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Publication Date
2018-04-01

DOI
10.1016/j.erss.2018.01.004

Peer reviewed

The geography of solar energy in the United States: Market definition, industry structure, and choice in solar PV adoption

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Abstract

The solar photovoltaic (PV) installation industry comprises thousands of firms around the world who collectively installed nearly 200 million panels in 2015. Spatial analysis of the emerging industry has received considerable attention from the literature, especially on the demand side concerning peer effects and adopter clustering. However this research area does not include similarly sophisticated spatial analysis on the supply side of the installation industry. The lack of understanding of the spatial structure of the PV installation industry leaves PV market research to rely on jurisdictional lines, such as counties, to define geographic PV markets. We develop an approach that uses the spatial distribution of installers' activity to define geographic boundaries for PV markets. Our method is useful for PV market research and applicable in the contexts of other industries. We use our approach to demonstrate that the PV industry in the United States is spatially heterogeneous. Despite the emergence of some national-scale PV installers, installers are largely local and installer communities are unique from one region to the next. The social implications of the spatial heterogeneity of the emerging PV industry involve improving understanding of issues such as market power, industry consolidation, and how much choice potential adopters have.

Keywords: solar; market definition; spatial analysis; industry

Acknowledgements

This work was supported by the Office of Energy Efficiency and Renewable Energy (Solar Energy Technologies Office) of the U.S. Department of Energy under Contract Nos. DE-AC02-05CH11231(LBNL) and DE- AC36-08GO28308 (NREL). For supporting this work, we thank Elaine Ulrich, Odette Mucha, Ammar Qusaibaty, Joshua Huneycutt, and the entire DOE Solar Energy Technologies Office team.

1. Introduction

The job title of solar photovoltaic (PV) installer only emerged near the end of the 20th century. However today, thousands of PV installation companies with hundreds of thousands of employees install more than 180 million PV panels per year worldwide (REN21 2016, The Solar Foundation 2017). Spatial analysis of demand in the emerging PV industry has received considerable attention, especially concerning peer effects and adopter clustering (Bollinger and Gillingham 2012, Noll, Dawes and Rai 2014, Palm 2016, Dharshing 2017, Palm 2017). However similarly sophisticated supply-side spatial analysis of the PV installation industry is unavailable. Improved supply-side spatial analysis, and more specifically geographic market definition, would provide insights into spatial PV market structure. In the absence of an alternative PV market definition, several studies have used jurisdictional lines by default to analyze spatial market structure (Gillingham et al. 2016, Nemet et al. 2017a, Pless et al. 2017). These studies have generally used county lines to calculate market structure metrics such as installer density and concentration. However, defining markets based on jurisdictional lines rather than economic forces limits market research on the effects of competitive conditions on firm behavior (Losch 1954, Stigler and Sherwin 1985, Brooks 1995, Davis and Garces 2010).

In this paper, we develop a method to define PV markets based on the spatial distribution of installers. We apply the method to a dataset of the U.S. PV installations. The method is meant to be practical for future applied research. However the results of the method applied to the U.S. data are also illustrative *per se*. Using our market definition, we show that the U.S. PV installation industry is spatially heterogeneous. An installer community in one city typically only weakly resembles installer communities in other nearby cities, in the sense that one city contains a group of localized installers that operate exclusively in that city. The resemblance between installer communities diminishes with distance. We show that the spatial heterogeneity of the PV industry may be one driver of the spatial patterns of installed prices. At the same time, the ubiquity of a few national-scale installers ensures some spatial homogeneity even over large distances. An improved understanding of the spatial distribution of PV installers will inform future research on spatial market structures.

Our market definition is broadly applicable in the context of other industries (e.g., distributed energy storage) and has applications for a variety of social science questions. For example, social scientists could use our approach to study how spatially heterogeneous installation industries affect local economies. The local economic impacts of highly localized and spatially heterogeneous installer communities could be compared with the economic impacts of a more spatially homogenous PV installation industry. Such analysis could inform policymaking to maximize the environmental and social benefits of the emerging PV industry.

The paper proceeds as follows. In Section 2, we provide a review of the market definition literature. In Section 3 we develop our methodology. In Section 4 we apply the method to a dataset of U.S. PV installers. In Section 5, we discuss the outcome of the method's application. In Section 6, we conclude by providing some guidance on the future application of the method.

2. Market definition literature review

A market may be broadly defined as the area within which supply and demand determine prices (Stigler and Sherwin 1985). However, there is no consensus on how to define this area in space (Klein, Rifkin and Uri 1985, Uri, Howell and Rifkin 1985, Brooks 1995, Brorsen, Bailey and Thomsen 1997, Geroski 1998, Massey 2000, Davis and Garces 2010). A body of literature provides a variety of approaches and some guiding principles for geographic market definition.

The task of market definition is to use economic forces, rather than political or geological features, to delineate geographic boundaries (Losch 1954). Early market definition models attempted the task using transportation costs (Losch 1954), trading areas (Reilly 1929, Huff 1964), and shipments data (Elzinga and Hogarty 1973). Subsequently, the theoretical focus has shifted toward price interdependence (Horowitz 1981, Stigler and Sherwin 1985, Uri et al. 1985, Asche, Salvanes and Steen 1997, Fackler and Tastan 2008, Davis and Garces 2010). Stigler and Sherwin (1985) cite price dependence (independence) between two areas as evidence of market integration (segregation). Price interdependence implies the temporal correlation of prices – rather than price equality – between two areas (Stigler and Sherwin 1985, Uri et al. 1985, Davis and Garces 2010, Asche et al. 1997). That is, price *levels* may vary within a market due to local factors, but all levels will correlate in time due to shared economic forces. Several studies have developed econometric models to establish price interdependence for market definition (Horowitz 1981, Klein et al. 1985, Uri et al. 1985, Slade 1986, Asche et al. 1997).

Price interdependence within a market follows from the interaction of firms with their rivals and their customers. Within a market, a firm's price behavior is necessarily constrained by the actions of rivals in the same market. The degree to which firms constrain their rivals' behavior in geographic space may therefore provide evidence of price interdependence and market integration (Stigler and Sherwin 1985, Baker 2007). Brooks (1995) defines an "enacted" market as the set of rivals that demands the strategic attention of a given firm. In other words, the enacted market is the geographic area that contains the rivals that constrain the prices of a given firm. Kay (1990) and Geroski (1998) propose an alternative view of the "strategic" market as the smallest geographic area over which a firm can profitably compete. The authors argue that firms may choose to compete in larger markets, but the relevant market for price formation is the smallest viable niche. For instance, in an industry with both local-scale and national-scale firms, the strategic market is defined from the perspective of the local, but profitable, firms. The national-scale firms compete in multiple strategic markets. A national-scale firm's prices in one strategic market are not necessarily constrained by the actions of rivals in a separate strategic market.

The U.S. Department of Justice (US DOJ 1997) developed a market definition for antitrust cases in the United States. The US DOJ hypothetical monopolist test (HMT) defines a market as the smallest geographic area over which a hypothetical monopolist could impose a small but significant and non-transitory increase in price (SSNIP). To implement the HMT, some candidate market area is first chosen. The potential for the hypothetical monopolist to exercise the SSNIP is then tested. If the SSNIP is not possible, the candidate market area is expanded and the process repeats until the area is large enough to accommodate the SSNIP (Coate and Fischer 2008, Davis and Garces 2010).

If any market definition rule exists, it is that the appropriate approach ultimately depends on the task at hand (Geroski 1998, Davis and Garces 2010). Ultimately, the goal of market definition is not to identify an objective reality based on the "right" approach but rather to define markets so as to be able to usefully explain economic phenomena (Geroski 1998).

3. Methodology

We develop a PV market definition approach based on the spatial distribution of installers. Our approach is closest in spirit to the enactment and strategic market definitions (Kay 1990, Brooks 1995, Geroski 1998), but novel in its application of spatial firm activity data to infer price interdependence. Our primary assumptions are that installer prices are interdependent within some geographic area and that the spatial distribution of installers provides evidence of this price interdependence. We first justify these assumptions.

3.1 Spatial distribution as evidence of price interdependence

The PV transaction process can be modeled as a competitive bidding process where one or more installers submit bids to a prospective customer. Assuming that installers bid strategically, bid prices are constrained by rival bid behavior (Friedman 1956, Milgrom and Weber 1982, McAfee and McMillan 1987, Rothkopf and Harstad 1994, Krishna 2002, Levin and Ozdenoren 2004, Lorentziadis 2016). For any given customer, installers do not know which or how many rivals will also submit bids. Installer bid behavior is therefore constrained by *potential* rather than actual rivals. Our point of departure is that PV installers observe some set of potential rivals within a geographic area and base bids on this group of potential rivals.

Let $\beta(\cdot)$ denote an optimal bidding strategy (Riley and Samuelson 1981). For a customer in area i, a strategic bidder's optimal price can be modeled:

$$(1) \quad p_i^* = c + \beta(\aleph_i, v_i, d_i)$$

where c denotes an installation cost, $\aleph_i$ denotes the set of potential rivals in area i, v_i denotes the value of solar in area i (defined further in the following paragraph), and d_i denotes idiosyncratic customer preferences in area i. The variable $\aleph_i$ captures all elements of the price constraints that installers in area i exert on one another, including any disproportionate market power held by any given installer.

The value of solar refers to the financial benefits that customers derive from solar adoption, including utility bill savings and the sum of all incentives received. Higher values of solar generally reduce customer demand elasticity, possibly allowing installers to bid up prices through Equation (1) (Gillingham et al. 2016, Nemet et al. 2017a). The value of solar tends to be spatially auto-correlated due to electricity rates and incentives set at the utility or state level. In other words, the influence of v_i in an area i tends to be close to the influence of v_j in an area j that is geographically close to i.

The idiosyncratic customer demand variable (d_i) allows for variation in customer valuation that may or may not be spatially auto-correlated. For instance, customers in one area i may exhibit similar environmental preferences on average as customers in a geographically proximate area j, even if individual preferences within these areas vary.

Consider two geographically proximate areas j and k where $v_j \approx v_k$ and $d_j \approx d_k$ due to their geographic proximity. If the sets of active installers are similar in both j and k, it follows from (1) that prices in the two areas are interdependent (temporally correlated):

$$(2) \quad \aleph_j \approx \aleph_k \ \rightarrow \ p_j^* \propto p_k^*$$

However if the sets of installers in j and k are dissimilar, it follows that prices in the two areas are independent (uncorrelated):

$$(3) \quad \aleph_j \not\approx \aleph_k \ \rightarrow \ p_j^* \perp p_k^*$$

Equation (2) establishes that a shared installer set is a sufficient condition for price interdependence (correlation) between two geographically proximate areas with correlated value of solar and customer characteristics. A shared installer set is a necessary condition for price interdependence when the assumptions on v_i and d_i are relaxed such that these values may vary between geographically proximate areas. For instance, two adjacent areas at a state border may have significantly different values of solar depending on state-level incentives, despite their geographic proximity. In this case, price *levels* may vary between two geographically proximate areas due to underlying differences in demand. However prices remain temporally correlated and thus interdependent if the two areas share a similar installer set.

Let M_i denote the market of area i. Taking price interdependence as evidence of market integration, it follows from (2) that:

$$(4) \quad \aleph_j \approx \aleph_k \;\rightarrow\; k \in M_j$$

and from (3):

$$(5) \quad \aleph_j \not\approx \aleph_k \;\rightarrow\; k \notin M_j$$

assuming j and k are geographically proximate.

Result (4) provides the justification for the use of the spatial distribution of installers as evidence of price interdependence. If the sets of installers in two geographically proximate areas are fundamentally similar ($\aleph_j \approx \aleph_k$), then an installer bidding in these areas is subject to the same price constraints and the installer's prices will be correlated over time ($p_j^* \propto p_k^*$). Price interdependence therefore follows from installer community similarity. A geographic market boundary is delineated at the point where one set of installers ceases to resemble another set of installers ($\aleph_j \not\approx \aleph_k$).

3.2 The installer overlap coefficient (IOC) approach

We now require some metric to determine installer set similarity ($\aleph_j \approx \aleph_k$). Let $\aleph_{jk}$ denote the installers that are active in both areas j and k. Let $\#\aleph_i$ denote the number of unique active installers in area i. We calculate the percentage of installers that are active in j that are also active in k:

$$(6) \quad \rho_x^y = \frac{\#\aleph_{jk}}{\#\aleph_{\mathrm{j}}}$$

Where ρ_j^k is the percentage of installers in j also found in k. The value ρ_j^k quantifies the degree to which the installer set $\aleph_{\mathrm{j}}$ resembles $\aleph_k$, but the reverse is not necessarily true. A very low value of ρ_j^k could mask a relatively high value of ρ_k^j (the percentage of installers in k also in j). We resolve this issue by developing an installer overlap coefficient (IOC):

$$(7) \quad IOC_{\mathrm{jk}} = \rho_j^k \rho_k^j$$

The IOC serves as evidence of market integration for geographically proximate areas.

The final step is to define a critical IOC value to delineate market boundaries. Let θ denote the critical IOC value. The market definition is:

$$(8) \quad IOC_{jk} > \theta \;\rightarrow k \in M_j$$

$$(9)\quad IOC_{jk} \leq \theta \ \rightarrow k \notin M_j$$

Rule (8) says that two areas j and k belong to the same market if IOC_{jk} exceeds the critical value θ. Put more simply, PV markets are defined as geographic areas over which a relatively homogenous group of installers competes. Market boundaries occur at points where installer homogeneity ceases and two fundamentally dissimilar groups of installers may be identified.

Our theoretical framework of price interdependence based on the spatial distribution of installers has strong empirical support. Installed PV prices exhibit clear geographic variation across and within states (Figure 1) (Barbose et al. 2015) and clear spatial correlation (Figure 2, see also Figure 10). Differences in local value of solar (e.g., incentives, electricity rates), explain only part of this geographic variation (Gillingham et al. 2016, Nemet et al. 2017a, Nemet et al. 2017b). Several studies have found significant effects of inter-installer competition on price variation (Gillingham et al. 2016, Nemet et al. 2017a, Nemet et al. 2017b, Pless et al. 2017), providing direct support to our theoretical framework. Remaining geographic variation may reflect additional unobserved factors such as variation in customer environmental preferences.

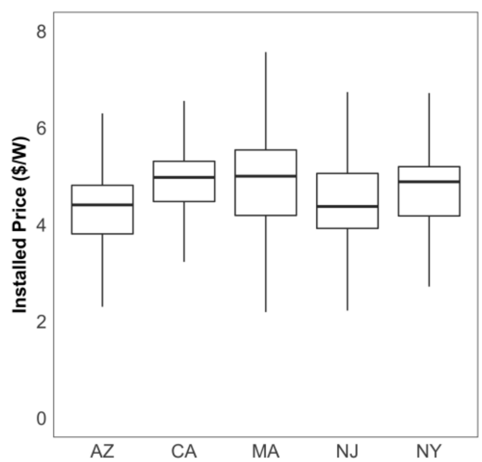

Figure 1. Installed price ($/W) distributions in five states. Dataset described in Section 4.

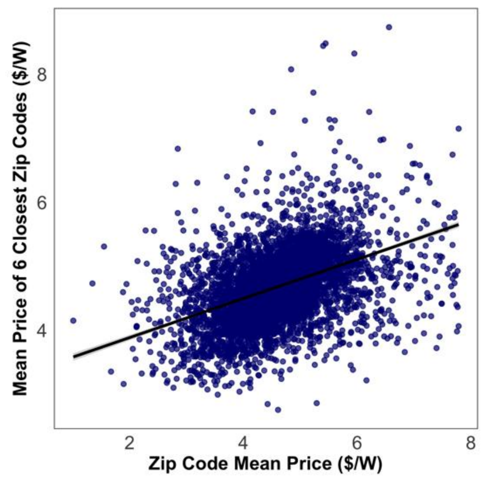

Figure 2. Visualization of spatial price correlation: Relationship between zip code-level mean prices and the mean prices of the nearest six codes. The figure illustrates how prices in one location correlate with prices in geographically proximate areas, a trend consistent with spatial price dependence. Data source is described in Section 4.

Like many market definitions, there remain several subjective choices in this framework that may vary application to application. First, some consistent concept of "area" is required. These areas may depend on data and country context. In the United States, for example, we propose the use of zip codes. Second, a method is required to identify the potential rival sets (ℵ). In our application, we propose identifying ℵ as the group of installers with at least one system installed in that area over some timeframe, however other approaches are possible. The third decision is the critical value θ. All else equal, a higher value of θ results in more market integration and larger markets, while a lower value of θ results in more market segregation and smaller markets. There is no extant literature on which to base the choice of θ, and the appropriate value may vary depending on the application.

4. Application to the U.S. PV industry

To demonstrate how the IOC can be applied in practice and what insights the IOC approach can provide, we apply the approach to a dataset of U.S. PV installers. We use installed system data from the Lawrence Berkeley National Laboratory's "*Tracking the Sun*" (TTS) data set (Barbose and Darghouth 2015). The full TTS covers about two-thirds of U.S. PV installations from 2000 to 2014. The data used in this study include 134,078 systems smaller than 15 kW installed between January 1, 2013 and December 31, 2014 by an installer firm, that is, the data set excludes self-installed systems. The data account for 2,867 unique installers in 6,103 zip codes in 22 states.

We use 5-digit U.S. zip codes to define lowest-level geographic areas in our application. There are over 30,000 zip codes in the United States.

We define the installer set for zip code i ($\aleph_i$) as all installers with at least one system installed in i in our dataset (1/1/2013-12/31/2014). We test two critical values: $\theta_{0.25} = 0.25$ and $\theta_{0.01} = 0.01$, to show how the choice of critical value affects market outcomes.[1]

We developed an algorithm to assign zip codes into markets based on a three step iterative process:

1. A candidate market was identified as the zip code with the maximum summed value of IOCs (in theory, installer communities in zip codes with high IOCs are more integrated with other zip codes than installer communities in zip codes with low IOCs)
2. Zip code centroid coordinates were used to identify the six closest zip codes or "nearest neighbors" to the candidate market.[2] Note that the six nearest neighbors refer to zip codes with at least one PV system installed and do not necessarily correspond to the geographically nearest neighbors if the candidate market was surrounded by zip codes with no systems.
3. Additional zip codes were assigned to the candidate market if (a) the IOC with the candidate market exceeded the market criterion (θ) and (b) the zip code was geographically contiguous with the candidate market. Functionally, the algorithm identifies the six nearest neighbors of each of the six nearest neighbors of the candidate market (n=36), then assigns zip codes to the candidate market that meet the market criterion (θ). The algorithm then repeats that step for the six nearest neighbors of the zip codes assigned to the candidate market in the previous step. Thus, every new zip code assigned to the candidate market is contiguous with the candidate market via zip codes previously assigned (Figure 3).

[1] There is no extant literature to draw upon for a basis for the market criterion. We therefore model two criteria to assess market outcomes under a range of IOC thresholds.

[2] The choice of k=6 nearest neighbors conforms to a convention in geographic analysis for the hexagonal partitioning of geographic areas. The use of hexagonal (k=6) rather than rectangular (k=4) grids can reduce edge effects and assigns equal weight to neighbors in any cardinal direction.

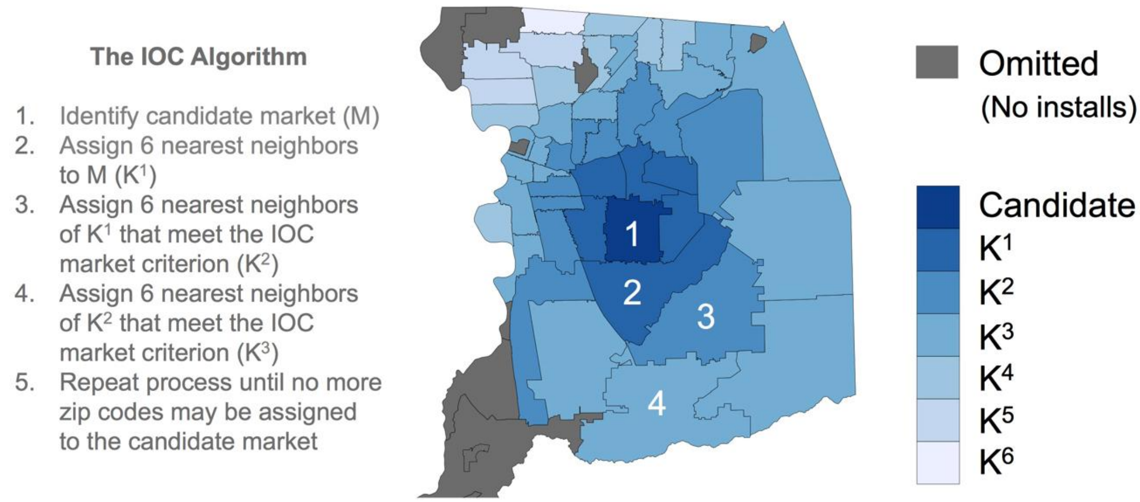

Figure 3. Visualization of the IOC algorithm in Sacramento County

Steps 1 through 3 were repeated until all zip codes were assigned to markets. Note that once a zip code was assigned to the candidate market, it was removed from the pool of eligible zip codes for market assignment; therefore all zip codes were assigned to a single market. This is only one potential application of the IOC approach. Alternatively, areas could be assigned to multiple markets to determine market sizes relative to any given area.

Our algorithm allowed some zip codes to be "islanded" from the market definition. For example, if a zip code with many installations is adjacent to a zip code with few installations, the shared IOC may be low simply because the two zip codes differ significantly in terms of the number of systems installed, even if prices between the two zip codes are likely interdependent. To reduce islanding, we apply a spatial smoothing process to develop a third criterion θ_S. The θ_S approach uses the $\theta_{0.01}$ criterion as a base, then assigns all islanded zip codes to the same market as the zip code's nearest neighbor, so that the minimum market size in θ_S is two zip codes.

5. Application results

Table 1 summarizes the IOC market definitions with comparisons to market definitions based on jurisdictional lines (county, zip). As expected, the higher critical IOC value in $\theta_{0.25}$ results in the most granular outcome with 1,946 distinct markets in contrast to $\theta_{0.01}$ with 1,759 distinct markets. The spatial smoother θ_S forces 901 islanded zip codes from the $\theta_{0.01}$ specification into neighboring markets, resulting in a lower granularity with 922 distinct markets.

Table 1. PV Market Definition Outcomes

	County	Zip	$\theta_{0.25}$	$\theta_{0.01}$	θ_S
# of markets	535	6,103	1,946	1,759	922
Mean # of zip codes	11.4	1	3.1	3.5	6.6
Mean # of systems	251	22.0	68.9	76.2	145.4

5.1 Benefits of the approach

The IOC approach provides more market granularity relative to a county-level market definition. The increased granularity allows for more precise characterization of local market structures and improves the statistical power of tests indexed by markets. The spatial smoother reduces granularity but eliminates islanded market areas (Figure 4).

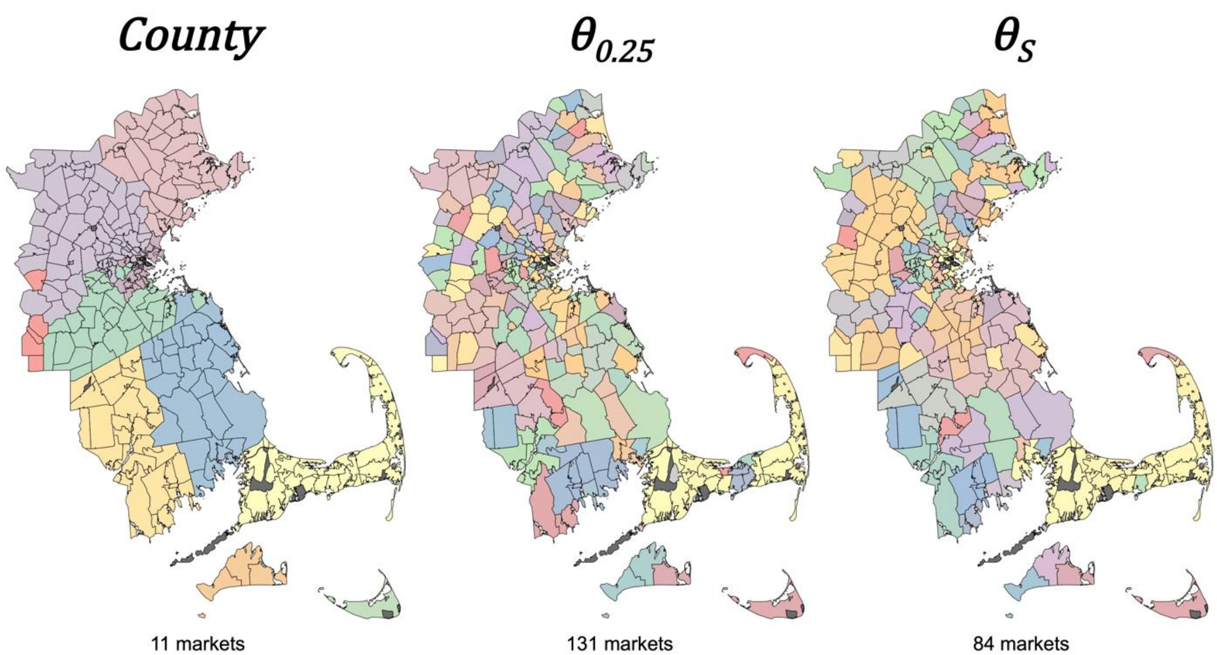

Figure 4. Illustrations of market outcomes in eastern Massachusetts. Separate colors correspond to separate markets

A second advantage of the IOC approach is more precise measurement of local market share. To illustrate, consider two installers X and Y in Los Angeles County, based on actual data. The two installers have comparable county-level market shares. However, installer X holds a stronger share in southwestern Los Angeles County, while installer Y holds a stronger share in southeastern Los Angeles County (Figure 5). County-level market analyses underestimate installer Y's market share in southeastern Los Angeles County by about a factor of three.

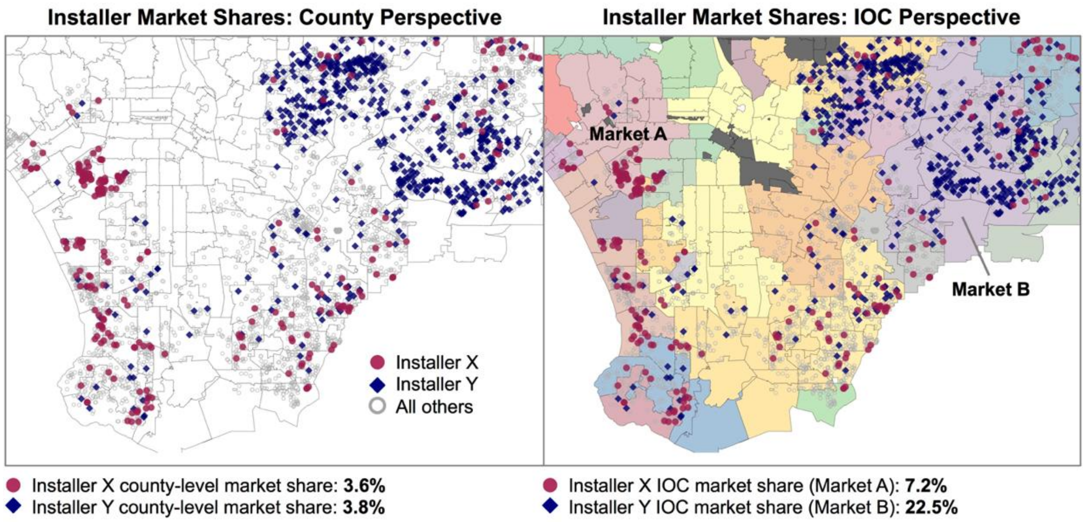

Figure 5. Visualization of installer market share measured at the county level (left panel) and IOC market level (right panel)

In contrast, the IOC approach captures more local market nuance. A county-level market definition gives the perception that installers X and Y operate at roughly a 4% market share throughout Los Angeles County. However, at the IOC market level, the installers hold significantly lower and higher market shares in certain areas of the County (Figure 6). The IOC approach will allow future researchers to make more precise inferences about the nature of installer competitive behavior based on local market presence.

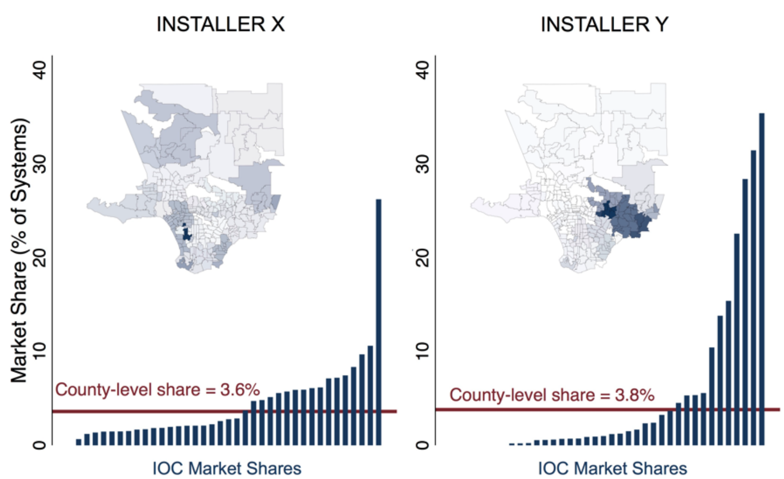

Figure 6. Local market shares (θ_S specification) compared to county-level market shares for Installers X and Y in Los Angeles County.

5.2 Using the IOC to describe PV spatial structures

The IOC as a metric has several descriptive uses in addition to its application for market definition. The IOC allows us to assess similarities between installer communities across space. Through the IOC we see that local installer communities become increasingly dissimilar with distance (Figure 7). Higher shared values of the IOC are observed between closer zip codes, suggesting installer communities in any given zip code resemble installer communities in nearby areas more than installer communities in more distant areas. The IOC confirms that installer communities are localized to some degree: the relationship between installer communities in two areas weakens with distance.

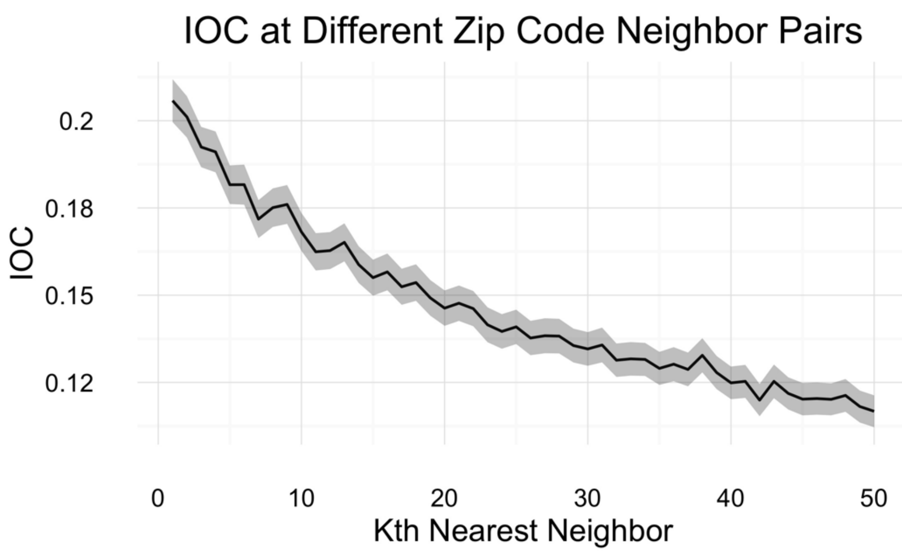

Figure 7. Mean IOC between zip codes and their K^{th} nearest neighbor zip code with 95% confidence interval in gray

The IOC shows that installer communities vary over relatively short distances. For example, about 33% of installers in San Francisco, CA (94110 zip code) were also found in Oakland (94611 zip code), and about 17% of installers in Oakland were found in San Francisco (IOC=0.06) (Figure 8). That is, fewer than half of the installers in either city operated in both cities, despite their geographic proximity. The installer community in the more suburban Walnut Creek blends into its environs more than the installer communities in urban San Francisco and Oakland. One possibility is that urban installer communities draw from a variety of existing companies in related service industries (e.g., electricians, roofers, construction), that make urban installer communities largely heterogeneous from one city to the next. In contrast, installers in more suburban and rural areas may be "imported" from urban centers.

Figure 8. IOC values from three base zip codes in the Bay Area, California

At the same time, installer communities show some similarities even over large distances (Figure 9). About 33% of San Francisco (94110 zip code) installers were also active in Los Angeles (93536 zip code), though only about 6% of Los Angeles installers were active in San Francisco (IOC=0.02). That PV installer communities show spatial heterogeneity over short distances and some degree of homogeneity even over long distances reflects the diversity of this nascent industry. The vast majority of installers are small local firms, yet a few national-scale installers are spatially ubiquitous. The spatial distribution of installers is thus akin to biological distributions with local pockets of endemic species coupled with ubiquitous species with expansive ranges.

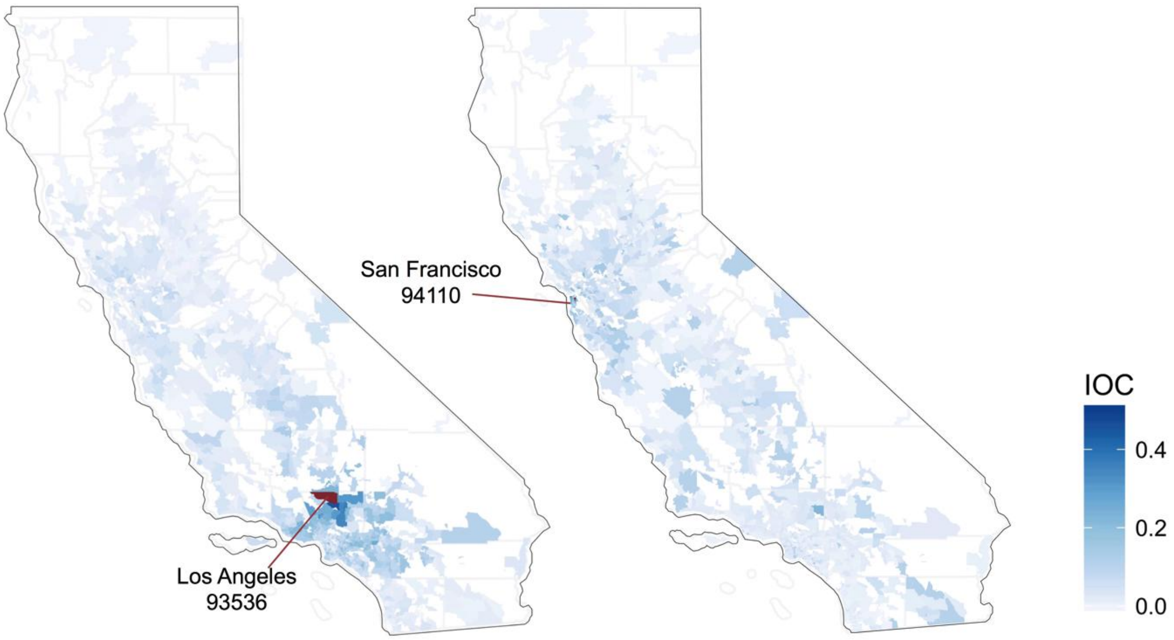

Figure 9. IOC values from two base zip codes in California

The inverse relationship between the IOC and distance affirms the logic of the IOC as a market definition approach. The IOC shows that an installer that operates in multiple geographically distant areas generally faces distinct sets of local rivals. For example, some high-volume installers operate in both San Francisco and Los Angeles. These high-volume installers likely constrain each other's prices at a state or national level. However the high-volume installers face different sets of competitive price constraints at a local level in the two cities. Differences between the local San Francisco installer community and the Los Angeles installer community could drive high-volume installers to offer different prices in these two markets, even if demand were identical in the two cities. In other words, the spatial heterogeneity of installers implies that prices should be spatially dependent. This conclusion holds even if some high-volume installers operate in multiple markets, and even if demand were identical across space.

Price spatial dependence can be quantified through a Moran's *I* statistic (Anselin 2001). A greater value of *I* indicates a stronger degree of spatial dependence. A Moran's *I* correlogram calculates Moran's *I* between two points at different distances from each other or, in our case, for increasingly distant zip code pairs. The Moran's *I* statistic for a spatially dependent process should generally decline as the distance between two points increases. This relationship is evident for installed PV prices (Figure 10). The average Moran's *I* for install prices between a zip code and its 10 nearest neighbors is about 0.23, compared to about 0.18 between a zip code and its 11th through 50th nearest neighbors (t=5.2). The Moran's *I* results provide clear evidence of price spatial dependence. At least part of this spatial dependence may be attributed to local demand

and policy differences. However, the IOC results suggest that the spatial heterogeneity of the installer community may also drive price spatial dependence.

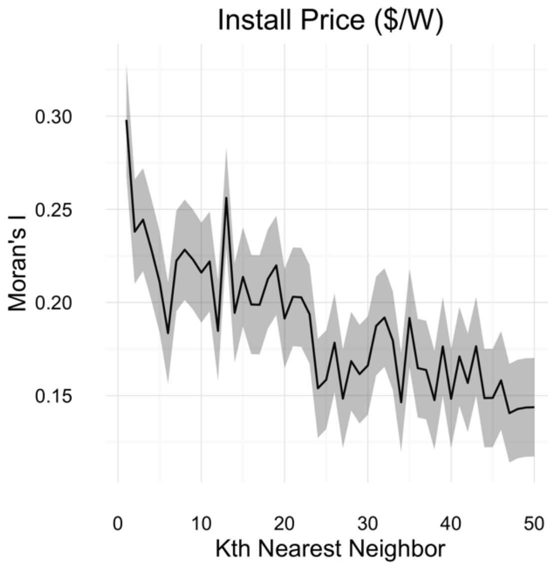

Figure 10. Moran's I spatial correlograms for installed prices. The x-axis corresponds to the *k*th nearest neighbor of any given zip code.

6. Conclusion

We have developed a PV market definition approach based on economic activity rather than jurisdictional lines. Our approach is broadly applicable in a variety of research contexts for the PV industry but also for other industries such as distributed energy storage, roofing, and electrical contracting where firm activity can be inferred from data on services rendered at customer sites. We conclude by noting the approach's limitations and some guidance on its application.

Among other uses, market definitions are fundamental to market structure research. Models of market structure research are susceptible to endogeneity issues that arise from the simultaneous relationship of market structure and economic behavior (Evans, Froeb and Werden 1993). For instance, market concentration may result in market power and high prices, but high prices also induce entry and reduce concentration. In other words, market structure may explain economic behavior, but economic behavior can also explain market structure. This simultaneous causality can bias estimates of the effects of market structure on market outcomes such as price. Our approach is susceptible to a specific type of endogeneity in certain research applications. We base our definition on the spatial distribution of installers. However, for at least some installers, firm location is an endogenous decision. Some high-volume installers may enter and exit local markets according to market dynamics. Endogenous firm movements would shift IOC market boundaries. Our approach is therefore not suitable for models of market structure dynamics of entry/exit, at least in the form presented in this paper.

However we believe that endogenous firm location is not problematic in most research applications. First, location is likely exogenous for most installers. Most entrepreneurs begin businesses close to home and firms, once established, tend to exhibit locational inertia (Boschma and Frenken 2006). Locational inertia implies that firm locations are more fixed than would otherwise be implied by classical economic models. That is, firms tend to stay in place rather than respond to changing market conditions by uprooting and relocating. Second, endogenous firm location does not contradict the theoretical notion of the market as the area of price formation. Indeed, the area of price formation must be sensitive to firm locational decisions. It is ultimately the collective actions of firms and their customers that determine prices, so market boundaries should be sensitive to changes in the behavior of these economic agents.

In our application, the IOC approach identifies mutually exclusive areas of price formation by delineating boundaries around heterogeneous installer communities. However the IOC approach need not identify mutually exclusive areas. For instance, it may be useful in certain applications to define customer- or installer-centric markets.

Last, we demonstrated that the IOC metric has applications beyond market definition. We used the IOC to describe the spatially heterogeneous U.S. installer industry. We showed that spatial heterogeneity may be one driver of the spatial dependence of PV installed prices. Social scientists may use the IOC approach to study the spatial distribution of the emerging PV industry and the potential impacts on local economies. The local economic impacts of spatially heterogeneous industries (low IOCs) may be compared with the impacts of spatially homogenous industries (high IOCs). The findings of research in this vein would inform policy directions for the future of the still emerging PV industry.

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