuggui, D., Mai, T., Sigrin, B., Zuboy, J. (2016) Planning for a Distributed Disruption: Innovative Practices for Incorporating Distributed Solar into Utility Planning. Ernest Orlando Laurence Berkeley National Laboratory – LBNL-1006047. At https://emp.lbl.gov/publications/planning-distributed-disruption last accessed on 22/09/2016.

[17] LeSage, J.P. (2014) What Regional Scientists Need to Know About Spatial Econometrics. *The Review of Regional Studies*, 44(1): 13-32. ISSN 0048-749X.

[18] Bronin, S. (2012) Building-Related Renewable Energy and the Case of 360 State Street. *Vanderbilt Law Review*, 65(6): 1875-1934.

[19] Rode, J., Weber, A. (2013) Does Localized Imitation Drive Technology Adoption? A Case Study on Solar Cells in Germany. *TU Darmstadt Working Paper*.

[20] Carstensen, F., Coghlan, J. (2013). Meeting the Challenge – The Dynamics of Poverty in Connecticut. Connecticut Center for Economic Analysis. At http://ccea.uconn.edu/studies/CT-PovertyReport_Final.pdf, last accessed on 06/09/2016.

[21] Connecticut GreenBank (CTGreenBank, 2016). *Multifamily Housing Program*. At http://www.ctgreenbank.com/programs/multifamily/, last accessed on 14/12/2016.

[22] Ong, S., Denholm, P., Clark, N. (2012). Grid parity for residential photovoltaics in the United States: key drivers and sensitivities. *National Renewable Energy Laboratory Conference Paper – 6A20-54527*.

[23] Energize Connecticut. *Residential Solar Investment Program*. At https://www.energizect.com/your-home/solutions-list/residential-solar-investment-program, last accessed on 20/03/2018.

[24] Solar Power Rocks and GreenTech Media (2018). *Connecticut*. At https://solarpowerrocks.com/connecticut/#policy, last accessed on 20/03/2018

[25] National Renewable Energy Laboratory (NREL) (2018). *The Open PV Project*. At https://openpv.nrel.gov/rankings, last accessed on 20/03/2018.

[26] Buchanan, M., Abraham, M. (2015). *Connecticut has more concentrated poverty (and wealth) than most metros* At http://trendct.org/2015/05/27/connecticut-has-more-concentrated-poverty-and-wealth-than-most-metros/, last accessed on 03/01/2017.

[27] Connecticut Energy Finance Investment Authority (2013). Solar Database, 2004-2013.

[28] Connecticut Secretary of State (CT SOTS, 2013) Registration and Enrollment Statistics Data. Retrieved 8/1/2013, at http://www.sots.ct.gov/sots/cwp/view.asp?a=3179&q=401492, last accessed on 01/11/2016

[29] MAGIC. (2013) University of Connecticut Map and Geographic Information Center. Retrieved At http://magic.lib.uconn.edu/ last accessed on 01/02/2016

[30] Bridges Jr., C.C. (1966) Hierarchical Cluster. *Psychological Reports*, 18: 851-854.

[31] Blashfield, R.K. (1976) Mixture Model Tests of Cluster Analysis: Accuracy of Four Agglomerative Hierarchical Methods. *Psychological Bulletin*, 83(3): 377-388.

[32] Kaufman, L. (2009). Finding Groups in Data: An Introduction to Cluster Analysis. Hoboken, NJ, USA: John Wiley & Sons, Inc.

[33] Boessen, A., Hipp, J.R., Butts, C.T., Nagle, N.N., Smith, E.J., The built environment, patial scale, and social networks: Do land uses matter for personal network structure? *Environment and Planning B: Urban Analytics and City Science*, 0(0): 1-17.

[34] Funkhouser, E., Blackburn, G., Magee, C., Rai, V. (2015). Business model innovations for deploying distributed generation: The emerging landscape of community solar in the U.S. *Energy Research & Social Science*, 10: 90-101.

[35] Klakbrenner, B.J., Roosen, J. (2016). Citizens' willingness to participate in local renewable energy projects: The role of community and trust in Germany. *Energy Research & Social Science*, 13: 60-70.

[36] Anselin, L. (2013). *Spatial Econometrics: Methods and Models*. Berlin, Germany: Springer Science & business Media B.V.

[37] Richter, L.-L. (2013) Social Effects in the Diffusion of Solar Photovoltaic Technology in the UK. *University of Cambridge Working Paper in Economics 1357*.

[38] Jackson, M.O., (2013). Unravelling peers and peer effects: comments on Goldsmith-Pinkham and Imbens' social networks and the identification of peer effects. Journal of Business Economics and Statistics 31, 270–273.

[39] Allan, G.J. and McIntyre, S.G. (2017), Green in the heart or greens in the wallet? The spatial uptake of small-scale renewable technologies. *Energy Policy*, 102: 108-115.

[40] Li, A.C., Harris, D.R. (2008). The Colors of Poverty: Why Racial and Ethnic Disparities Persist. New York, NY, USA: Russell Sage Foundation.

[41] Belotti, F., Hughes, G., Piano Mortari, A. (2013). xsmle: a Stata command for spatial panel-data models estimation. Italian Stata Users' Group Meetings 2013 04, Stata Users Group.

[42] Dăgulescu, A., Yakovenko, V.M. (2001). Exponential and power-law probability distributions of wealth and income in the United Kingdom and the United States. *Physica A: Statistical Mechanics and its Applications*, 299(1-2): 213-221.

[43] Nemet, G.F., Baker, E. (2009). Demand subsidies versus R&D: Comparing the Uncertain Impacts of Policy on a Pre-commercial Low-caron Energy Technology. *The Energy Journal*, 30(4).

[44] Johnston, R.J. (1997). Geography and Geographers: Anglo-American Human Geography since 1945. London, UK: Arnold.

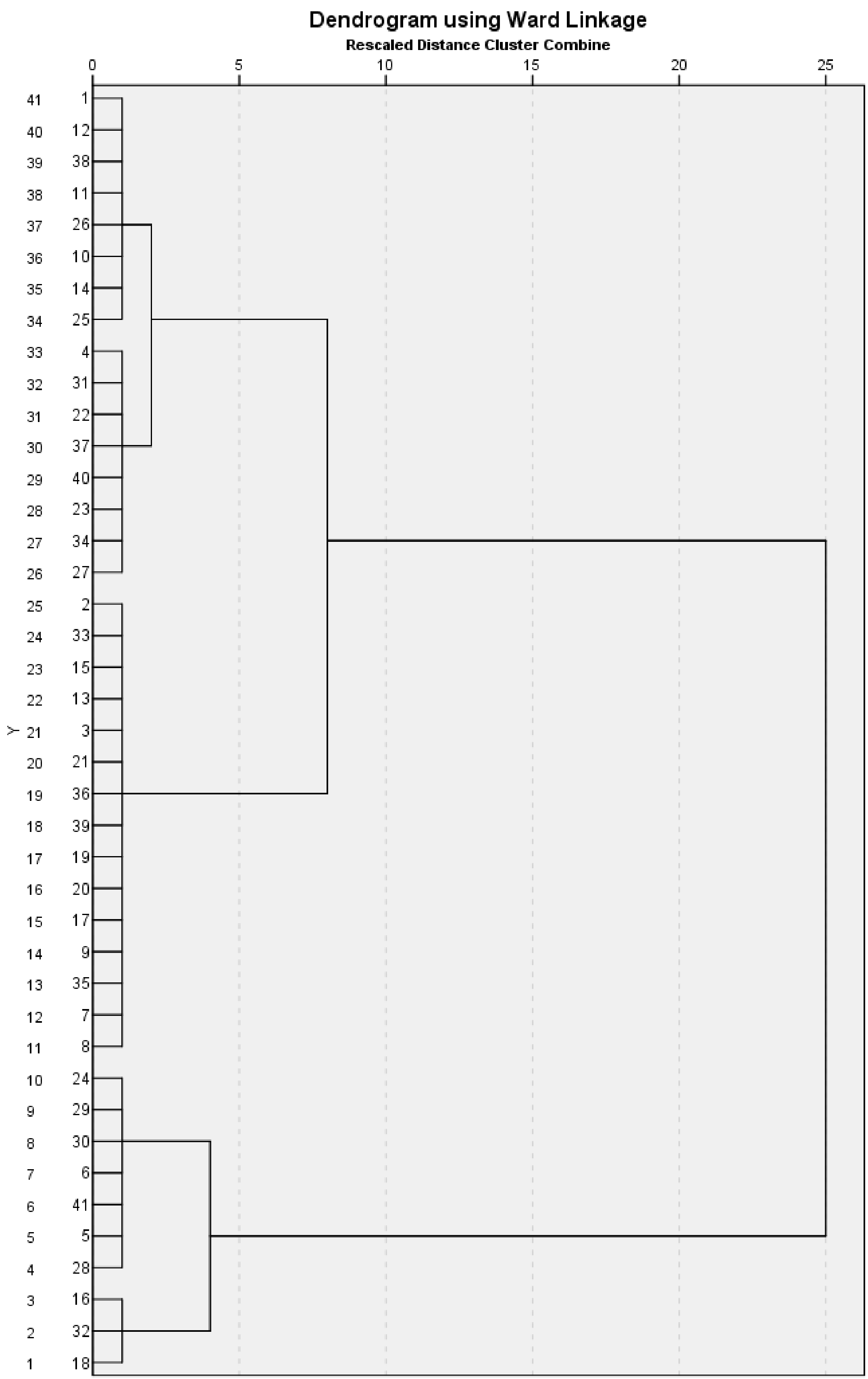
[45] Brown, L. (1981) Innovation Diffusion. New York, NY: Methuen.

[46] CEFIA (2015), *Market Analysis of Residential Solar Deployment and Housing Characteristics of CT's Low Income Sector*. CCEA/CEFIA. At http://www.ctcleanenergy.com/Portals/0/board-materials/6c_Role%20of%20a%20Green%20Bank_Market%20Analysis_Low%20Income%20Solar%20and%20Housing_Memo_121214.pdf, Last accessed on 22/10/2016.

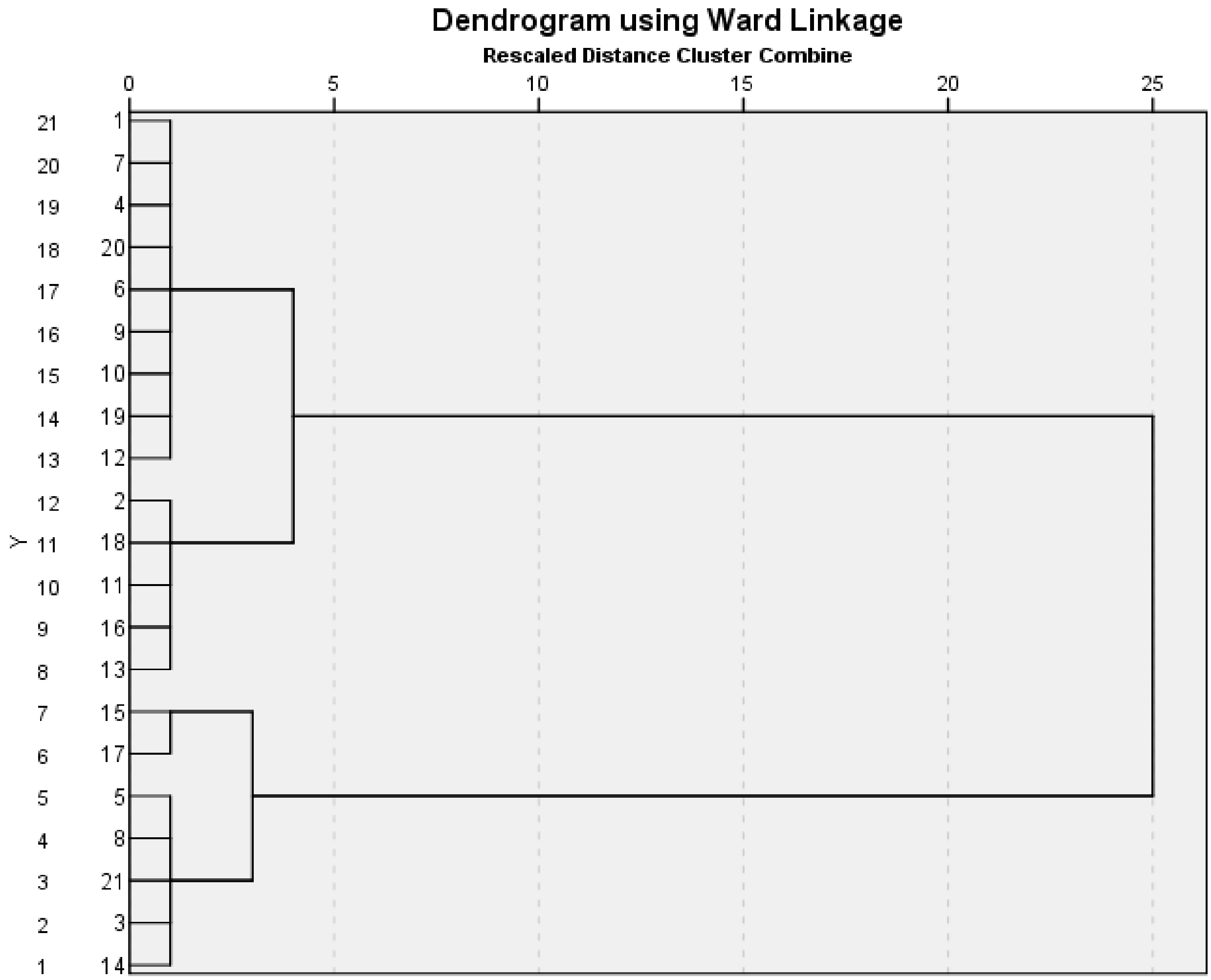
[47] Rai, V., Reeves, D. C., Margolis, R. (2016). Overcoming barriers and uncertainties in the adoption of residential solar PV. *Renewable Energy*, 89: 498-505.

Appendix A: Dendograms for each town

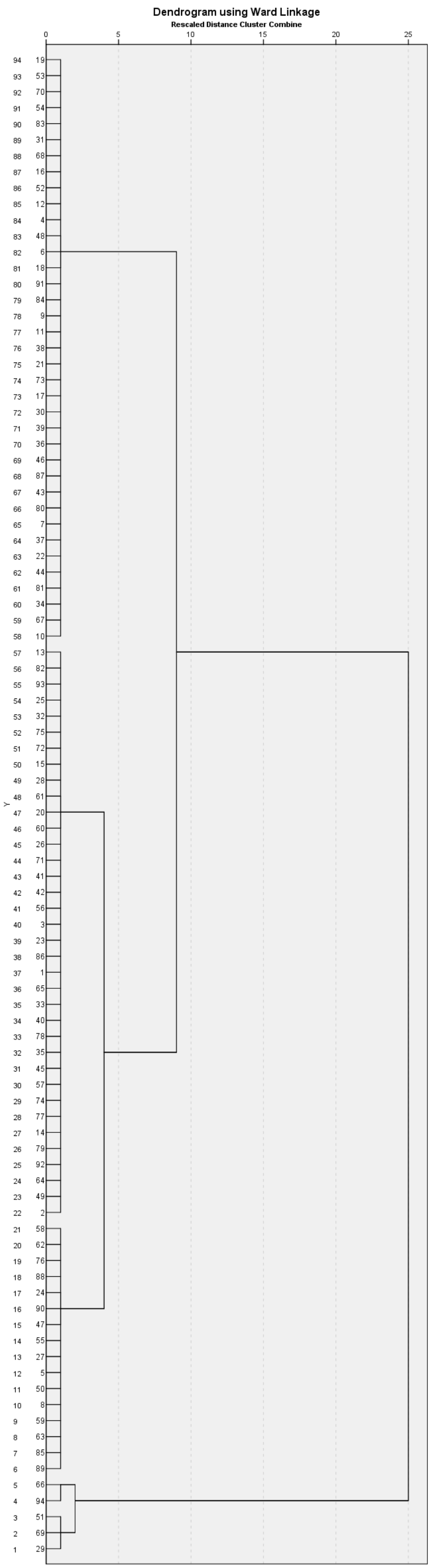
A1. East Hartford


Dendrogram using Ward Linkage
Rescaled Distance Cluster Combine
0
5
10
15
20
25
Y
1
12
38
11
26
10
14
25
4
31
22
37
40
23
34
27
2
33
15
13
3
21
36
39
19
20
17
9
35
7
8
24
29
30
6
41
5
28
16
32
18

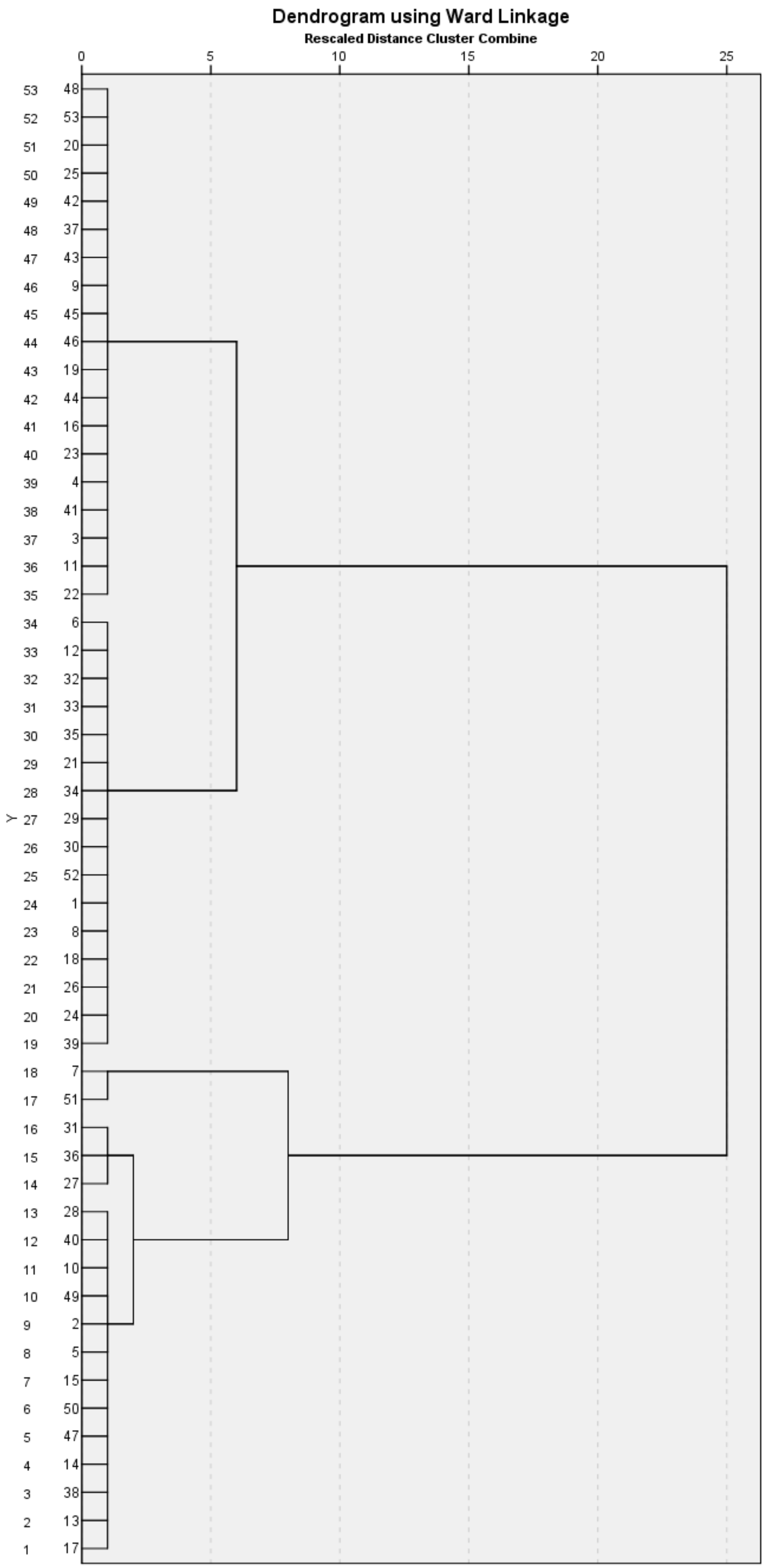
A2. Glastonbury



A3. Hartford


Dendrogram using Ward Linkage
Rescaled Distance Cluster Combine
0
5
10
15
20
25
Y

A4. Manchester



Dendrogram using Ward Linkage
Rescaled Distance Cluster Combine
0
5
10
15
20
25
Y

Appendix B: Full list of results

B1. Panel models – complete table

	BASE FE	BLOCK FE (6 Months)	BLOCK FE (12 Months)
# PV installed	0.716***	.	.
	(0.154)	.	.
Average Neighbours within 0.5 Miles (6 months)	.	4.125**	.
	.	(1.221)	.
Average Neighbours within 0.5 Miles (12 months)	.	.	1.082**
	.	.	(0.241)
Minority* Proximity (0.5 miles)	-0.083	-0.161**	-0.072
	(0.059)	(0.035)	(0.040)
Minority*Proximity (1.0 miles)	0.150**	0.139	0.140*
	(0.060)	(0.065)	(0.052)
Minority* Proximity (4 miles)	0.012	0.012	0.014
	(0.015)	(0.015)	(0.014)
Median HH Income * Proximity (0.5 miles)	0.141	-0.127	0.120*
	(0.103)	(0.113)	(0.040)
Median HH Income * Proximity (1.0 miles)	-0.128*	-0.038	-0.135**
	(0.074)	(0.066)	(0.034)
Median HH Income * Proximity (4 miles)	0.072**	0.083*	0.077*
	(0.034)	(0.034)	(0.029)
If income >$100,000	-0.007	-0.051	-0.043
	(0.091)	(0.076)	(0.046)
% of Renter-occupied houses	-0.001	-0.002	-0.002
	(0.001)	(0.002)	(0.002)
% pop who are white	0.003**	0.001	0.001
	(0.001)	(0.001)	(0.001)
% pop who are black	-0.000	-0.002	-0.002
	(0.001)	(0.002)	(0.002)
% pop who are Asians	0.001	0.003	0.003
	(0.002)	(0.003)	(0.002)
Median Pop Age	0.000	0.006	0.005
	(0.002)	(0.004)	(0.004)
If Median Age in Highest 5%	0.066	-0.027	-0.009
	(0.088)	(0.081)	(0.064)
% of houses with >5 bedrooms	-0.006*	-0.004	-0.002
	(0.004)	(0.005)	(0.004)
DJIA (Thousands)	0.010	0.034	0.046
	(0.018)	(0.036)	(0.052)
% registered Democrats	0.001	-0.001	-0.004
	(0.003)	(0.006)	(0.007)
% Registered Minority parties	-0.012	0.075	-0.015
	(0.069)	(0.054)	(0.049)
House Density* Proximity (0.5 miles)	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
House Density * Proximity (1.0 miles)	0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)
House Density * Proximity (4 miles)	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Number of Housing Units (1,000s)	-0.098	-0.163	-0.152
	(0.074)	(0.144)	(0.145)
Gross Housing Density	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Median Household Income ($10,000)	-0.015	-0.015	-0.021
	(0.013)	(0.013)	(0.016)
Quarter dummies	Y	Y	Y
Constant	Y	Y	Y

R-squared	0.450	0.419	0.481
Observations	7175	7175	7175

* p<0.10, ** p<0.05, *** p<0.010

B2. Cross section – complete table

	BASE	6 Months	12 Months
# PV installed	0.4425***		
	(0.0348)		
Average Neighbours within 0.5 Miles (6 months)		6.8583***	
		(0.8446)	
Average Neighbours within 0.5 Miles (12 months)			0.4057**
			(0.0837)
Number of Housing Units (1,000s)	-0.0600	-0.0043	0.0265
	(0.0934)	(0.0622)	(0.0449)
If income >$100,000	-0.1105	0.2059	0.4839
	(0.3056)	(0.4952)	(0.2990)
% of Renter-occupied Houses	0.0016	-0.0038**	-0.0035**
	(0.0016)	(0.0011)	(0.0008)
% of Single-family parcels	0.0015	0.0002	-0.0004
	(0.0021)	(0.0016)	(0.0008)
Net Housing Density (# residential parcels/sq.km of residential parcels)	0.0004	0.0001	0.0001**
	(0.0002)	(0.0001)	(0.0000)
Median Household Income ($10,000)	0.0210	-0.0051	-0.0293
	(0.0391)	(0.0473)	(0.0294)
% pop who are white	-0.0004	0.0027	-0.0007
	(0.0014)	(0.0020)	(0.0024)
% pop who are black	0.0020	0.0015	0.0000
	(0.0017)	(0.0019)	(0.0015)
% pop who are Asians	0.0084	0.0085	0.0109
	(0.0064)	(0.0070)	(0.0074)
Median age of the pop	0.0188	0.0225	0.0173
	(0.0090)	(0.0098)	(0.0091)
If Median Age in Highest 5%	-0.2159	-0.4135	-0.2794
	(0.2810)	(0.1970)	(0.2367)
% of Houses >5 bedrooms	-0.0097	-0.0116	0.0001
	(0.0095)	(0.0075)	(0.0043)
Constant	-1.5250	-0.8970*	-0.5531*
	(0.6533)	(0.2902)	(0.1922)
R-squared	0.2872	0.2046	0.4988
Observations	205	205	205

* p<0.10 ** p<0.05 *** p<0.01

B3. Spatial regression models – complete table

	SEM	SAR	SAC
Average Neighbours within 0.5 Miles (6 months Av.)	0.57424***	0.57522***	0.57764***
	(0.07432)	(0.07460)	(0.07804)
% of Renter-occupied houses	-0.00025	-0.00026	-0.00022**
	(0.00021)	(0.00021)	(0.00011)
Number of Housing Units (1,000s)	-0.01925	-0.01995	-0.00738
	(0.01979)	(0.01984)	(0.01243)
Gross Housing Density	0.00000	0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)
Median Household Income ($10,000)	-0.00076	-0.00083	-0.00050
	(0.00090)	(0.00090)	(0.00051)
If income >$100,000	-0.00454	-0.00430	-0.00383
	(0.01664)	(0.01635)	(0.01621)
% pop who are White	0.00001	0.00001	0.00002
	(0.00018)	(0.00017)	(0.00018)
% pop who are Black	-0.00026	-0.00028	-0.00013
	(0.00023)	(0.00023)	(0.00018)
% pop who are Asian	0.00055	0.00056	0.00087
	(0.00047)	(0.00046)	(0.00078)
Median Pop Age	0.00087	0.00086	0.00078
	(0.00055)	(0.00053)	(0.00056)
If Median Age in Highest 5%	-0.00281	-0.00295	0.00655***
	(0.00686)	(0.00694)	(0.00192)
% of houses with >5 bedrooms	-0.00072	-0.00070	-0.00032
	(0.00085)	(0.00086)	(0.00047)
% registered Democrats	-0.00044	-0.00039	-0.00011
	(0.00108)	(0.00102)	(0.00033)
% Registered Minority parties	0.00516	0.00470	0.02251***
	(0.01247)	(0.01203)	(0.00457)
Spatial variables			
lambda	0.05146**		-0.06670
	(0.02022)		(0.14950)
rho		0.06106***	0.14215
		(0.00770)	(0.11921)
Variance	0.01153*	0.01152*	0.01197*
sigma2_e	(0.00648)	(0.00647)	(0.00651)
R-squared	0.26060	0.26056	0.27338
Observations	7175	7175	7175

* p<0.10, ** p<0.05, *** p<0.010