5-6-2014

Adoption of Diffused Renewable Energy Technologies: Patterns and Drivers of Residential Photovoltaic (PV) Systems in Connecticut, 2005-2013

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University of Connecticut, 2014

Growing concern about global climate change and energy security are prompting reconsideration of how energy—particularly electricity—is generated, transmitted, and consumed in the United States and across the globe. While an increasing amount of households are adopting solar power across the developed world, the spatial and socioeconomic factors that shape whether or not people adopt this technology is under-theorized (especially with regard to spatial drivers), and not well researched from an empirical perspective. In my dissertation, I present a conceptual model to describe and understand the socioeconomic and spatial factors affecting the diffusion of PV systems. I build my model on the socio-technical tradition. Further, I present two empirical studies where I combine statistical and mapping techniques aimed at finding the spatial patterns and the underlying drivers influencing the adoption of PV systems in Connecticut since 2005. I develop an innovative spatiotemporal band to control for spatial peer effects, while using several socioeconomic and spatial variables to control for other factors. Contrary to previous literature, I find that medium-sized centers represent the source of the diffusion, rather than larger, more populous towns. Further, I find that spatial peer effects positively affect the adoption process, while the lack of more refined and spatially conscious policies tend to make adoption more difficult in densely populated areas. However, spatial peer effects tend to decrease in magnitude as time and space increase. Finally, I find that current policies, which do not taking in to account the differences in the socioeconomic and built environment among towns in Connecticut, fail to reach potential adopters residing in multi-family buildings or in renter-occupied houses.

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A Dissertation

Submitted in Partial Fulfillment of the

Requirements for the Degree of Doctor of Philosophy

at the

University of Connecticut

2014

APPROVAL PAGE

Doctor of Philosophy Dissertation

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Acknowledgements

The author would especially like to thank Carol Atkinson-Palombo for her help in advising this dissertation and the Connecticut Clean Energy Finance & Investment Authority for providing the dataset for this study. We also acknowledge partial support for this work from the Connecticut Center for Economic Analysis and the U.S. Department of Energy. In addition, I would like to thank GIS offices for the towns of Hartford, East Hartford and Manchester for assisting on the data collection process, Prof. John Glascock, Real Estate Center at the University of Connecticut for his suggestion and support during the data gathering process, and Mike Howser, for his continuous help in dealing with U.S. Census data. Finally, special thanks to the Connecticut Center for Economic Analysis (CCEA) and its director, Professor Fred V. Carstensen, CCEA senior fellows, William E. Waite and Peter Gunther, and CCEA associate Professor Richard Parnas for their support during these past years. To Noce and Pierina.

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Overview

Literature on the processes governing the diffusion of new goods and services is rich, both theoretically and empirically. Nevertheless, we still do not have a comprehensive, simple and temporal dynamic conceptual model describing the relationships linking the sources influencing the diffusion of diffused renewable energy technologies (DRETs). Furthermore, our knowledge of the interaction between spatial and socioeconomic drivers governing any diffusion process is limited, having become only recently central in the discourse on the transition towards more sustainable societies. In rooting my research within the socio-technical tradition, the work of Hägerstrand, and the works on diffusion studies hosted within economics, particularly the one of Bollinger and Gillingham (2012), I seek to expand our knowledge on how policies, space and socioeconomic factors interact to either support or impede the diffusion of DRETs. In operationalizing my model, I focus on a family of DRETs: residential rooftop photovoltaic systems (PV systems). Literature has only recently began to research the underlying factors driving the adoption of PV systems, as they become a more viable option to reduce our dependence on fossil fuels. However, as rich as it is, literature on DRETs diffusion and PV systems diffusion has yet to answer to the following questions:

1. How can we conceptualize the diffusion process of DRETs over space and time, accounting for the continuous changes occurring the elements of the process themselves?
2. Can researchers operate this conceptual model within case studies? Specifically, is it capable of describing the diffusion of PV systems?
3. Does the diffusion of PV systems follow a specific pattern across time and space? If so, what are the elements driving this diffusion?

4. How do policies regulating PV systems operate across space and time, as the geography of the area changes over time? Specifically, how does the diffusion process change in highly urbanized areas?
5. How do spatial peer effects affect the diffusion process?
6. Does time affect spatial peer effects?

Providing answers to these questions is the scope of my dissertation. Specifically, my research objectives are:

1. To develop a dynamic conceptual model inclusive of all the major components affecting the diffusion of DRETs over time and space;
2. To use the model as a guidance in the interpretation of two empirical studies on the diffusion of PV systems in Connecticut;
3. To identify specific spatial patterns in the diffusion of PV systems over time;
4. To identify the role played by the frictions occurring between current policies and the geography of the diffusion area of PV systems; and
5. To identify how spatial peer effects affect the diffusion of PV systems in Connecticut.

Answering to each of the questions above through the fulfillment of these objectives will provide important insights for policymakers. Accounting for the different settings within which they operate will make policies more effective and efficient. For instance, resources can be targeted differently for densely populated areas where households reside in multi-family buildings. These conclusions are mere speculations unless proven: this is the motif for developing this study under the rules and requirements of academic research and integrity.

To fulfill these objectives, I divide my dissertation in to three main chapters. In the first chapter, I provide a careful review of the literature on diffusion, highlighting the fundamental theoretical and empirical changes occurred since the 1950s. From this survey of the literature, I then develop a conceptual model that aims to understand what are the elements involved in the diffusion of DRETs. I root my model within the socio-technical tradition, particularly the work of Geels (2002), although I expand the sources of diffusion of innovations and introduce the role of both time and area geography as factors shaping the process itself, as suggested by Hägerstrand (1952). In the second chapter, I present an empirical work seeking to identify and to quantify the role of spatial peer effects and the area geography in the diffusion process of PV systems. This first empirical work extracts some of the concepts outlined within the conceptual framework, and in particular the interaction among adopters and the relationship between current incentive policies and the geography of the jurisdiction where these policies are implemented. Further, in my third chapter I present second empirical work on how variations in the relative profile and built environment among urban areas can affect the diffusion of PV systems when policies do not account for these variations. Finally, I provide a brief conclusion in which I link my empirical findings to the conceptual model.

Conceptualizing the Transition towards Sustainability: Adopters, Policies and Area Geography in the context of Time and Space.

Section I: Introduction

Growing concern about global climate change and energy security are prompting reconsideration of how energy—particularly electricity—is generated, transmitted, and consumed in the United States and across the globe (Devine-Wright 2008; Pasqualetti 2011; Freitas, 2012). Many jurisdictions have set ambitious renewable energy goals, targeting 20% of their electricity to be generated by renewable sources by 2020 (e.g. the European Union, EU 2012). Targets can be met using a variety of low-emission alternative energy projects at various technological scales. While an increasing amount of households are adopting solar power across the developed world, the factors that shape whether or not people adopt this technology is under-theorized (especially with regard to spatial drivers), and not well researched from an empirical perspective. One aspect of renewable energy technologies (RETs) that is particularly poorly understood is the way in which this technology diffuses over space and time, and what factors influence adoption. When studying innovations, the process of adopting the innovation itself is considered as important as the material development of innovation, sometimes referred to as 'invention' (Hägerstrand, 1962; Brown, 1981). The process of adoption, in which people or institutions decide to acquire the new good, finds its outcome in the diffusion of the innovation itself. The diffusion process is influenced by many factors, including geographic characteristics and homophilic-related effects, better known as peer-effects (Hägerstrand, 1967; Bollinger and Gillingham, 2012). Peer-effects are occur when '*the decision of others to adopt influences the utility an individual receives from adopting*' (Gillingham and Sweeney, 2012, p.13). Potentially, peer-effects generate externalities affecting the overall diffusion process, such as adoption even in the case of financial losses for emulating other agents (Bollinger and Gillingham, 2012). In the case of durable goods visible to others. Spatially-related peer effects may occur, creating an involuntary effect on nearby

residents. Similarly, the geography of an area can affect the diffusion process (Hägerstrand, 1967; Geels, 2001). Many technologies are adopted and operated with a context of spatially-uniform policies, which do not take in to account the nature of the specific technology and how the built environment could affect the adoption decision (Bronin, 2012).

Researchers recognize the existence of two main families of renewables: centralized and diffused (Gillingham and Sweeney 2012). The former, sometimes labeled as 'large-scale', resemble the spatial organization of current fossil plants. Large, capital intensive and efficient plants are built in selected locations and distribution is made possible through the construction of multi-modal systems (e.g. power-lines). These systems are not the focus of the present research. Although they similar barriers and drivers with diffused technologies, the key players involved and the relationships among stakeholders in the case of large plants are different (Gillingham and Sweeney, 2012). The second family of technologies, 'diffused renewable energy technologies' (DRETs)[1] have captured the interest of those regions where distribution is costly or the co-existence of renewable power and fossil-fuel power is more difficult for technical reasons.[2] Policymakers have considered DRETs as a way to diffuse renewable energies faster than large-scale projects and at a lower price.[3] Specifically, residential rooftop solar photovoltaic systems (PV systems) have become more common in certain regions of the USA and of the world (Guidolin and Mortarino, 2010). Between 2010 and 2011, residential photovoltaic systems have by 24% in the USA, with increases in every state thanks to the continuous implementation of

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1 With the acronym 'DRETs' I mean household-level, small scale renewable energy technologies. Example of these technologies are PV systems below 100 kW of capacity, thermal solar installations, and micro-wind turbines.

2 As an example, consider the instability of power production from solar farm, as the overall production decreases at night or during winter. The power lines would be subject to strong variations in the load that is delivered to the main grid, thus affecting the delivery of power to consumers.

3 The focus of my study is not to compare the two families of technologies: they are not mutually exclusive, and are usually adopted together in order to suit local needs.

Renewable Portfolio Standards (RPS),[4] local policies and improved information (Busche, 2010; Sherwood, 2012; Bollinger and Gillingham, 2012).

A better understanding of the relative importance of various factors that influence adoption such as socio-demographic characteristics, housing characteristics (e.g. tenancy) and socio-economic characteristics is needed in order to inform policies intended to promote the adoption of alternative energy. Despite being rich in studies dealing with diffusion and innovation processes in general, literature has yet to explain the specific mechanisms involved in DRETs diffusion in general and PV systems in particular.

I organize the remainder of the paper as follows: **Section II** we provide a thorough review of relevant literature on DRETs, highlighting the disadvantages of current socio-technical models, in particular those based on the work of Geels (2002) relative to DRETs. In **Section III,** we present the elements and the structure of the conceptual model. In **Section IV,** we explores the ways in which the elements of the model connect to each other and influence the diffusion process of DRETs. Finally, in **Section V,** I highlight the advantages of the proposed model compared to previous socio-technical models of diffusion.

Section II: Review of the Literature

Public institutions have long been using incentive schemes to promote the diffusion of RETs in general and DRETs more specifically. These incentives are necessary due to the higher costs of DRETs and RETs compared to fossil fuels (Gillingham and Sweeney, 2012; IEA, 2010). Even when operated at lower costs than non-renewable sources, adopters of DRETs may require additional financial incentives due to the initial capital costs for switching to the new energy

[4] 'A renewable portfolio standard (RPS) is a regulatory mandate to increase production of energy from renewable sources such as wind, solar, biomass and other alternatives to fossil and nuclear electric generation. It's also known as a renewable electricity standard' (NREL, 2013).

source (IEA, 2010; Gillingham and Sweeney, 2012). Even in presence of strong monetary incentives, it is important for policymakers to understand what other drivers contribute to the diffusion of DRETs. Recently, literature has shown mixed results on the effectiveness of monetary incentives for DRETs, thus suggesting that other policies (e.g. programs providing previous experiences) and factors related to the profile of residents influence the diffusion of renewable energies (Carley, 2009; Doris and Gelman, 2011). Consequently, the relationship between non-monetary policies, adopters and local/federal regulations and incentive schemes has been recognized as important in explaining the differences in adoption among regions, particularly in jurisprudential literature and economics (Busche, 2010; Bronin, 2012; Bollinger and Gillingham, 2012).

The first section of the literature review surveys the major works that inform on DRETs and the methodologies associated with DRETs diffusion. The second section is organized around the major fields of research from which the works generate.

[Figure 1 About Here]

As shown in Figure 1, research on DRETs diffusion draws from four main research streams, belonging to as many broader fields. Technology Diffusion Research (TD), research on Environmental Values, Policy Design and Spatial Analysis. As DRETs are durable goods, their adoption process follows the one of this category of goods (Bollinger and Gillingham, 2012). Usually, DRETs deliver energy at a price higher than non-DRETs, such as large-scale coal plants, or wind farms (EIA, 2013). Consequently, and in absence of major concern on delivery reliability, other factors influence the decision of adopting DRETs. Among others, researchers found peer-effect, personal attitude/values and favorable subsidies (Bollinger and Gillingham, 2012; Tate *et al*., 2012).

In Figure 1, the yellow block represents the research on policy design. Rules, incentives and barriers implemented by local and national authorities can influence the diffusion of DRETs (Bronin, 2012). The cluster dealing with environmental policies is a natural focus for DRETs, and includes regulations dealing with energy policies and those regulating the protection of the environment. Finally, the red block represents the contributions brought by Spatial Analysis in general and Behavioral Analysis in particular. Literature on behavioral analysis comes from different disciplines, although its origins are deeply rooted in geography and the original work of Hägerstrand (Johnston, 1997).

DRETs have some similarities with other technologies in their adoption patterns. DRETs are usually durable goods and adopters usually incur in monetary expenses for adopting these goods. Adopters would not incur these costs if they decided to maintain the current energy systems. Finally, spillover effects from adopters influence the decision of other agents (Bollinger, and Gillingham, 2012). Being durable goods, DRETs tend to be purchased few times, and their use spans over many years. Consequently, the commitment faced by adopters is higher than in the case of non-durable goods (Bass, 1969).

Additionally, DRETs can face similar opposition and barriers to non-DRETs technologies due to public perception, policy design, NIMBY[5] syndrome and lack of information about the impact on landscape and the environment (Warren *et al.*, 2005; Devine-Wright, 2007; Klick and Smith, 2010; Gillingham and Sweeney, 2012; Bronin, 2012). Adoption of DRETs is subject to the influence of environmental values (Dietz *et al*., 2005). Values shape and are shaped by the socio-geographical framework of the area proper to the DRET under examination (Hägerstrand, 2002). Consequently, the political framework, the economic profile and the geography of a location

[5] Not-in-my-backyard.

play a major role in defining specific DRETs diffusion (Hägerstrand, 2002; Verbeek and Slob, 2006; Gillingham and Sweeny, 2012; Verbruggen *et al*., 2010).[6]

II.1 Technology Diffusion and DRETs

Understanding the factors driving the diffusion of industrial processes, goods and behaviors is important for policy makers and market agents for formulating policies and strategies. In a paper published in 1952 on innovation waves, Hägerstrand was the first scholar to use mathematical modeling applied to Technology Diffusion research (TD) (Hägerstrand, 1952; Brown, 1981 and Johnston, 1997). Hägerstrand made many contributions to different fields of geography, including behavioral geography and spatial analysis. The latter field drove the research in TD until the beginning of the 1960s, when other disciplines started contributing to diffusion processes in general, and on TD in particular (Davies, 1979). After his initial contribution on TD analysis, Hägerstrand published a second body of work introducing the concept of time-geography (Hägerstrand, 1988 and 1993). This second work and the voluminous literature produced in the last forty years on time and space differs considerably from the linear dimension introduced by Bass (Sui, 2012). First, time-geography seeks to introduce time with an historical component, that is, effects become endogenous as time passes (Hägerstrand, 1982; Sui, 2012). Second, time plays an active role with and over space, thus ending to be provide one of the contexts within which action (e.g. adoption) takes place, and becoming an endogenous factor in the analytical process (Sui, 2012). Third, Hägerstrand's work brought the focus back on both individuals and their surrounding environment, with the latter being defined as any physical object surrounding agents, including those expanding their virtual and social space, such as communication devices (Sui, 2012; Ellegard, 1999). This dissertation focuses on spatial

[6] I use the term 'geographic setting' as equivalent of 'built environment' as used in Van Geehuizen *et al*. (2012). For a more specific definition, see the methodological section.

proximity: spatial spillovers alone have been found to affect positively the adoption of DRETs (Bollinger and Gillingham, 2012). Therefore, network peer effects are beyond the scope of the present work.

The major breakthroughs introduced by Hägerstrand and the subsequent adaptations and modifications, have created the basis upon which the study of TD has been developed in the last forty years (Sui, 2012). In social sciences, including geography, the study of TD has followed two pathways. The first focused on the adoption processes of single agents, usually households. This branch has its seminal works in those of Hägerstrand (1952), Rogers (1962) and Bass (1969). The second branch of study deals with TD within and among industrial organizations, and usually belongs to literature in economics and managerial sciences (Davies, 1979). Households' response to policies and market signals is the perspective followed by scholars to depict TD of DRETs (Bollinger and Gillingham, 2012). More recently, the study on the diffusion of DRETs has developed along with that of environmental and socio-technical approaches: scholars have been focusing more on the policy aspect of DRETs, and their public perception (Verbeek and Slob, 2006).

II.2 Policy Design and DRETs

Policies can either accelerate or slow down the diffusion of DRETs (Painuly *et al*., 2001; Verbruggen *et al*., 2010; Gillingham and Sweeny, 2012). Verbruggen *et al*. (2010) argued that policies affect directly DRETs costs, prices, and technology innovation. Further, policies are the original source of all man-made barriers, thus affecting the final potential of DRETs.[7] Previously, Painluy identified seven major categories of barriers affecting the diffusion of both RETs and DRETs. These families of barriers are 'Market failures', 'Market Distortions',

[7] For the specific definition of 'potential', see Verbruggen *et al*. (2010).

‘Economic and Financial’, ‘Institutional’, ‘Technical’, ‘Social, Cultural and Behavioral’ and ‘Other Barriers’ (Painluy, 2001). With the exception of few elements listed under ‘Technical’, all other barriers relate to or can become through policy design. Even in the case of those barriers grouped under ‘Social, Cultural and Behavioral’ education and information through public institutions can increase the acceptance towards RETs and DRETs. One important element emerging from Painluy’s work is the fact that these barriers are location-dependent. The author stated:

‘*However, several barriers, which may vary across countries, impede the penetration of RETs. The barriers need to be identified and overcome before this potential can be realized (sic)’.* [Painluy, 2001, p.88].

My research will draw from the work of Bronin (2012). In her work, the author argued that policies influence the adoption of DRETs in two stages. First, policies influence the adoption of DRETs before agents purchase them, for example by guaranteeing subsidies or imposing local fees. Second, policies influence the adoption of DRETs by regulating the way in which they can operate (Bronin, 2012). Other authors have worked on siting and operating DRETs looking at the regulatory context (see for example Outka, 2010 and 2011; Rule, 2010). This stream of research parallels the one on environmental values in that it recognizes that disputes over DRETs emerge between users and neighbors (Rule, 2010). Thus, perception and acceptance of DRETs is as important as the policies regulating their adoption, in that the former can prevent the emergence of conflicts between adopters and non-adopters. Recent studies have attempted to profile the potential users of environmentally responsible technologies (e.g. Gunther *et al.,* 2012). Although literature is not rich in studies on DRETs diffusion, researchers have been working on electric vehicles and mobility-related technologies (Hjorthol, 2013). This stream of research links diffusion of DRETs, TD analysis and studies on environmental values, by focusing on

understanding how perception and beliefs influence people's willingness to adopt electric vehicles. Mathisen *et al*. (2012) interviewed and surveyed companies to get responses on how electric vehicles (EV) were perceived by businesspersons. The authors found that the negative elements were associated with technical problems such as functionality in winter. Rodseth (2009) found that differences among social groups might provide valuable insight over the diffusion of EVs. The author found that one of the major factors affecting the decision to purchase an EV is the perception that they are environmental friendly, and this characteristic was considered more important than higher purchase costs compared to oil-fueled car.

II.3 Environmental Values and DRETs

Scholars have integrated DRETs diffusion within the broader research of pro-environmental behaviors and policies (Hägerstrand, 2002; Elzen, 2006; Laws; Verbeek and Slob, 2006b). Verbeek and Slob placed this work at the intersection of policy and research 'socio-technical' studies (Verbeek ad Slob, 2006). The terms indicates the importance of sociological and economic characteristics of each area of analysis combined with the character of the RET analyzed. This set of approaches requires deriving multidisciplinary and interdisciplinary perspectives integrating different disciplines across them (Gibbons, *et al.*, 1994). The work of Dietz *et al*. (2005) offers a well-documented overview of the advancements made in the literature on environmental values. This strand of literature on environmental values is central to any investigation of residential DRETs such as solar photovoltaic systems because the adoption decision is a change of the current *status quo* and includes a capital spending decision (Becker *et al*., 1981).

Researchers have started recognizing how people's perceptions of DRETs affect their diffusion. Sovacool (2009) argued that there is a disconnect between how electricity is produced and how it

is socially perceived. This disconnect was made possible through the centralized and remote generation of power, cheap access to electricity and the role of psychological resistance. This resistance is due to a strong preference for the *status quo* and the role of 'comfort' (Becker *et al*., 1981). All these factors play a major role through the decentralization of power-generating technologies and the 'intrusion' of DRETs into people's sight. Pasqualetti first introduced the concept of intrusion relative to landscapes and DRETs (Pasqualetti, 2000). In his work, the author argued that the remoteness of most of generating technologies have hidden the true cost of electricity generation, creating a sense of intolerance towards generating technologies once these re-enter citizens' landscapes (Pasqualetti, 2000). Gee found empirical evidence of the relationships between landscape and perception of offshore wind power projects in the North Sea (Gee, 2010). Warren *et al*. (2005) have found that knowledge of DRETs significantly reduces the negative perception of wind power turbines. Literature is rich in case studies on wind power and its perception, possibly because of the strong opposition by many groups despite its well-recognized advantages (Klick and Smith, 2010). Firestone and Kempton (2007) found that the perception of DRETs and the relation with the *status quo* depends on the demographic and socioeconomic profile of respondents. In their work, the authors found that opposition to a wind power project off the shores of Cape Cod, MA (USA) came mostly from wealthy, older residents. The respondents were concerned more about the changes occurring on the seascape rather than the advantages of wind turbines in terms of emissions reduction. Residential photovoltaic systems may face a lower degree of opposition due to their small-scale nature. Nevertheless, issues remain in defining solar rights (Bronin, 2009).

As mentioned in the previous section, there is a lack of literature profiling the potential adopters of DRETs. Nevertheless, research dealing with electric vehicles offers insights into the profile of

those who adopt environmentally friendly technologies. Scholars have found that psychological drivers may inhibit the adoption of electric vehicles, even when socioeconomic characteristics would support the adoption (Franke *et al*., 2012). Strategies such as information, training and education can counter these effects. These findings are consistent with those on wind power by Warren *et al*. (2005), thus creating a theoretical bridge among environmentally conscious technologies.

II.4 Spatial Analysis and DRETs

The original Bass diffusion model incorporated time and agent-specific characteristics, particularly in its later articulations (Bass, 1969). In his model, Bass tested the idea that durable goods are adopted in stages, with early adopters ('innovators') driving the passage from one technology to the other. The idea of stages and the role of early adopters was present in Rogers (1964). However, Bass provided both an empirical test of the stages.

Starting the 1980s, various authors conjugated spatial analysis, behavioral sciences and TD. Authors have focused on creating sophisticated concepts of time and space (Brown, 1981; Hägerstrand, 2002; Verbeek and Slob, 2006b).Time became 'history', meaning that agents have memories and technologies are not introduced in to a vacuum. Place and scale have become endogenous characteristic of the diffusion process. Models tried to look at the reasons behind certain distribution phenomena. While the first TD models were descriptive, later models have tried to discern the drivers behind certain diffusion patterns (Brezet, 2006 and Verbeek and Slob, 2006).

The socioeconomic and demographic characteristics of agents and those of the agents' surroundings are the focus of many studies in DRETs diffusion. Agents act like other 'peers' for

two main reasons: for emulating someone perceived as guidance; or for reducing the risk associated in being an innovator (Bollinger and Gillingham, 2012). Studies on TD in general have described the relationships between innovators and followers: Hägerstrand included information and emulation in his original work (Hägerstrand, 1967). Subsequent research developed in marketing sciences and economics has tested the role of social interactions and self-selection of reference groups (Manski, 1993; Soetevent, 2006).[8] For instance, Manski found that:

Inference is difficult to impossible if these variables are functionally dependent or are statistically independent. The prospects are better if the variables defining reference groups and those directly affecting outcomes are moderately related in the population. (Manski, 1993, p.1)

With the development of new sources of data and behavioral models, the problems stated by Manski have been solved (Soetevent, 2006). Soetevent provided a review of the recent development to account for neighborhood effects and peer-effect. In his work, the author argued that:

'Most reference group definitions put forward by empirical researchers are ad hoc and based on

- *Social proximity*
- *Geographical proximity.' (Soetevent, 2006 p.220)*

Bollinger and Gillingham found that a peer effect exists for solar photovoltaic in California (Bollinger and Gillingham, 2012). The authors used econometric models to estimate the spatial peer-effect in the case of PV systems in California, finding:

'[…] strong evidence for causal peer effects, indicating that an extra installation in a zip code increases the probability of an adoption in the zip code by 0.78 percentage points when evaluated at the average number of owner-occupied homes in a zip code. (Bollinger and Gillingham, 2012, p. 23)

[8] The definition of peer-effect used in my research is the one adopted by Bollinger and Gillingham (2012).

The findings of Bollinger and Gillingham shed light over the role of spatial peer-effect of DRETs and in general and PV systems in particular. The physical presence of the panels creates a sense of security, reducing the perceived risk for potential adopters and showing the change from the business-as-usual is possible. Other authors investigated the same effect in the UK; their results show stronger adoption in regions where agents first adopted photovoltaic systems and a concentric pattern, with lower adoption in the further areas (Snape and Rynikiewicz, 2012). The two authors partly used the same assumptions used by Bollinger and Gillingham in their 20112 study, although focusing on the spatial patterns, rather than using econometric techniques. MacEachren and Hanson (2008) identified three major streams of research in diffusion of technology: demand-focused, place-focused and a combination of the two, which is the one they used. The authors provided an interesting perspective in their work because they combined fieldwork and econometric models to study the adoption of PV systems in Sri Lanka. The authors analyzed how the socio-geographic context of villages influences the adoption decision, finding that social characteristics of villages influence the adoption patterns. The two scholars used linear regression models to estimate the weight of the socio-geographic drivers on the diffusion of PV systems due to the difficulty of collecting multi-year data. Through their study, the two authors managed to find empirical evidence supporting Brown's contentions that the diffusion of technologies is affected by market and infrastructural elements (Brown, 1981; MacEachren and Hanson, 2008). In addition, they found that informal relationship between villagers and between villagers and politicians affected the diffusion of solar home systems. Those villagers outside the social milieu tend to adopt faster, as they do not rely as much on social consensus and neither trust politicians, especially if the adopters belong to other ethnicities. One of the strength of their work is the inclusion of variables related to the area they

studied that made the predictors interesting for any policymaker interested in similar contexts. La Gennusa *et al.* (2011) and Theodoridou *et al.* (2012) looked at the characteristics of the cities. La Gennusa *et al.* employed a GIS-based approach to estimate the potential of power production from PV systems in an urban environment, specifically within inner cities. These approaches are certainly useful in that they spatially identify areas where DRETs could be installed. Nevertheless, their limits are evident: the authors focused purely on technical aspect and spatial aspects, excluding any consideration related to the political, cultural or socioeconomic landscapes in which these technologies were supposed to operate. Theodoridou et al. (2012) followed a similar approach: the authors assessed the profitability and energy potential of retrofitting building in densely populated urban areas. They concluded that:

"Conclusively, the general outcome obtained by current research, indicate that denser urban areas perform limited potential both for retrofitting interventions on buildings' envelope and solar systems applications, apart from the quality and the age of building constructions". (Theodoridou *et al.,* 2012, p. 6239).

Related to the work Theodoridou *et al. (*2012), Van Geenhiuzen *et al.* (2012) tried to find the best PV systems for urban areas. Specifically, the authors analyzed the various solar technologies for residential use, trying to find the best technology to expand the diffusion of PV systems in urban areas. The authors argued that incentives for specific PV systems design and technologies might be a solution for insuring that the most efficient and cheapest technologies are adopted in urban contexts. Maes and Van Passel (2012) studied how policies can affect the efficient diffusion of DRETs solar systems in the region of Flanders (Belgium) and the Netherlands, comparing how policies and uncertainty affect the diffusion of hybrid and cogeneration energy systems.[9] The authors found that uncertainty reduces the diffusion of DRETs: because of its

[9] Cogeneration systems produce electricity and heat simultaneously, thus increasing the overall efficiency of the system itself.

widespread use in greenhouses in the Netherlands, cogeneration reacts better when uncertainty is introduced, thus providing a better financial performance. Finally, the two authors found that public policies greatly influence whether a specific DRET diffuse over others or even over RETs in general. For instance, in the case of the Belgian region, the *"[…] strong support [by public authorities] might put other energy technologies in a less favourable position on the market. The support for cogeneration units in Flanders is so large, that solar panels are no longer interesting for the investor". (Maes and Van Passel, 2012 p.680).* Given solar panels reduce CO_2 emissions more cheaply than cogeneration systems. The authors concluded that:

"*The future evolution of public policy should take the current disequilibrium into account*" (Maes and Van Passel, 2012 p.680).

This conclusion highlights the importance of integrating institutions and policies in the study of DRETs diffusion: PV systems are found to be more convenient in the Flanders when compared to cogeneration, but, still, public policies made possible for cogeneration to spread faster. The authors did not detail the reasons behind the support towards cogeneration. It may have to do with reasons associated with local preferences, expertise, need of a specific sector, etc. These reasons, too, should be taken in to account before suggesting redirecting subsidies from one DRET to another.

Studying the barriers/drivers to the diffusion of DRETs is a need recognized at national level by the U.S. Department of Energy (DoE). The DoE has recently promoted a new initiative to study the diffusion and evolution of solar energy (DoE, 2012). The request for proposals of the DoE indicates that further research is required, and spatial models can play a major role in understanding solar energy adoption patterns.

II.5 An Historic Perspective of Literature on DRETs Diffusion

Literature on diffusion of innovations has multiple roots, spanning from the first third of the Twentieth century with the work of Sauer (Brown, 1981) to the latest development in recent years across a variety of disciplines. The first major theoretical and empirical work on diffusion research can be traced back to the works of Hägerstrand (1952, 1967), although this author drew from previous works by Sauer and others (Brown, 1981). In his work, Hägerstrand focused on the demand side to explain the diffusion of innovations, from the agent perspective, trying to understand the drivers behind the diffusion process. In particular, he focused on the role of 'information' as the way through which innovations diffuse. Consequently, Hägerstrand integrated the role of the geography affecting information with the diffusion of innovations (Webber, 2006). Aside from the specific methodological contributions and findings, Hägerstrand's work is crucial as it brings together various approaches; the author understood that a single perspective was simply not enough to explain the diffusion process of innovations. Consequently, the Swedish author first gathered data on the diffusion over time of several durable goods, labeled 'indicators'. He divided these indicators of innovation in to two categories:

1. Agricultural indicators:
    a. State subsidized pastures;
    b. Control bovine tuberculosis; and
    c. Soil mapping

2. General indicators:
    a. Postal checking services;
    b. The automobile; and
    c. The telephone.

The first set of indicators comprised only goods and services proper of farmers. The second set comprised goods that could be found among the entire population. Along these indicators, for which the author had consistent datasets across time and space was possible, Hägerstrand included ‘complementary indicators’, similarly grouped in the two categories ‘agriculture’ and ‘general’.[10] These goods served as control, and were though to either be adopter prior or necessarily after the adoption of the two sets of indicators listed above.

[Figure 2 About Here]

Subsequently, he prepared the population maps representing the demography for the study area (Southern Östergötland, in Sweden). This step, which occupies a significant of the book edited by Pred in 1967 may look obvious today, as digital maps are commonly available, particularly for population data. However, at the time, this was a fundamental step towards the development of the model, and a great research effort because no such maps existed. Then, the author adopted Markov-Chain Monte Carlo analysis is order to test the diffusion results over time, creating 3 models to test whether the diffusion of innovations take place as a decision of individuals or it is, in reality, a more complex and group-based, information-driven process. In his first model, Hägerstrand assumed that the diffusion of innovations was completely based on people’s choice, and hypothesized that the individual characteristics would predict the process. This model proved to be far from reality, as the control tests showed. In his second model, the author assumed that information could spread from people in all directions from a central point. The areas around these central points retain higher adoption rates as time passes. This second model proved superior when compared with reality, although discontinuity appeared as time elapsed. In

[10] These elements are tractor, automatic binder, milking machine, horse-drawn hoe, plumbing in barn, and plumbing in farmer’s residence (agricultural). Household plumbing, refrigerator and the electric range (general).

his third model, Hägerstrand introduced the concept of 'Resistance to the fictional innovation',[11] defined as "*The sum of direct contacts concerning the innovation made with already accepting individuals prior to P's own acceptance*" (Hägerstrand, 1967, p. 265). Where P is the accepting entity. The concept of barriers to diffusion and the introduction of information as part of the diffusion process was not new at the time. However, as Pred said in the postscript to the American edition of *Innovation Diffusion as a Spatial Process*, the novelty of Hägerstrand resides in the " […] *Weightiest ramifications of the models ultimately derive from their combination of random and non-random elements*" (Hägerstrand, 1967, p. 307). The method, the meticulous modeling, the testing and the inference of the results in light of the assumptions used was the greatest contribution of the Swedish scholar through his first works. These contributions distinguished Hägerstrand from previous authors such as Sauer, or those listed in the well-conceived review by Rogers (1962) in that simplified models were developed to deepen the knowledge of complex problems.

The rich literature on the topic that has emerged after the end of WWII requires some form of organization. I identify three major streams of research developed during the Twentieth century. The first stream started at the end of 1960s, finding its major work in the Bass' model (Bass, 1969). With his model, Bass attempted to forecast the diffusion of adoption of durable goods focusing on the demand side once again, although giving more weight on the data portion of the analysis. Later models, particularly in economics and marketing, adopted different mathematical approaches to model the diffusion of innovations from the perspective of organizations, individuals and the role of entrepreneurs/innovators (Davis, 1979; Brown, 2006). During the same years, another stream of literature was developing, this time closer to geography. The major work of this period is *Diffusion of Innovations* by Brown (Brown, 1981; Webber, 2006;

[11] The term 'fictional' here refers to the innovation in the stylized model developed by Hagerstrand.

Lutz, 2006). Brown built upon the ideas of Hägerstrand, expanding the concepts involved in understanding the process of diffusion. In particular, Brown added three major factors (Webber, 2006):

1. The supply side of innovations plays a major role in the diffusion process;
2. The role of agencies in helping the diffusion process;
3. The impacts that the innovations have on the area where they take place.

Brown admitted the role of factors, capable of reducing or encouraging the diffusion process (e.g. policies). For example, in the case of Hägerstrand's study on the diffusion of selected agricultural machineries in Southern Sweden, a post-1981 researcher would look at the role that various local and state agencies played in encouraging the diffusion of these technologies across time, including the how financing took place. In the field of DRETs, this advancement is important because incentives and requirements are fundamental in supporting the adoption of renewable technologies (Gillingham and Sweeney, 2012). Further, these same agencies can play an important role in spreading the information, thus forming the demand side studied by Hägerstrand. The third factor introduced by Brown adds the role of time more vigorously, creating a connection between how innovations spread and how they interact with future innovations and development (Webber, 2006). From the work of Brown, I identify an additional barrier towards DRETs diffusion, which includes by the later works of Hägerstrand and in particular his efforts to include the role of the environment in influencing people's choices (Hägerstrand, 1993).

I identified an additional tradition, whose roots can be found in the work of Rogers (1962). I labeled this tradition as 'sociological' not because purely influencing sociology but, rather, because of methodological approach focused on the theoretical aspects of defining and ordering

the concepts and the elements of the diffusion process. In time, this tradition has merged with the one formed upon the works of Hägerstrand and Brown, providing concepts and definitions used by social scientists to communicate and frame empirical findings.

The section of Figure 2 below the dotted line represent a close-up on the more relevant streams of research related to DRETs diffusion. The dotted arrows and the lines highlight the “jump” forward in time and the shrink in focus. I intentionally left out several major contributions (e.g. Hudson, 1969) in order to provide a better understanding of the more recent contribution in DRETs diffusion, rather than on diffusion in general.

In recent years, I identified two major streams of research dealing with DRETs diffusion process. Both these streams draw from the literature concepts, models and ways of inferring results. However, they differ in the focus of their approach. The first of these two approaches is ‘Socio-Economic Models’ (SEMs). These models are direct heirs of the tradition established in economics and marketing, and employ massive quantitative analysis, usually rooted in econometrics. Examples of these works are Rodseth (2009), Guidolin and Mortarino (2010), Pierre *et al.* (2011), Bollinger and Gillingham (2012), Snape and Rynickiewicz (2012), Freitas *et al*. (2012), and Tate *et al*. (2012). Conceptually, these valuable works have the intrinsic limit of focusing on either the supply or the demand side to explain the diffusion of DRETs. Even when the variables employed cover both sides, the overall understanding of the relationship among agencies/supply and demand is not considered. Nevertheless, this stream of research provides models about specific relationships among the diffusion subjects (e.g. spatial peer effects).

The other stream of literature has a wider breath: it includes analyses aimed at developing policies dealing with sustainability as a whole (Verbeek and Slob, 2006b; 2006). The difference from the last black block in Figure 1 is not in the methodologies used: in fact, some of these

studies employ quantitative tools and surveys (e.g. Firestone and Kempton, 2007; MacEacheran and Hanson, 2008; Gee, 2010; Donovan and Nunez, 2012). Rather, the two blocks differ in terms of perspective, for the literature descending directly from the economics/marketing tradition aims at exploring the specific drivers leading to adoption of DRETs, whereas the other stream of research aims at a more complete understanding of the causes of these drivers (Geels 2002; Verbeek and Slob, 2006).

Section III: Elements of the Conceptual model

The conceptual model[12] described in the following sections comprises three main elements:

1. The Area Geography (AG);
2. The institutional Framework (IF); and
3. The Adopting Agents (AA).

[Figure 3 About Here]

Figure 3 shows the overall model concept. Each elements within the model is explained in detail in this section. Overall, the three main elements in the model are nested and arranged in a loose hierarchy, based on the spatial width of each of them. The hierarchy is loose, as the IF can be larger than the AG: however, the AG will still provide the physical limits for the total energy available. The AG is filled to highlight the pervasiveness of its nature. There is a *file rouge* connecting all the elements: this is the sum of the relationships occurring between each pair of the elements.[13] These relationships are bi-directional, meaning that each elements affects and is affected by the others. The diffusion of a DRET takes place within this context: it reacts to the

[12] For clarity's sake, I will refer to it as 'model'.
[13] AG-IF; AG-AAs; IF-AAs; AAs-AG; IF-AG; AAs-IF.

changes and the set of pressures and frictions occurring along the borders of each of the elements.

I identify each of the components as a ‘subject’ of the diffusion process of DRETs. The term highlights the centrality of these three elements in defining and influencing the diffusion process. These three elements are not just places in which the diffusion of DRETs takes place. As subjects, they influence and are influenced by the diffusion of DRETs. These elements are active receiver and shaper of the process as a whole. Although using different labels and names, literature has recognized the role of each of these subjects separately. For instance, Verbruggen *et al*. (2010) and Maes and Van Passel (2012) recognized and explored the role of public organizations in the diffusion process of solar energy. Bollinger and Gillingham (2012) and Gee (2010) looked at how agents influence the adoption process itself, although from different perspectives. Although indirectly, Hägerstrand (1993) described the role of the environment, here AG, in influencing people’s attitudes and culture, which, in turn, influence agents’ behavior (Dietz *et al*., 2005). Within each of the subjects, there are interconnected elements, arranged in networks and interacting with each other, as described by Geels (2002). The strong hierarchical character of Geels’ work fails to take into account changes deriving from institutions, the human and the natural environment, and time.

III.1 Area Geography

Definition: ‘*The mise en scene of fabricated and natural elements within the study area*’.

Examples: Area geology, area morphology, area parcelization, districting, building set-ups, logistic set-up (e.g. roads).

I label the first subject of my model ‘Area Geography’ (AG). So far, the term ‘diffusion’ has appeared many times. The use of a spatial concept implies that the process itself has to take place

within a space, which is both physical and institutional (Buttimer, 2001; Geels, 2002). Previous literature has included this concept in different ways, almost following the two questions posed by Hägerstrand in his works dealing with the role of people and the environment in Regional Sciences (Hägerstrand, 1993). One major stream regards AG purely as a physical concept, focusing on the interaction between humans and the natural environment (Hägerstrand, 1993; Johnston, 1997). Other authors included both the natural and human environment under terms such as landscape, socio-technical landscape or alike (Hägerstrand, 1993; Rip and Kemp, 1998; Geels, 2002). Geels provides a clear definition of socio-technical landscape:

'*[…] a set of deep structural trends. The metaphor 'landscape' is chosen because of the literal connotation of relative 'hardness' and the material context of society […]*' (Geels, 2002, p.1260).

The character of 'hardness' mentioned by Geels is present in geography and diffusion studies since their very beginning, particularly in the works of Hägerstrand and Sauer (Brown, 1981; Johnston, 1997). The difference between these two visions lays in the relationship between agents, usually humans, and the AG and the conceptual width of AG. Socio-technical scholars tend to place the AG hierarchically higher, as depicted in Figure 4.

[Figure 4 About Here]

The hierarchy of the picture is in terms of macro-meso-micro levels, the macro level being the hardest/slowest to change. In Hägerstrand's work, the landscape is more directly associated with human's actions, and is one of the components in the author's dioramas (Hägerstrand, 1988; Sui, 2004). Further, the model depicted above confines agents and the relationships between them

and the IF at the meso-level ('patchwork of regimes'), with niches left to be the engine of innovation.

I define the Area Geography as '*The mise en scene of fabricated and natural elements within the study area*'. The definition retains the character of 'hardness' common to both Hägerstrand and Geels. Additionally, the use of the term '*mise en scene*' is important because it implies that the natural and fabricated components of the AG are arranged by the IF and/or the AAs. The immateriality of the AG arises when it is perceived, rather than from its mere existence. In itself, the AG provides AAs and the IF with possibly the only true limit: the total amount of energy when efficiency is 100%. When dealing with multiple DRETs, this limit is overcome using new technologies and fuels. For PV systems, the current efficiency is not nearly close to 100%, and, consequently, increases in efficiency are still possible (Goodrich *et al.*, 2012).

The term 'Area' indicates the geography of the location where diffusion takes place. Far from making diffusion a 'regionalist' field of study, this term highlights the importance of scale and location (Buttimer, 2001). However, these two factors can be changed in their size and focus, and uniqueness of areas is not implied. It is beyond the scope of this work to explore the implications of scale and location in natural resource and energy studies. I will defer to the importance of area specification to the work of Hägerstrand and Brown. Both these authors recognized that diffusion as a spatial process takes place somewhere, and that specific somewhere influences the process itself. Nevertheless, neither of these two authors implied regionalism in its classic meaning (Hägerstrand, 1967; Brown, 1981; Johnston, 1997).

III.2 Institutional Framework

Definition: '*The ensemble of private and public organizations, including local, national and international governing bodies and financial institutions'.*

Examples: Energy investment institutions, utility companies, national governments.

Nelson and Winters were the first to introduce the concept of 'technological regimes' as '*the outcome of organizational and cognitive routines*' (Nelson and Winters, 1982; Geels, 2002, p.1259). With the expansion of the concept by Rip and Kemp, the routines have become rules, and the participants in the process have expanded (Rip and Kemp, 1998; Geels, 2002). Figure 5 shows the meso-level in Geels conceptual framework embracing the definition provided by Rip and Kemp.

[Figure 5 About Here]

The multi-actor network depicted by Geels hosts some the elements forming the IF, for Public authorities, research networks and institutions, and financial networks are the elements of this subject. Based on the role of networks and interactions, previous socio-technical literature tends to focus on the interactions among these elements (Geels, 2002; Verbeek and Slob, 2006 and 2006b). In this conceptual model, the IF is an additional, smaller field of action for agents.[14] The relationships within each component of the IF is not described, and neither the inclusion of niches. This is because adopters find the IF as an integrated system of laws, financing and economic opportunities/risks and technical solutions.

The IF is not a static or unchangeable: the relationships depicted by socio-technical scholars are still in place. However, the IF is a 'stock' figure when the adoption decision is made. In other words, potential adopters will not decide whether to adopt or not based on the possibility of optimizing the IF. Rather, they will first change it and then make the adoption decision based on the current IF. At most, uncertainty and instability can be a character of the IF.

[14] See next section for agents' description.

Previous literature has studied the role of the IF on the diffusion processes in general, and the one of renewable energy technologies (RETs) and DRETs in particular. Authors such as Nelson and Winters (1982), Rip and Kemp (1998) and Geels (2002) focused on the coordinated relationships existing among institutions, private companies, researchers and societal groups. Others pictured the IF as a possible source of adoption impairment or, at most, research advancements. Gillingham and Sweeney listed public organizations among potential barriers to the diffusion of DRETs (Gillingham and Sweeney, 2012). Maes and Van Passel specifically studied how policy and incentive design can prevent the spread of certain DRETs to be adopted (Maes and Van Passel, 2012). The IF is not solely a negative element for the diffusion process of DRETs. Verbrueggen *et al*. (2012) introduced a positive aspect of IF.[15] In their work, the authors listed the IF as source of research alongside the usual source of barriers to the diffusion of DRETs. Despite focusing on networks, Nelson and Winters (1982), Rip and Kemp (1998) and Geels (2002) admitted that the IF could have either a positive or a negative effect on diffusion. In the sections dealing with the links among the three components of my model, I will explore how these connections take place.

III.3 Adopting Agents

Definition: '*The agent responsible for the final adoption decision'*.
Examples: Households, commercial estates, private organizations.

The third subject of the conceptual model are adopting agents (AAs). I identify AAs as the element responsible for making the adoption decision. This means that the agent can be any potential adopter of a DRET, where the smallest case is the individual person.

[15] In the present work, the adjective 'positive' indicates the presence of certain qualities rather than a moral qualification.

The agents are the atoms constituting each of the upper levels in the diffusion model. In socio-technical models, adopters are included in the meso-level and in the micro-level (Geels, 2002). At the micro-level, adopters are nested within niches, which represent the main engine of diffusion. At the meso-level, networks of adopters interact with other networks (e.g. producers) to enable change and modify the landscape (Rip and Kemp, 1998; Geels, 2002). In Hägerstrand's model, agents are the smallest unit of adoption: the have the ultimate decision of adoption and enable technologies to diffuse faster (Hägerstrand, 1967). I draw from both Hägerstrand and Geels: AAs are the basic subjects of the model. However, they are not necessarily households or people. Additionally, their network and interactions become part of the IF as societal groups or organizations.

Section IV: Interactions within the Conceptual model

This section describes how the various elements of the conceptual model interact with each other and how they affect the diffusion of DRETs. Within the model, each element is both active and passive at the same time. That is, each subject contribute to modify the others and it is affected by these changes through the new inputs coming from the other subjects.

DRETs enter the model either spatially exogenously or endogenously. Spatially-exogenous DRETs generate outside the AG and are imported in to it through the adoption. The adoption of a new DRET is part of the innovation process (Hägerstrand, 1967). Spatially-endogenous DRETs are generated within the AG and heavily rely on the role of the IF. The exogenous ones are imported within the AG. In his work, Geels describes the dynamic of innovation hierarchically through the sequence micro, meso and macro-levels. The first of these three levels is where innovation takes place: niches are the engine of innovation, and they provide the networks at the

meso-level with the fuel for changing the landscape (macro-level). The model presented here focuses on the diffusion process, allows innovation to arise within any level.

IV.1 How Area Geography influences the IF

Whether labeled as landscape, environment or Area Geography, the influence exercised by the physical elements of the world over human organizations and interactions has been one of the *leitmotif* in geography. Starting the 1910s, works on environmental and climate determinism have tried to uncover the links between nature and human activities, even if some authors assumed extreme positions (Johnson, 1997).

In the model presented here, the AG interacts with the IF providing the resource endowment available to DRETs. The endowment provided by the AG works like a budget constraint over the IF. DRETs need fuel to generate energy in all its forms. This fuel can be wind, solar radiation, biomass or any other renewable fuel. Every AG has a certain amount of fuel available. Partly, this availability depends on the physical setting of the AG. For instance, an area with extensive protected areas will have its resource endowment limited. An additional element defining the resource endowment is the efficiency of the DRETs available through the IF. For instance, solar panels that are more efficient result in an increased availability of solar energy. Figure 6 shows how this push-pull effect affect the resource endowment. The dynamic of this effect follows that one of a budget constraint usually adopted in microeconomics (Mass-Colell, 1995).

[Figure 6 About Here]

The AG does not only provides resources in a positive way. By imposing an endowment, even a one that can be modified, the AG generates a pressure over the IF. This pressure generates the incentive on the IF to find new renewable fuels.

IV.2 How the IF influences the Area Geography

In the model, I borrow from the definitions and concepts of Hägerstrand and Geels, recombining them in a way appropriate for the diffusion of process of DRETs. However, there are several conceptual differences in from these two author. First, my model allows the IF to change the AG at any time and at any rate. The IF can change the *status quo* of the AG for the diffusion of DRETs very quickly. This situation can take place, for instance, in the case of major shocks, such as the recent series of *moratoria* on nuclear power put in place in Germany after the Fukushima-Daichi disaster in 2011 (Wittneben, 2012). The immediate consequence, among others, has been the opening of new non-nuclear power plants and the consequent change in the built environment. Second, differently from Hägerstrand, I include private organizations within the IF.[16] This is because in DRETs diffusion processes private organizations are part of the 'offering' made to the adopting agents, providing services and goods and influencing public organizations in their legislative efforts.[17]

In my model, the IF has two major ways to shape the AG and influence the diffusion of DRETs:

1. **Legislation** (including Laws, Regulations and Policies, Hägerstrand, 2001);
2. **Research and Development** (Verbruggen *et al*., 2010; Fri, 2003);
3. **Deployment.**

According to Hägerstrand, '***Legislation** […] is the fundamental instrument of governing*' (Hägerstrand, 2001, p.43). Even those authors identifying public organizations as source of barriers in the diffusion of renewable energies focus on this particular instrument (Verbrueggen *et* al., 2010; Gillingham and Sweeney, 2012). Laws can modify the AG very quickly or over time, as their period of implementation vary considerably. There are two examples that best

[16] Unless all or part of these are among the potential adopters of a specific DRET.
[17] Describing the dynamics within each of the subjects of my model is beyond the scope of this paper. However, I accept the description of network-based interaction proposed by Geels (2002), although some of the elements part of the meso-level described by the Dutch author are presented here as Adopting Agents.

describe how legislation affect the AG of DRETs. First, consider the role of renewable portfolio standards (RPS). RPS is *'[…] a policy that requires electricity retailers to provide a minimum percentage or quantity of their electricity supplies from renewable energy sources. An RPS establishes a base level of demand but allows the market to determine which renewable energy resources will meet that demand*' (Cory and Swezey, 2007). In recent years, national and local governments have used RPS as a way to shift towards renewable energy generation. The combination of RPS and subsidies directed to RETs in general have expanded the number of RETs in adopting states.[18] The changes in the AG occur through the diffusion of RETs and the closure of non-RET plants (Gee, 2010). As a second example to show how legislation changes the AG, consider districting and panning regulations. Local governments can either boost of tap the availability of natural resources and locations for siting DRETs and RETs simply imposing a ban on parks or banning the installation of solar panels on multi-story buildings. Areas belonging to the AG have to be excluded as part of the resource endowment. This modification of the AG can happen very quickly once the law/regulation is approved, thus showing that the AG is not necessarily the most difficult level to modify.

The second tool is **Research**. The way Research changes the AG is easy to understand: increasing the efficiency (or reducing the relative cost). Consequently, thanks to new technologies and approaches, the same AG provides additional energy resources. Fri (2003) and Verbruggen *et al*. (2010) allocate research to public institution. However, private companies are among the largest investors in Research and Development (R&D) in most of the developed countries. For example, in the USA, private organizations investments in Research and Development amounted to 209.6% of investments in research from all other public sectors

[18] http://www.cleanenergystates.org/assets/2012-Files/RPS/RPS-SummitDec2012Barbose.pdf. Accessed on 08/11/2013.

(Battelle, 2011).[19] Similarly, within the European Union,[20] the private sector invests the equivalent of 1.26% of the gross domestic product in R&D, the public and non-profit sector only 0.76% (EUROSTAT, 2013). These data show the importance of including private organizations and organizations in to the IF.[21]

Deployment is the last tool through which the IF affects the AG. Deployment refers to the supply of DRETs and services in terms of market choices. Firms and public organizations make DRETs influences the availability of DRETs within an AG not just through subsidies or other policies. Marketing decisions and the physical availability of certain technologies are fundamental factors in the spread of DRETs. Additionally, services associated with DRETs are equally important. The lack of financing options or technologies such as smart and sub-metering may affect hurt the diffusion of DRETs. This last concept is probably the one most strictly dependent on the networks within the IF. Private organizations operate within their networks, which are usually regulated by laws and policies.

IV.3 How the Area Geography interacts with Adopting Agents

The AG affects the decision process of AA through **Culture**. The term 'Culture' is wide in its meaning. Authors such as Hägerstrand (1988), Geels (2001), Brown (1981), , Verbeek and Sloeb (2006), Elzen (2006), Gee (2010) and Verbrueegen *et al*. (2010) have introduced in one form or the other AG as a factor shaping the perceptions and behavior of people and human organizations. Possibly, the best work to understand the meaning of the word Culture and its role in shaping AA's behavior towards the diffusion of DRETs come from the works of Dietz *et al*. (2005) and Hägerstrand's (1988). With the work '*What about nature in Regional Sciences?*'

[19] The first number includes expenses by non-profit private organizations. Expenditures from Higher education institutions are aggregated in to federal and other U.S. agencies.
[20] EU-28.
[21] Hagerstrand calls these 'firms'. The terminology employed in the present paper ('private organizations' or 'private institutions') are more appropriate because of their broader meaning.

Hägerstrand eminently reintroduced the role of nature in to the discourse of diffusion. In particular, the Swedish scholar has focused on the problems associated with limited resources and the consequences these limits can have on development (Hägerstrand 2001). Hägerstrand had an initial intuition of the effects of the AG over AAs in its original work on diffusion, as he recognizes the spatiality of the adoption process through information and personal contact (Hägerstrand, 1967). In the previous section of the present paper, we saw how these limits might not be static, as the IF has the power to redefine the part of these constraints through research. Nevertheless, the presence of constraints and definitions imposed by the AG are perceived by the AAs through the formation of values-norms-beliefs. Figure 7 was developed by Prof. Atkinson-Palombo, and it is based on the work of Dietz *et al*. (2005).

[Figure 7 About Here]

In my model, I borrow from the concept developed by Prof. Atkinson-Palombo in that the model shown in the figure above describes the relationships creating AAs behaviors. Building on these concepts, I add the concepts of Culture, which generates memory. Through these memories, behaviors are continued through time. However, the modification of the AG through these behaviors ingenerate new changes in Values, which ignite changes in Beliefs and so on (Figure 8).

[Figure 8 About here]

AG contributes to the creation of Culture, which in turns affect values and, therefore, environmentalism. Adoption of DRETs depends on environmental values, especially when DRETs are more expansive then non-DRETs. The relationship between DRETs and the AG affects the perception of that AAs have of the AG. Some changes affect this perception

negatively to the point that agents oppose the diffusion of certain DRETs (Devine-Wright, 2007; Gee, 2010). The perception of the AG is 'passive': AAs react to a change in the AG that was not implemented by the AG itself, but, rather, by changes occurred by and within the IF. As an example, consider the case of incentives introduced for adopting solar PV systems. If there is an increase in adoption, the landscape will change, as more systems will appear on roofs and in backyards. At that point, AAs may react negatively due to negative perception of solar PV systems as part of the landscape. On the other hand, AAs may actually accelerate their adoption rate because they see their landscape modified by peers, therefore increasing their confidence in DRETs (Bollinger and Gillingham, 2012). The dynamicity of landscape changes reinforces the role of time in the diffusion process: Culture changes and perception changes along with the landscape. The relationship between Time, Culture and Technological Change is well established in geography since the 1980s (see Hägerstrand, 1988; Marchetti, 1988; Schwartz, 1988). The addition of time as a common denominator of the system is required because it reinforces the fact that not even the AG (or landscape in Atkinson-Palombo's Figure) remains the same. The 'dynamism of time' has to be the constant, rather than a variable (Schwarz, 1988) or a 'Cultural structure' (Marchetti, 1988), where the term 'structure' identifies a fixed element within the study of technology diffusion.

Despite being an extremely strong force in affecting adoption decisions and patterns, the relationship between the AG and AAs is complex, and still matter of study (Dietz *et al.*, 2005; Devine-Wright, 2007).

IV.4 How Adopting Agents influence Area Geography

AAs influence and modify the AG through their behavior. Any potential AA acts within the AG. A good example of this relationship involving DRETs is the behavior of households adopting solar PV systems. The adoption itself modifies the AG, particularly in case of small-scale solar farms. In general, any behavior of AAs affects the AG. For instance, increasing the demand of energy under the current scenario generates further emissions, thus accelerating the global increase in temperature and modifying the AG. As AAs, organizations affect the AG with their decisions: opening a new plant and powering it with DRETs will affect the landscape. Figure 9 shows the effects of AA behavior over the AG along time. The behaviors are consequences of the chain Values-Beliefs-Norms, particularly of those affecting environmentalism. This scheme draws from the findings of Dietz *et al*. (2005). Behaviors affect the AG over time, contributing to reshape the AG. The new form of the AG will affect Values through Culture, thus re-initiating the cycle. The role played by time is extremely important: the decision of adoption of DRETs does not face the same AG, and neither the same AAs. If this were the case, then diffusion of DRETs would happen always in the same way within the same AGs.

[Figure 9 About Here]

3.4.5 How the Institutional Framework influences Adopting Agents

The IF influences the perception, behavior and DRETs adoption patterns of AAs in three ways:

1. **Policies/Laws/Regulations (Policies);**
2. **Supply of DRETs; and**
3. **Education/Information (Education).**

Policies can either prevent, slow or encourage the adoption of DRETs. For example, the prohibition of sub-metering affects the diffusion of DRETs technologies in rental and multi-family complexes in Connecticut (Bronin, 2012). On the other hand, subsidies can help to make DRETs more affordable, lowering the barriers associated with capital requirements and increasing the speed diffusion (Sarzynski *et al*., 2012).

The **Supply of DRETs** is the second way the IF interacts with AAs. In most cases, firms are the suppliers, although there may be locations where public organizations play this role. The supply of DRETs is fundamental, for most of the times AAs are not the developers of the technologies. Additionally, when a potential adopter investigates the market to see what is available it will take her decision based on the products offered.

Education influences the adoption decision of AAs in two ways. First, it affects the pre-adoption process in that it provides AAs with the tools to understand and to know the direct and indirect advantages of adopting DRETs. Literature has shown that higher education attainment and training about DRETs increase the likelihood of adoption (Pierce *et al*. 2009; Tate *et al*., 2012). Information plays a key-role in the diffusion of DRETs. Knowledge about the existence of DRETs, their accessibility, their role and advantages positively affects acceptance and adoption (Warren *et* al., 2005; Devine-Wright, 2007; Pierce *et al*. 2009; Tate *et al*., 2012). In general, Education/Information shape the way in which AAs perceive DRETs, whereas Culture from the AG shape adopters' view of the environment and their environmental values.

IV.5 How the Adopting Agents influence the Institutional Framework

The last relationship arising within the factors of the model is the one generating from the AAs and directed towards the IF. This flux of influence is particularly important as it bonds the most

basic subject of the model with the container of the diffusion engine. AAs have influence the actions of the IF in two ways:

1. **Participation; and**
2. **Voting/Support.**

Participation in the IF is the positive way through which AAs affect the IF. Within governmental institutions, elected officials and administrative staff are both potential adopters and par of the IF. Similarly, in private organizations, owners, workers, researchers are potential adopters and part of the IF. Voting/Support is a less direct way through which AAs affect the IF. Certainly, the base of AAs potentially involved in this action is broader: in democratic countries, all citizens meeting certain age requirement can vote. In non-democratic countries, consensus is still an important component for the ruling authority to maintain the *status quo*. Additionally, organizations do not directly vote: nevertheless, they can affect voting decisions and divert political support to specific DRETs through lobbying (Hughes and Lipscy, 2013).

Finally, a remark about prices. The AG provides a first constraint in terms of resource endowment the IF and the AA can use. The networks within the AA and the IF are responsible for setting the first levels of demand and supply. The encounter of these two forces will generate the absolute and relative prices of DRETs. The IF through its internal networks generates any distortion of the perfect market. The AAs will face the price, which, in turn, will affect their decision. The decision of the AAs will influence the supply side, both at the production and at the political level. For example, public organizations (e.g. government) may decide to fund research to make DRETs cheaper, or cut tax subsidies towards fossil fuels.

IV.6 The Dynamic of DRETs Diffusion

Changes in the ‘field-of-play’ or in the configuration of potential adopters are easy to relate with changes in the diffusion

Figure 10 shows how a DRET will diffuse within the model. A similar figure would explain the aggregate diffusion of all DRETs. For simplicity’s sake, I assume the DRET at hand to be residential solar PV systems (RPV systems).

[Figure 10 about here]

The two constant in the diffusion process are Time and a measure of adoption (X and Y Axis respectively). The former measures the how long the process requires. The latter records how deep PV Systems have penetrated the study area. The additional axis measures the amount of energy produced by all users combined. The diffusion process occurs within the three nested subjects: the orange one, representing the total number of possible AAs is where the adoption curve evolves. The area between the three subjects is where the events affecting the diffusion take place. This area is the one where the connections described in the previous sections arise. In the curve depicted above, I introduced four symbols, two minuses and two pluses. The former represent events negatively affecting diffusion. The latter those boosting it. The region between the subjects is where these events generates, ‘dropping’ on the pathway of the diffusion curve. Initially, DPV Systems are introduced on the market and someone adopts them. The rate at which this initial step occurs and the condition of adoption derive from the AG-IF-AAs interaction. Usually, the increase in adoption at this stage is driven by factors inherent to the AAs, such as environmental values and information. Decline in the diffusion/adoption curve have multiple reasons. Decreases in energy prices can make a DRET too expensive. Similarly,

logistic and other technical problems may arise in during the diffusion process, thus impairing the adoption.

Section V

The model presented here allows understanding the three subjects affecting the diffusion of DRETs within and area. There are several major important contributions produced by this model. First, there is not specific hierarchy for the source of diffusion in terms of difficulty to modify one of the factors. Thus, the AG changes quickly or slowly. Second, the heart of the process lies not in one of the subjects, but, rather, in the relationships among them. Thus, if in Geels (2002) the source of the engine was in 'Niches', in the present model the engine is a dynamic force, emanated by the limits and structures existing within the study area. If not IF. AG or AAs existed the adoption would be zero. If only AAs existed, then adoption would be 100%. Of course, this case is impossible, as we should live in an endless world, with no resource-constraint, not even time and space. If no IF existed, then the AAs could not overcome the limitations imposed by the AG or develop DRETs at all.[22] Third, with the inclusion of public and private organizations together within the IF, the public sector is not necessarily a negative force anymore. Fifth, the inclusion of the AG, a concept similar to the socio-technical 'landscape' provides the model with space-dependency and scale dependency. As location matters, so does the interaction between the location and the IF: the AG is the *canvas* where the IF decisions are shown. Sixth, policies become spatially sensitive because of the need of spatial appropriateness introduced by the model and based on Buttimer (2001). Policies failing to recognize the importance of the way the AG is the reflection of the IF decisions may be incomplete, such as in the case of Connecticut (Bronin, 2012). Seventh, adopting agents are not passive receivers of the diffusion process whose

[22] Even in the case of 'free donations' from an exogenous IF (e.g. a foreign country) a minimal IF would be et-up to educate and inform the AAs of the DRET specifications.

decision rest in the adoption itself. Rather, they can actively change the AG and the IF, that is, they are the process itself. Whether they are depicted as networks (e.g. in Geels, 2002; Bollinger and Gillingham, 2012) or as single agents, AAs are affected by the diffusion process, which, in turn, modifies every level of the model. Finally, because the three subjects change, time becomes part of the model: situations or dioramas generated by the model are not static, but follow paths created by the interaction among the subjects of the diffusion process. The major consequence is that the model does not describes the diffusion process at a specific point in time, but, rather, provides the elements to understand the path followed by the adoption/diffusion process.

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Figures

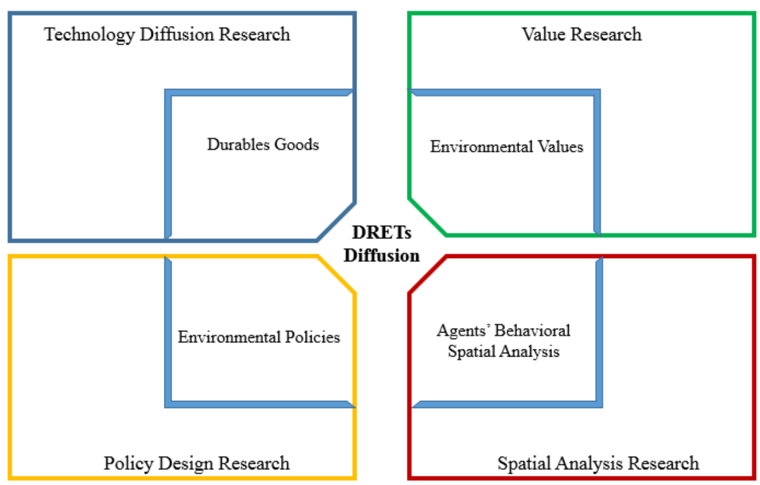

Figure 1. The Place of DRETs in Research

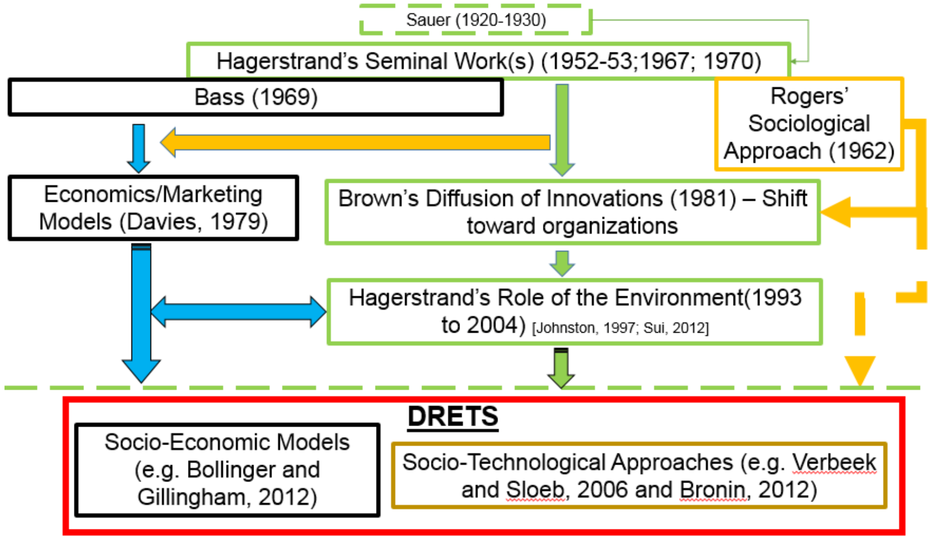

Figure 2. Historic Perspective of Literature on DRETs Diffusion

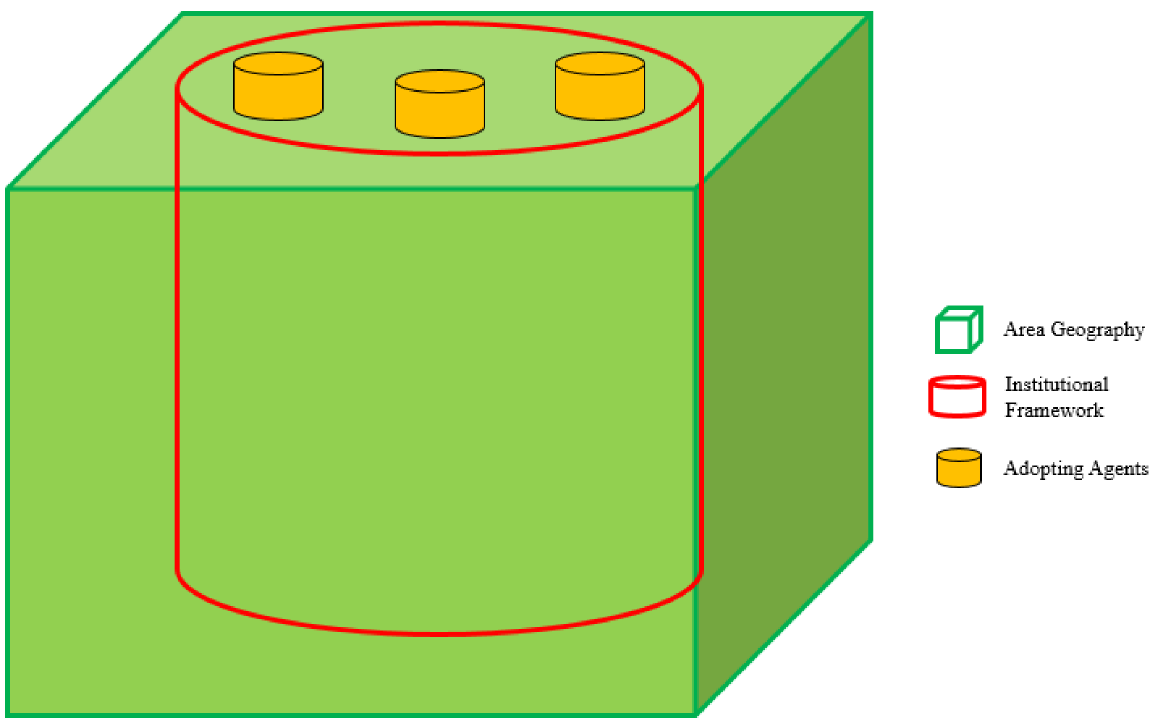

Figure 3. Components of the Conceptual model

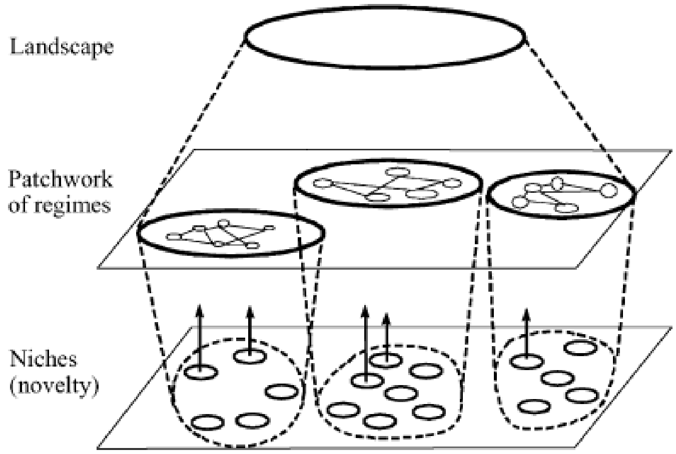

Fig. 3. Multiple levels as a nested hierarchy.

Figure 4. Multiple levels as a nested hierarchy (Geels, Fig.3, 2002)

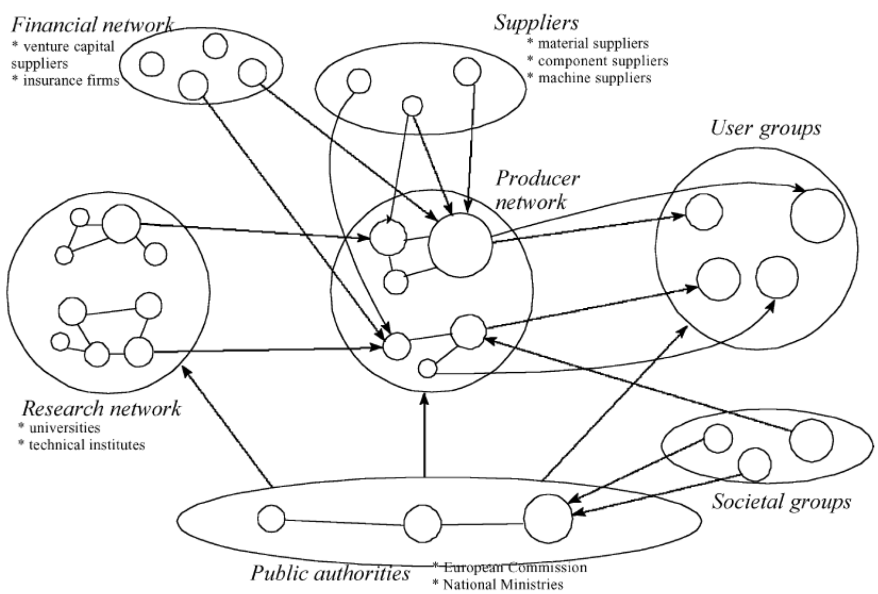

Fig. 2. The multi-actor network involved in sociotechnical regimes.

Figure 5. The multi-actor network involved in sociotechnical regimes. (Geels, 2002, Figure 2)

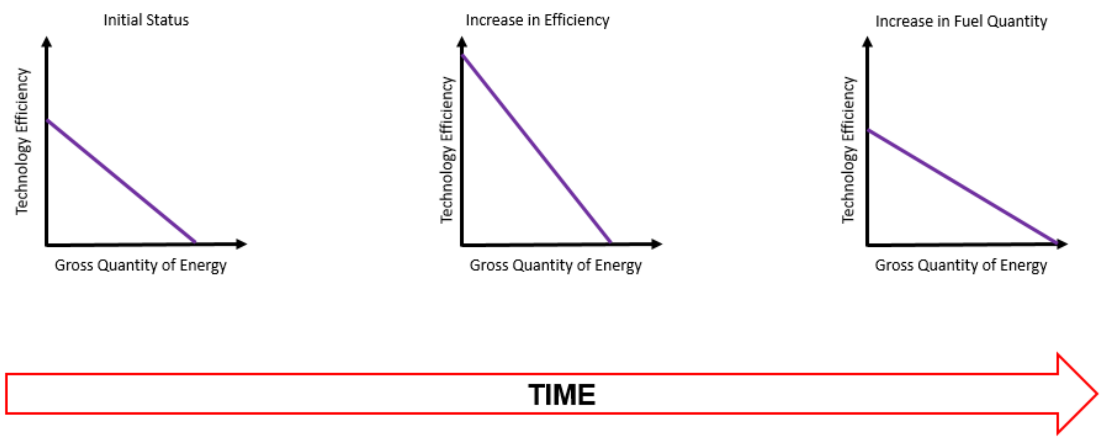

Figure 6 The Push-Pull Effect Defining the AG Resource Endowment

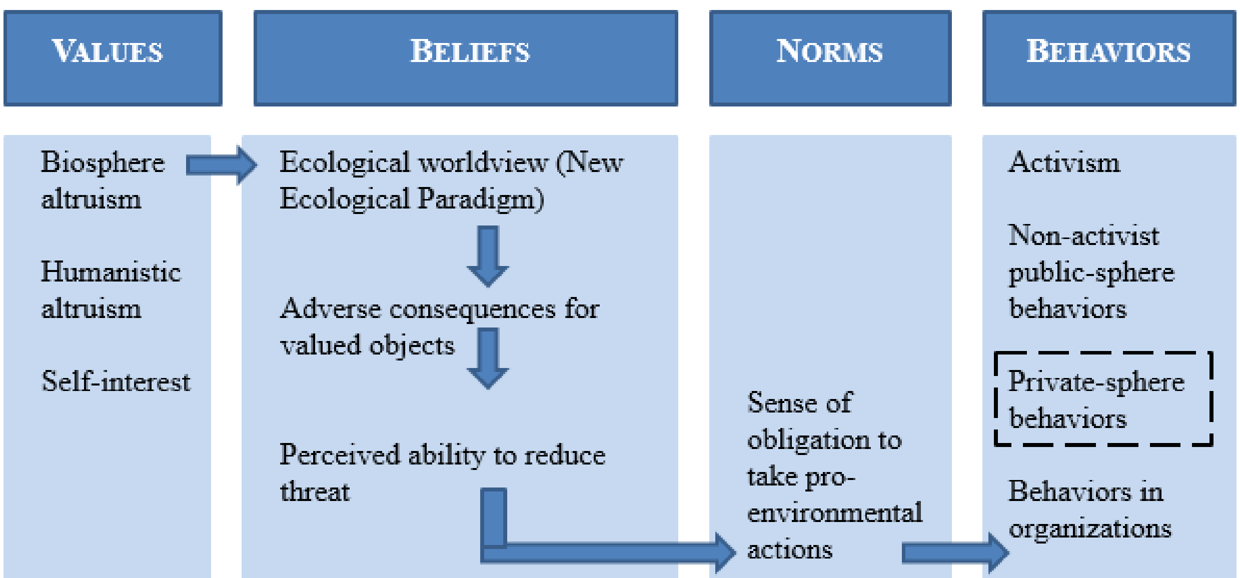

Figure 7. Values-Beliefs-Norms Influence over Behavior

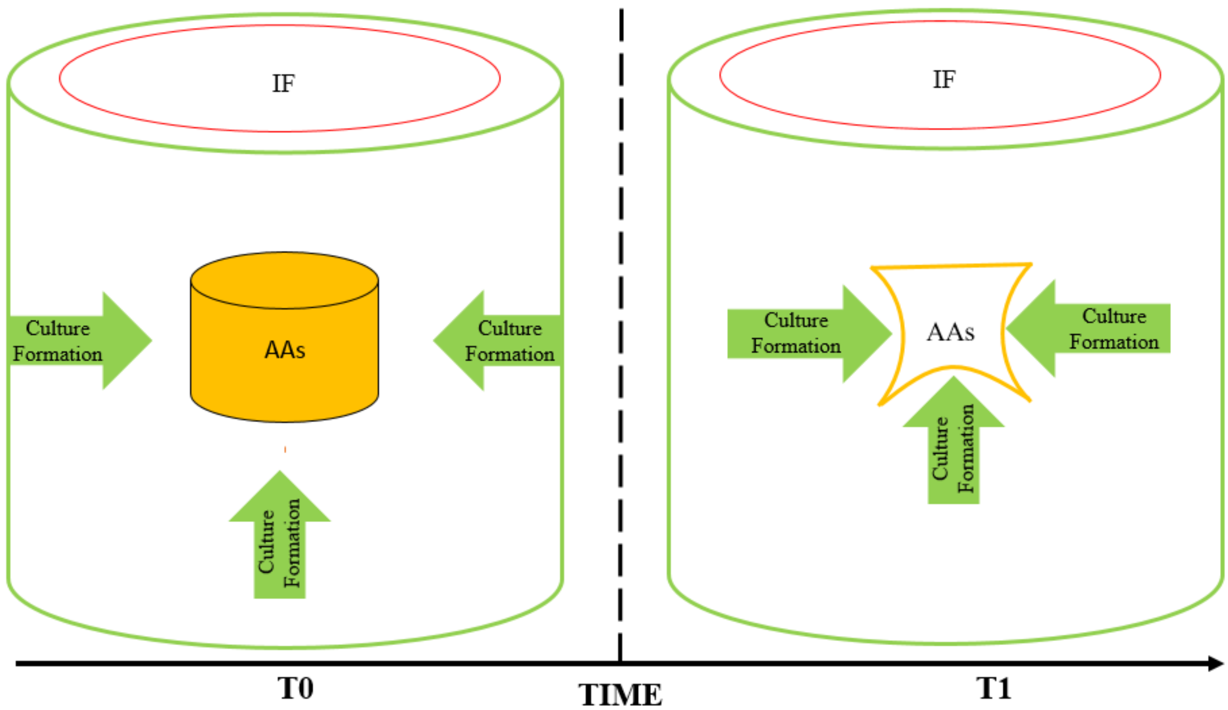

Figure 8. AG Influencing the Adopting Agents

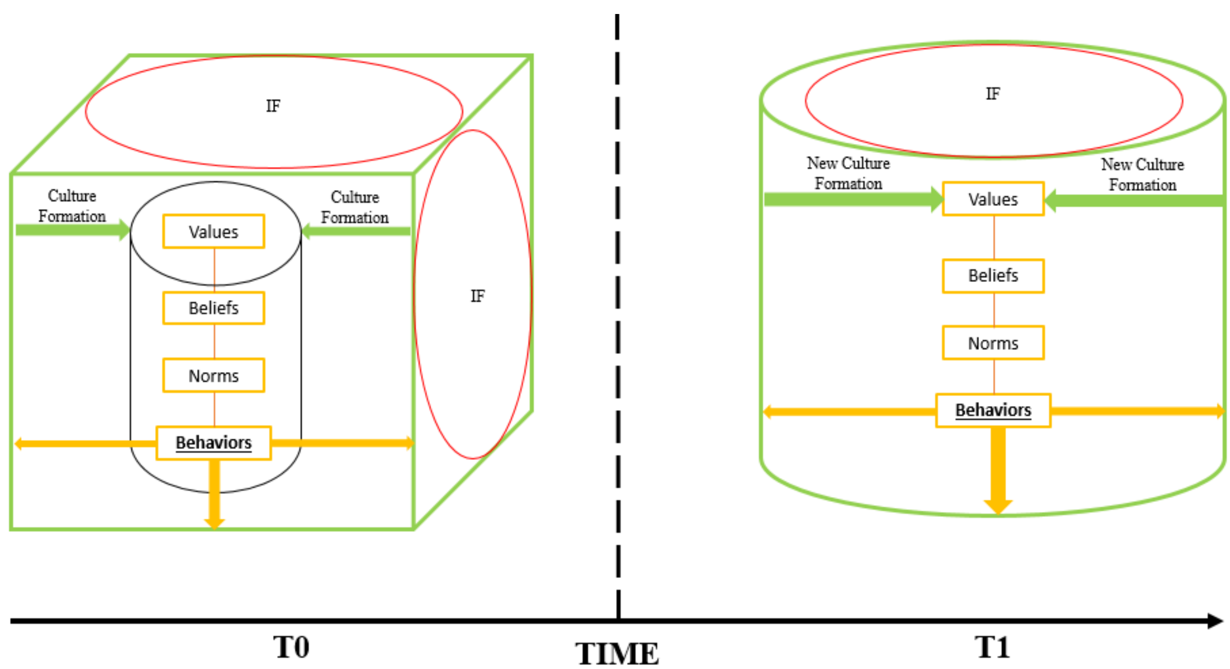

Figure 9. Values-Beliefs-Norms Influence over Are (see notes)

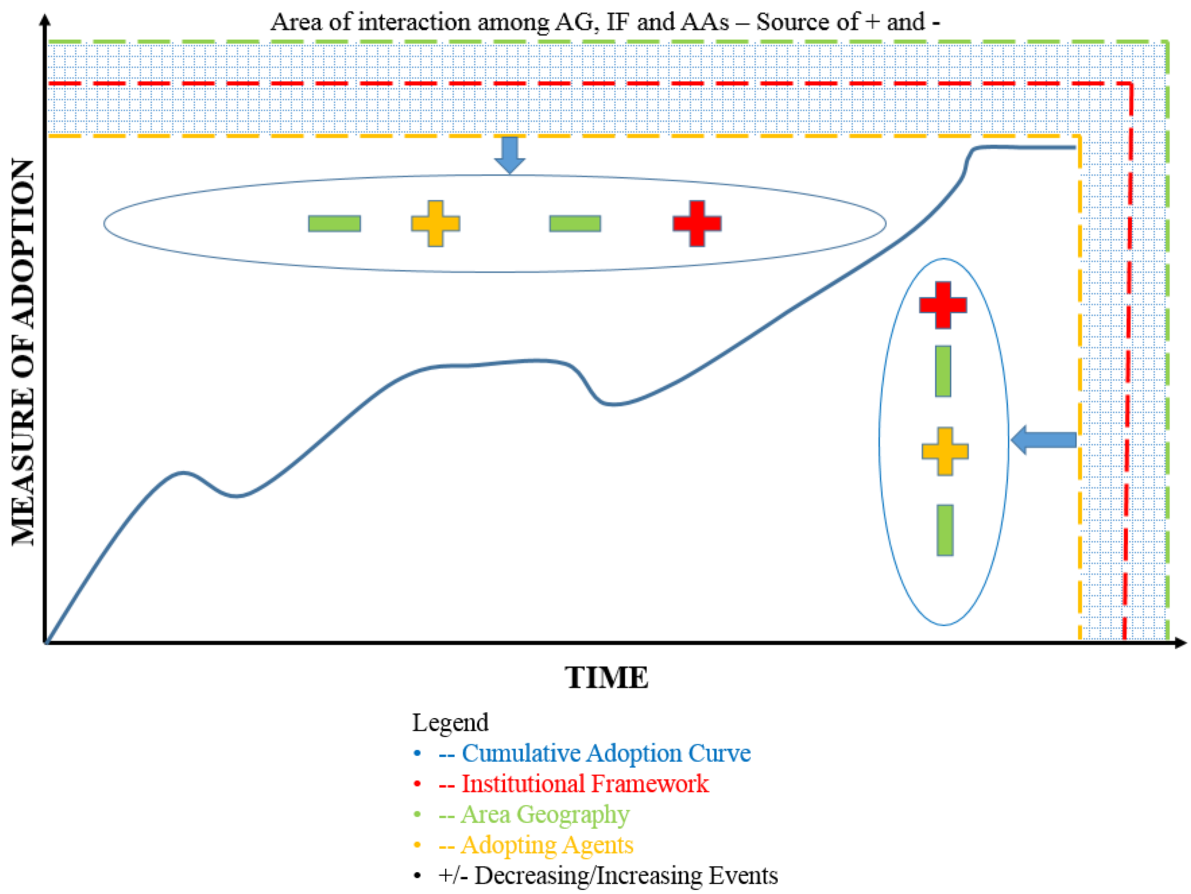

Figure 10. Diffusion of DRETs in Conceptual model

Spatial Patterns of Solar Photovoltaic System Adoption: The Influence of Neighbors and the Built Environment

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; Towe and Lawley, 2013). Understanding the patterns of diffusion—and particularly spatial patterns—is important not only from a scholarly perspective, but also from a policy and from marketing perspective. This is especially true when examining the diffusion of technologies with both private and public good characteristics, such as renewable energy technologies.

This paper 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, demographic, socioeconomic, and political affiliation variables on PV system adoptions. We develop a new 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 on average within 0.5 miles of adopting

households in the year prior to the adoption increases the number of installations in a block group by 0.30 PV systems. We also find that built environment variables, such as housing density and the share of renter-occupied dwellings, are also important factors influencing the adoption of PV systems that are just as important as factors such as median household income and political affiliation.

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 the government connecting 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 (e.g., Glaeser, Kallal, Scheinkman, and Shleifer (1992), Foster and Rosenzweig (1995), Bayer, Pintoff, and Pozen (2009), Conley and Udry (2010)).

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 (CA) 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. Such artificial boundaries also prevent an analysis of how the effect dissipates over time and space. Moreover, these 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 km to 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 diminishes with distance.[23] Neither Rode and Weber (2013) nor Müller and Rode (2013) explore the spatial patterns of diffusion of 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 & Durlaf, 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. If there is self-selection of peers, 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.[24]

[23] 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.
[24] See Bollinger and Gillingham (2012) for a mathematical exposition of each of these issues.

Hartmann et al. (2008) discusses 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.

The remainder of the paper is organized as follows. In the next section, 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 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.

2. Background on Solar Policy in Connecticut

The state of CT is a valuable study area for the diffusion of PV systems. Despite less solar insolation than 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 promoting solar PV technology, with several ambitious state programs. At the utility level, electric suppliers and distribution companies in CT are required to meet a Renewable Portfolio Standard (RPS) that requires 23 percent 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 December 31, 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 both state incentives, which started at $5/W in 2005 and are currently $1.25/W for resident-owned systems up to 5kW (there is a slightly different incentive scheme for third-party owned systems), as well as a series of community-based programs to promote PV systems (CADMUS, 2014).[25] 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. The program currently 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).[26]

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[25] As of 01/06/2014; incentive for system above 5kW is $0.75/W, up to 10 kW. These values refer to the Residential Solar Investment Program. Performance-based incentives are also available and are currently set at $0.18 kW/h.

[26] 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.

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.[27] Two variables are particularly important for this study: the application date and address. Using the address information, we successfully geocoded 3,833 PV systems that were installed in CT from 2005 through the end of September 2013 at the Census block group level out of the 3,843 installations in the database.

[FIGURE 1 ABOUT HERE]

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

[27] 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.

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 2,585 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 2,574 (99.6% of the block groups).

We employ socioeconomic and demographic data from several waves of the U.S. Census. We use the 2000 and 2010 U.S. Decennial Census as well as the 2005-2009, 2006-2010, and 2007-2011 waves of the American Community Survey (ACS) (U.S. 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 demographic data.[28] We also add the Dow Jones Industrial Average stock market prices (not varying over block groups), which may be particularly important in our setting, given the strong influence of the financial sector in CT (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

[28] 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, 70 years for a maximum median age, and we cut all probabilities at 0 and 100.

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.

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. In Table 1, we summarize the descriptive statistics for each variable.

[TABLE 1 ABOUT HERE]

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 above.

4. Spatial Patterns of PV System Diffusion

4.1 Adoption Rates across Towns in Connecticut

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 2013.[29] The two upper corners of the state show higher per-capita density, with northwestern Connecticut 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.

[FIGURE 2 ABOUT HERE]

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 U.S., yet displays a lower rate of adoption than much less wealthy towns in southeastern CT. This can be seen clearly in Figure 3.

[FIGURE 3 ABOUT HERE]

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 & Ord, 1992; Ord & Getis, 1995). These approaches have

[29] 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.

been applied to many fields, from epidemiology (Robinson, 2000) to land use change and sustainability (Su, Jiang, Zhang, & Zhang, 2011). By identifying agglomeration clusters and mapping them against other spatial factors, these approaches provide guidance on the underlying factors influencing adoption.

We run all three of these techniques using ESRI's ArcMap 10.2. All three require aggregated data, in order to achieve variability within the adoption values. Our scale is the block group level, thus we use the geographic center (centroid) of each bock group as the point. 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, in GOH, 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, Panel A shows the housing density in CT by Census block group and the geocoded PV systems. Panel B presents the results from the OGO approach and Panel C the results from the COA approach. Hartford is highlighted as a reference town across the maps.

[FIGURE 4 ABOUT HERE]

The results are quite 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 New Haven, Bridgeport, Meriden, and Waterbury. Remarkably, 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, and policymakers need to undertake other efforts in order to spread the adoption of PV systems. These maps greatly enrich our view of the diffusion of PV systems from Figure 4 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 (e.g., see Hägerstrand (1952) and Brown (1981)).

To examine the pattern of diffusion over time and space, we use fishnetting (Mitchell, 2005). We specify the size of each cell in the fishnet as 1.5 miles, 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 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 sq. miles.

[FIGURE 5 ABOUT HERE]

In Figure 5, we highlight two areas: Westport-Fairfield (black circle) and Windham-Mansfield (blue circle). In Westport-Fairfield, we see a case of town that already had PV system adoptions in 2005, and these adoptions multiplied substantially by 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 sq. 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 transform the number of PV systems in a locality in a short amount of 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. The ten largest towns by population are outlined in red and the ten smallest towns are outlined in black.

[FIGURE 6 ABOUT HERE]

If the adoption process of PV systems followed a wave-like centrifugal pattern based in the largest towns, we would expect to see initial concentrations within the largest towns in the state, with adoptions multiplying within these areas and diffusing to the smaller towns over time. The pattern we observe differs from these expectations in two ways.

First, it appears 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 7,388, which is about a 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. Second, new agglomeration centers appear over time in areas that did not have installations in 2005. For example, the town of Bethlehem (pop. 3,607) 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 by 2013, Bethlehem served as a small center, with neighboring areas also adopting PV systems in a centrifugal pattern around the center.

Why might we see medium-sized 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. Many of the better off-communities in CT are also small communities, and PV system customers must be able to afford the investment. 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 is 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 12 months prior to the installation, 24 months prior to the installation, and since 2005 (there were very few installations prior to 2005 in CT). In other words, for each PV system *k* we counted the number of neighboring installations *j*, such that:

$d_{k,j} <= D$

and

$t_k - t_j <= T$ or $t_k => t_j$,

where $d_{k,j}$ is the Euclidean distance (in feet) between PV system *k* and *j*, D is the distance specification (2640, 5280 or 21120 feet), t_k is the application date of PV system *k*, t_j is the application date of PV system *j*, and T is the temporal lag (12 months or 24 months). To more precisely examine the effect at each distance, we subtract the inner distances from the outer radii,

in order 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.

[FIGURE 7 ABOUT HERE]

Importantly, we remove other installations with applications during the same year-quarter (e.g., 2005Q1) as the household adopting in the count of recent neighbors adopting. This entirely avoids the simultaneity, or reflection, problem discussed in the introduction and reduces the likelihood that the decision to install is made before some of the other neighbors chose to install, for some households may have made the decision before the application is submitted.[30] 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

[30] It turns out that removing these installations does not change our primary results much at all, but for consistent estimation of our coefficients, we recognize that this is important.

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 are 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 introduction. 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:

$$PVcount_{i,t} = \alpha + \boldsymbol{N}_{i,t}\,\beta + \boldsymbol{B}_{i,t}\,\gamma + \boldsymbol{D}_{i,t}\,\theta + \pi\, S_{i,t} + \mu_i + \phi_t + \varepsilon_{i,t} \tag{3}$$

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 above (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 the percentage of installations in the block group-year that are from a Solarize campaign; μ_i are block group fixed effects; ϕ_t are time dummy variables; and $\varepsilon_{i,t}$ is a mean-zero error term.[31] 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, μ_i and ϕ_t would be combined into a single interaction fixed effect.

Vector $\boldsymbol{D}_{i,t}$ contains variables for the Dow Jones Industrial Average 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 in are important controls and are also useful to interpret. For example, the political affiliation variables help us understand the effects of environmental values on the adoption of PV systems, for democrats consistently tend to vote in favor of RPS regulations (Coley & 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

[31] 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.

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 estimates of 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., see 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.

6. Results

6.1 Primary Results

We are particularly interested in the vector of parameters β, 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. The first two columns present OLS results with year-quarter dummy variables, to control for changing trends in the PV system market, but no block group fixed effects. Columns 3 and 4 present results with both year-quarter dummy variables and block group fixed effects to control for unobserved heterogeneity at the block group level. Columns 5 and 6 present results with block group-year-semester fixed effects to address possible time-varying correlated unobservables. Each column uses a different vector of spatiotemporal variables. The first column includes all nearby installations in the previous 12 months and the second includes all nearby installations in the previous 24 months, and the third all nearby installations since the beginning of our dataset (January 1, 2005). Our preferred results are those

with block group-year-semester fixed effects in columns 4 through 6, although we are comforted that the results are quite similar regardless of the fixed effects used.

[TABLE 2 ABOUT HERE]

Our results show clear evidence suggestive of a spatial neighbor effect. Regardless of whether we include block group or block group-year-semester fixed effects, 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 5, the coefficient on the number of neighbors within 0.5 miles indicates that if the households that install PV systems have on average one additional nearby installation within 0.5 miles in the previous 12 months, then the number of installations in the block group per quarter will increase by 0.30 PV systems. At the average number of block groups in a town (15), this implies 18 additional PV systems per town due to the spatial neighbor effect.

Furthermore, the change in the results across space and time is intuitive. The coefficients are generally smaller when we consider installations that are further away, such as between 0.5 and one mile, and between 1 and 4 miles (although not always statistically significant). 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. Similarly, the coefficients for each of the spatiotemporal variables are smaller as we move from the 12 month to the 24 month results, suggesting a diminishing spatial peer effect over time.

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 to 4 mile range.[32] 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, while Wiesbaden has only 0.52 (Bank, 2013; DOE, 2013). We would expect spatial peer effects to 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 multi-family and renter-occupied dwellings (Bronin, 2012; Gillingham, Harding, & Rapson, 2012; Gillingham & 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 show less statistically significant results when it comes to most other socioeconomic 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

[32] We also performed specifications with a 1 to 2 and 2 to 4 mile range, which show a similar pattern, but with less statistical significance.

percentage of whites in the block group and a lower percentage of non-whites. There is weak evidence that a higher median age increases adoption, but block groups with the very highest median age appear to have lower adoption. The political affiliation variables are not statistically significant, nor is the Dow Jones Industrial Average.

On the other hand, the electricity price is positive and highly statistically significant until the block group-year-semester fixed effects are applied. The result can be interpreted as indicating that a one dollar increase in the electricity cost increases the number of adoptions in a block group and a year-quarter by 0.5 to 0.6 additional installations. The percentage of PV systems that are part of the Solarize program is an important control when we do not have block group-year-semester fixed effects, for it is a localized marketing campaign. Not surprisingly, it is highly statistically significant until we add the block-group-year-semester fixed effects. The results suggest that a one-percentage point increase in Solarize adoptions in a block group leads to small (0.005 additional installations) increase in adoptions in that block group. This may be more sizable at the town level when a larger percentage increase in Solarize programs is considered.

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 Robustness Checks

We perform a several robustness checks on our 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. We do report the results using the cumulative number of adoptions in each block group (the “installed base”) rather than the spatiotemporal variables in order to compare our specification to that in Bollinger and Gillingham (2012). Columns 1 and 2 in Table 3 shows the results of our specifications in columns 3 and 4 in Table 2 for reference. Column 3 shows the same specification with the same controls, only with the cumulative installed base, rather than our spatiotemporal variables. The results indicate a highly statistically significant positive effect, indicating that one additional installation in the installed base increases adoptions in a block group by 0.11 in that quarter. This is a 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 paper is that it allows for a much more detailed view of the levels at which neighbor effects work.

[TABLE 3 ABOUT HERE]

Table 3 also performs another useful robustness check. Columns 4 and 5 show the results of a Negative Binomial regression with comparable specification to our primary specifications in Table 2, only with year dummy variables (the model did not converge with year-quarter dummy variables or with block group fixed effects). As mentioned above 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 results in columns 4 and 5 are largely consistent with those in our preferred linear specification. 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.[33]

7. Conclusions

This paper 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.

Our geospatial analysis reveals that the pattern of PV system diffusion does not simply follow patterns of housing density or income, as might be expected. Indeed, the patterns we find indicate that small and mid-sized 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. Previous literature suggests that the diffusion would be expected to emanate from larger centers, while we find wave-like patterns of diffusion primarily from smaller and mid-sized centers. We speculate that this pattern in CT is a result of the state's jurisdictional and socioeconomic fragmentation, current regulations affecting adoption in multi-family 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

[33] 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.

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 an important role in influencing adoption. Our results indicate that there are important spatial neighbor effects: adding one more adoption on average increases the number of PV system adoptions in a block group per year-quarter by roughly 0.2 to 0.3 PV systems. Over a year, this is roughly one additional system in a block group or 12-18 per town when taken at the average number of block groups per town. Of course, CT is in the early stage of adoption of PV systems, so this effect is capturing the early stage of a classic "S-shaped" diffusion curve (Rogers, 1962). Eventually, nearly all rooftops suitable for PV systems have already adopted and block groups in CT will become saturated. This is an important context to keep in mind for extrapolating our results forward in time.

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 multi-family and rental properties (Bronin, 2012; Gillingham & 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 underscores 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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Figures

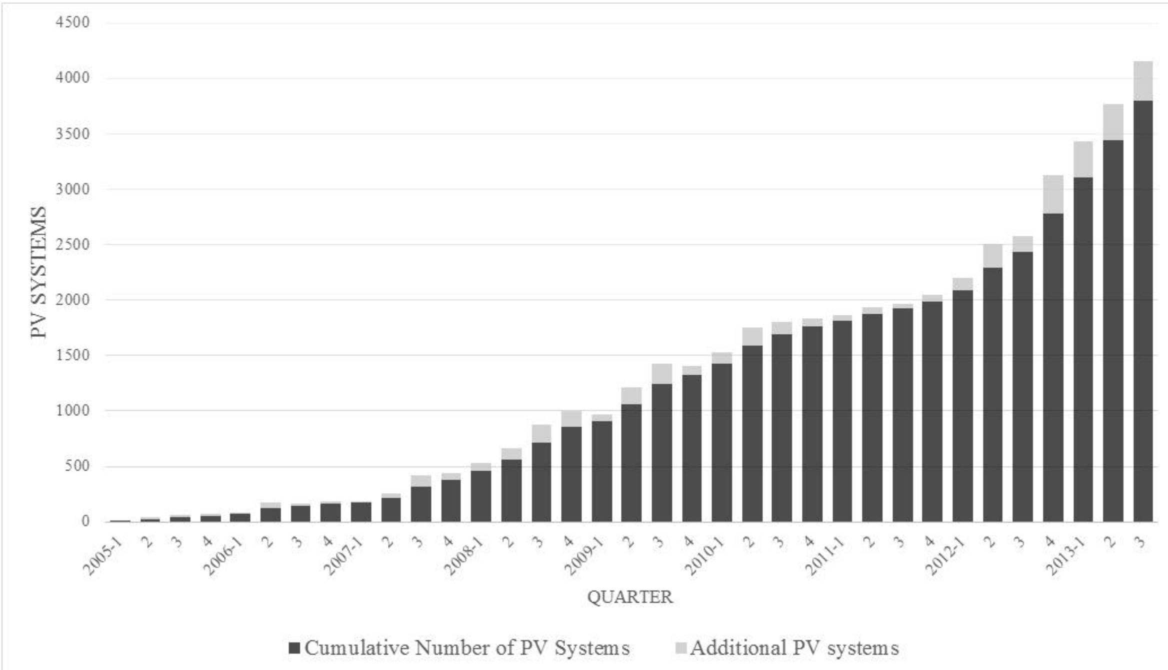


Figure 1. Total and additional adoptions PV Systems in CT over time.

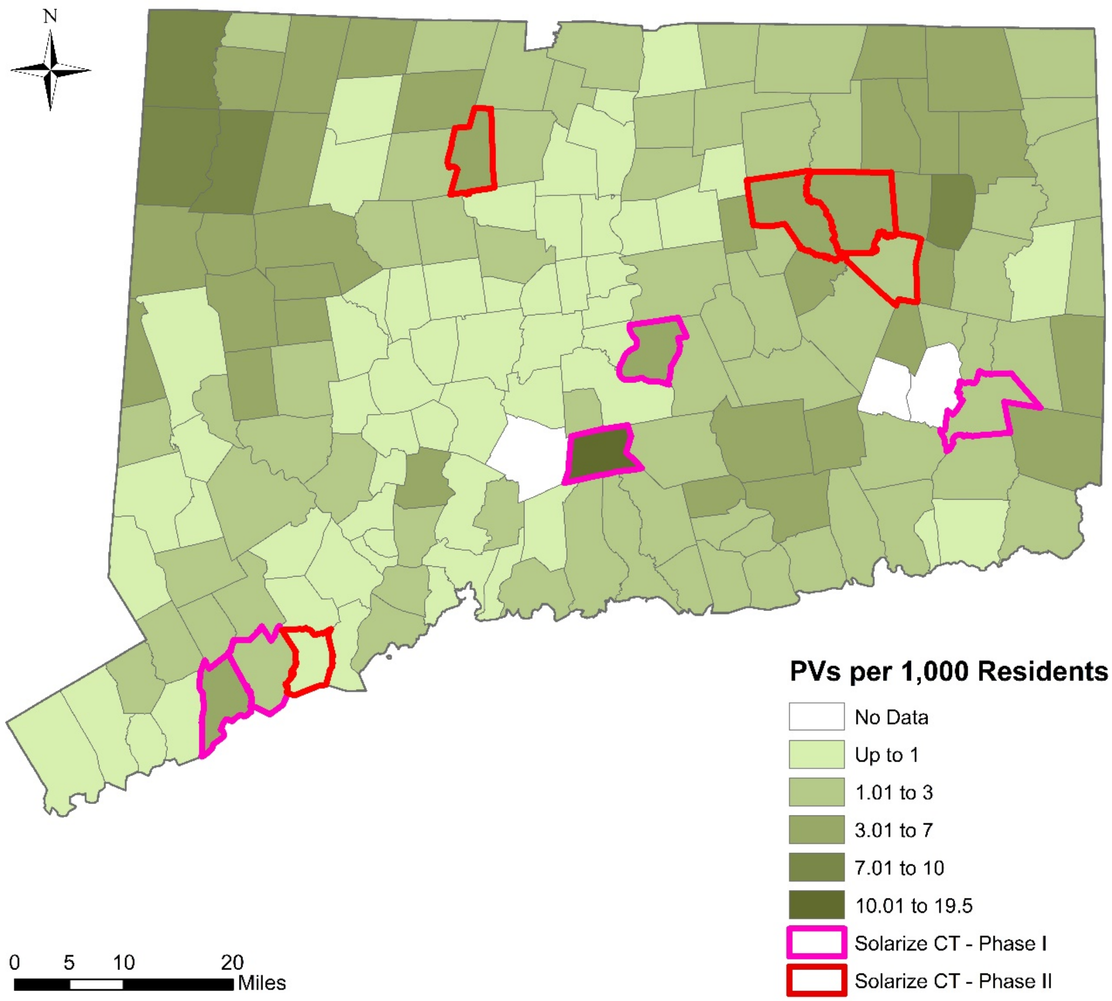


Figure 2. PV system density and Phase I and II Solarize CT towns in 2013.

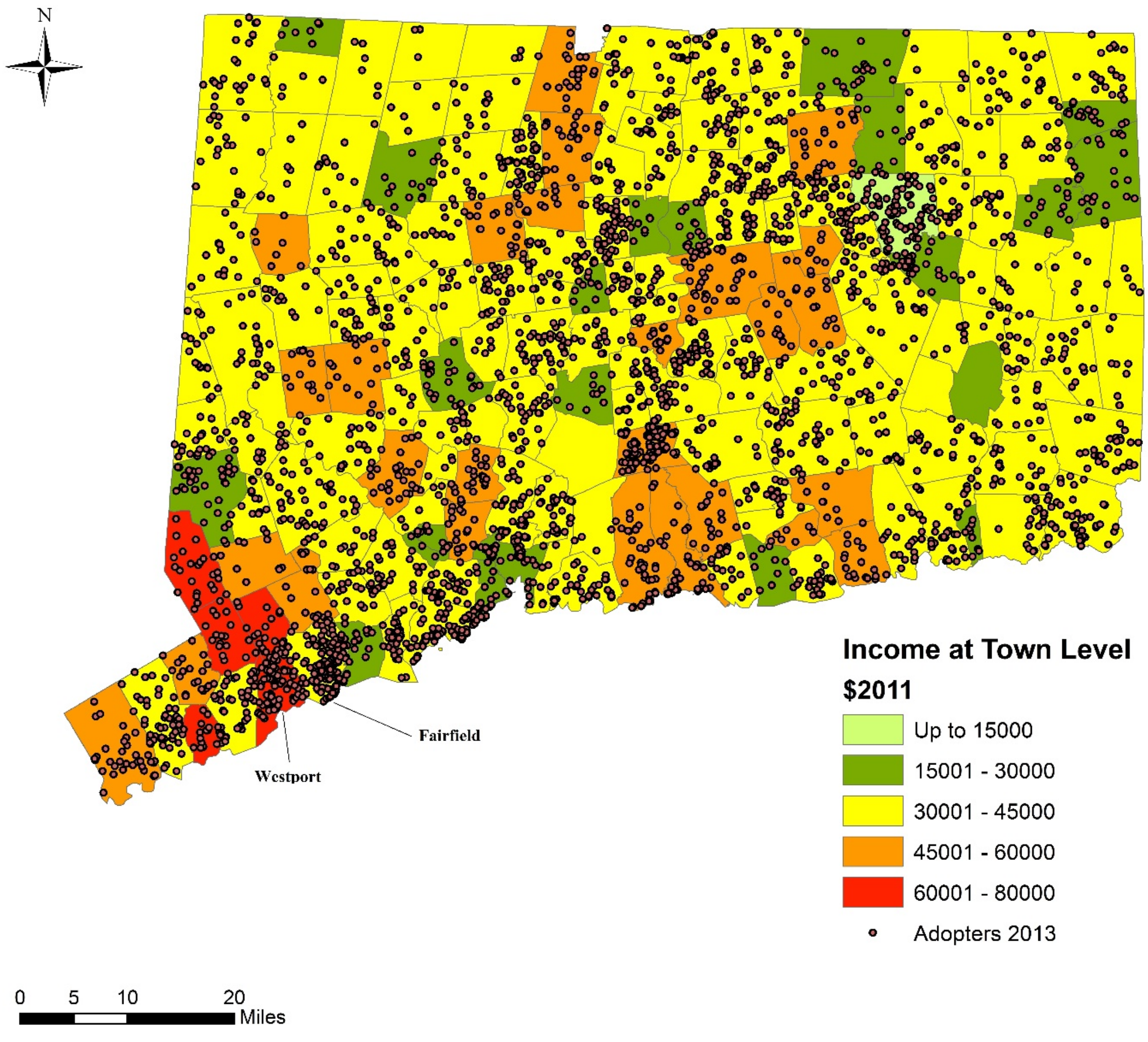
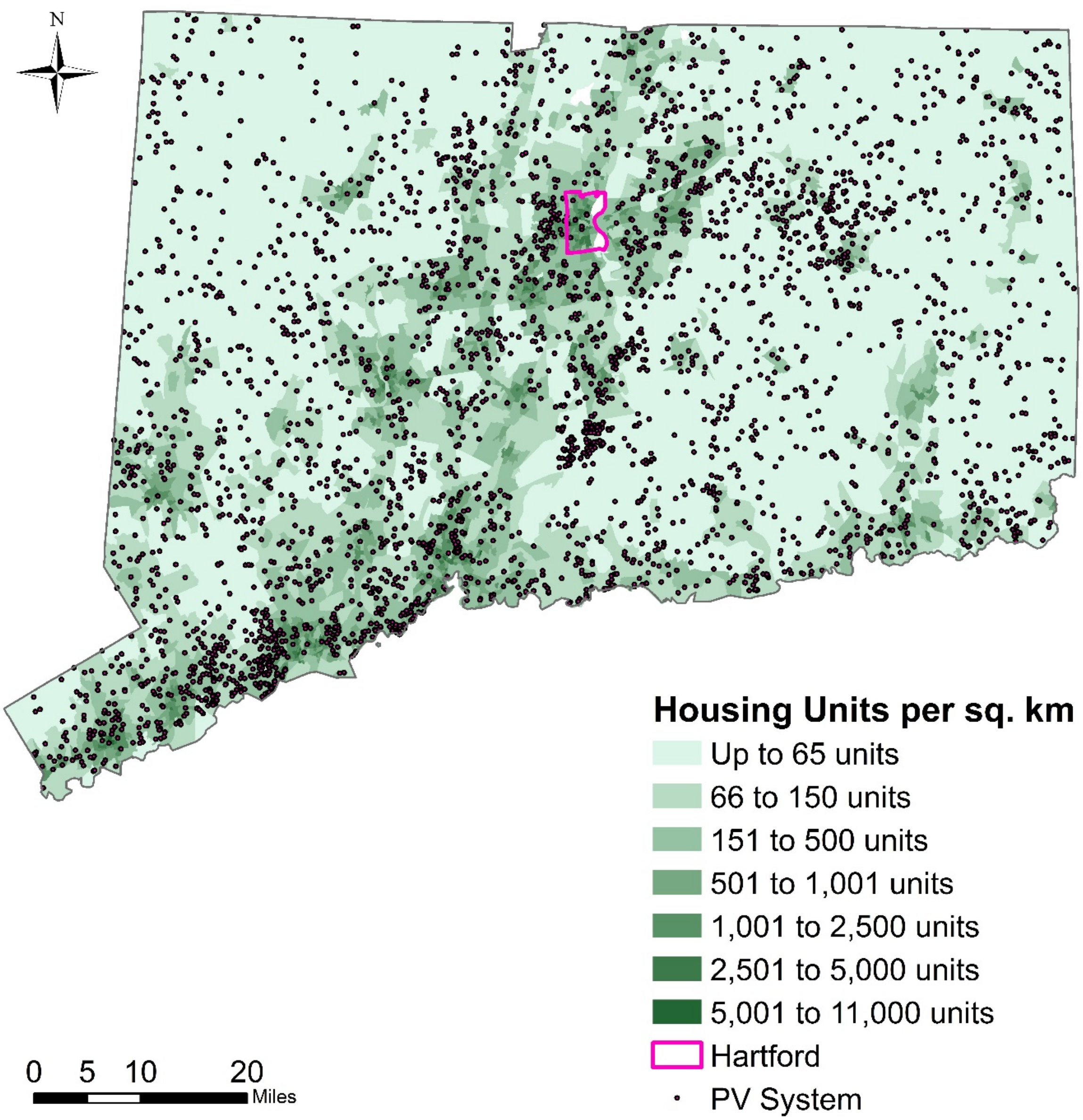
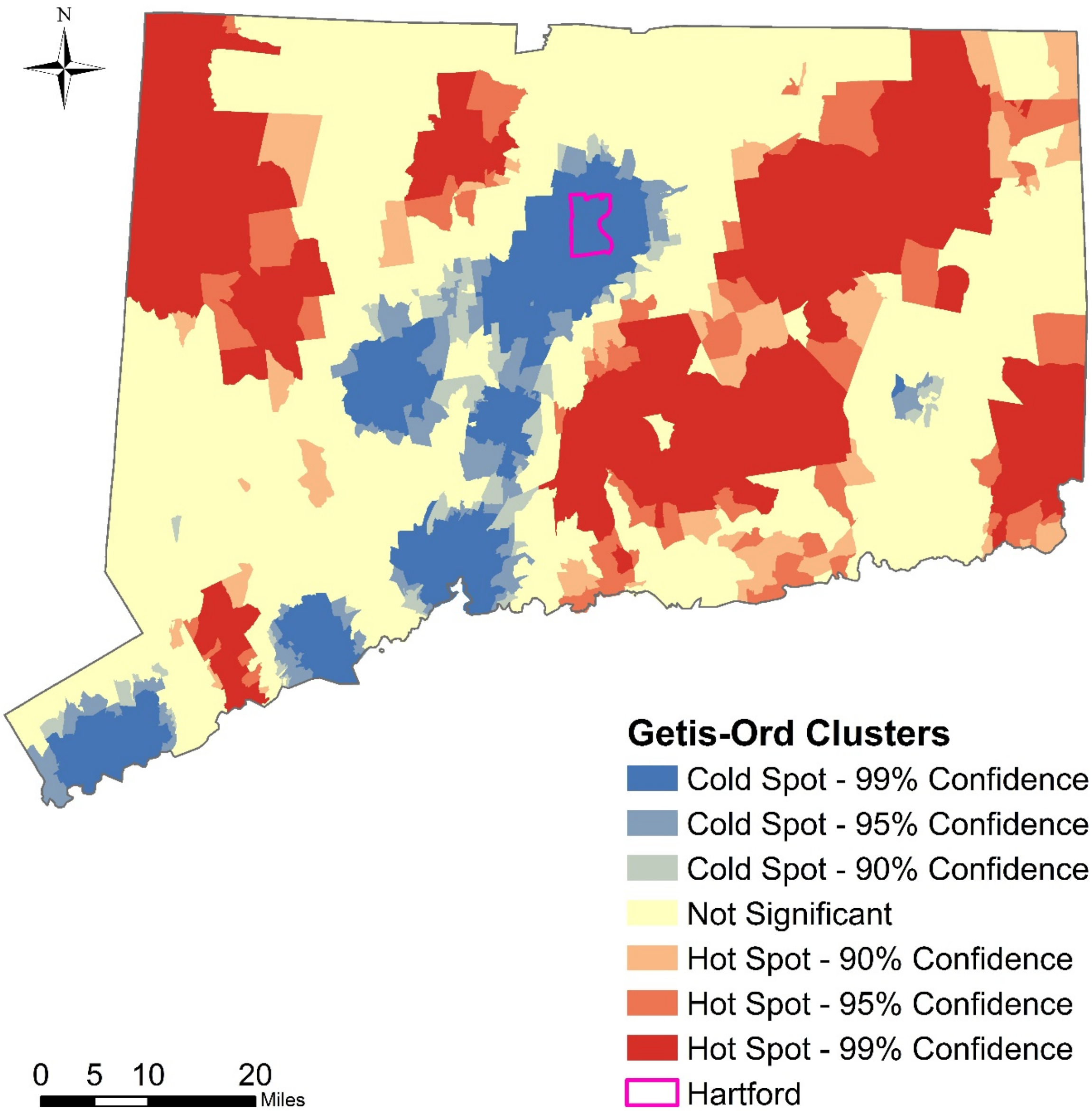


Figure 3. PV systems and median household income in Connecticut in 2013.

A.PV Systems and Housing Density (2013)



B. Block Group Level Optmized Getis-Ord Results (2013)



C. Block Group Level Local Moran's I, 10 Miles Cutoff (2013)

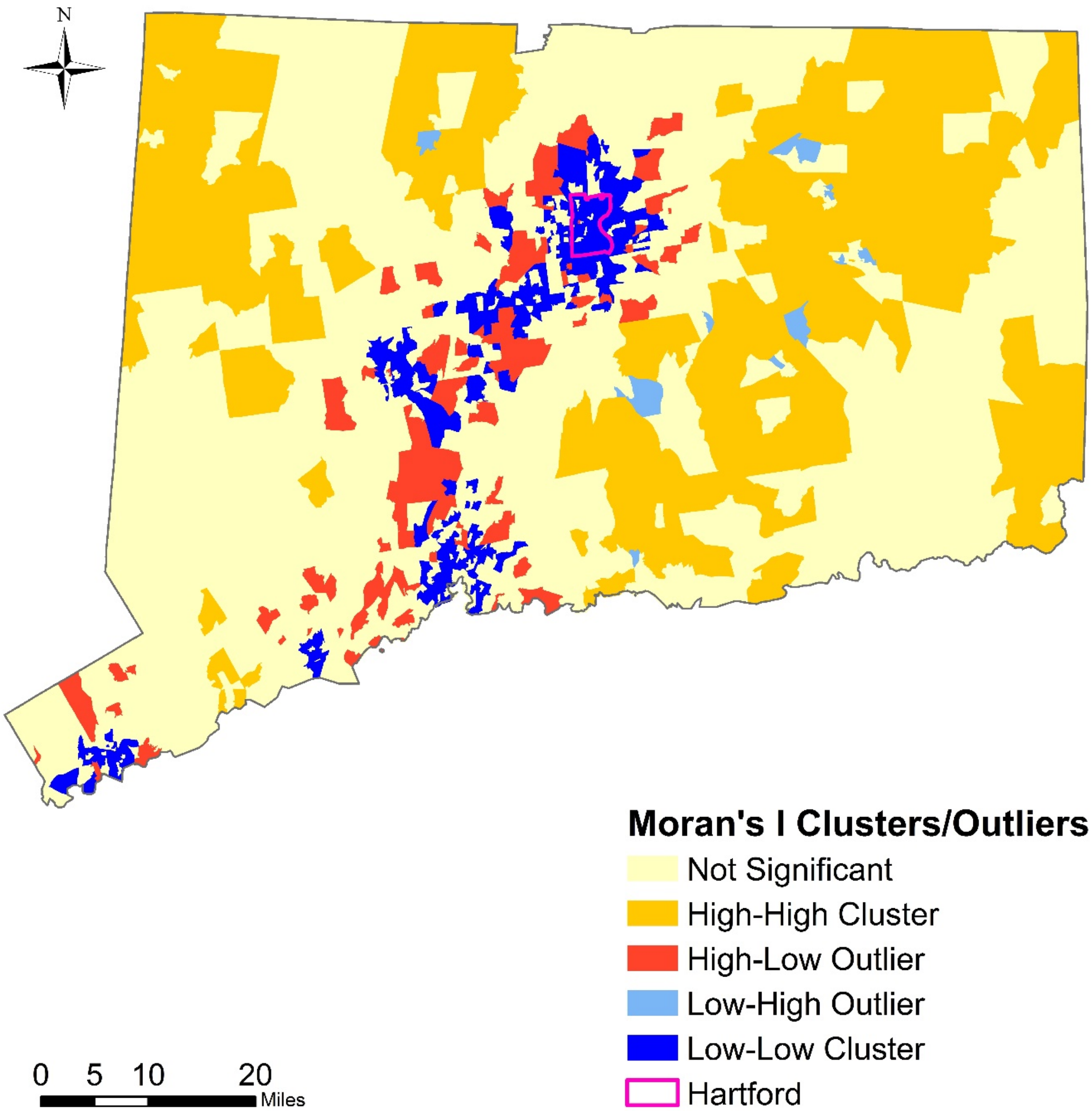


Figure 4. Spatial distribution of PV system hot spots and cold spots using different approaches. Panel A shows PV systems and housing density. Panel B Optimized Getis-Ord (OGO) and Panel C shows Local Moran's I (COA) results.

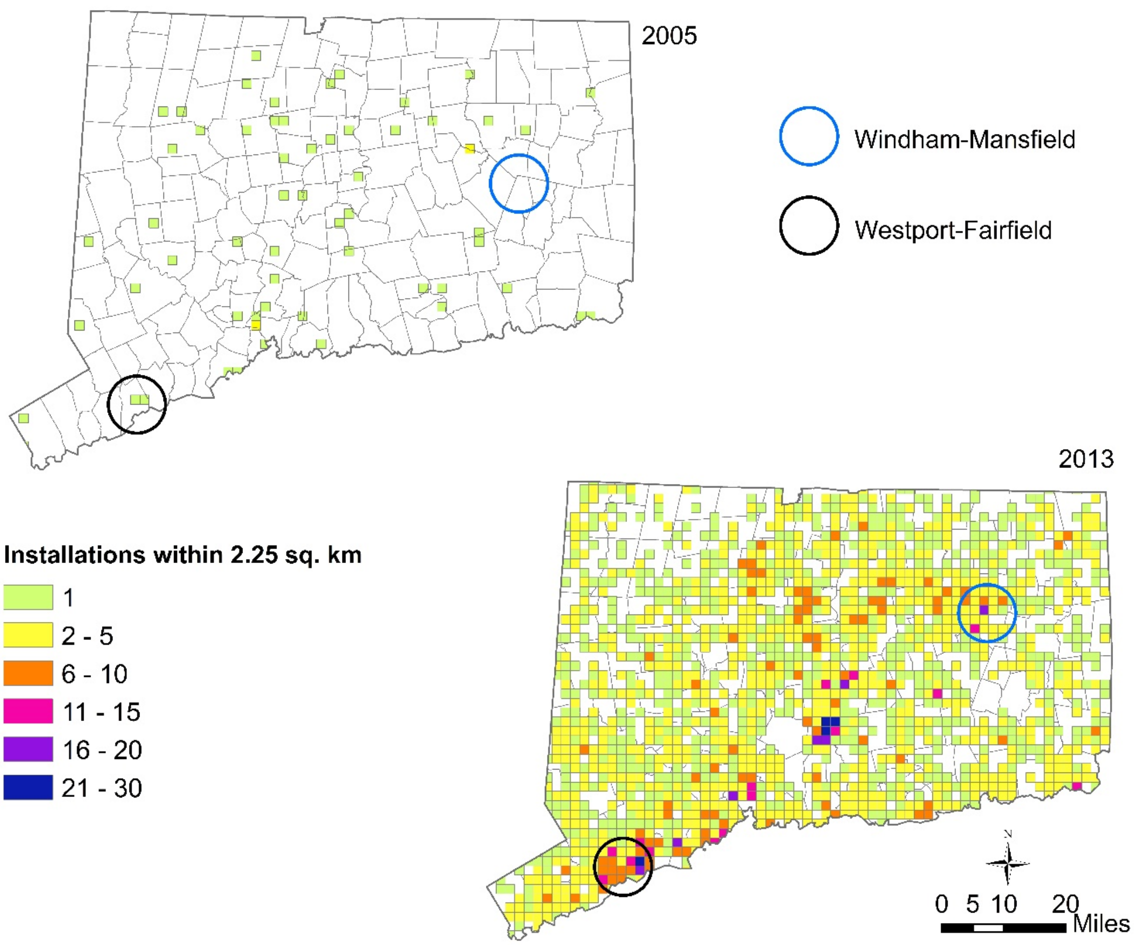


Figure 5. Using fishnetting to examine the pattern of adoption of PV systems between 2005 and 2013.

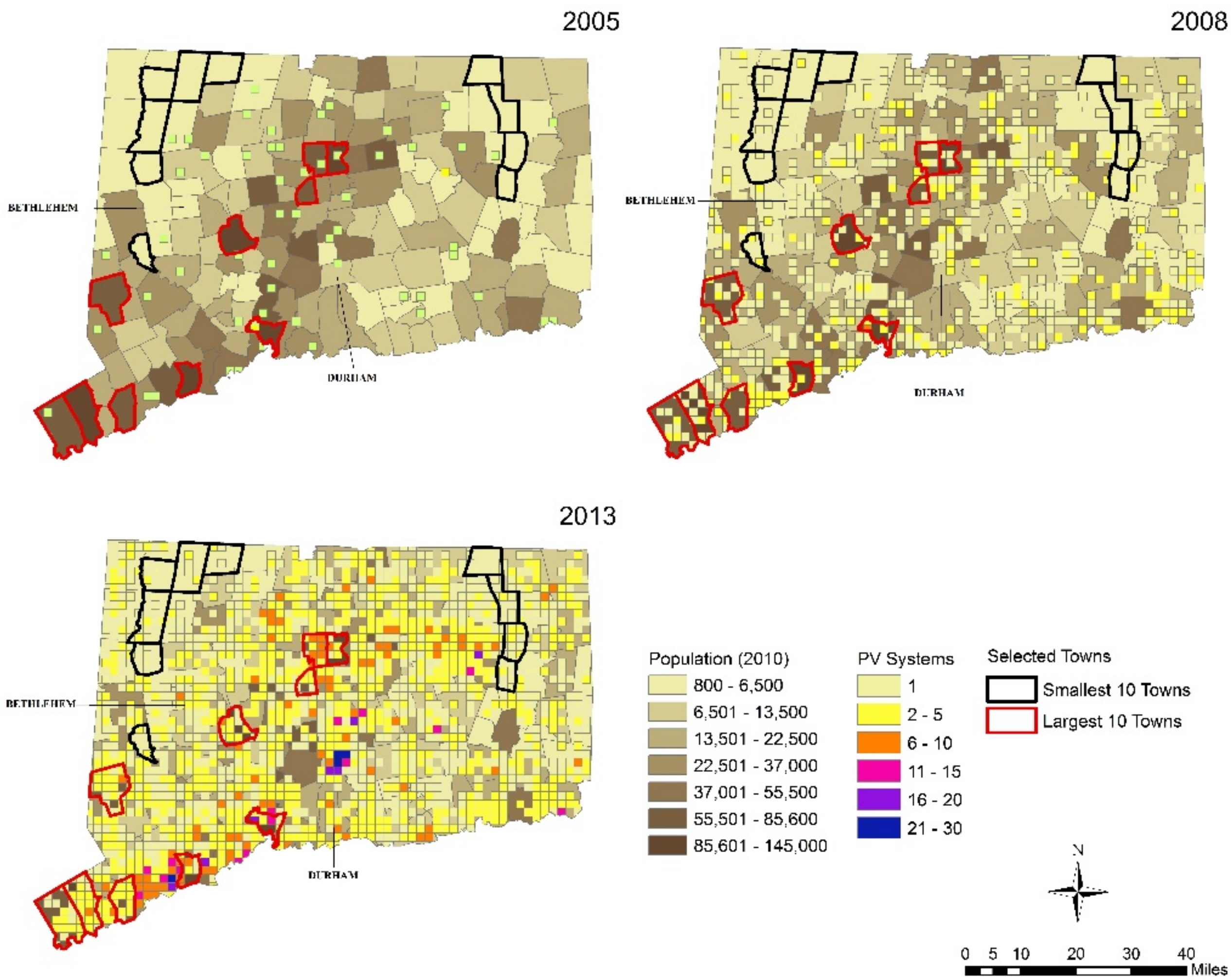


Figure 6. Fishnetting reveals patterns in PV systems adoption and population over time.

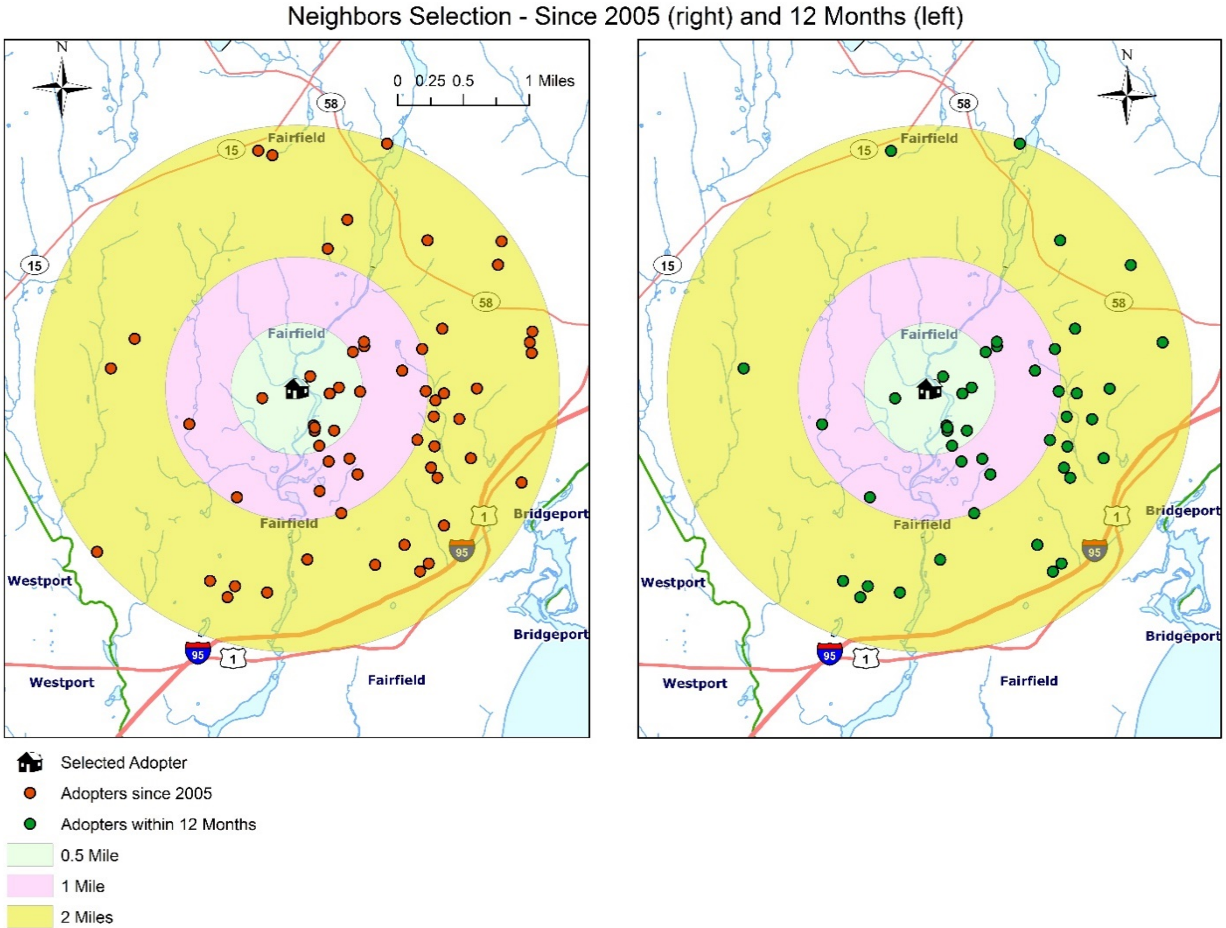


Figure 7. Selection of all neighbors since 2005 (left) and in previous 12 months (right).

Tables

Table 1. Summary Statistics

Variable	Mean	Std. Dev.	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 - 12 months	0.02	0.25	0	17	Calculated
Average neighboring installations, 0.5 to 1 mile - 12 months	0.02	0.24	0	15	Calculated
Additional number of new installations, 1 to 4 mile - 12 months	0.17	1.59	0	91	Calculated
Average Neighboring Installations, 0.5 Miles - 24months	0.03	0.34	0	19.33	Calculated
Average Neighboring Installations, 0.5 to 1 mile - 24 months	0.03	0.35	0	18	Calculated
Average Neighboring Installations, 1 to 4 mile - 24 months	0.28	2.31	0	108	Calculated
Number of Housing Units (1,000s)	0.61	0.37	0.01	13.38	U.S. Census
Housing Density (0.001s)	0.79	1.30	>0.01	28.91	Calculated
% of Renter-occupied Houses	32.03	27.82	0	100	U.S. Census
Median Household Income (tens of thousands of 2013 dollars)	7.89	4.71	0.15	76.86	U.S. Census
% pop who are white	77.38	23.45	0	100	U.S. Census
% pop who are black	10.70	16.86	0	100	U.S. Census
% pop who are Asians	4.34	5.79	0	73.12	U.S. Census
Median Age	40.41	8.50	11.10	80	U.S. Census
Median Age in Highest 5%	0.10	0.30	0	1	U.S. Census
% democrats	37.70	13.73	0	75.23	CT SOTS
% pop 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)
Dow Jones Level (1,000s)	116.46	17.02	77.58	152.86	FRED (2013)
% of Solarize CT PV Systems	0.43	6.30	0	100	CEFIA (2013)

Notes: all variables have 90,090 observations, where the observation is a block group-year-quarter.

Table 2. Primary Specifications

	Year-Quarter Dummies		Block Group FE & Year-Quarter Dummies		Block Group-Year-Semester FE	
	12 Months	24 Months	12 Months	24 Months	12 Months	24 Months
Average Neighbors within 0.5 Miles	0.18***	0.11***	0.17***	0.10***	0.30***	0.16***
	(0.0625)	(0.0380)	(0.0615)	(0.0369)	(0.0781)	(0.0462)
Average Neighbors 0.5 to 1 Mile	0.12***	0.069***	0.12***	0.071***	0.21***	0.097***
	(0.0420)	(0.0235)	(0.0420)	(0.0233)	(0.0587)	(0.0284)
Average Neighbors 1 to 4 Miles	0.050***	0.042***	0.052***	0.043***	0.065***	0.056***
	(0.0066)	(0.0042)	(0.0065)	(0.0042)	(0.0080)	(0.0048)
Number of Housing Units (1,000s)	0.032***	0.030***	0.015**	0.014**	-0.022	-0.057
	(0.0053)	(0.0052)	(0.0062)	(0.0060)	(0.0404)	(0.0545)
Housing Density (0.001s)	-0.0063***	-0.0059***	-0.0088***	-0.0083***	0.0015	0.0041
	(0.0009)	(0.0008)	(0.0014)	(0.0014)	(0.0094)	(0.0113)
% of Renter-occupied Houses	-0.00024***	-0.00021***	-0.00039***	-0.00038***	-0.000034	0.00042
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0006)	(0.0007)
Median Household Income ($10,000)	0.00074**	0.00067**	0.00041	0.00029	0.0033	0.010
	(0.0003)	(0.0003)	(0.0005)	(0.0005)	(0.0061)	(0.0082)
% pop who are white	0.00017**	0.00014**	0.00013	0.000088	-0.00026	-0.00090
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0017)	(0.0019)
% pop who are black	-0.000017	-0.000021	-0.00032**	-0.00034**	0.00061	0.00090
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0015)	(0.0014)
% pop who are Asians	-0.00071***	-0.00073***	-0.000070	-0.00016	0.0063	0.0054
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0065)	(0.0066)
Median Age	0.00029*	0.00029*	0.00012	0.00012	0.0031	0.0023
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0021)	(0.0024)
Median Age in Highest 5%	-0.0088*	-0.0076	-0.0093*	-0.0082*	-0.073	-0.0025
	(0.0047)	(0.0047)	(0.0048)	(0.0047)	(0.0578)	(0.0520)
% democrats	-0.000100	-0.00013	0.00028	0.00028	-0.00082	-0.0014
	(0.0001)	(0.0001)	(0.0003)	(0.0003)	(0.0037)	(0.0041)
% pop in minor parties	-0.00060	0.000011	0.0013	0.0018	0.0054	0.0052
	(0.0020)	(0.0019)	(0.0027)	(0.0026)	(0.0135)	(0.0188)
Electricity cost (Cent/kWh)	0.0056***	0.0038***	0.0064***	0.0045***	-0.0044	-0.0053
	(0.0013)	(0.0012)	(0.0014)	(0.0013)	(0.0050)	(0.0060)
Dow Jones Level	-0.00024	-	-0.000084	-0.00038**	0.00025	0.00017

(1,000s)		0.00053***				
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
% of Solarize CT	0.0055***	0.0061***	0.0051***	0.0057***	-0.00068	0.00038
PV Systems	(0.0013)	(0.0013)	(0.0012)	(0.0013)	(0.0008)	(0.0006)
Constant	-0.088**	-0.024	-0.10**	-0.038	-0.041	0.025
	(0.0404)	(0.0359)	(0.0412)	(0.0368)	(0.1751)	(0.2099)
R-squared	0.34	0.37	0.33	0.36	0.36	0.38
Observations	90,090	90,090	90,090	90,090	90,090	90,090

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

Table 3. Robustness Checks

	Block Group FE & Year-Quarter Dummies			Negative Binomial with Year Dummies	
	12 Months	24 Months	Installed Base	12 Months	24 Months
Average Neighbors within 0.5 Miles	0.17*** (0.0615)	0.10*** (0.0369)		0.47*** 0.1048	0.22*** (0.0677)
Average Neighbors 0.5 and 1 Mile	0.12*** (0.0420)	0.071*** (0.0233)		0.30*** (0.0983)	0.13** (0.0608)
Average Neighbors 1 and 4 Miles	0.052*** (0.0065)	0.043*** (0.0042)		0.52*** (0.0224)	0.34*** (0.0135)
Cumulative Installed Base			0.11*** (0.0088)		
Number of Housing Units (1,000s)	0.015** (0.0062)	0.014** (0.0060)	-0.038*** (0.0123)	0.86*** (0.1248)	0.83*** (0.1307)
Housing Density (0.001s)	-0.0088*** (0.0014)	-0.0083*** (0.0014)	0.017*** (0.0031)	-0.81*** (0.1894)	-0.97*** (0.2138)
% of Renter-occupied Houses	-0.00039*** (0.0001)	-0.00038*** (0.0001)	-0.000056 (0.0001)	-0.0078*** (0.0022)	-0.0076*** (0.0023)
Median Household Income ($10,000)	0.00041 (0.0005)	0.00029 (0.0005)	-0.00025 (0.0006)	-0.017*** (0.0052)	0.014** (0.0054)
% pop who are white	0.00013 (0.0001)	0.000088 (0.0001)	-0.00010 (0.0001)	0.018*** (0.0059)	0.014** (0.0064)
% pop who are black	-0.00032** (0.0001)	-0.00034** (0.0001)	0.00024* (0.0001)	-0.0079 (0.0080)	-0.014 (0.0086)
% pop who are Asians	-0.000070 (0.0003)	-0.00016 (0.0003)	0.00027 (0.0003)	-0.021** (0.0088)	-0.027*** (0.0094)

Median Age	0.00012	0.00012	-0.00027	0.012**	0.0096*
	(0.0002)	(0.0002)	(0.0002)	(0.0054)	(0.0056)
If Median Age in Highest 5%	-0.0093*	-0.0082*	-0.015**	-0.15	-0.10
	(0.0048)	(0.0047)	(0.0065)	(0.01071)	(0.1098)
% democrats	0.00028	0.00028	-0.0012***	-0.00039	-0.0013
	(0.0003)	(0.0003)	(0.0004)	(0.0047)	(0.0050)
% pop in minor parties	0.0013	0.0018	-0.0071*	0.16**	0.014***
	(0.0027)	(0.0026)	(0.0042)	(0.0376)	(0.0403)
Electricity cost (Cent/kWh)	0.0064***	0.0045***	0.00014	0.10***	0.081***
	(0.0014)	(0.0013)	(0.0018)	(0.0147)	(0.0153)
Dow Jones Level (1,000s)	-0.000084	-0.00038**	-0.0007***	0.0084	0.0091***
	(0.0002)	(0.0002)	(0.0003)	(0.0013)	(0.0014)
% of Solarize CT PV Systems	0.0051***	0.0057***	0.0069***	-0.00031	0.031
	(0.0012)	(0.0013)	(0.0007)	(0.0030)	(0.0026)
Constant	-0.1038**	-0.0382	0.13	-9.08***	-8.19***
	(0.0412)	(0.0368)	(0.0644)*	(0.6983)	(0.7403)
R-squared	0.34	0.37	0.23		
Observations	90,090	90,090	90,090	90,090	90,090

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

The Influence of Spatial Setting and Socioeconomic Profile of Urban Areas in the Diffusion of Residential PV System

1. Introduction

Due to rising concerns related to global warming, national security, rising energy prices and resource scarcity, scholars, policymakers and marketers in the energy sector have turned their attention to encourage the adoption of residential and commercial renewable energy technologies (RETs). In this context, the USA have devoted resources to encourage the adoption of residential photovoltaic systems (PV systems). The choice of this RET is not fortuitous. PV systems emit virtually zero CO_2 when producing power, marginal production costs are nearly zero, and they can be scaled down relatively easily, operating as stand-alone systems (Guidolin and Mortarino, 2010). However, in many regions of the USA and the world, PV systems remain relatively expansive, requiring jurisdictions to create monetary incentives for adopters (Gillingham and Sweeney, 2012). However, thanks to improved technology and rising energy prices, beginning 2012 PV systems have achieved grid parity in several regions within the USA and abroad (Zaman and Lockman, 2011). As this trend continues, policymakers will have to recognize that even generous monetary incentives may not actually increase the adoption of PV systems, and, consequently the transition towards a sustainable society. In the USA, states have acknowledged the role that non-monetary drivers play in the adoption process of PV systems. Several states have promoted programs with components aimed at exploiting network interactions such as peer effects, which previous research have found to influence positively the adoption of PV systems (e.g. Bollinger and Gillingham, 2012). These programs are linked with the local characters of the jurisdictions where they take

place. Within a U.S. state, for example, the role of smaller jurisdictional subdivisions, such as towns, increases as state programs try to exploit non-monetary incentives. Additionally, because many times these programs are designed at state level, they may not be capable of capturing local differences in the socioeconomic profiles of residents, thus not unfolding their full potential. Recently, literature on the diffusion of PV systems has highlighted the role of several socioeconomic and spatial drivers in the adoption process of PV systems. Within this stream of research, Bollinger and Gillingham (2013) were the first to the role of spatial peer effects, while controlling for other socioeconomic characters, such as income. The two authors focused their study in California, demonstrating that an additional PV system increases the adoption rate within each ZIP-code by 0.78%. Similarly, Richter (2013) found evidence of smaller, although statistically significant, spatial peer effects within postal area codes in the United Kingdom. Rode and Weber (2012) and Müller and Rode (2013) found evidences of spatial peer effects at two different scales in Germany. The first two authors use an epidemic diffusion model built around an artificial grid to test the existence of spatial peer effects, income levels and housing density across Germany. Müller and Rode (2013) focused on the town of Wiesbaden and its urban surroundings, using the actual Euclidean distance between adoptions, as well as a set of socioeconomic variables to control for additional adopters' characteristics. Both these works identified the limit of spatial peer effects at around 1-1.2 km. The generalization of this finding is partially disputed by Graziano and Gillingham (2014). The two authors focused on the role that spatial peer

effects, built environment and income play on the diffusion of PV systems in Connecticut. In their work, Graziano and Gillingham used a multi-ring spatiotemporal buffer based on the location of PV systems to control for spatial peer effect. This approach represents a novelty compared to the use of installed base, as in previous literature. The two authors found that spatial peer effects positively affect the diffusion of PV systems up to four miles and 24 months, although decreasing in magnitude over time and space. In addition, they found that housing density and renter-occupied houses tend to reduce the probability of adoption at block group level, while income appears to have no effect. Because of these results, the two authors suggested that difference in results between their work and the work of Rode and Weber (2012), and Müller and Rode (2013) in spatial and socioeconomic differences among the three study areas.

In the present work, we focus on the different profiles of adopters within four towns in Connecticut: East Hartford, Glastonbury, Hartford and Manchester. We draw from the previous studies of Graziano and Gillingham (2014), and Bollinger and Gillingham (2012) to understand the role of the jurisdictional and built environment in the adoption of PV systems, through their effect on other socioeconomic drivers such as spatial peer effects. Additionally, we seek to understand what degree of generalization can be reached by analysts when studying with social and spatial drivers to adoption of PV systems. To achieve this, we use partition our four towns in to block groups, and conduct a typology analysis of the block groups with higher adoption rates of PV systems in 2013. We find that the profile of the potential adopters changes between towns, with Hartford and

Glastonbury providing two quite interesting conflicting results in terms of area geography and socioeconomic status. In addition, we use the area-wide profile to understand how this matches the findings provided by panel and Cross-Sectional models based on Graziano and Gillingham (2014), for which we use more refined density values. We find that the built environment affects the diffusion of PV systems indirectly, as it limits the temporal and distance extent of spatial peer effects.

1.1 Connecticut and the Four Towns

Connecticut represents an interesting study area for PV systems diffusion. As of 2012, Connecticut has the third highest median household income in the USA (2012 $66,844), about 30% higher than the national value (Census, 2013). Despite appearing quite wealthy on aggregate, Connecticut has widespread income inequality, the third highest in the USA according to its GINI index, and poverty, which affects 21% of its residents (Census, 2012; Carstensen and Coghlan, 2013). These differences within the state are backed by the current jurisdictional fragmentation: the state is divided in to 169 towns, which retain wide powers in several regulatory matters. This fragmentation creates jurisdictional barriers dividing bordering towns and making them extremely socioeconomically varied. Relative to PV systems, Connecticut is currently investing heavily in this RET, offering monetary incentives and programs such as Solarize CT, conjugating monetary and social incentives (Graziano and Gillingham, 2014). Connecticut has reached grid parity as of 2014, 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 levels and typologies set equal for the state as a whole. Even in the case of Solarize CT, towns have to apply to be part of the program. Further, even Solarize CT acts similarly across various towns, despite great socioeconomic differences among them. Along with differences in the socioeconomic profile of potential adopters, Connecticut towns vary in terms of built environment. Residents of smaller towns reside in single-family houses, whereas those of larger, and older, urban centers such as Hartford or New haven live in multi-family buildings. Due to the statewide prohibition of sub-metering and the lack of split-incentives to encourage the adoption in these areas, even in presence of higher income neighborhoods adoption of PV systems might be difficult (Bronin, 2012). In 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, with an increase of 36.5% from December 2012 (CEFIA, 2013). However, given the socioeconomic and structural differences within and between towns, current statewide regulations and incentive programs might work below their potential because several potential adopters are effectively cut out from the incentive schemes.

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 at town level.

[Figure 1 ABOUT HERE]

The towns play different role 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 several 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, sub-urban community, although it hosts several plots of farmland. Overall, the four towns extend for about 300 sq. km of land, and is home to 268,000 people, or 7.5% of the state population (Census, 2012), with Hartford being the third most populous in the state.

The remainder of the paper is as follows: in section 2 we present a brief profile of the four towns and the data sources, including drawing some concerns about current data accessibility to scholars and policymakers. In section 3, we present the results of hierarchical clustering analysis; and the profile of PV adopters within the study area and within each town. In section 4, we present our panel and Cross-Sectional models. In section 5, we present and discuss the results of the econometric analysis, providing a comparison with the profile emerging from section 3. Finally, in section 6 we draw some conclusion related to current generalization associated with PV systems diffusion and policies.

2. Study Area and Data Sources

In the present study, we select four contiguous towns in central Connecticut: Hartford (the state capital), East Hartford, Manchester and Glastonbury. All combined, these four

contiguous towns account for about 10% of the state population and 7% of the state land surface, or 300 sq. km. We conduct our analysis at the block group level, selecting data at this aereal unit when possible. Table 1 provides an overview of the sources used.

[Table 1 ABOUT HERE]

2.1 Socioeconomic Data

In the present study, we use the socioeconomic data prepared by Graziano and Gillingham (2014). We selected the Block Groups belonging to Hartford, East Hartford, Glastonbury and Manchester from their main dataset using ESRI's ArcMap 10.2 and STATA 12. 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 (Census, 2013b). The time period covered is 2005 through September 2013. In the interpolation process, Graziano and Gillingham accounted for the changes in block group boundaries, using the newer boundaries assigned by the U.S. Census after 2008.

2.2 PV Systems Data and Neighborhood Effect

Data about PV systems location and date of application to the CEFIA incentive program come from the CEFIA Solar Database (CEFIA, 2013). The dataset contains several information about adopters, including address of location and the day, month and year of installation. The dataset records each residential installation since 2004. Because of the methodology used, we dropped the (few) observation available for the first year. Overall,

the period considered runs from January 2005 and September 2013, equal to 9 years or 35 quarters

To understand the role of spatial peer effects, we build upon the work of Graziano and Gillingham (2014), introducing the spatiotemporal variable developed by the two authors. This variable aggregates at block group level the number of PV installations within 12 and 24 months from each actual PV system location at various spatial distances starting 0.5 miles. In the present work, we allow the search model to account for installations in towns outside the study area. However, we change our specifications to account for the different total extent of our study area, as explained in the model specifications.

2.3 Spatial Data and Issues with 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 (MAGIC, 2013). For understanding the role of the built environment, we use the parcels data created by each of these towns. Compared to previous studies, we do not use gross housing density (e.g. Graziano and Gillingham, 2014) or population density (e.g. Rode and weber, 2012) for estimating differences in the urban setting and the built environment. Rather, thanks to the more refined scale, we calculate the net housing density. This density is expressed as:

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

We recognize that using the actual living area footage would have been better. However, data limitation, explained below in detail, do not allow for the use of that measure. Despite this limitation, this density is acceptable given the urban setting of the study area. 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 second measure controlling for the urban setting is the share of single-family houses within each block group. We define this variable as follows:

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

In the paragraph above, we did not report a single source for the parcels data. Indeed, Connecticut does not have a statewide or a region-wide depository of such data. Consequently, each of the 169 towns is responsible for collecting, storing and sharing its own parcels data. This extreme fragmentation is increased by a sub-fragmentation within each town: several offices (usually two or three) are responsible for parts of the dataset, and they seldom develop common fields in order to join the data in to a single dataset. Additionally, even when towns have their datasets displayed online in built-in GIS webpages, they either do not know how or are unwilling to make data available for

research purposes, or, even worse, do not know how to get the underlying dataset, which have been contracted out to private companies. Finally, no attempt has ever being made to standardize the quality, amount and recording procedures of the datasets. As an example, few towns consider the ‘living area’ the actual livable square footage, whereas others only measure the external size of a dwelling. Additionally, the dataset rarely coincide with the official town borders, and several towns claim as theirs parcels belonging to other towns according to the U.S. Census Bureau.

This situation rises concerns about the ability of towns and the state to take informed decisions, especially when it comes to projects involving more than one town, such as planning a new transportation corridor or a hospital servicing multiple towns.

3. Typifying Selected Towns

In our analysis, we focus 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 U.S. standards, some having being founded as early as the XVI 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. In the present work, we analyze the socioeconomic and the spatial differences among these towns. We find that these differences affect the profile of adopters among these towns. Consequently, statewide

policies and current limitations in terms of sub-metering and slit incentives curb the overall limit the efficiencies of the state's incentives.

3.1 Typology Analysis and Residential Spatial Barriers

To capture the differences within and among towns, we use two methodologies. First, we use hierarchical clustering to assess the number of clusters within each town, and the major breakdown components (Kaufman, 2009). We display these results in dendograms (in appendix A). From this analysis, we infer that 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. As a first step, we analyze the presence of spatial gaps within residential areas. These gaps reduce and cluster the strength of spatial peer effects. Recent literature on PV systems diffusion have greatly highlighted the positive influence that these effects have on adoption (e.g. see Bollinger and Gillingham, 2012). However, in urban environments these effects may be reduced in presence of large portions of land occupied by non-residential parcels. Once aggregated at block group, or tract level, these effects will influence the overall adoption. Understanding the extent of these spatial gaps provides a better understanding of the built environment within which policies and adopters interact with each other.

In Figure 2, we show the four towns, highlighting the residential parcels over all other town parcels. It appears quite clear that the four towns have quite different traits in terms of residential distribution within their boundaries.

[Figure 2 About Here]

Starting with Hartford, we can easily identify gap in the eastern part of the town, where very few residential parcels are located. This area coincides with the business district servicing both Hartford and the other surrounding towns, and hosts several headquarters of large multinational corporations (mostly insurance companies), as well as governmental buildings. The few residents of this area live in multifamily buildings, which are already penalized by the current policies (or lack of) regulating submetering in Connecticut (Bronin, 2012). Looking at the distribution of the (few) PV systems, we notice that six out of nine of the installations appear concentrated in distinct neighborhoods. Moving towards East Hartford, we notice that the town is almost a reversed copy of Hartford, in that the western portion is mostly non-residential. East Hartford has several spatial gaps represented by manufacturing plants. The larger plants, owned by Pratt and Whitney, a UTC subsidiary, has provided jobs for East Hartford residents for several years. This plant separate the town in to three residential areas. To the north, we find few adopters, spatially separated one from the other. In the center, adopters are closer, with an outlier laying in between two large non-residential areas.

Finally, the southern portion, towards Glastonbury, becomes more densely populated and PV systems are closer to each other. Moving to Glastonbury, one can notice that the northern portion of this town hosts several closely built installations, and it is continuous with the dwellings in East Hartford. The town develops further south, and it articulates in to several neighborhood relatively contiguous, with several installations very close to each other, although the distance increases in the southern portion of the town. Finally, Manchester offers an interesting case of old town that has recently undergone a suburbanization process. Founded in the late XVI century, Manchester became one of the main industrial centers in the USA, hosting several mills and mechanical companies (MHS, 2013). After a period of decline following the closure of many companies, the town now hosts one of the largest shopping areas in Connecticut ('Mall Area' in Figure 2). The original structure is still visible in the central-eastern portion of the settlement, delimited by the mall and other non-residential parcels. In this context, PV systems are concentrated within specific neighborhood. The clusters of PV systems are quite visible, suggesting that those areas have characteristics that encourage adoption.

Overall, the towns display several spatial gaps in their residential patterns. It is significant that the nature of these gaps changes. For example, parks and green spaces can be easily access and can provide places of aggregation. 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.

3.2 Profiling Adopters

We employ to scales for comparing the profile of adopters. First, the characteristics, both socioeconomic and related to the built environment, of the block groups within these towns. Second, 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.[34]

[Table 2 About Here]

The description of the average adopter within the study area could sound 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 profile within each town. In particular, income and race appear to vary across the towns. In Table 3, we present the same data in a different way: we present each characteristic compared to the average for the study area, displaying the actual value of reference and the ranking within each town's groups.

[Table 3 About Here]

Comparing the towns provides a different perspective about the profile and distribution of PV systems. Overall, the rate of adoption[35] (PV rate) is far higher in Glastonbury than in all other towns. However, most of these installations are contained within one block group, which display a value several times higher than the average for the area geography. The consequence of this difference is that while in Glastonbury adoption

[34] See Appendix B for full tables.
[35] PV systems installed as of September 2013/Residential Parcels in 2013.

appears more diffused, 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 different levels within each town. In Glastonbury, the same 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 are in areas with the highest percentage of white people. However, the 'diverse' neighborhood in Glastonbury has twice as much the share of white people than the one in Hartford.

3.3 Built Environment and Social Status

We turn out attention at the built environment. Following the findings of Bronin (2012), and Graziano and Gillingham (2014), it appears that current policies in support of PV systems in Connecticut tend to favor single-family, owner-occupied houses in low-density areas. The results from the study area as a whole seem to confirm these findings. However, when looking each town, we find a great deal of variation among characteristics such as housing density, size, tenure, age and housing type.

Within these characteristics, Hartford is an outlier compared to the other towns and the study area as a whole, except in the age of the adopting houses. Adopters live in smaller houses usually in areas with higher housing density and mixed housing types. These characteristics are consistent with the layout of Hartford (Figure 2): residential parcels are small and clustered together in several areas. Overall, the socioeconomic profile of adopters across these towns appear to be quite different from the overall profile across the study area. However, with the partial exception of Hartford, the area geography characterizing the presence of adopters is consistent with the one of the study area, and consistent with the findings of Graziano and Gillingham (2014). The higher adoption rate in low-density and single house block groups, combined with the mixed results from income confirm that additional elements influence the adoption patterns of PV systems. Additionally, overall low adoption rates among the more densely built towns, supports the finding of Bronin (2012) in that current policies favor adoption by owner-occupied, single-family houses.

4. Quantifying Drivers and the role of the Built Environment: Models and Specifications

The analysis of block groups' characteristics has provided us with two main results. First, we identified the general profile of PV adopters, or, more precisely, the profile of an adopter block group. Second, we established that this profile changes across the towns, and, in light of the state 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. In the present section, we build on the previous work of Graziano and Gillingham (2014), and Bollinger and Gillingham (2013) using panel fixed-effect and Cross-Sectional models.[36] Our specifications can be stated as:

$$PVcount_{i,t} = \alpha + \boldsymbol{N}_{i,t}\beta + \boldsymbol{B}_{i,t}\gamma + \boldsymbol{D}_{i,t}\theta + \mu_i + \psi_t + \varepsilon_{i,t} \qquad (3)$$

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 Graziano and Gillingham; $\boldsymbol{B}_{i,t}$ is the vector of built environment variables; $\boldsymbol{D}_{i,t}$ is a vector of socioeconomic and demographic variables; μ_i are block group fixed effects; ψ_t are time dummy variables; and $\varepsilon_{i,t}$ is a mean-zero error term. Compared to the work of Graziano and Gillingham, we limit maximum extent of the spatiotemporal variables to two miles. We choose a shorter cut-off distance to account for the relative size of the study area: four miles would equal the diameter of the largest of the towns (Glastonbury), thus extending the neighborhood effects to the whole town. This approach is consistent with the rationale in the paper by the two authors: the area geography and social characteristics vary compared to the analysis of the state as a whole. Consequently, a variation in the magnitude and spatial peer effects is expected. The vector $\boldsymbol{B}_{i,t}$ varies between the panel models and the Cross-Sectional models due to data limitation. In the former, we include the 'Gross Housing Density', presented above, to control for housing densities and, to a certain extent, housing type. In the Cross-

[36] 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

Sectional models, we replace this control with the ‘Net Housing Density’. Further, we introduce the share of single-family houses, thus actually controlling for the housing type. Finally, both models include the share of owner-occupied houses. As a whole, these variables control for the relationship between the built environment and current state policies. We seek to understand whether current regulations on sub-metering and split incentives would increase adoption of PV systems, as suggested by Bronin (2012). Additional controls for this group are the average year houses were built (Cross-Sectional models only) and share of houses with five or more bedrooms. The vector $\boldsymbol{D}_{i,t}$ contains the socioeconomic and demographic variables. The vector contains controls for median income, racial and age profile for each block group, with controls similar to those of Graziano and Gillingham. We include an additional income (dummy) control, *income100k*. This variable serves to control if the level of $100,000 positively affect adoption, as it appears from the towns’ profile. As usual for panel models, we use time dummy to capture year-specific effects.

4.1 Models Selection

In the present work, we use several different specifications following the research of Graziano and Gillingham (2014), Bollinger and Gillingham (2012). In line with the work of these authors, we use a series of fixed-effect (FE) models to estimate spatial peer effects and the other socioeconomic drivers. However, due to data limitations such as the lack of consistent historic parcels data, we have to use a much larger time-gap (the year)

and to make use of time-invariant models, specifically OLS and zero-negative inflated binomial. These second sets of models seeks to identify the influence of the area geography at a more refined scale than the previous works. We are confident that as historic parcels data will become available in the future, this work could be expanded to account for changes in the area geography of places. Due to the limited number of observations, we deem town-level analysis of little use, and, instead, focus on the study area as a whole.

5. Results

5.1 Panel and Cross-Sectional Analysis

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; and (iii) **the parameter** $\boldsymbol{\theta}$ associated with *Income100k*. Table 4 presents the results of our econometric analysis.

[Table 4 About Here]

Overall, our results are relatively consistent with previous literature: we identify spatial peer effect in several of our specifications, and these fade as time and space increase.[37] However, the controls associated with the adopter's socioeconomic profile and the built environment show less consistency across the various models. In Table 4, the first column shows the result of the OLS specification with year dummies. Column two

[37] We performed several additional runs, including quarter-level specifications and town-year FE. Results are available in Appendix B

through four shows the results for the actual panel FE models. Each of these columns uses a different set of spatiotemporal variables, leaving unchanged the other variables. Column 2 uses the installed base as a control for spatial peer effect. This is the more common control in works on PV diffusion (e.g. Rode and Weber, 2012), and provides a comparison with the other spatiotemporal estimates. Column (3) and (4) shows the results for our preferred panel specifications. The two models are identical except that in column (3) the peer effects are limited to the PV systems installed up to 12 months before the observation. Column (4) extends this temporal distance to 24 months, thus, potentially, including a higher number of neighboring adoptions.

Our results suggest that spatial peer effects fade for distances greater than 1 mile and when the temporal extent is increased to 24 months, and it is relatively constant even when we perform additional tests (Appendix B). Only distances up to 1 mile are constant in their prediction power, thus suggesting that spatial peer effects is relatively well established up to that distance within one year from the adoption. This result suggests that within the four towns, adopters are not influenced by changes in the urban landscape after one year. Furthermore, within the 12 months-period (column 3), the influence exerted by previous installations fades within a radius lower than the one previously found by Graziano and Gillingham (2012). In light of the empirical findings of these two authors, ad their comparison with previous works (e.g. Müller and Rode, 2013), these results highlight the sensitivity of spatial peer effects to the geography of the study area. In densely populated, although fragmented urban areas like the one analyzed in our work,

spatial and social interaction requires shorter distances than in suburban towns. Additionally, the urban environment is more variegated, and new installations become easily part of what agents perceive as 'familiar'. 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 (3) and (4) are consistent in 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 the Connecticut and in the USA (Carstensen and Coghlan, 2013; Li and Harris, 2008). Finally, Median household income and the control for income above $100,000 are not significant. Nevertheless, the indicator for the Dow Jones Industrial Average is positive for specifications (3) and (4). Although uniform across all block groups, this variable has the advantage of capturing the global influence the economic cycle exerts over the adoption decision. Unsurprisingly, when the economy is in good health adoption increases and for an additional 1,000 points in the Dow Jones average level, we would expect 0.014 additional installations within each block group.

Because of collinearity issues, we are forced to introduce our refined density and housing typology in Cross-Sectional models. We present these results in Table 5, and test those over five different specifications: OLS (12 and 24 months bands, and installed base) and Zero-Inflated Negative Binomial (12 and 24 months). The latter is used to account for the evident excess zeroes in the independent variable. We prefer this model to a Zero-Inflated

Poisson because the mean of the count variable is not equal to its variance. In our data, '*PVCount'* has variance 0.33 and mean 0.22.

[Table 5 About Here]

The Cross-Sectional models confirms the existence of spatial peer effects up to 1 mile, although the results of the count models are relatively disappointing. The very low numbers of non-zero values in the count variable may have contributed to this outcome, in spite of the inflated zero values. Our preferred specification is presented in column (1). Within these models, we are more interested in the effects of the built environment. We find that the net housing density negatively affect adoption. The magnitude of this parameter is relatively low because of the scale chosen. An additional house within one square kilometer is a relatively small addition, especially in an urban environment of 300 sq. km. This result conforms to the findings of Graziano and Gillingham (2014), and it is in line with the argument of Bronin (2012). It is true that single-family houses are not significant: however, this result may be due to aggregation issues at block group level. Income shows conflicting results. Median income appears to influence adoption negatively. However, this effect is more than balanced once we control for earners above $100,000 per year. This result suggests that income provides a socioeconomic level that allows the decision to take place. Additionally, and in light of the work of Graziano and Gillingham (2014), and our analysis on towns' profiles, we argue that income is a more complex variable. It interacts and defines the physical and social space of households,

thus affecting the adoption decision through the definition, for example, of the built environment or the educational level.

To summarize, we find that spatial peer effect within our study area contribute positively to the adoption process, although within a shorter time period (12 months) and a smaller distance (1 mile). This first result is consistent with the findings of Graziano and Gillingham (2014) and their consideration on differences across study areas and their geography. This brings us to argue that the jurisdictional, social and spatial extent of the study areas and its component may affect the analysis and the actual adoption process, thus making *a priori* assumptions about the temporal and spatial extent of spatial peer effects erroneous. In addition, this result raises questions about the ability of urban environment to 'absorb' new elements of the urban landscape faster than mixed areas. In terms of built environment, we find that only the net housing density affects adoption negatively, although single-family ownership does not constitute a good predictor. Finally, income does not provide any meaningful insight, except in our OLS specifications. In those, its prediction power is split between the negative effect of median household income, and the positive, strong effect that block groups with median household income above $100,000 have on the adoption process.

6. Conclusions and Future Research: New Regionalism or Flexible Modelling?

In the present work, we study present different drivers and profiles associated with PV systems adopters in four Connecticut towns. Comparing the results of the town and rea profiles with those of the econometric models, we find that the role of income and the built environment are greatly reduced in the latter. The differences in the adopter's neighborhood profiles among the towns and between the 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. In addition, in 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. Finally, we found that spatial peer effects last shorter within the urban environment of these four towns than what previously found for Connecticut as a whole, suggesting that PV systems are absorb faster within urban environments than in suburban areas (Graziano and Gillingham, 2014). Comparing our findings with those of other studies on spatial peer effects and socioeconomic profile of PV adopters, we persistently find differences related to the built environment, the jurisdictional fragmentation, and socioeconomic levels. We are not suggesting a return to a strong regionalism, where no region is similar to another. Several works have found sets of socioeconomic demographic and spatial elements that encourage or reduce adoption of PV and other energy systems across various study areas. However, we argue that the interaction among these elements does not always follow the same pattern. In our work, a different interaction emerge between spatial peer effects and

the built environment, for the former are reduced in time. Therefore, policies will have to allow adopters and marketers to operate within different spatial, socioeconomic and legal framework, using tools such submetering, split-incentives or income-based monetary incentive schemes.

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Figures

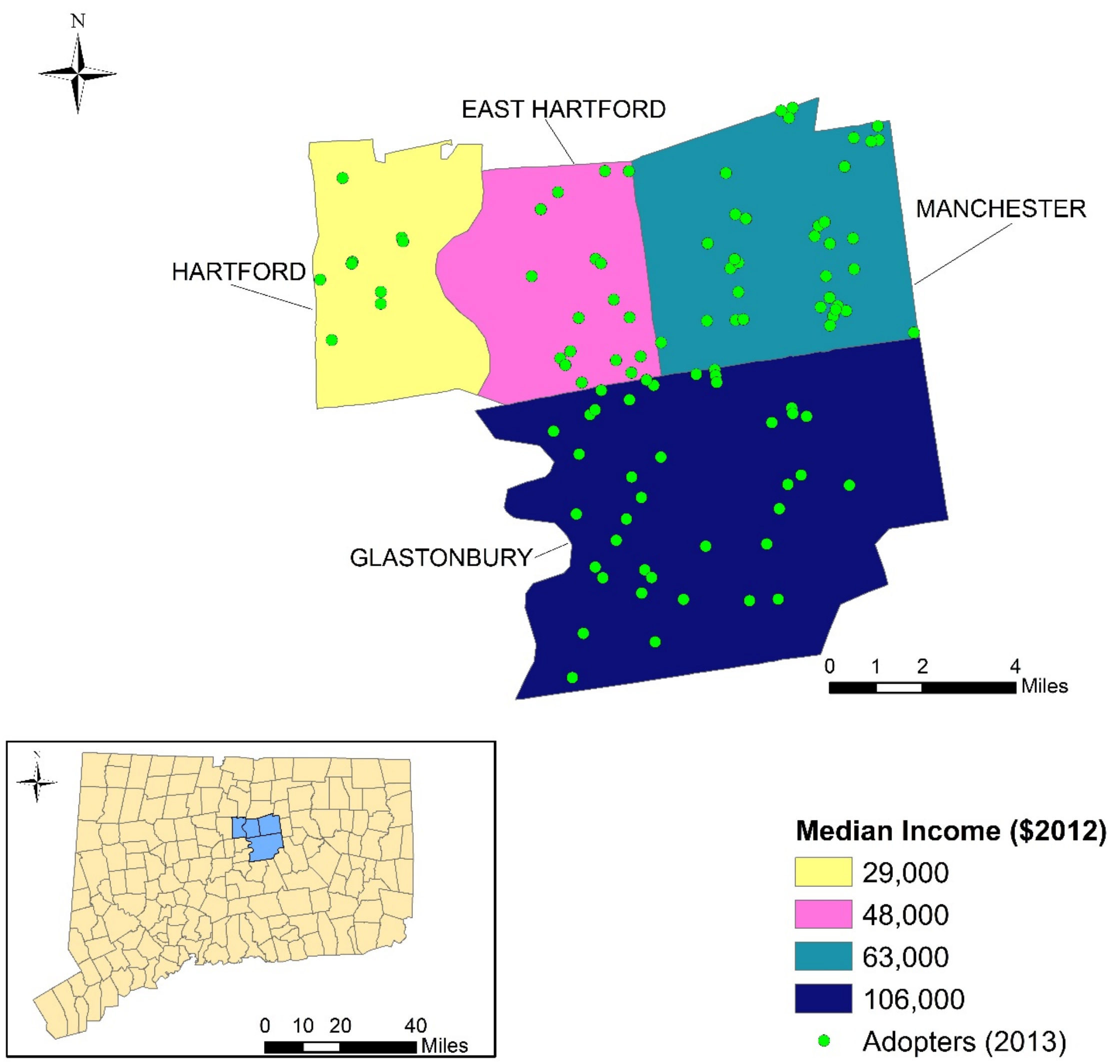


Figure 1 – Study Area with Median Household Income at town level, 2012

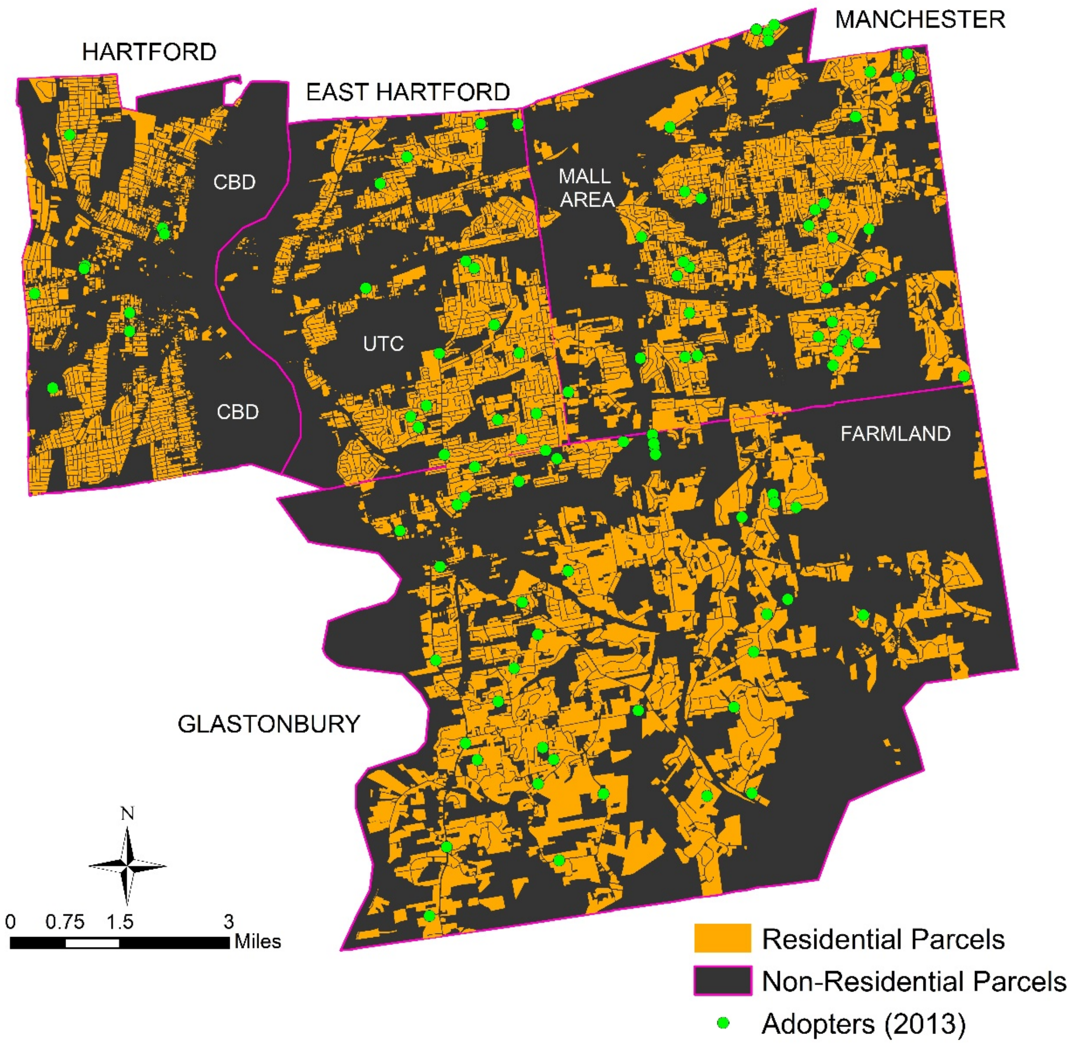


Figure 2 – Spatial Barriers and Adopters, 2013

Tables

Table 1. Summary Statistics and Sources

Variable	Mean	Std. Dev.	Min	Max	Source
Number of new Adoptions	0.06	0.29	0.00	3.00	CEFIA (2013)
Cumulative Installed Base	0.65	1.97	0.00	24.00	CEFIA (2013)
Average Neighbors within 0.5 Mile (12 months)	0.11	0.71	0.00	11.33	Calculated
Average Neighbors 0.5 and 1 Mile (12 months)	0.11	0.70	0.00	11.00	Calculated
Average Neighbors 1 and 2 Miles (12 moths)	0.23	1.39	0.00	23.00	Calculated
Average Neighbors within 0.5 Mile (24 months)	0.44	2.54	0.00	30.00	Calculated
Average Neighbors 0.5 and 1 Mile (24 months)	0.46	2.63	0.00	33.00	Calculated
Average Neighbors 1 and 2 Miles (24 months)	0.94	5.22	0.00	63.00	Calculated
Number of Housing Units (1,000s)	0.63	0.41	0.05	3.65	U.S Census
% of Owner-occupied Houses	49.18	33.80	0.00	100.00	U.S Census
% of Houses >5 bedrooms	3.52	6.42	0.00	65.86	U.S Census
Gross Housing Density	1541.59	2283.09	9.50	28908.94	Calculated

Median Household Income ($10,000)	5.60	3.71	0.15	25.57	U.S Census
If income >$100,000	0.16	0.36	0.00	1.00	U.S Census
Dow Jones Level (1,000)	11.75	1.65	8.89	14.87	FRED (2013)
% pop who are white	52.45	28.59	0.00	100.00	U.S Census
% pop who are black	25.57	24.83	0.00	100.00	U.S Census
% pop who are Asians	5.68	8.08	0.00	73.12	U.S Census
Median Age	36.71	9.47	11.61	80.00	U.S Census
If Median Age in Highest 5%	0.08	0.27	0.00	1.00	U.S Census
Cross-Sectional Variables					
Net Housing Density	886.49	524.47	0.00	2753.67	Calculated
Share of Single-Family Houses	55.67	35.12	0.00	100.25	Calculated

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

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.

Table 4. Panel Models

	Year Dummies	**Block Group and Year FE**		
	12 Months (1)	Installed Base (2)	12 Months (3)	24 Months (4)
Average Neighbors within 0.5 Miles	0.13*** (0.0117)		0.13*** (0.0396)	0.016 (0.0239)
Average Neighbors 0.5 and 1 Mile	0.13*** (0.0133)		0.13** (0.0558)	0.016 (0.0178)
Average Neighbors 1 and 2 Miles	0.022*** (0.0072)		0.027 (0.0294)	0.018 (0.0134)
Installed Base		0.076*** (0.0183)		
Number of Housing Units (1,000s)	0.040*** (0.0138)	-0.049 (0.0358)	-0.045 (0.0358)	-0.072* (0.0436)

% of Owner-occupied Houses	0.00054** (0.0002)	0.000054 (0.0008)	0.00073 (0.0005)	-0.00013 (0.0009)
% of Houses >5 bedrooms	0.00092 (0.0007)	-0.0051** (0.0020)	-0.00038 (0.0014)	-0.0025 (0.0020)
Gross Housing Density	-0.0000043* (0.0000)	0.0000013 (0.0000)	-0.000000066 (0.0000)	-0.0000039 (0.0000)
Median Household Income ($10,000)	-0.0041 (0.0025)	-0.000024 (0.0081)	-0.0052 (0.0035)	0.0012 (0.0070)
If income >$100,000	0.097*** (0.0206)	0.029 (0.0451)	0.014 (0.0424)	0.0068 (0.0504)
Dow Jones Level (1,000s)	0.011 (0.0070)	0.011* (0.0058)	0.014** (0.0054)	0.0065** (0.0026)
% pop who are white	0.000087 (0.0004)	0.0014** (0.0006)	-0.00037 (0.0005)	0.00015 (0.0006)
% pop who are black	-0.00016 (0.0003)	-0.00059 (0.0006)	-0.0010** (0.0004)	-0.0011* (0.0006)
% pop who are Asians	0.0010 (0.0006)	0.0022 (0.0015)	0.0022 (0.0014)	0.00074 (0.0016)
Median Age	-0.00028 (0.0007)	0.0019 (0.0014)	0.00085 (0.0011)	0.0049** (0.0019)
If Median Age in Highest 5%	0.075*** (0.0217)	0.026 (0.0484)	0.0098 (0.0359)	-0.030 (0.0415)
Constant	-0.15* (0.0884)	-0.23** (0.1059)	-0.13* (0.0753)	-0.19* (0.0981)
Year Dummies	Y	Y	Y	Y
R-squared	0.58	0.20	0.57	0.47
Observations	1845	1845	1845	1845

Notes: Dependent variable is the number of new installation in each block group each year, * p<0.10 ** p<0.05 *** p<0.010

Table 5. Cross-Sectional Models

	OLS			**Zero-Inflated Negative Binomial**	
	12 Months	24 Months	Installed Base - 12 Months	12 Months (4)	24 Months (5)

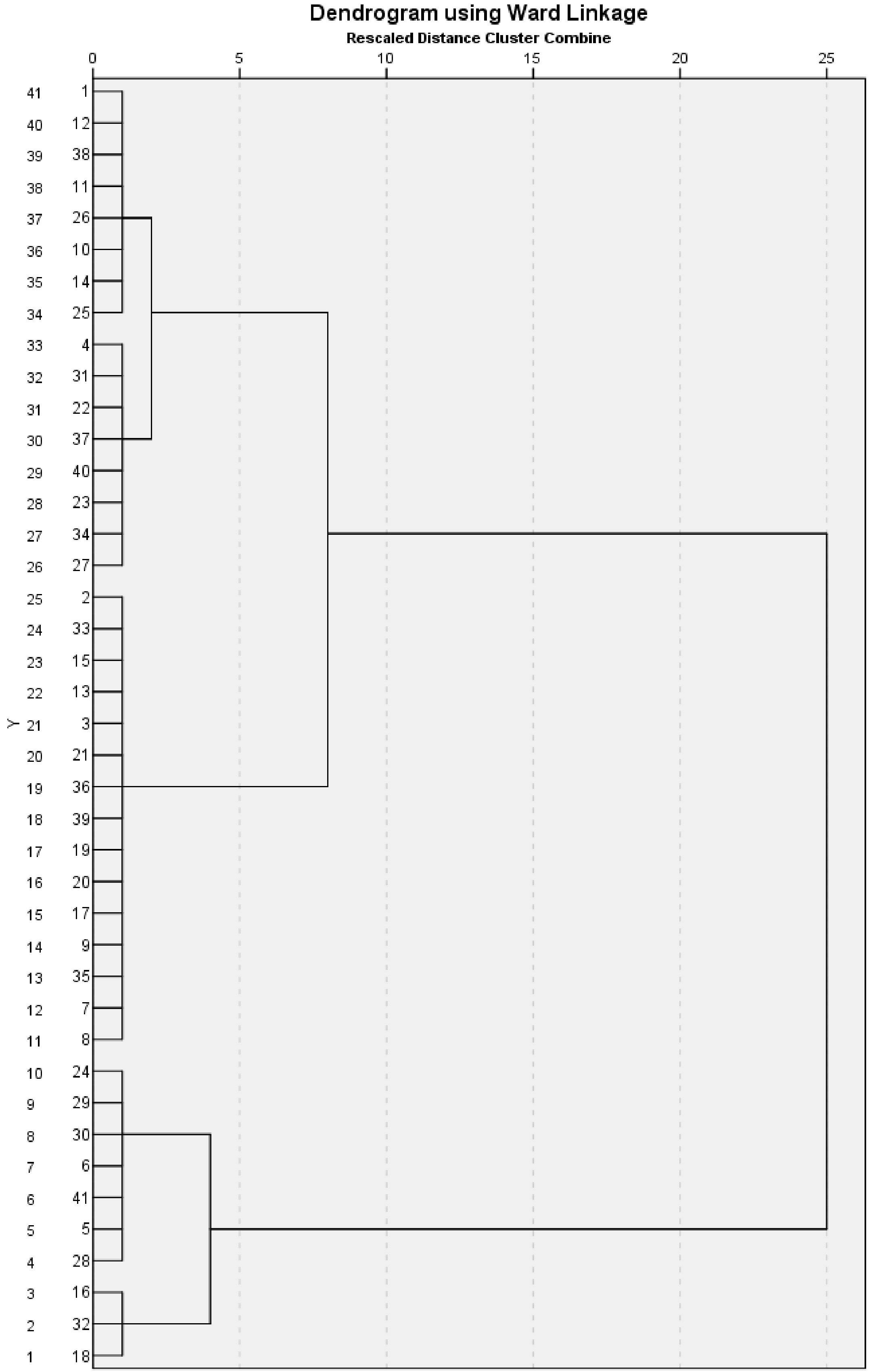
	(1)	(2)	(3)		
Average Neighbors within 0.5 Miles	0.13*** (0.0306)	0.047 (0.0456)		0.032 (0.1147)	0.027 (0.1251)
Average Neighbors 0.5 and 1 Mile	0.16*** (0.0289)	0.10** (0.0496)		0.067 (0.1017)	0.025 (0.1355)
Average Neighbors 1 and 2 Miles	-0.024 (0.0170)	0.017 (0.0237)		-0.019 (0.0568)	-0.022 (0.0731)
Cumulative Installed Base			0.11*** (0.0125)		
Number of Housing Units (1,000s)	0.031 (0.0379)	0.034 (0.0478)	0.023 (0.0500)	0.010 (0.5447)	0.070 (0.6994)
% of Owner-occupied Houses	0.0027** (0.0013)	0.0020 (0.0016)	0.00010 (0.0017)	-0.0029 (0.0236)	-0.0071 (0.0262)
% of Houses >5 bedrooms	-0.00035 (0.0024)	-0.0036 (0.0030)	-0.0074** (0.0031)	-0.0038 (0.0187)	-0.0074 (0.0186)
Net Housing Density (# residential parcels/sq.km of residential parcels)	-0.00013** (0.0001)	-0.00012* (0.0001)	0.000078 (0.0001)	-0.00013 (0.0006)	-0.000032 (0.0006)
% of Single-family parcels	-0.00032 (0.0010)	0.000080 (0.0013)	0.0012 (0.0014)	0.00067 (0.0125)	0.0019 (0.0123)
Median Household Income ($10,000)	-0.027*** (0.0083)	-0.013 (0.0105)	-0.0045 (0.0110)	-0.016 (0.0469)	-0.000077 (0.0442)
If income >$100,000	0.32*** (0.0950)	0.21* (0.1185)	0.083 (0.1257)	0.52 (0.5956)	0.45 (0.5739)
% pop who are white	0.00058 (0.0017)	0.00069 (0.0021)	0.0017 (0.0022)	0.019 (0.0321)	0.022 (0.0339)
% pop who are black	-0.00071 (0.0016)	-0.00079 (0.0020)	-0.00020 (0.0021)	0.020 (0.0333)	0.022 (0.0353)
% pop who are Asians	0.0020 (0.0029)	-0.00037 (0.0037)	0.0028 (0.0038)	0.031 (0.0383)	0.033 (0.0371)
Median Age	0.00074 (0.0031)	0.0069* (0.0038)	0.0061 (0.0040)	0.015 (0.0349)	0.027 (0.0412)
If Median Age in Highest 5%	0.089 (0.0894)	-0.070 (0.1126)	0.038 (0.1178)	0.13 (0.6738)	-0.063 (0.7470)

Constant	0.088 (0.1866)	-0.091 (0.2336)	-0.38 (0.2442)	-2.50 (2.9598)	-3.00 (2.993)
Inflated:					
# New Adoptions				-45.5 (18873.88)	-44.9 (15448.52)
Constant				23.8 (15705.55)	23.5 (12781.16)
Lnalpha					
Constant				-27.5 (656.27)	-20.0 (667.35)
R-squared	0.72	0.55	0.50		
Observations	205	205	205	205	205

Notes: Dependent variable is the number of new installation in each block group
* p<0.10 ** p<0.05 *** p<0.010

Appendix A

A1. East Hartford



Dendrogram using Ward Linkage
Rescaled Distance Cluster Combine
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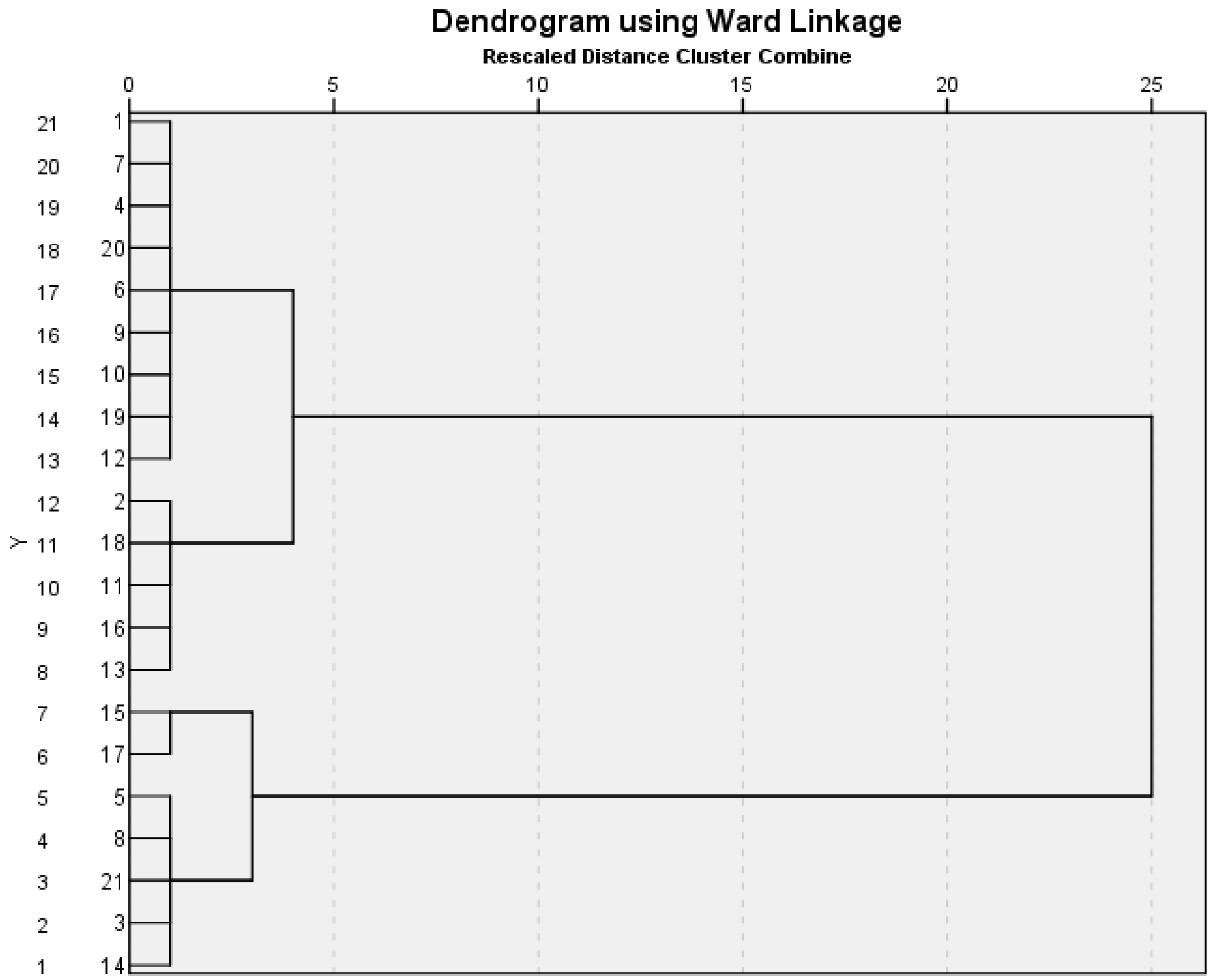
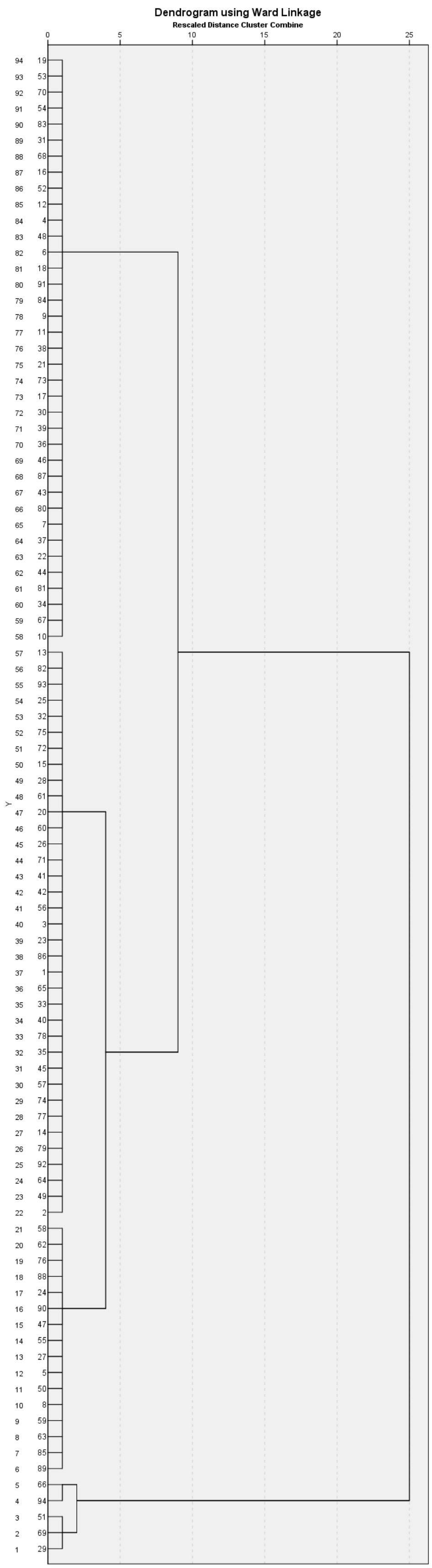
A2. Glastonbury



A3. Hartford



Dendrogram using Ward Linkage
Rescaled Distance Cluster Combine
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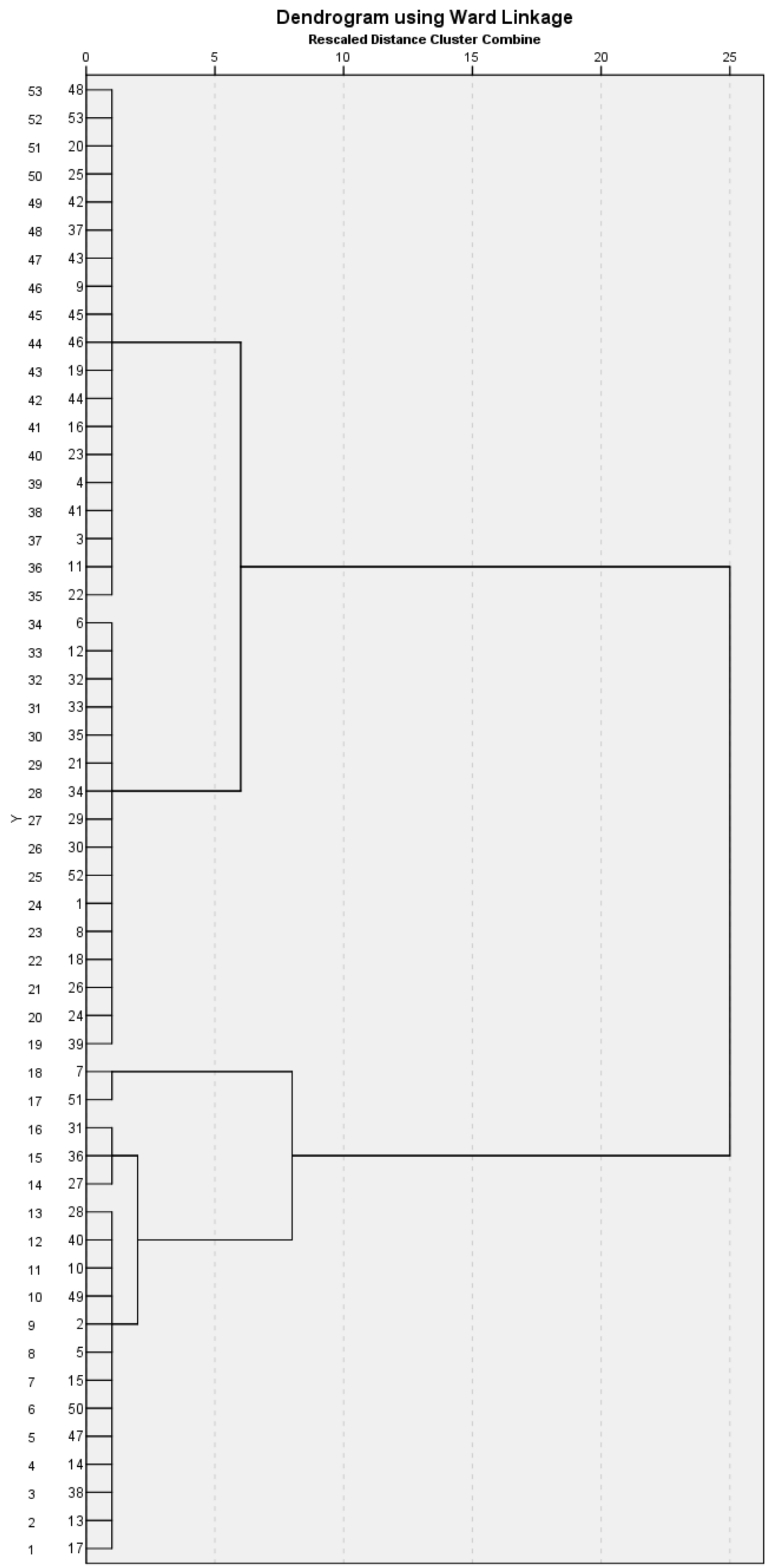
A4. Manchester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Rescaled Distance Cluster Combine
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Appendix B

B1. Town-Year Fixed Effect

	Town-Year FE 12 Months	**Block Group and Quarter FE** 12 Months	**Zero Negative Binomial Town-Year FE** 12 Months
Average Neighbors within 0.5 Miles	0.13*** (0.0426)	0.072*** (0.0069)	0.35** (0.1595)
Average Neighbors 0.5 and 1 Mile	0.13** (0.0537)	0.057*** (0.0091)	0.044 (0.1704)
Average Neighbors 1 and 2 Miles	0.027 (0.0259)	0.060*** (0.0049)	-0.036 (0.1056)
Number of Housing Units (1,000s)	0.028 (0.0172)	0.010** (0.0039)	0.71*** (0.2524)
% of Owner-occupied Houses	0.00079** (0.0003)	0.00018*** (0.0001)	0.019*** (0.0069)
% of Houses >5 bedrooms	0.0012 (0.0009)	0.00027 (0.0002)	0.0092 (0.0135)
Gross Housing Density	-0.00000079 (0.0000)	-0.000000040 (0.0000)	0.000038 (0.0001)
Median Household Income ($10,000)	-0.0096 (0.0061)	-0.00090 (0.0006)	-0.026 (0.0316)
If income >$100,000	0.089* (0.0507)	0.0094 (0.0066)	0.30 (0.3684)
Dow Jones Level (1,000s)		0.000047 (0.0002)	0.0015 (0.0142)
% pop who are white	0.00014 (0.0002)	0.000098 (0.0001)	0.044*** (0.0159)

% pop who are black	0.0000080 (0.0001)	0.000013 (0.0001)	0.023 (0.0166)
% pop who are Asians	0.0012* (0.0006)	0.00027 (0.0002)	0.058*** (0.0186)
Median Age	-0.00090* (0.0005)	-0.000041 (0.0002)	-0.00017 (0.0191)
If Median Age in Highest 5%	0.081** (0.0365)	0.016*** (0.0059)	0.32 (0.3883)
Constant	0.021 (0.0271)	-0.014 (0.0226)	6.15 (532.7771)
R-squared	0.54	0.39	
Observations	1845	7175	5083

Notes: Dependent variable is the number of new installation in each block group
* p<0.10 ** p<0.05 *** p<0.010

B2. Quarter and Year Level, No Dow Jones

	Block and Quarter FE, 12 Months	**Block and Year FE, 12 Months**
Average Neighbors within 0.5 Miles	0.072*** (0.0069)	0.13*** (0.0397)
Average Neighbors 0.5 and 1 Mile	0.057*** (0.0091)	0.13** (0.0559)
Average Neighbors 1 and 2 Miles	0.060*** (0.0049)	0.027 (0.0295)
Number of Housing Units (1,000s)	0.010** (0.0039)	-0.043 (0.0358)
% of Owner-occupied Houses	0.00018*** (0.0001)	0.00073 (0.0005)

% of Houses >5 bedrooms	0.00027 (0.0002)	-0.00047 (0.0014)
Gross Housing Density	-0.000000040 (0.0000)	-0.00000012 (0.0000)
Median Household Income ($10,000)	-0.00090 (0.0006)	-0.0050 (0.0035)
If income >$100,000	0.0094 (0.0066)	0.014 (0.0424)
% pop who are white	0.000098 (0.0001)	-0.00040 (0.0005)
% pop who are black	0.000013 (0.0001)	-0.0010** (0.0004)
% pop who are Asian	0.00027 (0.0002)	0.0020 (0.0014)
Median Age	-0.000041 (0.0002)	0.00083 (0.0011)
If Median Age in Highest 5%	0.016*** (0.0059)	0.010 (0.0360)
Constant	-0.0085 (0.0096)	0.033 (0.0463)
Temporal Dummies	Y	Y
R-squared	0.39	0.57
Observations	7175	1845

Notes: Dependent variable is the number of new installation in each block group
*** p<0.10 ** p<0.05 *** p<0.010**

Conclusions

In my dissertation, I have presented several result relevant to the current research on the diffusion of DRETs and PV systems. The three works presented here provide new answers to the questions outlined in the introduction, and represent useful findings for policymakers and scholars. In relation to the overarching objectives, I propose a temporally dynamic conceptual model capable of accounting for the role of organizations as well as the one of area geography, thus expanding the notion of innovation through the mere contribution of niches**.** I used two concepts within the model, the spatial relationships between agents (in terms of spatial peer effects) and the interaction between policies and area geography in the two empirical works on PV systems. In terms of spatial patterns, PV systems in Connecticut appear to contradict previous literature: towns with the largest populations are not the engine of the diffusion, which, instead, generates in medium-sized towns with populations within Connecticut's average. Further, my 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. Finally, I find that socioeconomic and spatial differences among urban areas within the same jurisdiction (Connecticut) can greatly affect the diffusion process, especially when policies aimed at encouraging the adopting of PV systems do not account for these spatial and social differences. Furthermore, in the four towns studied in the third chapter, I find that the

temporal extent of spatial peer effects is reduced in time and space. This result suggests that the urban environment could easily absorb and reduce the novelty effect of an additional installation, possibly because the landscape is already dominated by man-made objects. Due to data limitation and the risk of including effects due to 'green on green' effects, my dissertation does not include the effect of tree cover over the adoption's decision. I recognize that this, like other sources of shadowing effects, could potentially effect the diffusion of PV systems, especially in a highly forested region like Connecticut. However, the use of fixed effects in the two empirical studies account for the changes in land cover, without shifting the overall focus away from the stated objectives with issues beyond the scope of the current work.

As a whole, my dissertation provides new insight in the interconnected role of space, time and policies, and argues for the need of encouraging the adoption of PV systems through policies capable of addressing the socioeconomic and spatial differences, particularly within inner cities. Within the conceptual framework, these findings relate to the interaction between agents and those between agents, institutional framework and area geography. The existence of spatial peer effects, and enriched by the addition of time, confirms the results from previous literature, and relates to the adopting agents. The findings on built environment are more strictly related to the interactions between policies and area geography. In Connecticut, the study area of my dissertation, this interaction is regulated on the one hand by strong monetary and non-monetary incentives to promote the diffusion of PV systems. However, the same set of relationships are

regulated through the current prohibition of submetering and the lack of split incentives, which effectively limit the adoption to a sub-set of residents, mostly owners in areas with lower housing densities. Beyond the specific findings, my dissertation argues for the need of more empirical research to understand how the area geography, time and institutions operate and affect the diffusion of PV systems and other DRETs.