The Effects of Market Concentration on Residential Solar PV Prices: Competition, Installer Scale, and Soft Costs

Eric O’Shaughnessy

National Renewable Energy Laboratory

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List of Acronyms

2SLS	two-stage least squares
AD	associate’s degree
BIPV	building-integrated PV
BLS	Bureau of Labor Statistics
CBP	U.S. County Business Patterns
HHI	Herfindahl-Hirschman Index
MES	minimum efficient scale
NAICS	North American Industry Classification System
NPV	net present value
OLS	ordinary least squares
PBI	performance-based incentive
PV	solar photovoltaic
SREC	solar renewable energy certificate
TOU	time of use
TPO	third-party owned
TTS	Tracking The Sun

Executive Summary

The U.S. residential solar photovoltaic (PV) installation industry is evolving. The industry grew from fewer than 100 firms installing residential PV in 2000 to about 3,000 firms by 2016. Over time, some installers have accumulated market share and grown to scales of hundreds or thousands of systems installed per year. At the same time, the vast majority of installers operate at a relatively small scale, with most installers installing fewer than 50 systems per year. Variability in installer scale can be measured through market concentration: the distribution of market shares among competing firms. A market with many low-volume firms is said to be unconcentrated, while a market with fewer but higher-volume firms is said to be concentrated. In general, residential PV markets have become more concentrated over time. Changes in PV market concentration may affect PV prices, given that installer scale can affect installation costs and market power. Understanding the effects of market concentration on PV prices may help guide the policies needed to ensure residential PV continues to advance energy and environmental objectives. This study leverages a rich data set of 220,172 residential PV systems to examine the effects of market concentration on PV prices. It builds on previous studies through a strong grounding in economic theory, an improved econometric method for estimating the relationship between market concentration and prices, and a novel approach to defining market boundaries that more accurately reflect the PV price formation process.

The results show PV prices decline as markets become more concentrated in most PV markets in the United States. The results support the hypothesis that installers reduce costs through experience and returns to scale, and that the price-reducing benefits of installer scale outweigh the price-increasing effects of reduced competition in concentrated markets. Policymakers may be able to leverage the price-reducing benefits of installer scale through policies to help move small- and mid-scale installers up learning curves, policies that connect customers to small- and mid-scale installers to help these installers scale, and policies to foster experience spillovers from established installers to small- and mid-scale installers. Solarize campaigns are discussed as an example of a policy that increases installer scale while, at least temporarily, constraining competition. At the same time, the results show that the relationship reverses in highly concentrated markets, so that prices increase as already concentrated markets become more concentrated. Collectively, the findings suggest that prices are minimized through an optimal balance of market concentration and competition.

Though shifting market share from smaller- to larger-scale installers may reduce PV prices, this dynamic entails important nuances. Surprisingly, the data show small-scale installers or PV "dabblers"—installers operating at a scale equal to or less than one system per month—offer lower prices, on average, than mid-scale and established installers. Dabblers may represent companies that also offer related services such as electrical contracting, general contracting, and roofing. And, they may be able to offer lower PV prices by recouping fixed costs through revenues from other lines of business. Hence, while large-scale installers may reduce costs through experience and scale, small-scale PV dabbling may be a complementary strategy to increase PV market efficiency. Future research will explore these hypotheses and their policy implications.

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1 Introduction

The U.S. residential solar photovoltaic (PV) installation industry grew from less than 100 firms in 2000 to about 3,000 firms by 2016. During that time, some installers amassed large market shares by installing hundreds or thousands of systems per year, though the majority of installers installed fewer than 50 systems per year. The distribution of market shares among competing firms is known as market concentration. A market with many low-volume firms is said to be unconcentrated, while a market with fewer but higher-volume firms is said to be concentrated (Figure 1). In general, residential PV markets have become more concentrated over time (O'Shaughnessy 2018). Market concentration could affect residential PV prices in several ways. On the one hand, market concentration could reduce competition and allow installers to bid higher price markups, thus increasing PV prices. On the other hand, higher-volume installers in concentrated markets might reduce costs through returns to experience and scale, thus reducing prices. Understanding the effects of market concentration on PV prices may guide policies for residential PV price reduction, which will be necessary to ensure the ongoing contribution of residential PV to energy and environmental policy objectives.

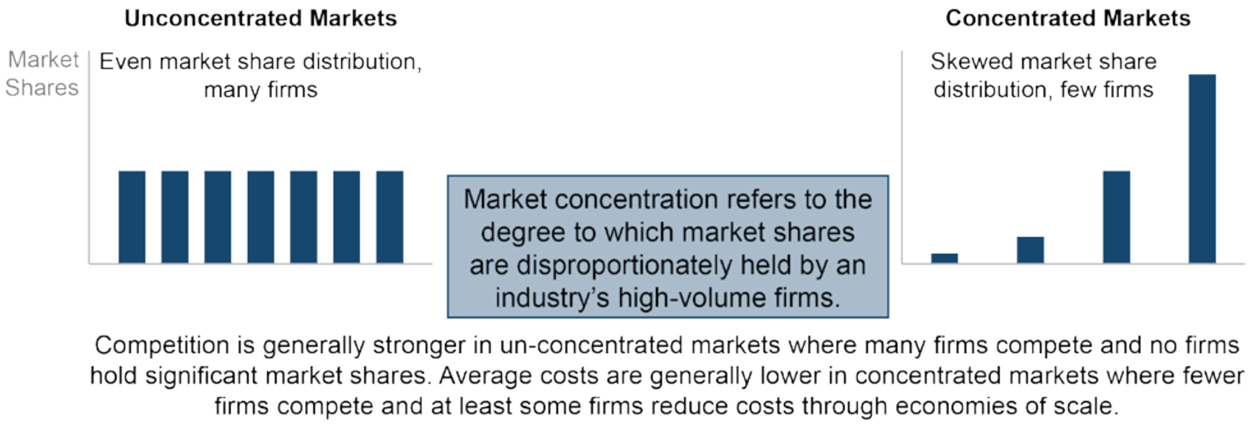

Figure 1. Schematic showing differences between unconcentrated and concentrated markets

Though PV prices have fallen significantly (Barbose and Darghouth 2017), the marginal value of PV also declines as more PV capacity is added to the grid (Mills and Wiser 2015; Sivaram and Kann 2016). As a result, PV prices must fall at least as quickly as the marginal social value of PV falls with additional deployment; otherwise, PV may become cost-prohibitive even at prices that are low relative to current prices (Sivaram 2018). Historical PV price reductions are attributable primarily to reductions in the costs of PV hardware, such as modules and inverters (Barbose and Darghouth 2017; Fu, Feldman et al. 2017). However, further price declines will require reductions in soft costs (Ardani, Seif et al. 2013; Schmalensee, Bulovic et al. 2015; Woodhouse, Jones-Albertus et al. 2016). Encouraging efficient PV markets to reduce soft costs such as markups and installation labor could provide a key policy pathway for future PV price reductions.

Classical economic theory generally shows that firms charge lower price markups in less concentrated markets (Tirole 1988; Weiss 1989; Perloff, Karp et al. 2007), because marked-up prices are more likely to be undercut in markets where many rivals compete. Though inter-installer competition may yield lower price markups, it does not necessarily yield lower prices if competition also affects installation costs (Demsetz 1973; Peltzman 1977; Dasgupta and Stiglitz 1988; Schmalensee 1988; Azzam 1997). Previous research has shown that installation costs decline as installers learn to improve efficiency through installation experience (Duke, Williams et al. 2005; van Benthem, Gillingham et al. 2008; Gillingham, Deng et al. 2016). Experienced installers may be able to reduce costs further through economies of scale, such as by spreading fixed overhead costs over a larger number of installations. Installation experience and scale are split among fewer installers in concentrated markets, meaning markets with few installers or those in which few installers hold high market shares. As a result, installers may scale and reduce costs more effectively in concentrated than in unconcentrated markets. This framework presents a conundrum: unconcentrated markets may reduce the ability of installers to mark-up prices, but concentrated markets may reduce installation costs. The net effect of market concentration on prices depends on the relationships among installer competition, installer scale, and soft costs.

Earlier research has generally supported the hypothesis that the installer scale benefits of market concentration outweigh the costs of higher price markups. Gillingham et al. (2016) find that residential PV prices are lower in concentrated markets. Similarly, Nemet et al. (2017) find that low-priced systems are more prevalent in concentrated markets. Both of these studies have methodological limitations that may bias the results, as discussed in Section 3. Pless et al. (2017), who provide the first attempt to address the methodological issues, also find an inverse relationship between market concentration and prices. Their study, however, only analyzes a single county and is restricted to third-party owned (TPO) systems (see Section 3 for further discussion of TPO systems).

The present study leverages a rich data set of 220,172 residential PV systems to examine the relationship between market concentration and prices, building on the existing literature in three ways. First, a framework based on economic theory is developed to contextualize the econometric results. The theoretical framework provides the basis for the novel hypothesis that market concentration may have different effects on prices in unconcentrated versus concentrated markets. Second, this study builds on Pless et al. (2017) by applying a more rigorous method to estimate the relationship between market concentration and prices. Third, whereas previous studies relied on county boundaries to estimate market concentration, this study develops a novel approach to defining market boundaries that more accurately reflect the PV price formation process. The use of economic theory—rather than jurisdictional boundaries—should improve the reliability of estimates of the effects of market concentration on prices.

The remainder of this report is organized as follows. Section 2 develops a theoretical framework for the relationship between market concentration and PV prices. Section 3 describes the data and methods for the empirical study. Section 4 provides results. Section 5 discusses the results and offers conclusions.

2 Theoretical Framework

This section develops a theoretical framework to explore possible relationships between market concentration and PV prices. The framework assumes that installers aim to maximize profits by strategically setting prices according to the perceived behavior of rivals. In practice, installers are more likely to apply rough heuristics than sophisticated strategic-pricing techniques. However, even heuristic techniques should yield installer behavior consistent with the framework presented here, given that firm behavior tends to approximate profit maximization, and competitive pressures punish inefficient strategies (Schmalensee 1988). Highly simplified economic models are presented to establish some basic intuition around the implications of the economic theory. Rigorous derivations are available in the citations.

2.1 Strategic Bidding Model

PV installers generate business by submitting installation price quotes to customers. Installers estimate job-specific installation costs for the purposes of quoting. Profit-maximizing installers also add a price markup. The average market price (p) is the sum of the average installation costs (c) and markups (Φ) on accepted quotes. Costs and markups can be written as functions of market concentration ($\mathcal{H}$), such that market prices can be modeled as the following function:

$$p(\mathcal{H}) = c(\mathcal{H}) + \Phi(\mathcal{H}) \tag{1}$$

The objective of this study is to model the effects of market concentration on prices:

$$\underset{\textit{effect on prices}}{\beta_{\mathcal{H}}} = \underset{\textit{effect on costs}}{\beta_{\mathcal{H}\to c\to p}} + \underset{\textit{effect on markups}}{\beta_{\mathcal{H}\to\Phi\to p}} \tag{2}$$

Where $\beta_{\mathcal{H}}$ is the effect of market concentration on prices, $\beta_{\mathcal{H}\to c\to p}$ is the effect of concentration on price via costs, and $\beta_{\mathcal{H}\to\Phi\to p}$ is the effect of concentration on price via price markups.[1]

2.1.1 Installer Experience, Scale, and Installation Costs

PV installers reduce costs through experience in a process known as learning-by-doing or simply learning (Duke, Williams et al. 2005; van Benthem, Gillingham et al. 2008; Bollinger and Gillingham 2014). Experienced installers may also reduce costs through economies of scale such as spreading fixed overhead costs over a larger number of installations. Because the implications of returns to experience and scale are generally similar (Spence 1981), the term *scale* is used hereafter to capture both concepts, unless otherwise noted. A key implication of returns to scale is that installers reduce costs as they accumulate market share. All else equal, average installation costs are thus lower in markets where more systems are installed by large-scale installers, i.e., in concentrated markets. Given that installer offer prices correlate positively with installation costs, the predicted effect of market concentration on prices via installation costs is negative:

$$\beta_{\mathcal{H}\to c\to p} < 0 \tag{3}$$

[1] Technically: $\beta_{\mathcal{H}} = \frac{dp}{d\mathcal{H}} = \frac{dp}{dc}\frac{\partial c}{\partial \mathcal{H}} + \frac{dp}{d\Phi}\frac{d\Phi}{d\mathcal{H}}$

Returns to learning are diminishing (Arrow 1962), suggesting that inexperienced installers generally learn more from each additional system installed than do experienced installers. Returns to scale may also be diminishing, especially in terms of customer-acquisition costs (Fu, Feldman et al. 2017; Mond 2017). Small-scale installers tend to rely on word-of-mouth or low-cost referrals to acquire customers, whereas large-scale installers must use higher-cost methods such as lead purchasing to sustain high sales volumes. Diminishing returns complicate the simplified relationship represented by Equation (3). The extent to which Equation (3) holds depends on the scale at which installers exhaust returns to scale, known as the minimum efficient scale (MES). Equation (3) should generally hold as long as the MES is large relative to market size (Ornstein, Weston et al. 1973; Schmalensee 1988). An empirical estimate of the MES for residential PV installation is unavailable in the literature. According to the midpoint firm size method proposed by Weiss (1963), the MES in the residential PV industry in 2016 was about 230 systems installed per year.[2] According to another proxy proposed by Comanor and Wilson (1967), the MES was about 660 systems per year.[3] Though these rough proxies are subject to scrutiny (Davies 1980), they suggest the MES is on the order of hundreds of systems per year.[4] If so, more than 90% of PV installers install fewer than 100 systems per year and hence operate below the MES, and most installers operate far below the MES. In 2016, about 87% of installers installed fewer than 50 systems, and about 63% of installers installed fewer than 10 systems.

An additional argument in favor of the relationship in Equation (3) is that installers that innovate and reduce costs are more likely to accrue scale and experience than are less efficient installers. Market concentration, in this line of reasoning, reflects the accrual of market shares by the most efficient installers (Demsetz 1973; Peltzman 1977; Klepper and Graddy 1990). Though speculative, this intuitive relationship between market concentration and efficiency would establish a relationship consistent with Equation (3) without appealing to returns to scale.

2.1.2 Installer Competition and Price Markups

All firms set prices equal to marginal costs in perfectly competitive markets. The ability of a firm to add a price markup is evidence of imperfect competition, showing that the firm has some market "power" to set prices above costs (Tirole 1988; Perloff, Karp et al. 2007). In theory, all PV installers wield market power, because PV is a search good (Stigler 1961): customers must spend time and effort to obtain quotes, and generally satisfice by selecting an installer offer after obtaining one to five quotes (Moezzi, Ingle et al. 2017; EnergySage 2018). PV installers must only compete against the rival installers that submit quotes for any given customer; hence installers can mark up prices higher than they otherwise would if customers obtained quotes from all potential installers. Several studies find evidence of installer market power (Bollinger, Gillingham et al. 2017; O'Shaughnessy and Margolis 2017; Pless and van Benthem 2017).

[2] Weiss's proxy is the smallest firm size among the industry's largest companies accounting for 50% of all sales.
[3] Comanor and Wilson's proxy is the mean firm size among the industry's largest companies accounting for 50% of all sales. Both of these proxies were estimated using data described in Section 3. The estimates provided are based on customer-owned systems only. The same proxies calculated for TPO systems yield MESs on the order of thousands of installations per year.
[4] A PV installation generally takes 1-2 days to complete. A scale of 100 systems per year thus implies about 100–200 days of installer activity. Scales below 100 systems per year generally imply that installers are inactive for much of the year. However, some installers may generate revenue by offering other related services, as discussed further in Section 5.

Economic theory generally suggests that firms possess less market power in unconcentrated markets (Tirole 1988; Perloff, Karp et al. 2007). Applying this theory in the context of PV suggests that PV price markups should be higher in concentrated markets:

$$\beta_{\mathcal{H}\to\Phi\to p} > 0 \tag{4}$$

There are at least two other plausible but more speculative routes to the same conclusion. First, customers may perceive differentiated qualities between installers, especially given the important role of installer trustworthiness in adoption decision making (Rai, Reeves et al. 2016; Moezzi, Ingle et al. 2017). Customers may attribute reputational values to large-scale installers with more experience and brand names (Scitovsky 1950; Nelson 1974; Rao and Monroe 1989; Bollinger and Gillingham 2014). To the extent that large-scale installers enjoy reputational advantages, those installers may wield more market power, such that shifting market shares to large-scale installers should establish the relationship in Equation (4). Second, large-scale installers may use large customer-acquisition budgets to preempt smaller-scale competitors by actively manipulating customer search levels. This hypothesis is supported by findings that large-scale installers invest more per watt installed in customer acquisition than do their smaller-scale rivals (Fu, Feldman et al. 2017; Mond 2017). Large-scale installers' use of higher customer-acquisition budgets to increase market power would establish a relationship consistent with Equation (4). However, as discussed in Section 2.1.1, the higher customer-acquisition costs may simply reflect diseconomies of scale.

2.2 Synthesis

The frameworks in Section 2.1 provide predicted signs on the two effects from Equation (2):

$$\begin{array}{rcccc} & \beta_{\mathcal{H}} = & \beta_{\mathcal{H}\to c\to p} & + & \beta_{\mathcal{H}\to\Phi\to p} \\ \textit{predicted effect:} & & - & & + \end{array} \tag{5}$$

The model presented in Equation (5) suggests that the effects of market concentration on PV prices depend on the magnitude of the effects of installer scale on costs and the effects of competition on price markups. This model provides a basis for two competing hypotheses:

> ***Hypothesis 1: Concentrated markets yield lower prices if the price-reducing effects of installer scale dominate the price-increasing effects of market power at currently observed levels of market concentration.***

> ***Hypothesis 2: Unconcentrated markets yield lower prices if the price-increasing effects of market power dominate the price-reducing effects of installer scale at currently observed levels of market concentration.***

In addition to strict inverse or positive relationships, a third potential outcome is a non-monotonic relationship, meaning that market concentration may be price-reducing at certain levels of market concentration and price-increasing at other levels of concentration. Non-monotonic effects would arise if the price-reducing effects of installer scale dominate over some range of market concentration, but the relationship inverts over another range of concentration. Given diminishing returns to scale, the price-reducing effects of installer scale may likewise diminish with increasing market concentration. Given findings that price markups fall exponentially with competition (O'Shaughnessy and Margolis 2017), the price-increasing effects of market power may increase with increasing market concentration. In other words, the effects of installer scale may be strong in unconcentrated markets and weak in concentrated markets, while the effects of market power may be weak in unconcentrated markets and strong in concentrated markets. This framework provides the basis for a third hypothesis:

> ***Hypothesis 3: Prices inversely correlate with market concentration at low concentration levels owing to the price-reducing effects of installer scale, but positively correlate with market concentration at high concentration levels owing to the price-increasing effects of market power.***

Figure 2 depicts this possible non-monotonic relationship. Evidence of a relationship consistent with Hypothesis 3 would suggest that prices are minimized through some optimal balance of competition (low market concentration) and installer scale (high market concentration). The following section describes the data and methods uses to test these hypotheses.

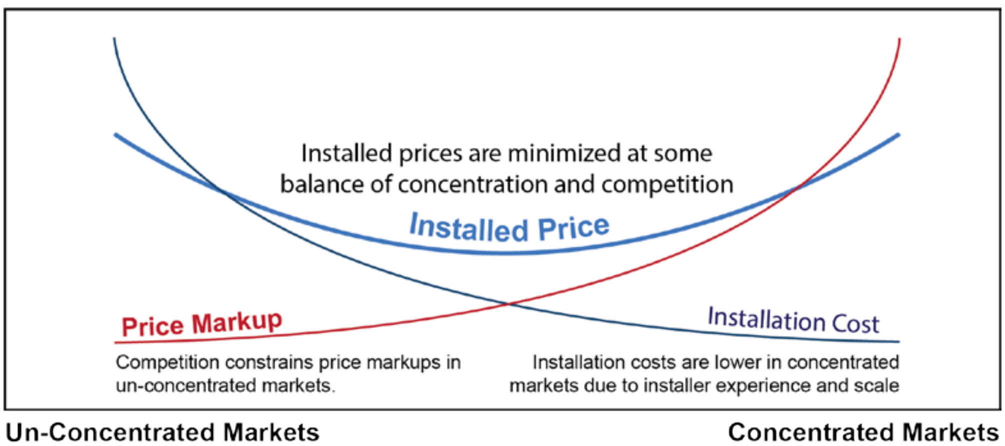

Figure 2. Hypothetical non-linear effect of market concentration on PV prices

3 Data, Descriptive Statistics, and Methods

Customer-level data for this study are from Lawrence Berkeley National Laboratory's *Tracking The Sun* (TTS) data set (Barbose and Darghouth 2017). TTS aggregates data from more than 60 state and utility incentive programs. The full TTS data set covers more than 80% of the U.S. PV market, making it the most comprehensive extant U.S. PV data set. See Barbose and Darghouth (2017) for a more complete description of the data.

Observations with installed prices below $1/W or above $25/W and observations with system sizes smaller than one kilowatt were dropped as likely data-entry errors. To ensure all observations represent residential customers, observations that self-reported as non-residential were dropped, as were all systems larger than 15 kW. Observations without a valid installer name and owner-installed systems were dropped. Observations without a valid zip code or with zip code coordinates unavailable in the U.S. Census database of zip code centroid coordinates were dropped.[5] Observations without information about system hardware, which is needed to control for hardware costs, were also dropped. Observations without a valid reported utility name or with utility rate information unavailable from the Utility Rate Database were dropped. Last, observations associated with four types of premium products were dropped: systems integrated into building materials, systems with tracking capabilities, systems using thin film PV, and systems integrated with batteries. In these case, prices may vary due to price differences in the premium products in ways that are not adequately controlled for through a dummy variable. Fewer than 2% of systems incorporate these premium products.

The econometric model (Section 3.3) in this study measures the effects of market concentration on installed PV prices paid by residential customers. In the United States, roughly half of residential PV customers procure PV through TPO financing. In the TPO model, customers make ongoing payments for PV output rather than an upfront system purchase. These ongoing payments could be annualized and converted into an installed price, but ongoing payment amounts are not reported to incentive programs and thus are not included in the TTS data. Instead, TPO prices in the TTS data represent the installed price paid by the third-party system owner or an appraised value estimating the installed price when the installer is also the system owner.

Previous studies have dropped appraised values while retaining the intermediate transaction prices paid by third-party system owners (Gillingham, Deng et al. 2016; Barbose and Darghouth 2017; Nemet, O'Shaughnessy et al. 2017). The rationale behind this approach is that intermediate prices still reflect real transaction prices and thus convey meaningful information about price determinants. The drawback is that all coefficients on price determinants reflect the aggregate effects of the determinants for the two transaction types. To illustrate the problem, consider a typical PV price model structure:

$$p = \mathcal{H}\beta_{\mathcal{H}} + \boldsymbol{X}\beta + \varepsilon \tag{6}$$

[5] Zip code centroid coordinates are required for the market definition approach. Centroids refer to the coordinates at the geographic center of each zip code. Zip code centroid coordinates from the U.S. Census were available for more than 99% of observations.

Where p is a vector of end-user and intermediate prices, $\mathcal{H}$ is market concentration, and $\boldsymbol{X}$ is some matrix of control variables. The coefficient $\beta_{\mathcal{H}}$ must be interpreted as the aggregate effect of concentration in both the end-user and intermediate markets on prices in both markets. The value of this coefficient is limited if concentration has heterogeneous effects on prices in the two markets, in which case an interaction term would be necessary to tease out the heterogeneous effects. Yet even this approach must implicitly assume that all the relationships in $\boldsymbol{X}$ are equal in the two markets, further complicating the validity and usefulness of the approach.

For these reasons, this study excludes data from TPO transactions. Any effects of TPO penetration on customer-owned system prices are controlled for through a TPO variable described in Section 3.3. See Pless et al. (2017) for a similar study applied to TPO systems. The elimination of TPO observations effectively eliminates about half of the data set. However, the focus on customer-owned rather than TPO systems can be justified by market trends. The TPO share of annual U.S. residential PV fell from about 72% in 2014 to 52% in 2016, and is projected to decline to about 28% by 2020 (Litvak 2016; Perea, Honeyman et al. 2017). The results of this study should be increasingly representative of the relationship between market concentration and PV prices as markets pivot toward customer ownership.

The final data set comprises 220,172 customer-owned residential PV systems installed from 2010 to 2016 in 13 states. This represents about 20% of residential PV systems installed in the United States in that timeframe. About 68% of systems in the data were installed in California, so the results are largely driven by dynamics in California, which is consistent with other PV studies. Arizona, California, Massachusetts, New Mexico, and New York collectively account for 91% of the data. State fixed effects are used to control for geographic differences in prices.

3.1 Market Definition

Market concentration measurements are sensitive to the approach used to define market boundaries. Previous PV market studies have used county boundaries to approximate market boundaries. However, jurisdictional boundaries do not necessarily reflect the underlying economic forces that should guide market definition (Stigler and Sherwin 1985; Brooks 1995; Geroski 1998; Davis and Garces 2010). Specifically, market boundaries should reflect the areas within which prices are determined (Stigler and Sherwin 1985). For any given customer, PV prices are determined by the bidding strategies of the installers that are active in the customer's vicinity (O'Shaughnessy, Nemet et al. 2018).

Building on this theory, this study takes a novel approach by defining a customer's market as the group of zip codes that fall within a given radial distance of the customer's zip code (Figure 3). The theoretical basis is that the geographic area around a customer comprises the group of installers that could bid to the customer and therefore defines the potential prices offered to the customer. O'Shaughnessy et al. (2018) develop an approach to identify groups of installers competing in geographic space. The median market size from that study for markets with more than 100 systems installed was 11 zip codes.[6] Conceptually, this result implies that an area of approximately 11 zip codes comprises the group of installers that could bid to a typical customer.

[6] Limiting the analysis to markets with more than 100 systems installed eliminates smaller fringe markets that may not represent the market environments of most customers. Sensitivity analyses are provided in Section 4.2 to test the robustness of results to other market boundary specifications.

In the full TTS data set, the mean distance in sets of 11 zip codes between the central zip code and the furthest zip code is about 17 km, based on zip code centroid coordinates. Based on this distance, geographic boundaries are defined for all customers based on the set of zip codes that fall within 17 kilometers of the customer's zip code (Figure 3).[7]

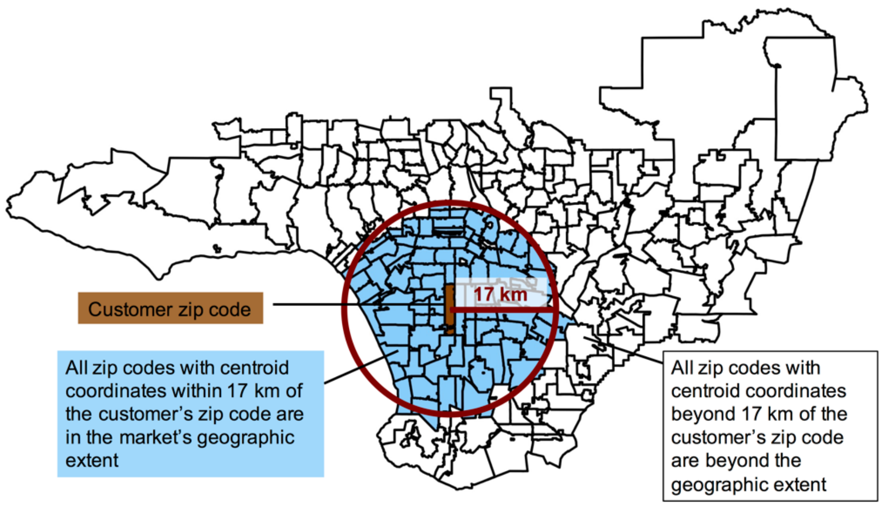

Figure 3. Visualization of the market definition for an example of a zip code in southern Los Angeles County

Consistent with previous studies (Gillingham, Deng et al. 2016; Nemet, O'Shaughnessy et al. 2017; Nemet, O'Shaughnessy et al. 2017), systems installed within the 12 months prior to time *t* are considered within the market of a customer with installation at time *t*. Based on the geographic and temporal restrictions, the market definition approach for this study is defined as follows:

> The market of a customer in zip code **z** with installation at time **t** is defined as the group of installers active in the set of zip codes within 17 km of **z** and within 12 months before time **t**.

The choice of the geographic market size may influence market concentration measurements, and the estimate based on a 17-km radius might overestimate or underestimate the true market size. Sensitivity analyses with markets defined at 10 km and 50 km are provided in Section 4.2. A potential limitation of this approach is that market sizes may vary based on local factors such as population density and transportation infrastructure. Future research may study how these local factors affect market size.

[7] Zip codes can vary significantly in geographic size. The use of the distance criterion rather than the number of zip codes ensures that all markets are roughly the same geographic size.

3.2 Market Concentration

To simplify discussions of market concentration, installers are organized into the four scales summarized in Table 1. "Singletons" are companies that installed a single system, while "dabblers" are companies that operate on a scale of less than one install per month.[8] These small-scale companies are likely not dedicated PV installation firms, rather they may be companies from related service industries that occasionally install PV as a side business. For instance, all licensed electricians and general contractors are allowed to install PV in California, hence pre-existing companies can relatively easily dabble in PV installations without dedicating themselves to PV installation. The term *established installer* is used to refer to installers operating above 10 installs per month. An analysis of the market shares of the installer scale groups shows that PV markets are somewhat concentrated. About 52% of installers are dabblers, but these installers only account for about 15% of systems in the data. In contrast, only about 1% of installers are established, yet these installers account for about 39% of systems installed in the data.

Table 1. Breakdown of Installer Scales

Scale	Definition	% of Installers	% of Systems
Singleton	Single install	29	0.7
Dabbler	≤1 install/month	52	15
Mid-Scale	2–10 installs/month	18	46
Established	> 10 installs/month	1	39

The Herfindahl-Hirschman Index (HHI) is a unitless metric used to quantify market concentration. The HHI is equal to the sum of squared market shares of all installers in a given market in the year prior to a given installation. The HHI approaches zero in highly unconcentrated markets and takes on a maximum value of one in markets with a single installer. The HHI is the most common metric applied in econometric research owing to several desirable properties (Weiss 1989). Importantly, the HHI always increases when market shares shift toward larger-scale firms, and it always decreases when more firms enter the market, all else being equal (Tirole 1988).

To establish some intuition around the interpretation of the HHI, Figure 4 illustrates the breakdown of installer scales across HHI levels.[9] The figure breaks markets into three concentration levels based on U.S. Department of Justice standards: low concentration (HHI < 0.15, 77% of systems), medium concentration (0.15 ≤ HHI ≤ 0.25, 12% of systems), and high concentration (HHI > 0.25, 11% of systems). The figure is limited to markets with more than 100 systems installed per year.[10] It shows how established installers hold greater market shares in more concentrated markets. Established installers account for about 41% of systems installed in unconcentrated markets but about 57% of systems in highly concentrated markets.

[8] The terms singletons and dabblers are used for the purposes of this report, the terms are not accepted technical or industry standards.
[9] Installations per month were calculated by the total number of systems installed by an installer divided by the total number of months the installer is present in the data set. The small-scale category includes installers that installed a single system.
[10] Small markets tend to have high HHI measurements, given that even small-scale installers tend to hold high market shares when the overall market size is small.

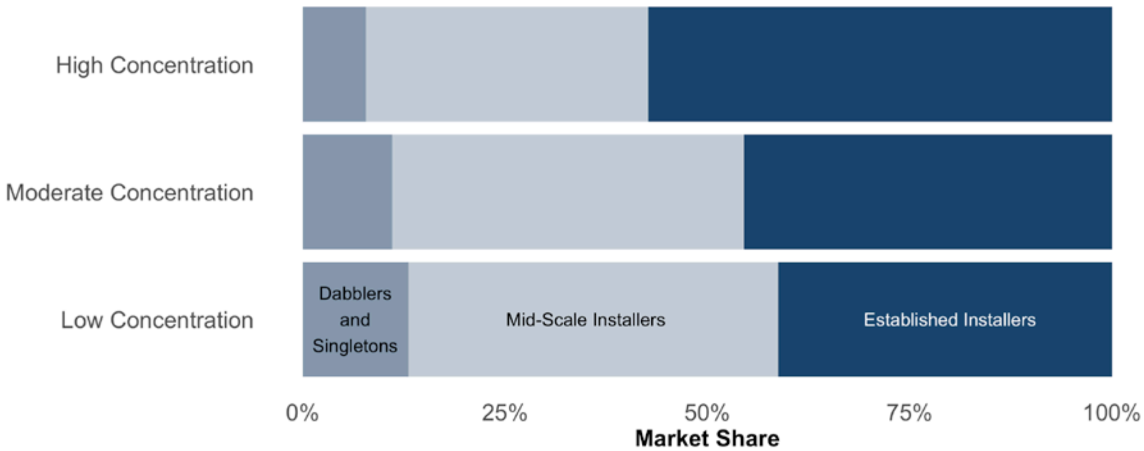

Figure 4. Breakdowns of installer scales by market concentration levels

Limited to markets larger than 100 systems/year (77% of systems)

Figure 5 illustrates the benefits of the customer-centric market definition used in this study, using four counties in eastern Massachusetts for illustrative purposes. The left pane of Figure 5 illustrates HHI calculated at the county level, while the right pane illustrates HHI calculated relative to the customer's location. Defined at the county level, HHI is uniform across large geographic expanses, shows sharp discontinuities at county borders, and masks within-county variation. In contrast, the customer-centric definition allows for improved granularity in HHI measurement and reduces border discontinuities, such that HHI is spatially correlated.

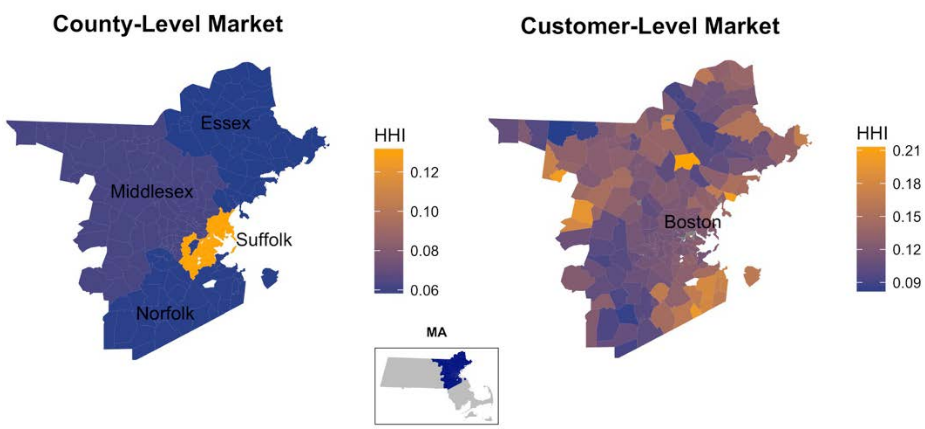

Figure 5. Comparison of market concentration estimates (HHI) in county-level versus customer-level market definitions

Gray areas in right pane reflect zip codes with no systems

Figure 6 illustrates measurements of market concentration (left) and installed system prices (right) over geographic space in three PV-heavy regions. The figure provides some intuition behind the research questions and methods of this study. A relationship between HHI and prices can be estimated by evaluating the correlation of the two variables over geographic space while controlling for other factors. For example, in the greater Phoenix area, the area north of the urban core is associated with relatively high market concentration and relatively low prices. The econometric model developed in the following section evaluates such correlations for all markets in the data set.

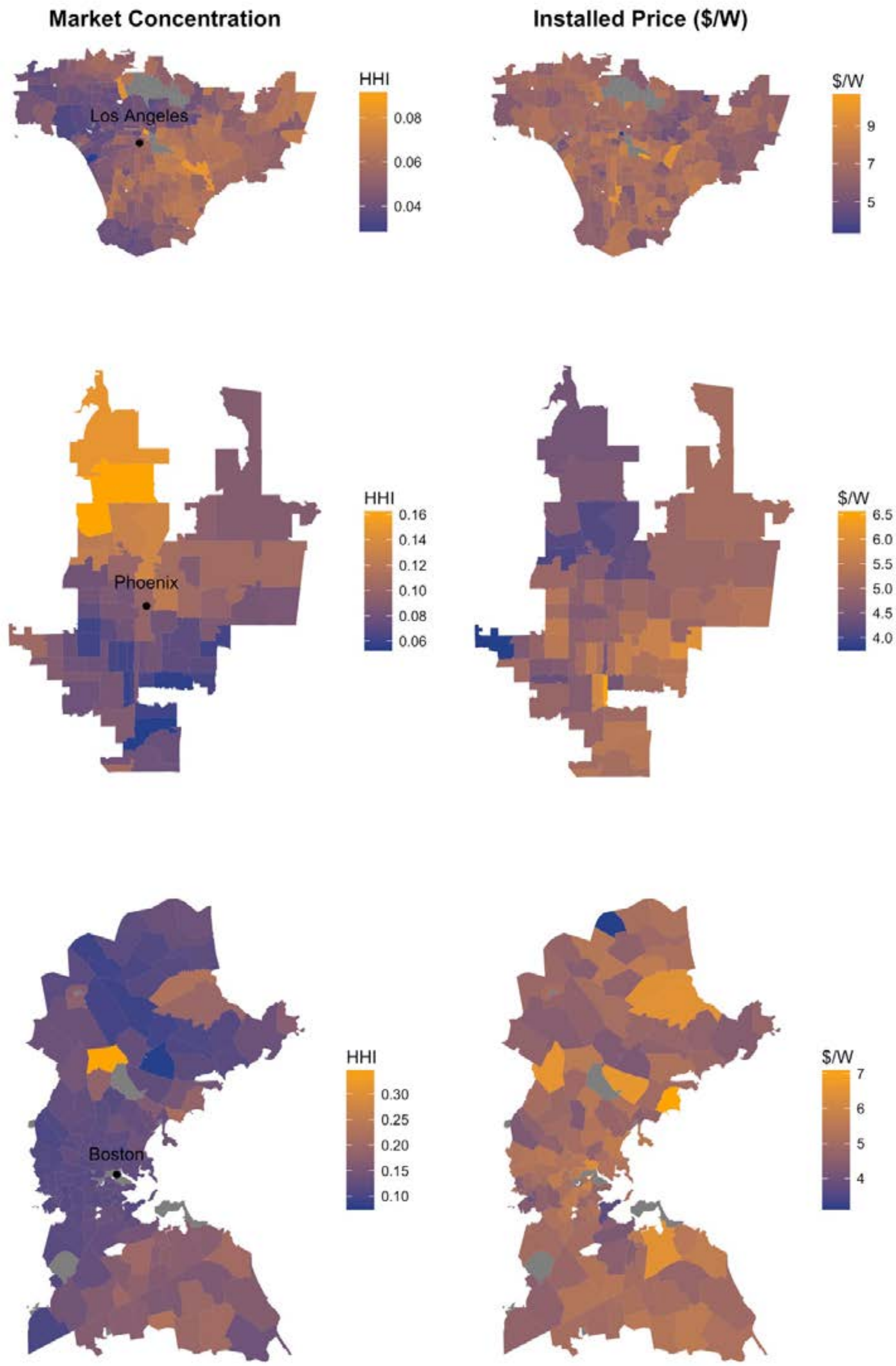

Figure 6. Mean market concentrations and installed prices in three sample regions

3.3 Model Framework

The econometric model takes the general form:

$$p = \mathcal{H}\beta_{\mathcal{H}} + \boldsymbol{X}\beta + \varepsilon \qquad (7)$$

Where $\mathcal{H}$ is HHI, $\beta_{\mathcal{H}}$ is a coefficient estimating the effect of changes in HHI on prices, and $\boldsymbol{X}$ is a matrix of control variables. Hypothesis 1 predicts that the price-reducing effects of installer scale dominate at currently observed levels of market concentration, so $\beta_{\mathcal{H}}$ will be negative. Hypothesis 2 predicts the opposite result with a positive $\beta_{\mathcal{H}}$ coefficient. To test Hypothesis 3, the term $\mathcal{H}$ is converted to a vector including the squared term of HHI, and two coefficients are estimated in $\beta_{\mathcal{H}}$ for the two orders of HHI. Hypothesis 3 predicts that the first order of $\beta_{\mathcal{H}}$ will be negative (price-reducing), while the second order of $\beta_{\mathcal{H}}$ will be positive (price-increasing).

The matrix of control variables $\boldsymbol{X}$ is based largely on the models described in Gillingham et al. (2016) and Nemet et al. (2017). The controls include market, policy, demographic, and system variables (Table 2). See the appendix for detailed information about the control variables. To control for the influence of TPO penetration on prices for customer-owned systems, an additional TPO variable was generated equal to the percentage of systems in the customer's market that used the TPO model. State fixed effects are used to control for unobservable differences across geographies. Standard errors are clustered at the utility level to control for additional variation at the utility level due to unobserved differences in rate structures. Quarterly fixed effects and hardware cost indices are used to control for changing PV prices over time. The system variables included in the model control for hardware-related costs such as module and inverter costs.

Table 2. Summary Statistics for Regression Variables (N = 220,172)

	Mean	Std Dev	Min	Max	Source
Pre-incentive Installed Price					
price (2016$/W)	5.21	2.06	1.00	24.98	TTS
Market Concentration					
HHI	0.12	0.13	0.02	1.00	calculated
Market Variables					
market size (x 1,000 aggregate installations)	0.73	1.08	0	7.27	calculated
installer experience (x 1,000)	0.76	1.70	0	12.99	calculated
TPO penetration	0.44	0.23	0	0.99	calculated
Policy Variables					
NPV utility bill savings ($/W)	3.76	1.27	0.24	6.75	calculated
up-front incentives ($/W)	0.50	0.72	0.00	10.23	TTS
NPV ongoing incentives ($/W)	0.24	0.71	0.00	3.77	TTS
sales tax per watt	0.09	0.08	0.00	0.31	TTS
Demographic Variables					
household density (1,000 hh/mi^2)	1.05	1.56	0	35.6	Census
% high school grad to AD	50.8	12.85	0	100	Census
% bachelor's or above	38.3	17.88	0	100	Census
% $25k–$44,999	18.4	6.41	0	100	Census
% $45k–$99,999	29.0	5.80	0	100	Census
% >$100k	36.6	15.63	0	100	Census
local labor cost ($/week)	849.70	130.00	331.00	1,279.75	BLS
System Variables					
system size (kW)	5.96	2.80	1.00	15.00	TTS
module efficiency	0.17	0.02	0.06	0.22	TTS
new construction dummy	0.06	0.24	0	1	TTS
inverter price index ($/W)	0.24	0.09	0.16	0.46	*
module price index ($/W)	0.92	0.35	0.65	1.95	*

* Composite indices compiled from GTM and Bloomberg.

AD = associate's degree, BIPV = building-integrated PV, BLS = Bureau of Labor Statistics, hh = households, NPV = net present value, PBI = performance-based incentive

The model described in Equation (7) attempts to estimate the effects of market concentration on prices. The causal direction may also be reversed: prices can affect market concentration by affecting installer decisions to enter and exit certain markets (Clarke and Davies 1982; Klepper and Graddy 1990; Evans, Froeb et al. 1993; Perloff, Karp et al. 2007; Singh and Zhu 2008). The potentially simultaneous relationship between prices and market concentration violates necessary assumptions in order for standard regression to yield valid estimates. Two-stage models are commonly used to address this simultaneity (Geroski 1982; Kelton and Weiss 1989; Delorme, Kamerschen et al. 2002; Resende 2007; Manuszak and Moul 2008; Singh and Zhu 2008; Pless, Langheim et al. 2017). The basic concept of a two-stage model is to identify variables called *instruments* that correlate with the simultaneously caused variable but do not directly correlate with the dependent variable. The relationship between the instrument and the problematic variable is estimated through a system of equations:

$$p = \mathcal{H}\beta_{\mathcal{H}} + \boldsymbol{X}\beta + \varepsilon \tag{8}$$

$$\mathcal{H} = \boldsymbol{Z}\alpha_Z + \boldsymbol{X}\alpha + \varepsilon_{\mathcal{H}}$$

Where $\boldsymbol{Z}$ is some matrix of instruments that affect market concentration but do not directly affect prices.

Valid instruments correlate with HHI but do not correlate with prices when conditioned on the variables in Equation (7). The number of firms from related services (e.g., roofing, HVAC installation) should meet these criteria, because many PV installers emerge from related service industries (EnergySage 2018), but the number of these firms should not directly correlate with prices. Potentially problematic correlation between the number of related-service firms and PV market size (more firms will generally be found in larger markets) should be addressed through the control variables for market size and household density in Equation (7). According to one survey, about 40% of PV installers continue to offer electrical contracting services (EnergySage 2018). Further, electrical contracting and PV installation are classified under the same North American Industry Classification System (NAICS) code. Hence the number of electrical contracting firms may correlate with prices even after conditioning on HHI, given the ongoing links between PV installation and electrical work. The instrument is therefore restricted to the number of roofing (NAICS 238160) and HVAC (NAICS 238220) contractors.[11]

The number of related-service firms inversely correlates with PV market concentration, as expected (Figure 7, left pane).[12] However, the relationship is relatively weak at low concentration levels owing to the skewed distribution of the instrument, which takes on very large values in some urban areas. For instance, all the points above 700 related-service firms in Figure 7 correspond to customers in the New York City area. The correlation between PV HHI and the instrument is greatly improved by taking the logarithm of the number of related service firms (Figure 7, right pane).[13] The logarithm places less weight on some of the extreme values of the instrument in urban areas such as New York City.

[11] Based on data from U.S. County Business Patterns (CBP). Year 2016 CBP data were unavailable at the time of publication. Year 2015 data were used as a proxy, given that the CBP data do not generally change significantly year over year.

[12] EnergySage (2018) survey data suggest that PV installation is most closely related to electrical contracting. However, PV installers are classified as electrical contractors in the CBP data. As a result of this classification, the correlation between the number of electrical contractors and PV market concentration is not necessarily exogenous. Electrical contractors are therefore excluded from the instrument.

[13] The instrument value was equal to zero for less than 1% of observations. The logarithms of these observations were set to zero to avoiding dropping observations owing to missing values.

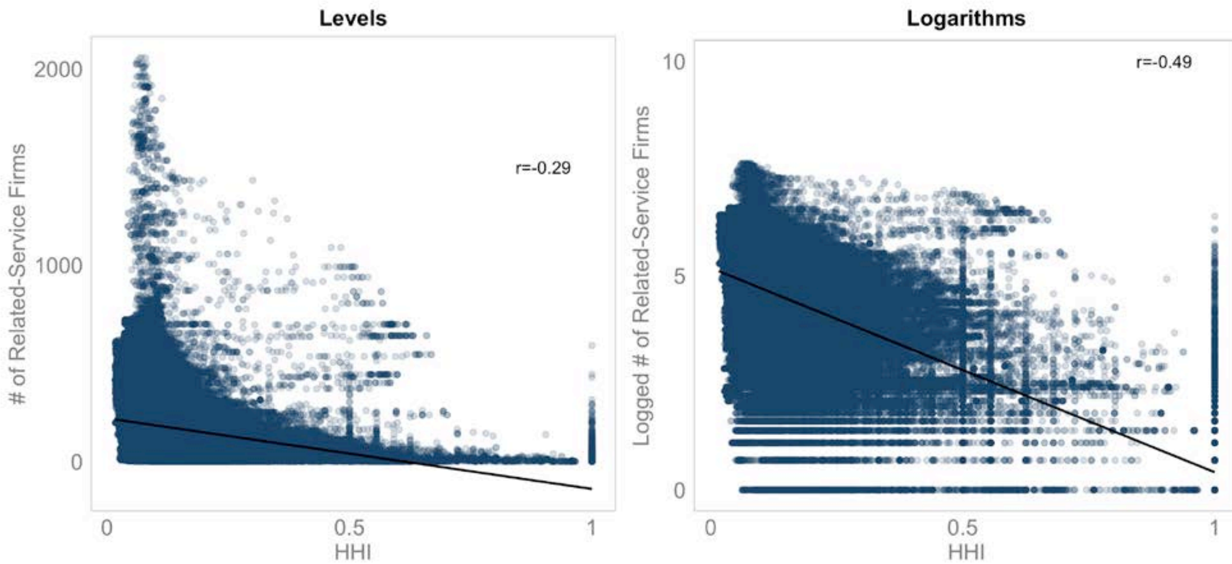

Figure 7. Correlations of instrument level (left pane) and logarithm (right pane) with HHI

An additional instrument is necessary for regressions that test non-monotonic effects through a squared HHI term. One candidate is the squared term of the number of related-service firms (Haans et al. 2016). The left pane of Figure 8 shows the relationship between the squared level of the number of related-service firms and the squared term of PV HHI. The skew of the original instrument's distribution is exacerbated when examining the squared terms, weakening the correlation. The right pane of Figure 8 shows how the correlation is significantly improved by comparing the squared term of the logarithm of the number of related-service firms with PV HHI.

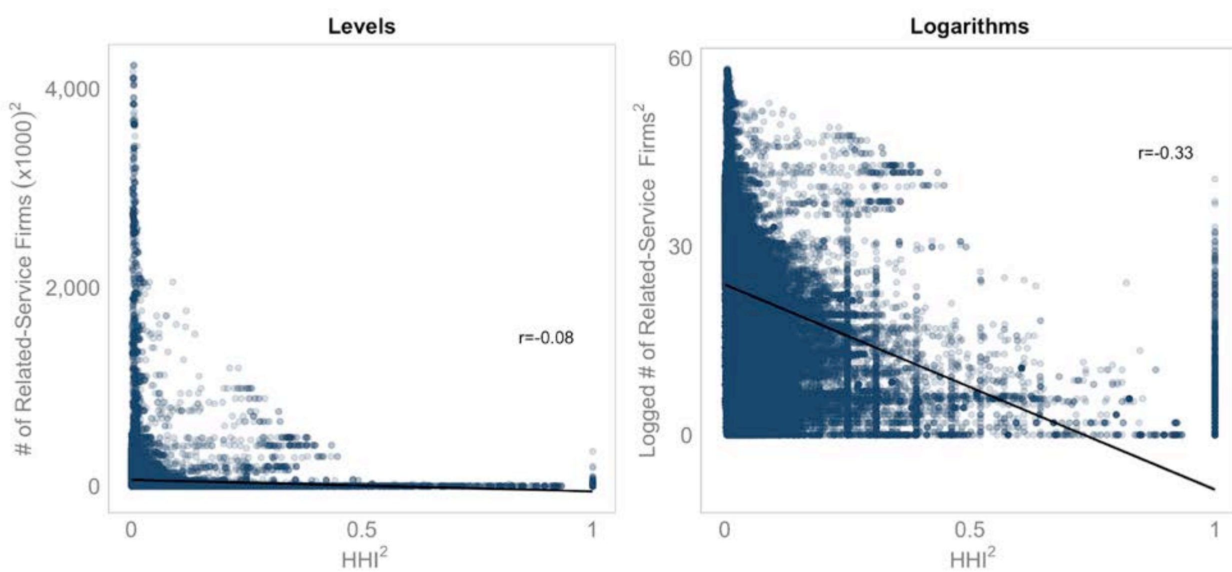

Figure 8. Correlations of second-order terms of instrument level (left pane) and logarithm (right pane) with HHI

To yield consistent results, the relationship between the problematic variable (HHI) and the instrument (number of related-service firms) must be sufficiently "strong." The strength of the relationship can be tested by comparing the F statistics of two first-stage models through a Wald F test (Stock and Watson 2007; Kennedy 2008). The first stage models are:

$$\widehat{\mathcal{H}}_0 = \boldsymbol{X}\hat{\alpha} \quad , \quad \widehat{\mathcal{H}}_{\mathcal{N}} = \mathcal{N}\widehat{\alpha_\eta} + \boldsymbol{X}\hat{\alpha} \tag{9}$$

Where $\mathcal{N}$ is the number of roofing and HVAC contractors in the customer's market.

Any difference in the F statistic between $\widehat{\mathcal{H}}_0$ and $\widehat{\mathcal{H}}_{\mathcal{N}}$ can be attributed to the explanatory power of the instrument. Table 3 shows the Wald F test results for the levels, logarithms, and squared terms of the instruments. A large Wald F suggests that the proposed instrument provides additional explanatory power in the models in (9) such that the correlation between HHI and the instrument is sufficiently strong. The Wald F results show that the logarithmic form of the instrument greatly increases the explanatory power of the instrument, especially for the non-linear model, consistent with the relationships depicted in Figure 7 and Figure 8. The logarithms rather than the levels are thus used as the instrumental variables.

Table 3. Wald Statistics for Instrument Strength

Problematic Variable	Instrument	Wald F
HHI	$\mathcal{N}$	8,662*
HHI+HHI2	$\mathcal{N} + \mathcal{N}^2$	30*
HHI	$\log(\mathcal{N})$	45,000*
HHI+HHI2	$\log(\mathcal{N}) + \log(\mathcal{N})^2$	4,510*

* Statistically significant ($p < 0.05$) Cragg-Donald Wald F statistic with utility-clustered and heteroskedasticity robust standard errors, estimated with the ivreg2 package in Stata.

The predicted market concentration variable in Equation (9) is then used to estimate the effects of market concentration on prices in a two-stage least squares (2SLS) regression:

$$p_{2S} = \widehat{\mathcal{H}}\beta_{\mathcal{H}2S} + \boldsymbol{X}\beta_{2S} + \varepsilon \tag{10}$$

Where the subscript $2S$ denotes that this model is the second stage of the 2SLS. The coefficient $\beta_{\mathcal{H}2S}$ provides the estimated effects of market concentration on price while controlling for the possible simultaneous causation between prices and market concentration.

4 Results

Table 4 presents the results of four models. Models (1) and (2) present results for ordinary least squares (OLS) regressions, while models (3) and (4) use the 2SLS approach described in Section 3. Models (1) and (3) explore purely linear effects, while models (2) and (4) explore non-linear effects with a quadratic term for market concentration. The coefficients in the first two rows quantify the effects of changes in market concentration on prices. HHI is normalized for easier interpretation of the results.[14] The coefficients can be interpreted as the change in price ($/W) per standard deviation increase in HHI.

Focusing first on the linear models (1) and (3), the results suggest that prices inversely correlate with market concentration. A standard deviation increase in market concentration is associated with a $0.05/W reduction in prices in the OLS model (1) and a $0.24/W reduction in prices in the 2SLS model (3), though neither effect is statistically significant with utility-clustered standard errors; standard error clustering generally increases standard errors, resulting in smaller confidence intervals and more rigorous t-statistics. In contrast, the HHI coefficients in the non-monotonic models (2) and (4) are statistically significant with utility-clustered standard errors. Models (2) and (4) suggest that prices inversely correlate with market concentration at low concentration levels but positively correlate with concentration at high concentration levels. This outcome is consistent with Hypothesis 3: the price-reducing effects of installer scale appear to dominate in relatively unconcentrated markets, but the price-increasing effects of market power appear to dominate in concentrated markets. Mathematically, the coefficients suggest that prices are minimized at HHI = 0.19. About 83% of systems installed were in markets with an HHI below this critical value. In other words, prices generally decline as market concentration increases for most currently observed levels of PV market concentration, but prices increase as market concentration increases in already concentrated markets. Hence, the results generally support Hypotheses 1 and 3, and reject Hypothesis 2.

Note that all models control for installer experience. These coefficients suggest that average prices fall by about $0.15/W for each 1,000 systems installed by any given installer. By controlling for installer experience, the coefficients on HHI reflect the effects of market concentration on the price behavior of installers while holding installer experience constant. Hence installer experience alone may not fully capture the price-reducing benefits of installer scale, and installers may find other ways to reduce costs through scaling. The result may also suggest that installer experience has spillover benefits (Bollinger and Gillingham 2014). For instance, employees may leave an experienced installation company and bring that experience to a less experienced installer. Insofar as experience spills over to some extent, the presence of experienced installers in concentrated markets should drive cost reductions for all installers within a market.

[14] Mean HHI is equal to 0.12 with a standard deviation of 0.13 (see Table 2). If H_i is the HHI of the ith system, the normalized HHI is roughly $(H_i - 0.12)/0.13$.

Table 4. Regression Results

Y = installed price ($/W)
Heteroskedasticity-robust t statistics in parentheses, based on utility-clustered standard errors

	(1)	(2)	(3)	(4)
HHI (normalized)	-0.045	-0.185	-0.244	-1.301
	(1.91)	(3.21)[b]	(1.79)	(2.25)[a]
HHI2		0.134		1.232
		(3.40)[b]		(2.26)[a]
market size	-0.07	-0.08	-0.09	-0.15
	(2.35)[a]	(2.60)[a]	(2.54)[a]	(1.96)[a]
installer experience	-0.15	-0.15	-0.15	-0.14
	(9.97)[b]	(9.86)[b]	(10.04)[b]	(9.53)[b]
%TPO	0.39	0.36	0.16	0.20
	(2.70)[b]	(2.43)[a]	(0.79)	(0.82)
bill savings	-0.21	-0.21	-0.22	-0.22
	(1.20)	(1.21)	(1.23)	(1.28)
up-front incentives	0.47	0.48	0.48	0.48
	(4.16)[b]	(4.22)[b]	(4.19)[b]	(4.50)[b]
ongoing incentives	0.42	0.42	0.41	0.39
	(1.19)	(1.19)	(1.15)	(1.20)
sales tax	-0.49	-0.40	-0.30	0.31
	(0.52)	(0.42)	(0.31)	(0.27)
Household density	0.08	0.08	0.07	0.06
	(6.51)[b]	(6.90)[b]	(7.79)[b]	(4.38)[b]
% high school to AD	-0.01	-0.01	-0.01	-0.01
	(4.43)[b]	(4.43)[b]	(3.86)[b]	(4.31)[b]
% Bach. or higher	-0.02	-0.02	-0.02	-0.02
	(6.20)[b]	(6.20)[b]	(6.28)[b]	(5.45)[b]
%income $25k-50k	0.004	0.004	0.002	0.003
	(1.46)	(1.42)	(0.41)	(0.89)
%income $50k-100k	0.006	0.007	0.004	0.01
	(1.99)[a]	(2.19)[a]	(1.27)	(2.55)[a]
% >$100k	0.01	0.01	0.01	0.01
	(3.41)[b]	(3.29)[b]	(3.29)[b]	(2.79)[b]
labor index	-0.000	-0.000	-0.000	-0.000
	(0.41)	(0.41)	(0.46)	(0.36)
sys size	-0.67	-0.67	-0.68	-0.68
	(7.02)[b]	(7.02)[b]	(6.96)[b]	(6.78)[b]
sys size2	0.03	0.03	0.04	0.04
	(6.39)[b]	(6.40)[b]	(6.36)[b]	(6.20)[b]
efficiency	10.65	10.72	10.88	11.29
	(2.44)[a]	(2.45)[a]	(2.50)[a]	(2.61)[b]
new construction	-2.23	-2.21	-2.18	-2.06
	(5.11)[b]	(5.11)[b]	(5.44)[b]	(5.81)[b]
inverter index	X	X	X	X
module index	X	X	X	X
state fixed effect	X	X	X	X
quarter fixed effect	X	X	X	X
intercept	3.85	3.88	*	*
	(3.28)[b]	(3.32)[b]		
R2	0.43	0.43	0.29	0.25
N	220,172	220,172	220,172	220,172

[a] Statistically significant at $p < 0.01$; [b] $p < 0.05$. * Intercepts are partialled out to accommodate clustered standard errors in the 2SLS regression, see Cameron and Miller (2015).

Coefficients on the remaining control variables accord with previous findings and theoretical expectations:

- *Market variables:* Lower prices are associated with larger markets (higher demand) and more experienced installers.
- *Policy variables:* Previous studies using a model similar to Model (1) generally find that prices are higher in markets with higher customer values of solar (Gillingham et al. 2016; Nemet et al. 2017). For the first time, this study breaks the customer value of solar into component parts: electricity bill savings, up-front rebates, and ongoing incentives. The results across the models indicate that prices are higher in markets with higher upfront rebates, but that the other two policy variables have statistically insignificant effects. One potential explanation is that rebate values are more certain than electricity bill savings and the value of ongoing incentives, so customers and installers more closely align system value with certain rebates rather than other less certain incentives.
- *Demographic variables:* Lower prices are associated with less densely populated areas and more educated customers.
- *System variables:* Lower prices are associated with larger systems (economies of scale), less efficient modules, installations integrated into new construction, and standard installations without components such as tracking systems and batteries, all consistent with previous findings.

4.1 Analysis

The results suggest that the price-reducing effects of installer scale dominate the price-increasing effects of market power at most currently observed levels of market concentration. This result might imply that markets with many small-scale installers are relatively inefficient owing to lack of installer scale, even if such markets are highly competitive. Further, some small-scale installers may represent companies from related services industries, especially electrical contracting, that occasionally “dabble” in PV installation as a side business. Dabbling may be inefficient, because potential installer scale benefits are lost when sales accrue to companies that only occasionally install PV.

However, the data suggest a nuanced relationship between prices and installer scale. Figure 9 illustrates price distributions by installer scale, using state- and year-normalized prices to reduce the influence of temporal and geographic price variation.[15] Surprisingly, singletons and dabblers are associated with lower prices than mid-scale and established installers (installer groups are defined and discussed in Section 3.2). On average, singleton prices are 0.18 standard deviations below state and year averages and dabbler prices are 0.10 standard deviations lower. Similar results are obtained after controlling for the factors in the econometric model. Dummy variables for the different installer scale levels were added to Model (4) while excluding the installer experience variable (owing to collinearity with installer scale). The model shows that prices for systems installed by singletons and dabblers are statistically significantly lower than for systems installed by mid-scale installers. The model likewise shows that established installer prices are lower, though the effect is not statistically significant.

[15] If $\bar{p}_{st}$ is the average price in state *s* in year *t*, and $\bar{\sigma}_{st}$ is the standard deviation, the normalized price for system *i* is equal to $(p_{ist} - \bar{p}_{st})\backslash\bar{\sigma}_{st}^{-1}$.

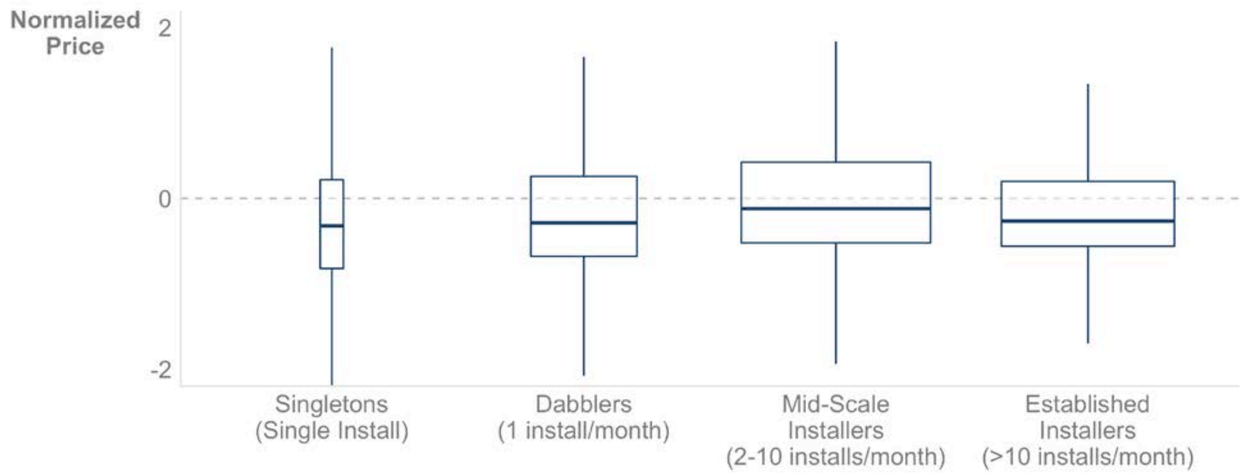

Figure 9. Normalized price distributions by installer scale (outliers omitted)

Box widths vary with the aggregate market share of that installer scale group.

Figure 10 plots mean prices by installer scale in unconcentrated and concentrated markets. The trends depicted in Figure 10, together with the regression results, suggest that two factors contribute to the observation of lower prices in more concentrated markets. First, installers at three of the four scales appear to offer lower prices in more concentrated markets, consistent with the cost- and price-reducing effects of returns to scale. That singletons and dabblers appear to offer lower prices in more concentrated markets may suggest that the prices of these smaller installers are constrained by the lower costs of established installers in concentrated markets. Second, the figure illustrates that market shares shift from dabblers and mid-scale installers to established installers when moving from unconcentrated to concentrated markets. The shift from dabblers to established installers may, if anything, increase average prices given the relatively low prices associated with dabblers. However, the shift from mid-scale to established installers reduces average prices by reducing the number of systems installed by higher-priced mid-scale installers.

Figure 10. Normalized prices and market shares by installer scale in unconcentrated versus concentrated markets

Figure limited to markets larger than 100 systems/year. Unconcentrated=HHI<0.15, concentrated=HHI>0.25.

Though the econometric results generally imply that large-scale installation yields lower prices in concentrated markets, the comparisons of prices across different installer scales suggest small-scale installation may likewise have price-reduction benefits. Hypotheses about why small-scale installers may be able to offer lower prices are offered in Section 5.

4.2 Sensitivity Analyses

As discussed in Section 3.1, market concentration estimates are sensitive to the approach used to define markets. The regression results in Table 4 are based on markets defined by a 17-km radius around each customer's zip code. To test the sensitivity of the results to different geographic market sizes, Table 5 presents the results for the HHI coefficients from models (3) and (4) at three different market sizes. The results are generally robust: the coefficient in the linear model (3) remains negative at all three market thresholds and is statistically significant at a market threshold of 50 km. The non-monotonic relationship is also retained at all three market thresholds, with negative coefficients on HHI and positive coefficients on the second-order HHI term, though these coefficients lose statistical significance at a market threshold of 50 km.

Table 5. Regression Results at Three Market Boundary Thresholds

Market Size (radius)	Model (3) HHI	Model (4)	
		HHI	HHI^2
10 km	-0.23	-1.52[a]	1.45[a]
17 km	-0.24	-1.30[a]	1.23[a]
50 km	-0.39[b]	-2.09	2.02

[a] Statistically significant at $p < 0.01$; [b] $p < 0.05$.

To test whether the results are driven by trends over some particular period, Table 6 presents the HHI coefficients from models (3) and (4) when limiting the data to systems installed in each year from 2010 to 2016. The results are robust in most years, with statistically significant negative coefficients in model (3) and the predicted non-linear pattern in model (4). The results in Table 6 generally indicate that prices have consistently inversely correlated with market concentration over time. The effects lose statistical significance (with clustered standard errors) in 2012 and 2015, but they retain the same non-linear pattern.

Table 6. Robustness Check: HHI Coefficients by Year

Year	Model (3) HHI	Model (4)	
		HHI	HHI^2
2010	-0.28[a]	-2.53[a]	19.9[b]
2011	-0.48[a]	-3.77[a]	38.1[a]
2012	-0.03	-0.32	2.89
2013	-0.16[a]	-0.60[a]	4.63[a]
2014	-0.09	-0.85[a]	7.32[a]
2015	-0.55	-2.93	28.1
2016	-0.67[a]	-2.27[a]	23.3[b]

[a] Statistically significant at $p < 0.01$; [b] $p < 0.05$

Last, to test whether market size is a factor in the relationship between market concentration and prices, Table 7 presents regression results across three market sizes. The signs of the coefficients are consistent across market size, but the effects lose statistical significance in small markets (<100 systems installed) and in Model (4) in large markets (>800 systems). The robustness check generally suggests that market concentration has a stronger influence on prices in larger markets, possibly because larger markets yield more experienced installers but also enough competition to curb price mark-ups.

Table 7. Robustness Check: HHI Coefficients by Market Size

	<100 Systems		100–800 Systems		>800 Systems‡	
	(3)	(4)	(3)	(4)	(3)	(4)
HHI	-0.06	-0.34	-0.49a	-1.86a	-2.40a	-19.9
HHI2		0.23		2.21a		87.7
N	50,863	50,863	111,406	111,406	57,903	57,903

[a] Statistically significant at $p < 0.01$; [b] $p < 0.05$
‡ Utility rather than state fixed effects are used, given that California accounts for 96% of observations at this market size.

5 Discussion and Conclusions

This study shows PV prices generally decline as market concentration increases, suggesting the price-reducing benefits of installer scale dominate the price-increasing effects of market power in concentrated markets—at least at current levels of PV market concentration. Because of the study's improved methods and expansive data set, this result imparts confidence in similar findings from previous research (Gillingham, Deng et al. 2016; Nemet, O'Shaughnessy et al. 2017; Pless, Langheim et al. 2017). And, this result has important policy implications. Though competition can reduce market power and reduce PV prices (Bollinger, Gillingham et al. 2017; O'Shaughnessy and Margolis 2017), the benefits of competition must be assessed against the foregone benefits of increased installer scale. Policymakers may be able to leverage the price-reducing benefits of installer scale through policies that help move small- and mid-scale installers up learning curves, connect customers to small- and mid-scale installers to help these installers scale up, and foster experience spillovers from large- to small- and mid-scale installers.

Solarize campaigns provide one example of a policy that leverages installer scale while constraining competition, at least temporarily. In a Solarize campaign, a community contracts with one or a limited number of installers to install several PV systems within the community. Solarize campaigns use collective bargaining power to obtain lower prices—even though installers are protected to some degree from competition (Bollinger, Gillingham et al. 2017). The results of this study suggest that Solarize campaigns may have additional benefits as programs to support local installer scaling. The experience accrued by installers during Solarize campaigns may allow the same installers to offer lower prices in the long term.

Shifts in market shares from smaller- to larger-scale installers may reduce PV prices due to the price-reducing benefits of installer experience and scale. However, a closer look at the data reveals a more nuanced relationship between installer scale and PV prices, which has not been analyzed in the literature to date. Systems installed by singletons and dabblers are lower-priced, on average than systems installed by mid-scale or established installers (see Section 3.2 for installer scale definitions). This surprising result appears to contradict hypotheses based on installer experience and scale: small-scale installers should face higher installation costs due to inexperience and high overhead costs (relative to scale). One hypothesis for this result is that many dabblers are companies from related service industries that occasionally install PV systems as a side business. According to one survey (EnergySage 2018), about 60% of PV installers offer such related services, primarily electrical contracting. Dabblers may be able to bid on PV customers without making longer-term commitments to specialize in PV installation. Dabblers may cover overhead expenses through revenues from their primary line of business and may face lower customer-acquisition costs owing to preexisting relationships with their clients, allowing dabblers to offset any costs associated with inexperience. Low singleton prices may reflect under-bidding due to lack of experience or an attempt to establish a foothold in the PV market.

Mid-scale installers (2–10 installations per month) are associated with the highest prices among the four installer scale groups. A hypothesis for this result is that some mid-scale installers represent companies transitioning from a related service to full-time PV installation. If that is the case, these mid-scale installers may increasingly need to recoup overhead costs through PV installation revenues and invest in costlier customer-acquisition methods, unlike dabblers. At the same time, mid-scale installers may be too small to capitalize fully on the experience and scale benefits of established installers. As a result, transitioning mid-scale installers may face higher costs than do dabblers or established installers.

The data descriptively support the dabbling and transitionary hypotheses. Figure 11 shows the percentages of companies by scale that use the terms *solar*, *sun*, and *electric* in their installer names. Though the names do not confirm whether these companies specialize in PV or offer additional services, the names indicate how these companies promote themselves and are perceived by customers. Singletons and dabblers are the least likely to use the terms *solar* or *sun* in their names and the most likely to use the term *electric*. Established installers are more likely to use *solar* or *sun* in their names and less likely to use *electric*. The mid-scale installers fall in between these groups.

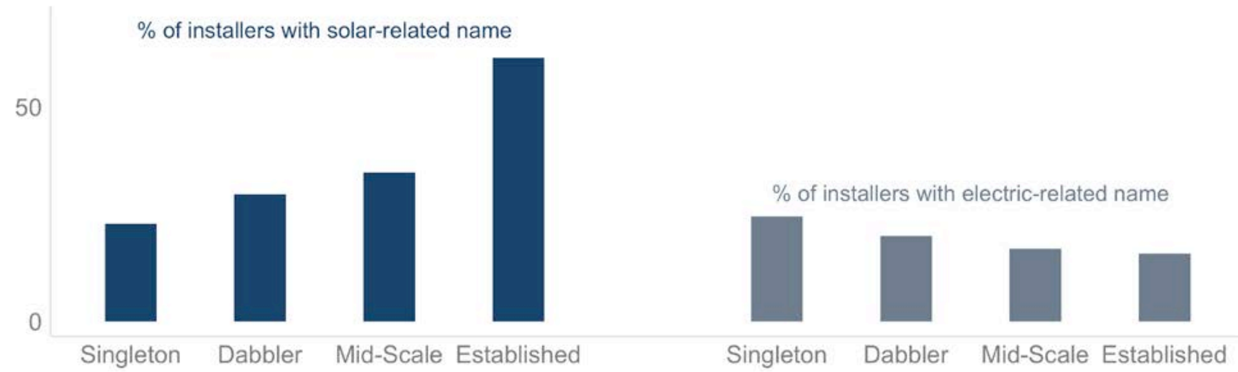

Figure 11. Percentages of installers that use the terms *solar*, *sun*, and *electric* in their names, by installer scale

The dabbling and transitionary hypotheses are speculative and require further research. If installers do incur higher costs during transition phases, policies that incentivize companies with similar technical skill sets to incorporate PV installation may help reduce PV prices. It may be possible to minimize costs and PV prices through business models combining the cost-distribution benefits of dabbling with the efficiency gains of large-scale installation by incorporating large-scale PV installation into a related service industry. For instance, Ardani et al. (2018) explore the increased integration of PV installation with roofing as a potential soft cost reduction pathway. The relationships among dabbling, industrial transitions, scale, and PV prices are areas for future research.

Finally, the results of the non-monotonic models show the price-reducing effects of installer scale may be diminishing, with the relationship between market concentration and PV prices reversing in concentrated markets. From a policy perspective, the objective could be to strike an optimal balance between installer scale (concentrated markets) and competition (unconcentrated markets), for example, through competitive Solarize campaigns. A rough estimate for the optimal market concentration level might be derived from the relationship of the market size to the minimum efficient scale (MES)—the scale at which installers minimize costs through returns to experience and scale. Suppose hypothetically that most installers must install at least 500 systems per year to minimize costs through learning and scale. In this case, a market with demand of 10,000 systems per year could support no more than 20 efficiency-maximizing installers. In other words, the market size and the MES would determine a minimally efficient level of market concentration (Ornstein, Weston et al. 1973; Tirole 1988). Markets where many installers operate below the MES might be under-concentrated, while markets where some installers operate above the MES might be over-concentrated. At the same time, the data suggest at least some small-scale installation by dabblers may be efficient. Future research could explore the MES in the context of PV installation to estimate ways to optimize PV market concentration.

In conclusion, this study uses an econometric approach to test the relationship between market concentration and PV prices. The results show PV prices generally decline as market concentration increases, suggesting the price-reducing effects of installer scale dominate the price-increasing effects of market power in concentrated PV markets at today's levels of market concentration. The results of non-monotonic models suggest the price-reducing effects of installer scale are diminishing and that the price-increasing effects of market power could dominate in already concentrated markets. PV prices likely could be minimized through an optimal balance of market concentration and competition.

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Appendix: Variable Descriptions

Table A-1 describes the variables included in the econometric models. The set of control variables is modeled largely on the model first described by Gillingham et al. (2016).

Table A-1. Control Variables

Variable	Description
Pre-incentive Installed Price	
price (2016$/W)	Full installed price paid by customer to installer in real 2016 dollars, normalized by system size
Market Concentration	
HHI	HHI in the customer's market (see Section 3)
Market Variables	
market size (x 1,000 aggregate installations)	Aggregate number of systems installed in the customer's market at time of customer's installation
installer experience (x 1,000)	Number of systems installed by installer, depreciated at 20% per quarter
%TPO in market	Percentage of systems installed in customer's market using TPO
Policy Variables	
NPV electricity bill savings ($/W)	Estimate of the customer's lifetime electricity bill savings from PV adoption (see note below table)
up-front incentives ($/W)	Sum of state and local rebates and state investment tax credits, if any.
NPV ongoing incentives ($/W)	Estimate of lifetime revenue of ongoing incentives, including production-based incentives and revenue from solar renewable energy certificates (SRECs). SREC revenues are estimated using the methodology described in Nemet et al. (2017).
sales tax per watt	Sales tax paid (if any), normalized by system size
Demographic Variables	
household density	Number of households per square mile in the customer's zip code, based on U.S. Census data
high school grad to AD	Percentage of individuals in customer's zip code with high school degree but no bachelor's, based on U.S. Census data
bachelor's or above	Percentage of individuals in customer's zip code with bachelor's degree or higher, based on U.S. Census data

Variable	Description
$25k-$44,999	Percentage of households in customer's zip code with income between $25,000 and $44,999, based on U.S. Census data
$45k-$99,999	Percentage of households in customer's zip code with income between $45,000 and $99,999, based on U.S. Census data
>$100k	Percentage of households in customer's zip code with income greater than $100,000, based on U.S. Census data
local labor cost ($/week)	Blended average weekly labor cost for electrical and roofing contractors in customer's metropolitan area, based on Bureau of Labor Statistics data
System Variables	
system size (kW)	System rated capacity in kW direct current
module efficiency (effic)	Module conversion efficiency (%), based on average module efficiency of the module brand where specific model efficiency was unavailable
new construction dummy	=1 if system was installed as part of new building construction
inverter price index ($/W)	Composite quarterly inverter price index based on GTM and Bloomberg indices
module price index ($/W)	Composite quarterly module price index based on GTM and Bloomberg indices

Note on Estimation of Electricity Bill Savings
Customer electricity rates are based on data from the U.S. Utility Rate Database. For customers in utility service areas with flat volumetric ($/kWh) rates, the electricity rate is equal to the average of residential rates offered by the utility. Some residential customers pay tiered and time-of-use (TOU) rates. In a tiered rate, the customer pays a certain volumetric rate up to some point of daily electricity use, beyond which the customer pays a separate, generally high volumetric rate. For tiered-rate customers, daily electricity use was estimated based on data from the U.S. Energy Information Administration's "Residential average monthly bill" data by state. It was assumed that typical PV customers use twice the average, given that PV customers tend to be above-average electricity users and may use more than twice as much electricity than the average in states such as California (Darghouth, Barbose et al. 2013). Based on estimated daily use, the percentage of the customer's daily use occurring below and above the tier use threshold was estimated, and an average electricity rate was calculated. In a TOU rate, customers pay different volumetric rates at different times of day. For TOU customers, the electricity rate is based on the average rate from 8 am to 4 pm, corresponding roughly to peak PV output hours. System output was estimated based on solar insolation data from NREL's National Solar Radiation Database. System output assumes a degradation rate of 0.5%. Future savings are discounted at 7%.