Learning-by-Doing in Solar Photovoltaic Installations*

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Abstract

The solar photovoltaic (PV) industry in the United States has been the recipient of billions of dollars of subsidies at the federal and state level, often motivated by environmental externalities and dynamic spillovers from learning-by-doing in the installation of the technology. This paper investigates cost reductions due to learning using comprehensive data on all solar PV installations in California over 1998-2012. We develop a model of installer firm pricing behavior that allows for learning-by-doing, economies of scale, market power, and dynamic pricing to quantify both learning and learning spillovers to other firms in the market. We find strong evidence of both appropriable and non-appropriable learning, suggesting a role for solar PV subsidies to improve economic efficiency.

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1 Introduction

Policies to promote solar photovoltaic (PV) panel adoption have been gaining momentum throughout the world, as concerns over global climate change and energy independence continue to grow. In the United States alone, commercial and residential solar installations are eligible to receive a 30% solar energy investment tax credit, which was temporarily converted to a cash grant by the American Recovery and Reinvestment Act of 2009. This federal subsidy comes on top of individual state incentive programs, the most prominent of which is the California Solar Initiative (CSI), a $3.3 billion 10 year program providing substantial subsidies for solar installations through 2016. Moreover, California, along with several other states, has adopted a Renewable Portfolio Standard, which in California’s case requires electric utilities to generate 33% of their electricity from renewable sources by 2020, a major boon for centrally generated solar. With such considerable policy interest and high costs of implementation, it is critical to determine whether these policies are economically justified.

In addition to environmental externalities, these policies may be justified if the industry exhibits supply-side spillovers due to learning-by-doing (LBD), whereby the cost of the technology declines as a function of cumulative experience in working with the technology. The concept of LBD in economics dates to the early 1960s, with theoretical work by Arrow (1962) and empirical work by Alchian (1963). Since then, a sizable literature of both theoretical and empirical work on LBD in economics has developed.\(^1\) Similarly, LBD has long been used to examine new energy technologies, beginning with Zimmerman (1982), and more recently as a common descriptive methodology for modeling technological change in renewable energy technologies.\(^2\)

Much of the literature on LBD simply studies the aggregate industry effect of LBD, testing whether the cost of a technology to all firms in an industry declines along with cumulative production of all firms in that industry. However, it is important to understand what is happening at the firm-level if LBD is to be used as a justification for policy intervention. At the firm level, the process by which learning occurs can be conceptualized as


\(^2\)See Grubb et al. (2002) and Gillingham et al. (2008) for overviews of modeling endogenous technological change in climate policy models, and Nordhaus (2009) for a critique of the use of LBD in such models.
a firm building a stock of knowledge through experience—and the cost of the technology is a function of this stock of knowledge. However, the cost reductions from firm-level learning may or may not spill over to other firms. The firm may manage to appropriate much of the knowledge gained from their trial-and-error experience. This appropriated knowledge is sometimes called “internal learning.” In contrast, other firms may be able to hire away the firm’s employees or copy the latest techniques that the firm acquired through trial and error, allowing them to also lower their costs. This LBD spillover is sometimes called “external learning” or “nonappropriable” learning.

In this paper, we study the effect of own and competitor experience on contractors’ non-hardware costs, the costs net of solar panel and inverter prices. While the costs of solar panels and inverters have declined considerably over the last decade and especially in recent years, the balance of systems (the difference between the installation price and hardware costs, which includes markup) remain high, and reductions in non-hardware costs are seen as one of the most promising avenues in making solar energy cost-competitive with traditional generation sources and is a current priority of the Department of Energy’s Sunshot initiative. It has often been claimed that as solar contractors gain experience with additional installations, they are able to improve their installation processes and reduce their installation costs. However, the distinction between external and internal learning is critical when examining the costs and benefits of solar incentives.

Just as firms do not take into account avoided environmental externalities in their decision of how many solar panels to produce, firms have no incentive to take into account welfare benefits from external learning. Policymakers in California recognized this and used it as one of the primary justifications for the CSI and its declining incentives over time. Indeed, van Benthem et al. (2008) perform an ex-ante policy analysis and find that prior to the additional federal subsidies, the CSI can be justified on economic grounds based on avoided environmental externalities and LBD spillovers - assuming learning follows the rates found in the literature and all of that learning is external learning. Both Borenstein (2008) and van Benthem et al. (2008) find that it would be difficult to justify the CSI on economic efficiency grounds based on environmental externalities alone. Thus, retrospective empirical work on the extent of LBD spillovers is important to inform the policy process, while at the same time providing valuable insights into the nature of diffusion of an important energy technology.
Measuring LBD in practice without full data on marginal costs is a difficult task, especially when both appropriable and non-appropriable LBD may be present. LBD is usually assumed to affect firms’ static marginal costs. However, in the presence of appropriable LBD, firm prices should reflect dynamic marginal costs, as noted in Irwin and Klenow (1994). In studies of LBD where the dependent variable is quality or the number of defects as in Levitt et al. (2013), dynamics are less important since it is never optimal for a firm to increase its number of defects. But when the variable of interest is cost, and we instead have data on price, we need to account for the fact that firms have the incentive to price low in early periods in order to reduce costs and increase profits in later periods. Benkard (2004) estimates a dynamic model of aircraft pricing, using marginal cost data, and shows that it may be optimal for firms to begin pricing considerably below static marginal costs. In addition to the challenge of accounting for dynamic pricing by firms, estimation of LBD with price data is further complicated if firm market power changes over time, especially if market power is correlated with cumulative installations.

Our approach in this paper is to develop a dynamic oligopoly model of contractor pricing and then use the model to motivate a reduced form empirical model of soft costs that captures dynamic pricing incentives and potential correlation between quality (or perceived quality) and experience. In our reduced-form model, we incorporate these controls for both changing market power and dynamic pricing incentives, while avoiding restrictive assumptions on the nature of demand and competition, assumptions which would allow us to directly calculate markups but which would lead to less robust results. These controls are possible due to the rich data we have on each installation, which include installation size and panel and inverter costs for each installation.

Our primary finding is that although BOS have not declined much over the past decade, there is clear evidence for both appropriable and non-appropriable learning. Prices, and therefore BOS, do not decline at the same rate as static marginal costs for two reasons. The first is because of firms’ ability to internalize the benefits from appropriable LBD which pushes prices down for firms with low levels of experience, since they have a high value for additional learning. The second is due to the fact that market power can increase with experience which also leads to less of a decline in price relative to static marginal costs. Controlling for these forces, we find that 1,000 own installations inside (outside) the county decrease costs by 23 (13) cents for firms with the average level of
experience. In contrast, 1,000 installations by other firms decrease costs by 0.33 cents per watt. However, since the number of installations by other installers are so high, the elasticity is seven times as large as for own installations within the county and almost twice as high as own installations outside the county. This evidence of non-appropriable learning suggests that a solar PV subsidy policy may be economic efficiency-improving.

We structure the remainder of this paper as follows. Section 2 provides background on the California solar market and describes our rich dataset of solar installations in California. Section 3 develops our model of optimal firm pricing, which we use to motivate our empirical specification. Section 5 describes our results and section 7 concludes.

2 Background and Data

2.1 Solar Policy

There has been a long history of government support for solar energy in both the United States in general and in California specifically. At the federal level, incentives for solar date back to the Energy Tax Act (ETA) of 1978. More recently, the Energy Policy Act of 2005 created a 30% tax credit for residential and commercial solar PV installations, with a $2,000 limit for residential installations. The Energy Improvement and Extension Act of 2008 removed the $2,000 limit and as mentioned above, the American Recovery and Reinvestment Act of 2009 temporarily converted the 30% tax to a cash grant.

California’s activity in promoting solar pre-dates the federal activity, with efforts beginning as early as the creation of the California Energy Commission (CEC) in 1974. For several decades much of the emphasis was on larger systems and the interest in distributed generation solar PV did not pick up until the late 1990s. In 1997, California Senate Bill 90 created the Emerging Renewables Program, which directed investor owned utilities to add a surcharge to electricity bills to promote renewable energy. The proceeds of this surcharge supported a $3 per watt (W) rebate for solar installations, a major step in California support for the solar industry (Taylor 2008). This support was built upon in the following years with the addition of “net metering” (allowing owners of solar PV
systems to receive credit for electricity sold back to the grid) in 1998, and an up to 15% state tax credit for solar PV installations starting in 2001 (CPUC 2009).³

While the California incentive program put in place in 1997 was substantial, it was renewed on a year-by-year basis, leading to much uncertainty in the solar market. The elements for a longer-term, more predictable policy were put in place in California in August 2004, when Governor Schwarzenegger announced the “Million Solar Roofs Initiative,” setting a goal of one million residential solar installations by 2015. In January 2006, the California Public Utilities Commission (CPUC) established the CSI, the $2.167 billion, 10-year program aiming to install 1,940 MW of new solar and “to transform the market for solar energy by reducing the cost of solar” (CPUC 2009). The CSI was a unique subsidy policy in that it counted on LBD bringing down the cost of solar, for the subsidy was designed to be decline in steps over time as the number of installed MW increases (Figure (1)). As shown in Figure 1, the CSI has a separate step schedule for each of the three major investor-owned utilities in California: Pacific Gas & Electric (PG&E), Southern California Edison (SCE), and San Diego Gas & Electric (SDG&E).⁴ Outside of these, there are also municipal utilities, such as the Los Angeles Department of Water and Power. Both the investor-owned and municipal utilities are part of a larger “Go Solar” program in California. This larger program aims to install 3,000 MW of solar PV by the end of 2016, for a total statewide budget of $3.3 billion.

Notably, the increase in the number of installations in California has exceeded expectations and the incentives in all three utility regions are either exhausted or near-exhausted as of March 2014. The next sections will provide an overview of the market trends in solar PV in the United States and California.

### 2.2 Solar Installations and Costs in the United States

For a comprehensive overview of solar PV installations and costs in the United States, we refer the reader to the 2013 “Tracking the Sun” report by Lawrence Berkeley National Laboratory (LBNL) (Barbose et al. 2013). The data used by LBNL in this study are the same

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³The state tax credit remained in place through the end of 2005.
⁴SDG&E’s CSI program is run by the California Center for Sustainable Energy (CCSE)
data used in our California analysis, only the LBNL study covers all of the United States. The dataset includes approximately 72% of all grid-connected PV capacity installed in the United States from 1998 through 2012, as shown in Figure 2. California accounts for 49% of total US residential and commercial capacity, and 22% of total utility-scale capacity (defined as ground-mounted systems over 2 MW in size) (Figure 3. Figure 4 indicates how the total MW of capacity is distributed over installation sizes. There are many more smaller installations, but the larger ones make up a high percentage of the total installed capacity. The dataset includes the type of installation (residential, commercial, government or nonprofit), price and size of the installation, the module and inverter costs, any incentives, PV installer and manufacturer information, zip code of the installation, and the NAICS industry code if applicable.\textsuperscript{5}

Figure 5 shows the path of average installation prices over time in the United States (for the residential and commercial installations less than 10 kW), along with the Navigant Global Module Price Index (Navigant 2009). As this figure indicates, the largest component of the total installation price is the cost of the PV module (i.e., the physical panel) itself, which in the past has made up roughly half of the total cost of the installation. Inverters are used to convert electricity from direct current (DC) to alternating current (AC) and account for roughly 6%-15% of the total cost. Both panels and inverters are widely accepted to be global market, with manufacturing in Asia, Europe, and North America for use anywhere in the world, including California (IEA 2009).\textsuperscript{6} Figure 5 reveals an increase in the price of modules starting in 2003 and continuing through 2006 before flattening out and eventually dropping rapidly beginning in 2008. This short-term increase in the price of modules is uniformly ascribed in industry publications to the increase in the price of the primary raw material for the modules, silicon, due to increased global demand and capacity constraints.

The remainder of the installation price, often called the “balance-of-system” (BOS), is made up of non-hardware costs (e.g., overhead, labor costs, marketing costs, site visit costs) and a markup. The next section discusses the BOS in the California context.

\textsuperscript{5}The data are reported by the installer in order to receive the rebates from the CSI or municipal programs. Prior to the CSI, similar solar installation data were tracked by the CEC’s Emerging Renewables Program and other municipal programs. 99.5% of the installations prior to 2008 are in the IOU regions.

\textsuperscript{6}In fact, Navigant Consulting’s Global Module Price Index and SolarBuzz North America Module Retail Module Price Index (Navigant 2009) tend to follow each other relatively closely. The same is true for the SolarBuzz European Price Index (SolarBuzz 2009).
2.3 California Solar Installations

We plot the number of installations in California (in our data) over time in Figure 6. During the period of the CSI, we see rapid acceleration of solar PV adoption. Over that time, the average installation price has declined from approximately nine dollars per watt to under six dollars per watt, as shown in Figure 7.\footnote{For reference, we can compare the levelized cost (i.e., the present value cost of owning and operating the generation asset) of solar to other electricity generation sources. We assume a 30 year solar system lifespan, a 30 year mortgage with an interest rate of 3\%, an inverter lifespan of 8 years, solar PV system output from Borenstein (2008), limited losses from soiling, and a PV panel decay for multi-crystalline silicon panels of 0.5\% corresponding to the best available evidence (Osterwald et al. 2006). Our calculations suggest that the 2009 residential system average cost of $8 per DC W corresponds to a levelized cost of roughly $0.30-$0.35 per kWh before any incentives, whereas centrally generated electricity sources, such as coal or natural gas currently have a much lower levelized cost, usually in the range of $0.05-$0.07.} Tables 1 and 2 provide installation characteristics summary statistics for residential and non-residential systems in our dataset, indicating the sizeable dispersion in installation prices and hard costs.

Examining the change in average installation prices over time in Figure 7 reveals that while installation prices have dropped along with the hard costs of the installation, the BOS has not had a corresponding drop. One hypothesis for this feature of the data is that a changing markup over time may counteract evidence of learning. Suggestive support for this hypothesis can be seen in Figure 8, which illustrates the mean and standard deviation of BOS for installations performed by the largest and smallest contractors (defined by the number of installations over the period of our data). It is clear that BOS declines over time for the smallest firms while it actually increases over time for the largest firms, which presumably have greater market power.

Previous studies examining evidence for LBD in the solar industry have focused on the global market for producing modules. The evidence so far for learning in the module cost is very weak at best. Papineau (2004) finds the effect of cumulative experience on total solar PV cost reductions to be significant in some specifications, but becomes insignificant when a time trend is included. Nemet (2006) performs an engineering analysis of the costs of PV modules and finds that learning can only weakly explain cost reductions in the most important components of the cost of producing a PV module. In contrast, we attempt to determine the presence of LBD on the installer side, which would be through the BOS. While learning in module costs would likely be at the global level, learning in
BOS costs will likely be at the regional level, corresponding to the geographic scope of most contractors.

Some authors have argued that LBD may be important at the regional level in lowering contractor non-hardware costs (Duke et al. 2005) and may manifest itself in different ways. Along with each additional installation, contractors may learn through experience with managing and marketing technologically similar installations, and their workers from experience in performing the installation. If the learning that comes about through these processes spills over to other contractors, the spillovers are most likely to occur at the regional level, to other competing firms in the same geographic region who may be able to replicate the same cost-reductions. Moreover in the solar PV market in California, it is common for contractors to use temporary labor from a limited set of companies for large jobs or during times when there are many jobs—possibly leading to further spillovers at the regional level. Our solar PV panel supply estimation is the first to distinguish LBD spillovers in contractor BOS costs.

In our data, we observe 2,991 contractors over the span of our data 1998-2012. There were 21 in 1998 and 1,184 in 2012. Table 3 shows that on average, installers operate in 2.4 counties and have performed 33.2 installations. Most installers in this market are small. Figure 9 illustrates that even if we remove the very smallest installers (fewer than 10 installations over the whole time period), there is still a large number of small and medium-sized installers. Since LBD spillovers are most likely to occur between competing contractors, we create a variable for the cumulative installations of each contractor’s competitors in any given year, where we define a competitor to be any other contractor who has installations in a county in which the contractor operates in that year. Each contractor faces a different set of competitors, due to the different geographic coverage of each contractor, and the contractor’s competitors will vary over time.

One possible criticism of many empirical estimates of LBD is that LBD can be confounded with capacity constraints and economies of scale. To control for this, we first created a variable for the number of ongoing contracts for an installer, defined as the number of installations requested but not completed. We then calculated each contractor’s share of current ongoing contracts (also summarized in Table ??) which we used to multiplicatively affect non-hardware marginal costs, capturing capacity constraints and economies of scale. However, these factors should affect costs very differently if the num-
ber of ongoing contracts increases as a result of a merger - we would not expect the same realization of either capacity contracts or economies of scale since capacity increases with a merger and the organization and communication within the new firm may be different. For this reason, we coded up every California merger and acquisition found in the Bloomberg and Thompson One databases and we treat a contractors as a different firm in the regression after it is involved in a merger. Table 4 provides the summary statistics for our final dataset of just over 91,000 observations, where an observation is a solar installation.

3 Model of Installation Pricing

To account for the dynamic incentives that arise with appropriable LBD, we develop a dynamic pricing model. This is complicated by several factors. First, we need to control for firm heterogeneity in costs and in markups. Solar installations are not a homogenous good, since each installation must be uniquely sized for the roof and electricity use of the consumer. Moreover, the drop in global module prices after 2008 did not correspond to as much of a drop in installation price, suggesting that there may be considerable time-varying market power at the contractor level.

3.1 Preliminaries

3.1.1 Contractor profits

Each contractor $j \in J$ profits from installation $i$ at time $t$ be given by:

$$\pi_{ijt} = (p_{ijt} - c_{ijt} - w(S_{it}, q_{ijt}, e_{ijt}, W_{it}))S_{it},$$

(1)

where $p_{ijt}$ is the price per watt charged for the installation, $c_{ijt}$ is the per-watt cost of the solar panels and inverters, and $w(\cdot)$ denotes the non-hardware costs, defined here as
all true costs minus the module and inverter costs. The non-hardware costs are a function of the system size $S_{it}$ (in kilowatts), the megawatts of relevant installations currently underway by the contractor $q_{ijt}$, the contractor’s knowledge or experience, $e_{ijt}$, and the prevailing wage rate in the vicinity of the installation $W_{it}$. The system size accounts for possibly installation-specific economies of scale, while the current on-going contracts account for contractor economies of scale or capacity constraints. The on-going contracts are subscripted by $i$ for the relevant on-going contracts may different by the location of installation $i$.

Solar installation prices are typically set on an installation-by-installation basis since each potential installation has idiosyncracies that influence the cost. Furthermore, the size of every installation is generally set in large increments (i.e., with the addition or removal of a large panel) and is a function primarily of the available suitable roof space and the amount of electricity the consumer uses. Importantly, it is not a strategic choice variable for the installer. However, in our robustness checks, we examine a specification where we instrument for the system size, to address potential endogeneity.

We assume that a contractor quotes an installation price to each potential customer. Let the probability that a contractor is selected be $\delta_{ijt}(\cdot)$, which is a function of the price offered by this contractor $j$, the prices offered by other contractors $j'$, and any preference for a contractor based on previous installations. This probability can most easily be thought of as the expected realization of the contractor performing the installation, i.e., $\delta_{ijt} = \mathbb{E}[Y_{ijt} = 1]$ where $Y_{ijt}$ is an indicator function equal to one if the contractor performs the installation. We drop the arguments from the marginal cost function for notational convenience, and with slight abuse of notation write $w(S_{it}, q_{ijt}, e_{ijt}, W_{it})$ as $w_{ijt}$. Let $Q_t$ be the number of available potential installations at time $t$. The firm expected profits are:

$$
\Pi_{jt} = \sum_{i=1}^{Q_t} \left\{ [p_{ijt} - c_{ijt} - w_{ijt}] S_{it} \delta_{ijt} \right\} - F_{jt}.
$$

(2)

Here $F_{jt}$ are contractor fixed costs, which are assumed not to vary with the size of the systems installed. We assume that the firm is at least breaking even in the medium-run and will not shut down. Let $q_{ijt} = \mathbb{E} \sum_{i=1}^{Q_t} \delta_{ijt}$ be the expected number of installations firm
performs that are close-enough in timing and proximity to potential installation \( i \) to be relevant for economies of scale or capacity constraints. We call these the firm’s on-going installations at time \( t \).

A naïve firm that maximizes static profits with respect to prices would maximize (2) with respect to \( p_{ijt} \). In contrast, a forward-looking profit maximizer accounts for the effect of its pricing decision on both current profits and the expected future stream of profits. The forward-looking contractor maximizes

\[
\mathbb{E}V_{jt} = \sum_{\tau=t}^{\infty} \rho^{(\tau-t)} \Pi_{j\tau}(p_{ij\tau}),
\]

where \( \rho \) is the discount rate.

### 3.1.2 Experience

We follow the literature in modeling the contractor’s experience as a function of the installer’s and competitors’ cumulative previous installations. The experience that is relevant to each installation \( i \) may also differ by geographic range, so experience is installation-specific. Denote installer \( j \)’s own experience with \( e_{ijt}^{\text{own}} \) and installer \( j \)’s competitors’ experience by \( e_{ijt}^{\text{comp}} \). We can then define installer \( j \)’s total experience as its own experience plus any contribution from its competitors’ installations due to spillovers:

\[
e_{ijt} = e_{ijt}^{\text{own}} + e_{ijt}^{\text{comp}}.
\]

We now define each of these terms as a linear combination of the relevant depreciated installed base variables at each locality or geographic range \( l \):
Here $b_{ijtl}^{own}$ is the depreciated cumulative previous installations surrounding installation $i$ by firm $j$ in geographic range $l \in L$. Similarly, $b_{ijtl}^{comp}$ is the depreciated cumulative previous installations surrounding installation $i$ by firm $j$’s competitors in geographic range $l \in L$. For simplicity, we assume the set of potential geographic ranges of influence $L$ is the same for both own and competitors’ depreciated installed base variables.

We can define these depreciated installed base variables as

$$
b_{ijtl}^{own} = q_{ijtl}^{own} + \mu \sum_{s=0}^{t-1} q_{ijsl}^{own}$$

$$
b_{ijtl}^{comp} = q_{ijtl}^{comp} + \mu \sum_{s=0}^{t-1} q_{ijsl}^{comp},$$

where $q_{ijtl}^{own}$ is firm $j$’s completed installations at time $t$ that fall within the location or region $l \in L$ that installation $i$ is situated in, and $q_{ijtl}^{comp}$ is firm $j$’s competitors’ completed installations at time $t$ that fall within the location $l \in L$ that installation $i$ is situated in. $\mu$ is the carryover of experience between periods, so that $1 - \mu$ is the rate of forgetting.

This definition is designed to allow for several different installed base variables to capture the distinct ways that learning could occur. The first logical experience variable is the contractor’s total experience in California or nationwide. This would capture firm-wide learning. However, contractors may have regional offices, so a variable capturing the contractor’s experience in a given county or region may be more relevant. Similarly, if experience obtained by the contractor’s competitors spills over to the contractor, the competitors’ experience would be a useful variable. Of course, this raises the question of how a competitor should be defined. One definition is any competing firm in the same geographic area, e.g., county, can be considered a competitor.
3.2 Static Profit Maximization

A naïve firm maximizes static profits with respect to prices, and so by the chain rule we have:

\[ \frac{d \Pi_{jt}}{dp_{ijt}} = \frac{\partial \Pi_{jt}}{\partial p_{ijt}} + \frac{\partial \Pi_{jt}}{\partial \delta_{ijt}} \frac{\partial \delta_{ijt}}{dp_{ijt}}. \]  

(7)

We can thus write the first order condition for each installation as:

\[ \delta_{ijt} S_{it} + \left( p_{ijt}^* - c_{ijt} - w_{ijt} \right) S_{it} \frac{\partial \delta_{ijt}}{dp_{ijt}} = 0. \]

Rearranging, we can solve for the optimal installation price:

\[ p_{ijt}^* = \underbrace{c_{ijt}}_{\text{hardware costs}} + \underbrace{w_{ijt}}_{\text{non-hardware costs}} - \underbrace{\delta_{ijt} \frac{\partial \delta_{ijt}}{dp_{ijt}}}_{\text{static markup}}. \]

As usual, we have price equal to marginal costs, \( c_{ijt} + w_{ijt} \), plus a standard markup in an imperfectly competitive market.

3.3 Forward-looking profit maximization

When the firm is forward looking, the first order condition must now account for several new effects. The choice of price today may influence the number of on-going contracts for installations in the near future, which may affect non-hardware costs through economies of scale or capacity constraints. As well, the choice of the price today influences both own learning and competitors’ learning. Additional experience affects future profits by building experience that reduces future non-hardware costs. Furthermore,
adding to the stock of previously completed installations may allow for a higher markup
to be charged on future installations (as seen in section 2). Additional experience by com-
petitors may spill over and lower non-hardware costs, but at the same time installations
by competitors today may reduce the markup that can be charged by the firm on future
installations.

Accounting for these effects, the first-order condition with respect to $p_{ijt}$ is given by:

$$
\frac{\partial \Pi_{jt}}{\partial p_{ijt}} + \frac{\partial \Pi_{jt}}{\partial \delta_{ijt}} \frac{\partial \delta_{ijt}}{\partial p_{ijt}} + \\
\sum_{\tau=t+1}^{\infty} \rho^{(\tau-t)} \sum_{j' = 1}^{Q_{\tau}} \frac{\partial \Pi_{j\tau}}{\partial w_{j'\tau}} \frac{\partial q_{j'\tau}}{\partial q_{j'\tau}} \frac{\partial q_{j'\tau}}{\partial \delta_{ijt}} \frac{\partial \delta_{ijt}}{\partial p_{ijt}} + \\
\sum_{\tau=t+1}^{\infty} \rho^{(\tau-t)} \sum_{j' \in J} \sum_{\nu = 1}^{Q_{\tau}} \sum_{l \in L} \frac{\partial \Pi_{j\tau}}{\partial q_{ij't}^{own}} \frac{\partial q_{ij't}^{own}}{\partial \delta_{ijt}} \frac{\partial \delta_{ijt}}{\partial p_{ijt}} = 0.
$$

This expression provides intuition on the forward-looking decision process. The first
line shows the static profits from sales at time $t$. Note that the current profits of firm $j$
do not depend on $\delta_{ij't}$ for $j' \neq j$. The next two lines show how choices today influence
discounted future profits. The second line shows how change the price today influences
the number of installations today, adding another contract which may still be in process
at the time of installation $i'$. This additional on-going contract may reduce potential in-
stallation $i'$’s non-hardware costs due to economies of scale or increase the costs due to
capacity constraints.

The third line models firm $j$’s dynamic pricing and dynamic markup incentives by
showing how today’s completed installations affect future profits in time $\tau$. The dynamic
pricing incentive comes about because lowering the price today increases the firm’s own
future experience and may lower future non-hardware costs. But in a second-order ef-
fect, lowering the price today would also reduce experience from other firms, limiting
spillovers from the competitors to firm $j$’s experience. These two opposing factors work
by differentiating the $w_{ijt}$ term within the profit equation.

The dynamic markup comes about through the direct effect of a change of price today
on the probability of making a future installation. This effect may work directly through installer experience or be a different function of the installed base. In fact, it may even simply be a function of the duration of time that the firm has been in the market. We consider the duration of time the firm has been in the market to be exogenous, so this effect is zeroed out if duration is the primary pathway. In our results and robustness checks, we explore specifications in which this effect is based on experience, as defined above, or is another function of the installed base. The fourth line allows both firm j’s previous installations and firm j’s competitors’ previous installations to influence firm j’s profits.

By rearranging and plugging in several derivatives to simplify the first order condition, we can solve for the profit-maximizing price of installation i as follows:

\[ p^*_{ijt} = \frac{c_{ijt}}{1} + \frac{w_{ijt}}{1} - \frac{\delta_{ijt}}{\partial \delta_{ijt} / \partial \delta_{ijt}} + \sum_{t'=1}^{\infty} \rho^{(\tau-t)} \sum_{j'=1}^{Q_{r}} S_{r\tau} \partial p_{ijt} / \partial \delta_{ijt} \partial q_{ijt}^{*} \partial q_{ijt}^{*} + \]

\[ \sum_{j'=1}^{Q_{r}} \sum_{j'=1}^{Q_{r}'} \sum_{j''=1}^{Q_{r}''} S_{ijt} \partial p_{ijt} / \partial q_{ijt}^{*} \partial q_{ijt}^{*} \partial q_{ijt}^{*} + \]

\[ \sum_{j'=1}^{Q_{r}} \sum_{j'=1}^{Q_{r}'} \sum_{j''=1}^{Q_{r}''} S_{ijt} \partial p_{ijt} / \partial q_{ijt}^{*} \partial q_{ijt}^{*} \partial q_{ijt}^{*} + \]

\[ \sum_{j'=1}^{Q_{r}} \sum_{j'=1}^{Q_{r}'} \sum_{j''=1}^{Q_{r}''} S_{ijt} \partial p_{ijt} / \partial q_{ijt}^{*} \partial q_{ijt}^{*} \partial q_{ijt}^{*} + \]

This expression shows that forward-looking installers will set price such that it equals the marginal cost (panels and inverters plus non-hardware costs) plus the current period markup and three dynamic pricing terms. The first internalizes the effect of a change in price on economies of scale or capacity constraints. The second internalizes the effect of a change of price on experience experience. The experience term is the classic dynamic pric-
ing effect. The last captures the additional profits in the future from the higher markup the firm may be able earn with more a larger installed base, accounting for the fact that this markup is also influenced by the competitors’ installed base.

3.4 Non-hardware Cost, Markup, and Dynamic Pricing Specifications

One identification challenge should be clear to the reader at this point. If marginal costs and market power are both a function of previous installations, then the direct effect of previous installations on costs, the static markup term, and the dynamic terms all are functions of the key explanatory variables of interest. We address this by first assuming that the static markup is a function of the current price level. We will elaborate on this below. Furthermore, since firms learn by performing installations, we model experience as a function of the number of installations. Our assumption allows learning to occur with total megawatts installed, but it must occur with the number of installations. Under this assumption, the dynamic pricing incentive is smaller for larger installations. This can be seen since the dynamic pricing term is proportional to the inverse size of the installation. The intuition for our assumption is that the learning gained from reducing price is less valuable relative to the current profits for larger installations. Figure 10 provides support for this assumption: BOS has declined more for larger systems, suggesting that dynamic pricing is less important of an incentive for larger systems.

3.4.1 Non-hardware costs

We begin with a general specification by denoting \( h(\cdot) \) as a function that relates firm \( j \)'s experience to marginal non-hardware costs. Let firm experience enter the costs in the following form:

\[
 w_{ijt} = h(e_{ijt})g(X_{ijt}^{mc}) + \xi_j^w + \eta_m^w + \zeta_t^w + \epsilon_{ijt}^w. \tag{10}
\]

Here \( X_{ijmt}^{mc} \) is a vector of factors that multiplicatively affect non-hardware marginal
costs through the function \( g(\cdot) \), such as average wage rates for electrical work and roofing work; whether or not the system is third-party system (e.g., a solar lease or power-purchase agreement); the size of the installation; and the number of on-going contracts to capture economies of scale or capacity constraints. An indicator for third-party owned systems is important to include for they may be priced differently for a variety of reasons: the cost of capital, higher risk, and possibly inflated reported prices in order to be eligible for a larger rebate. This specification also allows non-hardware marginal costs to differ with indicator variables for contractor \((\xi^w_j)\), local market \((\eta^w_m)\), and year-month \((\zeta^w_t)\). We define the local market as a zip code and each \( i \) is in a single zip code \( m \).

### 3.4.2 Static markup

Recall that in section 2, we observed that firms with a larger installed base tend to have higher prices than those with a smaller installed base. There is also ample anecdotal evidence that consumers prefer installers who have performed more installations and have been in the market longer. This motivates modeling the static markup term in (9) as a function of the installed base and possibly market duration variables. With very few restrictions, the static markup will depend on the level of the hardware costs; we formally show this in the Appendix. We can then use the exogenously-determined hardware costs as a shifter of prices, and hence, of the static markup. For suggestive evidence that the effect of experience is shifted by the hardware costs we can regress BOS (which contains the costs reduced by experience) on the hardware costs (a price shifter) with county and year-month indicator variables. We find a statistically significant relationship indicating that a one-dollar increase in hard costs is associated with a 43 cent decrease in BOS.

We thus flexibly model the static markup by interacting experience or market duration with the hardware costs and a contactor-specific coefficient, along with indicator variables or fixed effects for contractor \((\xi^s_j)\), market \((\eta^s_m)\), and year-month \((\zeta^s_t)\):

\[
\frac{\partial \delta_{ijt}}{\partial p_{ijt}} = \alpha_1^j c_{ijt} \phi_1^j (b_{ijt}^{own}, d_{ijt}^{own}) + \alpha_2^j c_{ijt} \phi_2^j (b_{ijt}^{comp}, \bar{d}_{ijt}^{comp}) + X_{ijt}^s \alpha^s + \xi^s_j + \eta^s_m + \zeta^s_t + \epsilon^s_{ijt}.
\]
The functions $\phi^1_j(\cdot)$ and $\phi^2_j(\cdot)$ are functions of the vector of own installed base variables ($b_{ijt}^\text{own}$), competitors’ installed base variables ($b_{ijt}^\text{comp}$), the duration over which the firm has been installing ($d_{ijt}^\text{own}$), and the average duration the competitors have been installing ($\bar{d}_{ijt}^\text{comp}$). We assume that the derivative of these functions with respect to the different installed bases and market durations approach zero as the installed bases and market duration variables approach infinity. $X_{ijt}^s$ is a vector of quantity variables that affect the static markup, such as the contractor’s number of newly requested installations, both at the firm level and at the county level, as well as the analogous variables for its competitors, the Herfindahl-Hirschman Index (HHI), and the number of competitors by geographic range $l, N_{ijtl}^\text{comp}$.

An important special case of (11) models the static markup as a function of own and competitors’ experience:

$$\frac{\partial \delta_{ijt}}{\partial \pi_{ijt}} = \alpha^1_j c_{ijt} \phi^1(\epsilon_{ijt}^\text{own}) + \alpha^2_j c_{ijt} \phi^2(\bar{\epsilon}_{ijt}) + X_{ijt}^s \alpha^s + \xi^s_j + \eta^s_m + \zeta^s_t + \epsilon^s_{ijt}, \quad (12)$$

where $\bar{\epsilon}_{ijt} = \sum_{l \in L} \frac{1}{N_{ijtl}^\text{comp}} b_{ijtl}^\text{comp}$. In this special case, the $\beta^\text{own,l}$ coefficients enter into both our non-hardware cost in (10) and our static markup. The $\phi^2(\bar{\epsilon}_{ijt})$ term captures the fact that market power gained by an installer’s competitors also affects the installer’s market power. As well, the $\phi$ functions are not installer-specific. This still provides considerable flexibility, for the $\phi$ terms are interacted with contractor-specific coefficients. We can further restrict the functional form by assuming that the $\phi$ functions are equal to the $h$ function in (10). This assumption is perhaps the most challenging for identification, since firm experience enters both the markup and non-hardware costs with the same functional form. If we can identify learning in this case, we can be more confident that the variation in the data drives identification, and not functional form assumptions.

### 3.4.3 Dynamic Pricing and Markup

To progress further towards an estimable equation, we can note that each of the three dynamic terms is a contractor-specific expectation. Thus, it follows that each of the terms can
be rewritten in a form more suitable for estimation. We begin with the effect of economies of scale or capacity constraints. Note that for any $i$, $\frac{\partial w_{ijt}}{\partial q_{ijt}} = \frac{\partial g(X_{ijt}^{mc})}{\partial q_{ijt}} h(e_{ijt})$. The contractor has an expectation about the future values of each of these terms at time $\tau$ that is proportional to the values at time $t$, so we can write the future values as a multiplicative function of a contractor-specific coefficient and the values at $t$. Furthermore, the other terms in the second line in (9) can be subsumed in the contractor-specific coefficient. This allows us to greatly simplify the expression as follows:

$$-\frac{1}{S_{it}} \frac{1}{\partial p_{ijt}} \sum_{t=t+1}^{\infty} \rho^{(\tau-t)} \sum_{i'=1}^{Q_{t}} - S_{i'\tau} \partial v_{i'j\tau} \partial q_{i'j\tau} \partial \delta_{ijt} \partial p_{ijt} = -\frac{1}{S_{it}} \gamma_{j} \frac{\partial g(X_{ijt}^{mc})}{\partial q_{ijt}} h(e_{ijt}).$$

Moving on to the dynamic pricing term, we can note that $\frac{\partial e_{ijt}}{\partial q_{ijt}} = \mu^{(\tau-t)} \sum_{l \in L} \beta_{own} l$ (for $\tau > t_c$, where $t_c$ is the completion time of installations on-going at time $t$), and $\frac{\partial e_{ijt}}{\partial q_{ijt}} = \mu^{(\tau-t)} \beta_{c} \sum_{l \in L} \beta_{comp} l$ for $j' \neq j$ (for $\tau > t_c$). So, since we have a contractor-specific expectations of each of the terms, we can similarly rewrite the dynamic pricing term in the third line in (9) as follows:

$$-\frac{1}{S_{it}} \frac{1}{\partial p_{ijt}} \sum_{t=t+1}^{\infty} \rho^{(\tau-t)} \sum_{j' \in J} \sum_{i'=1}^{Q_{t}} - S_{i'\tau} \partial v_{i'j\tau} \partial e_{i'j\tau} \partial q_{ijt}^{own} \partial \delta_{ijt} \partial p_{ijt} = -\frac{1}{S_{it}} \gamma_{j} \left( \frac{\partial h(e_{ijt})}{\partial e_{ijt}} g(X_{ijt}^{mc}) \right).$$

The dynamic markup term can be addressed similarly. To begin, for firm $j$, we have $\frac{\partial \delta_{ijt}}{\partial q_{ijt}^{own}} = \partial \delta_{ijt} \alpha_{1} c_{ijt} \frac{\partial \delta_{ijt}}{\partial q_{ijt}^{own}}$. For firms $j' \neq j$, we have $\frac{\partial \delta_{ijt}}{\partial q_{ijt}^{own}} = \partial \delta_{ijt} \alpha_{2} c_{ijt} \frac{\partial \delta_{ijt}}{\partial q_{ijt}^{own}}$. We also have $\frac{\partial e_{ijt}}{\partial q_{ijt}^{own}} = \mu^{(\tau-t)}$, which can be subsumed in a contractor-specific individual effect. As before, we can allow firm expectations of the future values at time $\tau$ of the terms in the fourth line in (9) to be a firm-specific coefficient multiplied by the values at time $t$. We can thus, rewrite this expression as follows:

---

8This follows since $\frac{\partial e_{ijt}}{\partial q_{ijt}} = 0$, which is the case because the installed base variables are a function of completed contracts, rather than on-going contracts, at time $\tau$.

9Note $\mu^{(\tau-t)} (\sum_{l \in L} \beta_{own} l + \beta_{c} \sum_{l \in L} \beta_{comp} l)$ can be subsumed in $\gamma_{j}^b$ since the $\beta$ parameters are identified based on the other terms of the first-order condition.
\[-\frac{1}{S_{it}} \frac{\partial^2}{\partial p_{ijt} \partial \tau} \mathbf{1}^{\tau-t} \sum_{\tau=t+1}^{\infty} \sum_{j' \in J} \sum_{i' = 1}^{Q_i} \sum_{l \in L} \left[ p_{ijt}^* - c_{ijt} - w_{ijt} \right] S_{\tau} \frac{\partial \delta_{ijt}}{\partial \delta_{ijt}} \frac{\partial b_{own}^{ijt}}{\partial \delta_{ijt}} \frac{\partial q_{ijt}}{\partial \delta_{ijt}} \frac{\partial \delta_{ijt}}{\partial \delta_{ijt}} \frac{\partial p_{ijt}}{\partial \delta_{ijt}} = \sum_{l \in L} -\frac{1}{S_{it}} \left( \gamma_{jl}^c \frac{\partial \phi_1}{\partial b_{own}^{ijtl}} + \gamma_{jl}^d \frac{\partial \phi_2}{\partial b_{comp}^{ijtl}} \right). \]

In the special case described above, we have that:

\[ \sum_{l \in L} -\frac{1}{S_{it}} \left( \gamma_{jl}^c \frac{\partial \phi_1}{\partial b_{own}^{ijtl}} + \gamma_{jl}^d \frac{\partial \phi_2}{\partial b_{comp}^{ijtl}} \right) = -\frac{1}{S_{it}} \left( \gamma_{jl}^c \frac{\partial \phi_1}{\partial e_{ijtl}} + \gamma_{jl}^d \frac{\partial \phi_2}{\partial \bar{e}_{ijtl}} \right). \]

We can then use these three observations about the dynamic terms to rewrite (9) in the following quasi-linear form, in which we collapse the stochastic terms and the firm, market, and time fixed effects:

\[ p_{ijt} = c_{ijt} + h(e_{ijt})g(X_{ijt}^{mc}) + \alpha_j^1 c_{ijt} \phi_1^1(b_{own}^{ijt}, d_{own}^{ijt}) + \alpha_j^2 c_{ijt} \phi_2^2(b_{comp}^{ijt}, d_{comp}^{ijt}) + X_{ijt}^s \alpha_s^s \] (13)

\[ + \frac{\gamma_j^1}{S_{it}} \frac{\partial g(X_{ijt}^{mc})}{\partial q_{ijt}} h(e_{ijt}) + \frac{\gamma_j^2}{S_{it}} \frac{\partial h(e_{ijt})}{\partial e_{ijt}} g(X_{ijt}^{mc}) + \sum_{l \in L} -\frac{1}{S_{it}} \left( \gamma_{jl}^c \frac{\partial \phi_1}{\partial e_{ijtl}} + \gamma_{jl}^d \frac{\partial \phi_2}{\partial \bar{e}_{ijtl}} \right) \]

\[ \text{economies of scale or capacity constraints, dynamic pricing, and dynamic markup} \]

\[ + \xi_j + \eta_m + \zeta_t + \epsilon_{ijt}. \]

An important aspect of our approach is that we do not impose strict assumptions on the nature of firms' expectations to calculate the value of the optimal dynamic markup term or strict assumptions on consumer demand to calculate the value of the static markup. This formulation allows us to flexibly control for these pricing terms using contractor-specific multipliers.\(^{10}\) There is also a clear intuition for why the dynamic pricing terms contain the \( h \) function interacted with other terms: as a firm moves down a convex experience curve, there is less to be gained by pricing installations lower. The next section

\(^{10}\)This also removes the assumption that firms are indeed internalizing the dynamic pricing incentives while still allowing for this forward-looking behavior.
discusses our specification for \( h \).

3.5 Functional Form Specifications

The most commonly assumed relationship between costs and experience posits that is 
\( w_{ijt} \propto e_{ijt}^\nu \) for \( \nu < 0 \). This functional form assumes a very high initial rate of learning which rapidly declines with experience. In our data, BOS costs only exhibit a slight decline, regardless of the size of the firm. Thus, we do not feel that this common power law assumption is justified in our empirical setting. Instead, we assume that marginal costs decline exponentially with experience. Specifically, we assume 
\[ w_{ijt} \propto \exp(e_{ijt}). \]

Note that this departs from the literature only in our use of the level of experience rather than the log, since 
\[ e_{ijt}^\nu = \exp(\nu \log(e_{ijt})). \]

We can justify our choice in a few ways. First, our data suggests the traditional specification is unlikely. But beyond this, there are reasons to be concerned about whether the traditional specification is always appropriate. For example, Thompson (2012) notes that the power law formulation does not follow either the original specification in Wright (1936) or the theory model in Arrow (1962), and that there is evidence that the formulation both performs poorly over longer time horizons and has poor out-of-sample prediction.

Papers using the traditional specification often find either a positive time trend (Thornton and Thompson 2001; Nemet 2012; Levitt et al. 2013) or a high rate of forgetting (Benkard 2004; Levitt et al. 2013) in LBD. Either a positive time trend or high rate of forgetting could be used to compensate for a mis-specified model which assumes (through its functional form) too steep of a learning curve. The positive time trend leads to less total decline in the explained dependent variable, and the high rate of forgetting lowers the experience level of firms on the steeper part of the learning curve (the power law assumes only steep initial learning followed by relatively little afterwards). To visually compare our specification to the standard, we plot both in Figure 11 using parameters to make the total learning by unit 100 approximately the same.

The functional form of cost dependencies on experience can be important in the price setting behavior of forward-looking forms. Ghemawat and Spence (1985) show that
the optimal price can be set using some weighted combination of current and terminal marginal costs as the current costs. Using the power law specification, the high rate of initial learning can lead to optimal prices well below static marginal costs, as shown in Benkard (2004).

Irwin and Klenow (1994) use the standard power law assumption in static costs, with an instrumental variables regression to address endogeneity since the dynamic term is simply included in the error term. However, for their primary results, they then assume that the dynamic (rather than static) marginal costs follow the power law specification. Unfortunately, this latter method is not consistent with a power law specification in static costs: To see this, consider a forward looking firm with static cost \( w_{ijt} = e_{ijt}^\nu \) which would have to add a (negative) dynamic pricing markup term proportional to \( e_{ijt}^{\nu-1} \). One of the advantages of our choice of the exponential form is that experience can enter both the static costs and the dynamic markup term with the same form, which reduces the likelihood of identification based solely on structural assumptions. For similar reasons we also specify \( g(\cdot) \equiv \exp(\cdot) \).

Thornton and Thompson (2001) provide some further justification of our functional form. They assume that:

\[
\log q_{ijk} = A_{jk} + \alpha \log K_{ijk} + \beta \log L_{ijk} + \gamma T_{ijk} - f(E_{ijk}) + \epsilon_{ijk}, \tag{14}
\]

where \( f(E) \) is the vector of functions determining the dependency of quantity of ships produced on experience. In their semi-parametric estimation of \( f(\cdot) \), they find that the spillover effects of experience within shipyard within product, across shipyards within product, and across shipyards across products are all approximately linear, which is constant with our modeled log-linear relationship. The effect of own-years experience is actually concave in Thornton and Thompson (2001), whereas the power law formulation would force it to be convex, indicating that in this context even our specification might assume too rapid initial learning.

Following this discussion above, we define \( h(e_{ijt}) \equiv \beta_0 \exp(e_{ijt}) \) where experience \( e_{ijt} \) is a function of \( \beta^h \equiv [\beta^{own}, \beta^{comp}] \). Similarly, we define \( g(X_{ijt}^{mc}) = \exp(X_{ijt}^{mc} \beta^g) \). For consistency, and to ensure that we are identifying the coefficients of interest using the data rather than arbitrary differences in functional form, we use the same exponential
specification for the $\phi$ functions, and we also make the simplifying assumptions describes above in the special cases, so we have:

$$
\phi^1_j(b_{ijt}^{own}, d_{ijt}^{own}) = \phi(e_{ijt}^{own}) = \exp(e_{ijt}^{own})
$$

$$
\phi^2_j(b_{ijt}^{comp}, d_{ijt}^{comp}) = \phi(\bar{e}_{ijt}) = \exp(\bar{e}_{ijt})
$$

### 3.6 Final Specification

Using the above functional forms, we can rewrite (16) as:

$$
p_{ijt} = c_{ijt} + \beta_0 \exp(e_{ijt}) \exp(X_{ijt}^{mc}) + \alpha^1_j c_{ijt} \phi^1_j(e_{ijt}^{own}) + \alpha^2_j c_{ijt} \phi^2_j(\bar{e}_{ijt}) + X_{ijt}^s \alpha^s
$$

$$
+ \gamma^1_j \frac{1}{S_{it}} \frac{\partial \exp(X_{ijt}^{mc} \beta)}{\partial q_{ijt}} h(e_{ijt}) + \gamma^2_j \frac{1}{S_{it}} \frac{\partial \exp(e_{ijt})}{\partial e_{ijt}} \exp(X_{ijt}^{mc}) + \frac{1}{S_{it}} \left( \gamma^3_j \phi^1_j(e_{ijt}^{own}) + \gamma^4_j \phi^2_j(\bar{e}_{ijt}) \right)
$$

$$
+ \xi_j + \eta_m + \zeta_t + \epsilon_{ijt}.
$$

In this expression, we redefine the $\gamma$ parameters in order to combine terms where possible.

### 4 Estimation

#### 4.1 Method

In almost all cases, we do not expect the decline in non-hardware costs to be linear in experience, and this it true of our exponential cost function. However, the non-linear equation in (16) is not trivial to estimate. With the large number of control variables, and with the contractor-specific interactions in the dynamic pricing and market power terms,
non-linear estimation procedures using dummy variables for market (i.e., zip code) fixed
effects are not tractable. We therefore use Taylor series approximations to linearize (16),
mean-differencing the market fixed effects, and iterate until we achieve convergence.\footnote{This is a simple modification of the procedure described in chapter 7 of Green (2008). Our convergence criteria is that the sum of the values of the coefficients do not change more than our set tolerance of 0.0001. We have experimented with a tighter tolerance and it does not affect our results.}
We do this using the exponential form for non-hardware costs but the method can be
used for any differentiable cost function.

Let \( h_{kh} \) be a vector in which the \((k^h + 1)\)th element is the derivative of \( h(\cdot) \) with respect
to the kth element of \( \beta^h \), and the first element is the derivative of \( h(\cdot) \) with respect to \( \beta_0 \).
Similarly, let \( g_{kg} \) be a vector in which the \(k^g\)th element is the derivative of \( g(\cdot) \) with respect
to the kth element of \( \beta^g \). Define \( h^0 = h(\beta^h_0) \) where \( \beta^h_0 \) is the starting value for the vector \( \beta^h \) and \( g^0 = g(\beta^g_0) \) where \( \beta^g_0 \) is the starting value for the vector \( \beta^g \). We can write:

\[
w_{ijt} = h(e_{ijt}) g(X^{mc}_{ijt}) \approx h^0 g^0 + \sum_{k^h=1}^{K^h} g^0 h_{kh}^0 \beta^h - g^0 h_{kh}^0 \beta^h_0 + \sum_{k^g=1}^{K^g} h^0 g_{kg}^0 - h^0 g_{kg}^0 \beta^g_0 \beta^g.
\] (17)

Let \( w^0 = h^0 g^0 = \beta_0 \exp(-b_{ijt} \beta^h_0 + X^{mc}_{ijt} \beta^g_0) \). Because the exponential form allows us to combine the \( h(\cdot) \) and \( g(\cdot) \) expressions with their first derivatives as we did in (??), our
final estimation equation is then:

\[
p_{ijt} - c_{ijt} + \frac{w^0}{\beta_0} - w^0 b_{ijt} \beta^h_0 + w^0 X^{mc}_{ijt} \beta^g_0 = \beta_0 \frac{w^0}{\beta_0} - w^0 b_{ijt} \beta^h + w^0 X^{mc}_{ijt} \beta^g
\] + \( X^{s}_{ijt} \alpha + \alpha_j c_{ijt} h^0 + \gamma_j \frac{1}{S_{it}} w^0 + \gamma_j^2 \frac{1}{S_{it}} + \xi_j + \eta_m + \zeta_t + \eta_{ijt}；
\] (18)

where \( \eta_{ijt} \) now includes the approximation error of the Taylor expansion.

After we perform this linear regression, we can update our values of \( \beta_0, \beta^h_0, \) and \( \beta^g_0 \) and perform the same regression, and continue to do so until the parameters converge to their true values. Unfortunately, convergence is not guaranteed, so careful choice of starting values is critical. One advantage of this methodology is that the last iteration provides us with an estimate of the asymptotic standard errors (Green 2008). Another advantage is
that it can easily be extended to allow for instrumenting of possible endogenous variables in $X_{ijt}$.

### 4.2 Identification

Separate identification of the LBD parameters from static markup and dynamic pricing incentives comes from our key assumptions: First, we assume that static markup is a function of the price level. This means that the effect of firm experience, operationalized through the installed base variables, on markup will change as the hard costs of the installations change. Second, we assume that size of the installations are exogenous and that learning depends at least partly on the number of installations, which means that the effect of firm experience on the dynamic pricing incentive is smaller for larger installations. By capturing these two forces through contractor-specific interactions of the experience term with hardware costs and the inverse size of the installations, we are left with the effect of experience on non-hardware costs.

The assumption that the choice of size does not influence the effect on learning on pricing is reasonable, but the idea that size itself is exogenous to pricing may be questionable. Thus as a robustness check we restrict the main analysis to installations less that 100 kW to avoid large commercial and utility scale installations, and we exclude ground mount systems as well which do not have the roof size constraints that many installation have. However, this may still not address the endogeneity of size. So we also instrument for size in a robustness check. As the instrument, we use the electricity rate, which is a plausible demand shifter that should increase the size of the installation, but should not influence supply.

Similarly, we may be concerned about endogeneity of the current on-going contracts variables due to simultaneity. Accordingly, we instrument for the on-going contracts interaction variables using an instrument created using solar radiation data. The idea behind this instrument is that particularly sunny months relative to the mean will shift out demand for solar installations, for consumers are more likely to think about solar power. Particularly cloudy months should have the opposite effect. Thus, we use interactions between the deviation from the mean solar insolation by county and the contractor indi-
individual effects as an instrument for the on-going contracts interaction variables.

Finally, we may be concerned about serial correlation leading to endogeneity due to a correlation between our installed base variables and the error. This is less of an issue in our setting for there is on average six month lag between when an application for an installation is submitted (i.e., when the sale is made) and when the installation is completed. Thus, the serial correlation would have to be quite substantial. Examining the Durbin-Watson statistic in our specification, we find serial correlation of only a few periods, indicating that this is not a concern.

5 Results

5.1 Descriptive Results

We begin by providing a set of descriptive results where we regress the BOS on the installed base variables and controls. Table 5 presents these results with an OLS specification (column 1), fixed effects specification (column 2), and instrumental variables specification (column 3). These descriptive results do not attempt to model changing markups or dynamic pricing behavior, and thus may be suspect.

Despite these caveats, we find these results to be an illustrative benchmark. We find statistically significant evidence suggestive of a moderate own-installed base effect. Taking these results at face value, an increase in the contractors installed base outside of the county by 1,000 installations appears to decrease BOS by 32 cents per watt (out of a mean of $2.90 per watt). None of the other installed base variables are statistically significant and the magnitude of the competitor coefficients is very small.

5.2 Primary Results

In our primary specification used to estimate our model developed in section 3, we assume no organizational forgetting. The result of this estimation is given in Table 6. Col-
umn one presents the results of an ordinary least squares estimation, while column two presents the results of an instrumental variables estimation. We instrument for the system size and the ongoing contracts variables using the following demand shifters: daily solar radiation, average monthly solar radiation, monthly solar radiation deviations, electric rates, house values, EPBB rebates per W, and interactions with year dummy variables.

In both sets of estimation results, we find significant evidence of both appropriable and non-appropriable LBD, for installations both inside and outside the county. Our preferred IV estimation results show statistically and economically significant installed base effects for the contractor’s own installations. The competitor installed base within a county is close to zero and statistically insignificant, while the competitors installed base outside of the county is small and statistically significant. To interpret the coefficients, it is important to note that the coefficients indicate the degree of learning at the outset with a negligible installed base. So for example, for installations by a contractor within a county, our estimate indicates that adding 100 installations decreases non-hardware costs by $0.035 per watt. This is a substantial decline, but 100 installations is a substantial increase to the installed base. For installations by a contractor outside of the county, our estimate indicates that adding 100 installations reduces non-hardware costs by $0.023 per watt. The coefficient indicates that 1,000 installations outside of the county reduces non-hardware costs by $0.005 per watt, a relatively small effect considering that the mean of the total California installed base in the dataset is 69,023.

Our specification implies that learning decreases with the installed base, so it is perhaps more useful to examine the estimated marginal effect at the mean of the installed base in our data. The average effect in our estimation sample of increasing an installer’s own installed base by 1,000 installations is a decline in non-hardware costs of $0.23 for installations within the county and $0.13 outside the county. The analogous figures for increasing the competitors’ total installed base by the same absolute amount is $0.33 for installations outside of the county. However, we must remember that competitors’ installed base is much larger. The elasticity of new installations are these marginal increases multiplied by the relevant average installed base and divided by the average non-hardware cost. The mean elasticities are -0.048, -0.215, and -3.41 for a contractors own installations in the county, own installations outside the county, and competitors’ installations outside the county, respectively. As we can see, although the effect of a contractors’ own installa-
tions is larger than its’ competitors’ installations, because there are so many more installations performed by competitors than by a single installer, non-appropriable learning is larger in terms of elasticities. Similarly, because there are so many more installations outside of a county than within, we find that more learning occurs due to installations outside the county.

The coefficients on several of the other coefficients are sensible in sign and magnitude. Consistent with system-level economies of scale, larger installations have a very slightly lower cost per watt, so that an increase in system size of 1 kW leads to a decline in non-hardware costs by 0.4 cents per watt. An increase in the roofing wage rate by $1,000 increases the non-hardware costs by $0.088 per watt. Increasing the contractor ongoing contracts by 1,000 increases the non-hardware costs by $1.26 per watt, consistent with capacity constraints overwhelming economies of scale.

To better compare the estimated non-hardware costs over time with the observed BOS, we plot the average BOS and the average estimated non-hardware costs for the installations performed each week, setting the other non-hardware cost variables equal to the averages observed in the data. The difference between BOS and non-hardware costs is the markup, so this graph provides insight into the changing markup over time. We plot these two time series for both our OLS estimation (Figure 7) and our IV estimation (Figure 7). The results are intuitive: we see a decline in non-hardware costs, corresponding with learning. These figures provide visual evidence of the changing market power and learning in non-hardware costs over the past decade.

To highlight the importance of controlling for dynamic pricing and changing market power, Table 7 shows the results of our OLS estimation with no controls (i.e., simple model), with no dynamic or static markup terms, and with no static markup term. The results are illustrative: without our controls, the signs on the competitor installed base coefficients are positive and the contractor’s own installed base coefficients are much larger. Figure 7 illustrates how much better the fit is for our full model than for the models that do not account for the changing markup and dynamic pricing.
5.3 Robustness Checks

This section is a work-in-progress. We run a series of further robustness checks. We examine an estimation with a monthly rate of forgetting of 5 percent (the order of magnitude estimated in Kellogg (2011) and Benkard (2004)) and find very little difference in the primary results. We also examine a specification using the installed base calculated on geographic radii rather than the county. Finally, we examine a specification were we assume that when a merger happens none of the previous installed base is added. We also are considering a robustness check where the static markup is a function of the duration of time that the firm is in the market, rather than the installed base.

6 Economic Efficiency of Solar PV Subsidy Policy

This is a placeholder for a short subsidy policy analysis based on van Benthem et al. (2008). The level of learning spillovers that we find is likely to find that a solar production subsidy may be economic efficiency improving.

7 Conclusions

With policy interest and activity in promoting solar greater than it has ever been, there is a pressing need for retrospective analysis to understand whether there is evidence for other market failures leading to an under-adoption of solar besides the environmental market failures. This is particularly crucial in a state such as California, where the environmental externalities are now being at least partly internalized with California’s tradable permit system under Assembly Bill 32. Non-appropriable LBD represents a clear market failure if it can be demonstrated.

This paper develops a model of solar PV installer pricing to examine evidence for both appropriable LBD and nonappropriable LBD in the California solar PV market. The model leverages a rich data set of solar installations in California from 1998 to 2012 and
develop a novel approach to flexibly account for changing market power, economies of scale, capacity constraints, and the possibility of dynamic pricing.

We find clear evidence of economically-significant appropriable and non-appropriable learning in solar PV installations. These findings have important ramifications for solar policy. Absent other market failures, policy action is warranted if the benefit from correcting the LBD market failure and the environmental benefits together are greater than the cost of administering the policy and the distortionary cost of raising the revenue.

There are several avenues for future research. It is possible that greater spillovers may occur in certain regions of California where there is a sufficient density of installers. There may also be relationship-specific spillovers between some contractors and not others, and our estimates would not pick up this pathway for learning. Finally, examining the copious entry and exit into this market in more detail is a promising topic for future research.

References


Appendix

We assume that the static markup is a function of the hard costs, i.e.:

$$\frac{d}{dc_{ijt}} \left( -\frac{\delta_{ijt}}{\partial p_{ijt}} \right) \neq 0$$  \hspace{1cm} (19)

We can write:

$$\frac{d}{dc_{ijt}} \left( -\frac{\delta_{ijt}}{\partial p_{ijt}} \right) = \frac{\partial}{\partial c_{ijt}} \left( -\frac{\delta_{ijt}}{\partial p_{ijt}} \right) + \frac{\partial p_{ijt}}{\partial c_{ijt}} \frac{\partial}{\partial p_{ijt}} \left( -\frac{\delta_{ijt}}{\partial p_{ijt}} \right)$$  \hspace{1cm} (20)

Since from (9) the first term on the right hand side of (20) is equal to negative one, and since $\frac{\partial p_{ijt}}{\partial c_{ijt}} = 1$, we can write our assumption as:

$$\frac{\partial}{\partial p_{ijt}} \left( -\frac{\delta_{ijt}}{\partial p_{ijt}} \right) \neq 1.$$ \hspace{1cm} (21)

We can simplify this to:

$$\delta_{ijt} \frac{\partial^2 \delta_{ijt}}{\partial p_{ijt}^2} \neq 0.$$ \hspace{1cm} (22)

This expression makes it clear how benign our assumption is. All we assume is 1) that the purchase probability $\delta_{ijt}$ is non-zero and 2) that purchase probability is not a linear function of price.

Although not necessary, let us assume that consumers make a discrete choice between installers. If the consumer chooses between $J$ installers and the outside no purchase option designated by $j = 0$, then we can model the probability of purchasing from installer
\[ \delta_{ijt} = F_{-j} (u_{ijt} \iota_J) \]  

where \( F_{-j} \) is the joint cumulative probability distribution of utilities for all other options given the choice \( j \), which allows for an arbitrary correlation between options and does not require additive separability of the stochastic term, and \( \iota_J \) is a vector of ones of length \( J \). Therefore the assumption that \( \delta_{ijt} \) not be linear in price in a random utility setting is the same as assuming that the cdf of the stochastic utility is not linear.
Figure 1: The California Solar Initiative incentive steps.

Figure 2: U.S. capacity installed (LBNL 2013)

Data source for U.S. total grid-connected PV capacity additions: Sherwood (2013). LBNL modified those values by deducting the capacity associated with the operational phases of several large utility-scale PV projects that were still under construction as of year-end 2012.
Figure 3: U.S. capacity by state (LBNL 2013)

Figure 4: U.S. capacity by size (LBNL 2013)

Table 1: Installation price and size, residential

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>system size in DC STC (kW)</td>
<td>5.53</td>
<td>3.808</td>
<td>0.6</td>
<td>98.88</td>
<td>90,869</td>
</tr>
<tr>
<td>price (2012$ per W)</td>
<td>7.27</td>
<td>1.802</td>
<td>1.413</td>
<td>11.997</td>
<td>90,869</td>
</tr>
<tr>
<td>hard costs (2012$ per W)</td>
<td>4.33</td>
<td>1.697</td>
<td>0.379</td>
<td>10.976</td>
<td>90,869</td>
</tr>
</tbody>
</table>

Table 2: Installation price and size, non-residential

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>system size in DC STC (kW)</td>
<td>20.38</td>
<td>18.354</td>
<td>1.17</td>
<td>99.75</td>
<td>2,402</td>
</tr>
<tr>
<td>price (2012$ per W)</td>
<td>7.46</td>
<td>1.854</td>
<td>1.82</td>
<td>11.985</td>
<td>2,402</td>
</tr>
<tr>
<td>hard costs (2012$ per W)</td>
<td>4.77</td>
<td>1.687</td>
<td>0.373</td>
<td>10.275</td>
<td>2,402</td>
</tr>
</tbody>
</table>
Figure 5: U.S. solar PV prices have declined (LBNL 2013)

Notes: The Global Module Price Index is Navigant Consulting’s module price index for large-quantity buyers (Mints 2012) and the successor index for first-buyer ASPs published by Paula Mints Solar PV Market Research (Mints 2013). “Implied Non-Module Costs” are calculated as the Total Installed Price minus the Global Module Price Index.

Figure 6: Average requested installations per month

Table 3: Installations by contractor

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contractor number of installations</td>
<td>33.219</td>
<td>285.725</td>
<td>1.00</td>
<td>11,435</td>
</tr>
<tr>
<td>Contractor MW of installations</td>
<td>0.204</td>
<td>1.691</td>
<td>0.001</td>
<td>68.654</td>
</tr>
<tr>
<td>Contractor number of counties</td>
<td>2.406</td>
<td>3.707</td>
<td>1.00</td>
<td>52</td>
</tr>
<tr>
<td>Number of contractors</td>
<td>2,991</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 7: CA Solar Prices

Figure 8: Balance-of-System (BOS) over time by firm size
Figure 9: Distribution of firms by firm size

Figure 10: Balance-of-System (BOS) over time by installation size
Figure 11: Our LBD specification versus a common specification

Figure 12: BOS vs. non-hardware costs, OLS
Figure 13: BOS vs. non-hardware costs, IV

BOS and total non-hardware costs

<table>
<thead>
<tr>
<th>Year</th>
<th>BOS</th>
<th>Total Non-Hardware Costs</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2004</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2006</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2008</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2012</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Figure 14: Model comparison

BOS and total non-hardware costs

- BOS
- simple model
- no dynamics
- no markup
- full model

Cost ($/W) vs. Week
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>CA installed base (1000s)</td>
<td>69.023</td>
<td>35.016</td>
<td>1.824</td>
<td>138.08</td>
<td>94,109</td>
</tr>
<tr>
<td>contractor installed base (1000s)</td>
<td>1.156</td>
<td>2.088</td>
<td>0.00</td>
<td>16.426</td>
<td>94,109</td>
</tr>
<tr>
<td>contractor’s county installed base (1000s)</td>
<td>0.127</td>
<td>0.259</td>
<td>0.00</td>
<td>2.465</td>
<td>94,109</td>
</tr>
<tr>
<td>competitors’ county installed base (1000s)</td>
<td>3.835</td>
<td>3.861</td>
<td>0.00</td>
<td>18.844</td>
<td>94,109</td>
</tr>
<tr>
<td>contractor’s on-going contracts (1000s)</td>
<td>0.305</td>
<td>0.517</td>
<td>0.001</td>
<td>2.258</td>
<td>93,412</td>
</tr>
<tr>
<td>monthly market share in CA</td>
<td>0.038</td>
<td>0.063</td>
<td>0</td>
<td>0.778</td>
<td>94,109</td>
</tr>
<tr>
<td>monthly market share in county</td>
<td>0.135</td>
<td>0.158</td>
<td>0.001</td>
<td>1</td>
<td>94,109</td>
</tr>
<tr>
<td>HHI in CA</td>
<td>0.046</td>
<td>0.049</td>
<td>0.012</td>
<td>0.606</td>
<td>94,109</td>
</tr>
<tr>
<td>HHI in county</td>
<td>0.145</td>
<td>0.13</td>
<td>0.028</td>
<td>1</td>
<td>94,109</td>
</tr>
<tr>
<td>roofing wage rate (1000s 2012$)</td>
<td>40.123</td>
<td>5.877</td>
<td>11.366</td>
<td>53.518</td>
<td>94,109</td>
</tr>
<tr>
<td>third party-owned system</td>
<td>0.355</td>
<td>0.478</td>
<td>0</td>
<td>1</td>
<td>94,109</td>
</tr>
<tr>
<td>appraised value system</td>
<td>0.123</td>
<td>0.329</td>
<td>0</td>
<td>1</td>
<td>94,109</td>
</tr>
<tr>
<td>average electricity rate (2012$)</td>
<td>0.152</td>
<td>0.011</td>
<td>0.095</td>
<td>0.177</td>
<td>94,067</td>
</tr>
<tr>
<td>monthly average radiation (W/m²)</td>
<td>5468.665</td>
<td>1849.59</td>
<td>1559.458</td>
<td>8457.046</td>
<td>94,109</td>
</tr>
<tr>
<td>dev. from monthly avg radiation (W/m²)</td>
<td>-111.195</td>
<td>324.363</td>
<td>-1346.515</td>
<td>883.237</td>
<td>94,109</td>
</tr>
<tr>
<td>Census zip code percent democrats</td>
<td>0.584</td>
<td>0.126</td>
<td>0.284</td>
<td>0.844</td>
<td>91,275</td>
</tr>
<tr>
<td>EPBB rebate per W</td>
<td>1,205.309</td>
<td>1,094.579</td>
<td>0.00</td>
<td>9,369.735</td>
<td>94,109</td>
</tr>
<tr>
<td>monthly housing prices (1000s 2012$)</td>
<td>494.785</td>
<td>344.536</td>
<td>57.00</td>
<td>3,807.60</td>
<td>93,748</td>
</tr>
</tbody>
</table>
Table 5: Descriptive Results
Dependent Variable: BOS (i.e., price - hard costs; mean=2.9)

<table>
<thead>
<tr>
<th>Linear installed base variables</th>
<th>(OLS)</th>
<th>(FE)</th>
<th>(IV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>contractor installed base within county (1000s)</td>
<td>-0.62***</td>
<td>0.13</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>(0.16)</td>
<td>(0.08)</td>
<td>(1.20)</td>
</tr>
<tr>
<td>contractor installed base outside county (1000s)</td>
<td>-0.20***</td>
<td>-0.32***</td>
<td>-0.32**</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.01)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>competitor installed base within county (1000s)</td>
<td>0.01</td>
<td>-0.01</td>
<td>-0.04</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.06)</td>
</tr>
<tr>
<td>installed base outside county (1000s)</td>
<td>-0.00</td>
<td>-0.01</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>third party-owned</td>
<td>0.12</td>
<td>-0.07*</td>
<td>-0.07</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.03)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>appraised value system</td>
<td>3.13***</td>
<td>2.37***</td>
<td>2.45***</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.10)</td>
<td>(0.26)</td>
</tr>
<tr>
<td>size (kW)</td>
<td>-0.01***</td>
<td>-0.01***</td>
<td>-0.01***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>contractor on-going contracts</td>
<td>-0.03</td>
<td>0.04</td>
<td>0.66**</td>
</tr>
<tr>
<td></td>
<td>(0.11)</td>
<td>(0.04)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>roofing wage rate</td>
<td>0.00</td>
<td>0.00*</td>
<td>-0.00</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>contractor monthly CA mkt share</td>
<td>1.88**</td>
<td>-1.23*</td>
<td>-11.46</td>
</tr>
<tr>
<td></td>
<td>(0.61)</td>
<td>(0.48)</td>
<td>(12.29)</td>
</tr>
<tr>
<td>contractor monthly county mkt share</td>
<td>0.31</td>
<td>-0.05</td>
<td>-4.91</td>
</tr>
<tr>
<td></td>
<td>(0.26)</td>
<td>(0.13)</td>
<td>(10.15)</td>
</tr>
<tr>
<td>constant</td>
<td>2.32***</td>
<td>2.37***</td>
<td>3.34***</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
<td>(0.24)</td>
<td>(1.01)</td>
</tr>
</tbody>
</table>

HHI county & state | X | X | X |
year-month dummies | X | X | X |
contractor dummies | X | X |
zip FE | X | X |

R-squared | 0.364 | 0.662 | 0.560 |
N | 93,412 | 93,412 | 93,055 |

*** indicates sig. at 1% level, ** sig. at 5% level, * sig. at 10% level. s.e. clustered on county in parentheses.

IVs: solar radiation deviations, electric rates, house values, EPBB rebates per W
Table 6: Main Results

<table>
<thead>
<tr>
<th></th>
<th>OLS</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>contractor installed base</td>
<td>-0.323***</td>
<td>-0.352***</td>
</tr>
<tr>
<td>within county (1000s)</td>
<td>(0.076)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>contractor installed base</td>
<td>-0.163***</td>
<td>-0.235***</td>
</tr>
<tr>
<td>outside county (1000s)</td>
<td>(0.035)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>competitor installed base</td>
<td>-0.001</td>
<td>0.002</td>
</tr>
<tr>
<td>within county (1000s)</td>
<td>(0.007)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>competitor installed base</td>
<td>-0.006**</td>
<td>-0.005***</td>
</tr>
<tr>
<td>outside county (1000s)</td>
<td>(0.002)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>intercept in $X_{w1}$</td>
<td>0.888*</td>
<td>0.172***</td>
</tr>
<tr>
<td></td>
<td>(0.336)</td>
<td>(0.049)</td>
</tr>
<tr>
<td>roofing wage rate</td>
<td>0.126</td>
<td>0.088***</td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>size (kW)</td>
<td>-0.001</td>
<td>-0.004***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>contractor on-going contracts</td>
<td>0.273***</td>
<td>1.261***</td>
</tr>
<tr>
<td>(1000s)</td>
<td>(0.070)</td>
<td>(0.011)</td>
</tr>
</tbody>
</table>

|                                | X | X |
| mkt share/county mkt share     |   |   |
| HHI in state & county          | X | X |
| zip code fixed effects         | X | X |
| static markup controls         | X | X |
| forward-looking controls       | X | X |
| R-squared                      | 0.861 | 0.798 |
| N                              | 93,391 | 93,050 |

*** indicates sig. at 1% level, ** sig. at 5% level. s.e. clustered on county in parentheses. IVs: daily solar radiation, average monthly solar radiation, monthly solar radiation deviations, electric rates, house values, EPBB rebates per W, and interactions with year dummies.
Table 7: Ordinary Least Square Results Without All Controls

<table>
<thead>
<tr>
<th>variable</th>
<th>simple model</th>
<th>no dynamics</th>
<th>no markup</th>
</tr>
</thead>
<tbody>
<tr>
<td>contractor installed base</td>
<td>-2.236*</td>
<td>-2.496***</td>
<td>-0.418***</td>
</tr>
<tr>
<td>within county (1000s)</td>
<td>(0.850)</td>
<td>(0.530)</td>
<td>(0.077)</td>
</tr>
<tr>
<td>contractor installed base</td>
<td>-0.514*</td>
<td>-1.714***</td>
<td>-0.193***</td>
</tr>
<tr>
<td>outside county (1000s)</td>
<td>(0.203)</td>
<td>(0.192)</td>
<td>(0.038)</td>
</tr>
<tr>
<td>competitor installed base</td>
<td>0.044*</td>
<td>0.014**</td>
<td>-0.012***</td>
</tr>
<tr>
<td>within county (1000s)</td>
<td>(0.022)</td>
<td>(0.005)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>competitor installed base</td>
<td>0.006</td>
<td>-0.003*</td>
<td>-0.007***</td>
</tr>
<tr>
<td>outside county (1000s)</td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>intercept in $X_{w1}$</td>
<td>-2.591*</td>
<td>1.000***</td>
<td>0.355</td>
</tr>
<tr>
<td>roofing wage rate</td>
<td>1.535*</td>
<td>0.134</td>
<td>0.216**</td>
</tr>
<tr>
<td>size (kW)</td>
<td>(0.577)</td>
<td>(0.122)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>contractor on-going contracts</td>
<td>1.222***</td>
<td>0.859***</td>
<td>0.563***</td>
</tr>
<tr>
<td>mkt share/county mkt share</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>HHI in state &amp; county</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>zip code fixed effects</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>static markup controls</td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>forward-looking controls</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td>0.428</td>
<td>0.567</td>
<td>0.819</td>
</tr>
<tr>
<td>N</td>
<td>93,412</td>
<td>93,391</td>
<td>93,391</td>
</tr>
</tbody>
</table>

*** indicates sig. at 1% level, ** sig. at 5% level. s.e. clustered on county in parentheses.