Learning-by-Doing in Solar Photovoltaic Installations∗

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December 23, 2014

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-by-doing (LBD) using comprehensive data on all solar PV installations in California from 2002 to 2012. We develop a model of installer firm pricing behavior that allows for economies of scale, market power, and dynamic pricing to quantify both appropriable and non-appropriable LBD. We find strong evidence for both, suggesting a role for solar PV subsidies to improve economic efficiency by addressing a non-appropriable LBD positive externality. However, our results suggest that the California Solar Initiative cannot be justified by non-appropriable LBD alone.

Keywords: learning-by-doing; innovation; imperfect competition; diffusion; new technology; energy policy.
JEL classification codes: Q42, Q48, L13, L25, O33, O25.

∗The authors would like to thank the participants at seminars at the Harvard Kennedy School, University of Chicago Booth, University of Michigan, London School of Economics, Yale University, University of Pennsylvania Wharton, Duke University, New York University, Stanford SITE Meetings, and the NBER EEE Summer Institute for their valuable comments and insights. We also acknowledge the excellent research assistance of Divita Bhandari and Hao Deng and support from the U.S. Department of Energy under contract DE-AC02-05CH11231. All errors are solely the responsibility of the authors.
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1 Introduction

Policies to promote solar photovoltaic (PV) system adoption have been gaining momentum throughout the world, as concerns over global climate change and energy independence continue to grow. In the United States, commercial and residential solar installations are currently eligible to receive a 30% solar energy investment tax credit. This federal subsidy comes on top of individual state incentive programs, the most prominent of which is the California Solar Initiative (CSI), a $2 billion program began in 2006 to provide substantial subsidies for solar installations. Interestingly, policies like the CSI are often justified based on both emissions reductions and the existence of learning-by-doing (LBD), whereby the cost of the technology declines as a function of cumulative experience with the technology.

This study investigates learning in solar PV installations in California. For LBD to justify government intervention, there must exist learning spillovers across firms. Such learning spillovers are often called “non-appropriable” LBD, similar to the non-appropriable benefits from research and development, which are a standard justification for innovation policy. We develop an approach that allows us to separately identify appropriable LBD (internal learning) and non-appropriable LBD (external learning) in the cost of an installation. Since solar PV panels and inverters are traded on a global market, we focus on localized learning in non-hardware costs, which include labor, overhead, and marketing costs.

Our estimation method uses a semi-parametric control function approach motivated by the optimality conditions of profit maximizing solar PV contractors in a potentially imperfectly competitive market. We use rich data on all installations in California over the period 2002 through 2012 to find strong evidence of both appropriable and non-appropriable learning-by-doing in contractor non-hardware costs. Our results indicate that 1,000 additional installations by an contractor in a county reduces non-hardware costs by $0.36 per watt (W) on average, while 1,000 installations by competitors spills over and reduces the contractor’s non-hardware costs by $0.005 per W. Such non-appropriable
LBD can provide justification on economic efficiency grounds for a subsidy policy to address the positive externality. However, our illustrative calculations suggest that the spillovers alone are not sufficient to justify the CSI.

The concept of LBD in economics dates to the early 1960s, beginning with theoretical work by Arrow (1962). Since then, economists have developed a wealth of theoretical findings based on LBD. For example, learning from cumulative experience has been shown to play a critical role in both the functioning of markets (e.g., Spence 1981; Fudenberg and Tirole 1983; Ghemawat and Spence 1985; Cabral and Riordan 1994; Besanko, Doraszelski, Kryukov, and Satterthwaite 2010) and in theories of endogenous growth (e.g., Stokey 1988; Young 1991, 1993; Jovanovic and Nyarko 1996). One notable theoretical finding is that when firms can appropriate the benefits from learning, they have an incentive to price dynamically by initially pricing below the short-run marginal cost in order to allow for future market dominance. We provide evidence suggestive of this force in our empirical context.

LBD also underpins an extensive empirical literature. Studies have estimated the speed of learning in a wide variety of contexts, including aircraft manufacturing (Alchian 1963; Benkard 2004), chemical processing (Lieberman 1984), semiconductor manufacturing (Irwin and Klenow 1994), agricultural technology (Foster and Rosenzweig 1995), shipbuilding (Thompson 2001; Thornton and Thompson 2001), oil drilling (Kellogg 2011; Covert 2014), and automobile manufacturing (Levitt, List, and Syverson 2013). LBD has also long been used to examine the cost of new energy technologies, beginning with Zimmerman (1982), and more recently as a common descriptive methodology for modeling technological change in renewable energy technologies.

Given the importance of differentiating between internal and external learning, it is not surprising that several empirical studies distinguish between the two. Learning spillovers across firms have been studied in several contexts (Zimmerman 1982; Irwin

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1See Grubb, Khler, and Anderson (2002) and Gillingham, Newell, and Pizer (2008) for reviews of the modeling of endogenous technological change in climate policy models, and Nordhaus (2014) for an important critique of the naïve use of LBD in such models.
and Klenow 1994; Thornton and Thompson 2001; Kellogg 2011; Covert 2014). These spillovers have also been shown to influence market structure by undercutting barriers to entry (Ghemawat and Spence 1985) and at the same time may represent a classic positive externality (Stokey 1985; van Benthem, Gillingham, and Sweeney 2008; Gillingham and Sweeney 2010). Both effects may be important in the solar PV market. van Benthem, Gillingham, and Sweeney (2008) perform an ex-ante welfare analysis of the CSI assuming non-appropriable LBD. They find that prior to the addition of Federal tax credits, the CSI can be justified on economic efficiency grounds based on the avoided environmental externalities and LBD spillovers—provided that learning follows the rates found in the literature and all of that learning is non-appropriable. This is important because the CSI was explicitly justified in the policy process based on both environmental grounds and learning. However, Borenstein (2008), van Benthem, Gillingham, and Sweeney (2008), and Burr (2014) clearly show that the CSI cannot easily be justified on economic efficiency grounds based on environmental externalities alone—non-appropriable learning is critical.

Learning can be expected to lower non-hardware costs for solar PV installations at a regional or localized level by improving labor productivity. Employees can increase the speed of installation with different types of roof layouts, discover ways to modify the hardware to facilitate installation, refine the site-visit software, and improve the processing of permits. Spillovers may occur through pathways such as hiring employees of other firms, watching competitor strategies, increased efficiency of permitting by building permit offices, and more widespread adoption of best practices as are publicized by industry organizations. Of course, labor markets may adjust in response to some of these pathways based on labor productivity, but if there are sticky wages and sufficiently high unemployment, as was the case in much of our empirical setting, LBD may still bring down labor costs.

To estimate how own experience (internal learning) and competitor experience (spillovers) reduce the non-hardware costs, we face an empirical challenge: we observe hardware costs (i.e., module and inverter costs) and the price of the system, but we do not sep-
arately observe the non-hardware costs and the markup. We would expect firms that anticipate LBD to be dynamic pricing, so the markup would be lower in early periods and higher in later periods. For example, 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, in a fledgling market such as the solar PV market, larger firms may have a perceived quality advantage, so market power may be correlated with the cumulative installations of the firm.

Our approach is to develop a dynamic oligopoly model of contractor pricing and then use this to motivate a reduced-form empirical model that captures dynamic pricing incentives and potential correlation between quality (or perceived quality) and experience. This can be thought of as a semi-parametric control function approach, where the control function is based on the first-order conditions for optimal contractor pricing. A key advantage of our approach is that we can account for changing market power and dynamic pricing incentives while avoiding restrictive assumptions on the nature of demand and competition. We can separately identify learning-by-doing from economies of scale given our rich dataset, which provides the ability to include variables for both cumulative installations and the number of on-going installations. Our identification relies on instrumenting for the quantity variables in our pricing equation using solar PV demand shifters such as deviations from the average solar radiation and electricity rates.

We find clear evidence for both appropriable and non-appropriable learning, at the county and California level. We quantify the elasticities of non-hardware cost with respect to experience, finding results at the mean of our data of -0.049, -0.229, and -0.304 for a contractor’s own installations in the county, own installations outside the county, and competitors’ installations outside the county, respectively. In a set of illustrative calculations, we find that the estimated non-appropriable LBD can provide motivation for a solar PV subsidy policy in California. However, the extent of learning spillovers that we quantify—implying a Pigouvian subsidy of just under $0.60 per watt on average under our baseline assumptions—is not sufficient to justify the CSI.
This paper is organized 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 4 describes our estimation methodology. Section 5 presents our results, section 6 describes the results of illustrative calculations for the Pigouvian subsidy, 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 the American Recovery and Reinvestment Act of 2009 temporarily converted the 30% tax to a cash grant.

California’s activity in promoting solar began as early as 1974 with the creation of the California Energy Commission (CEC). For several decades much of the emphasis was on larger systems. 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 distributed solar PV installations (Taylor 2008). Beginning in 1998 “net metering” allowed owners of solar PV systems to receive credit for electricity sold back to the grid. Moreover, from 2001 to 2005, a 15% state tax credit was granted for solar PV installations (CPUC 2009).

While the California rebate program put in place in 1997 was substantial, it was renewed on a year-by-year basis, leading to uncertainty in the solar market. The elements
for a longer-term, more predictable policy originated in August 2004, with the announce-
ment of the “Million Solar Roofs Initiative,” a program with a goal of one million residen-
tial solar installations by 2015. In January 2006, the California Public Utilities Commission
(CPUC) established the CSI, the $2.167 billion program aiming to install 1,940 MW of new
solar by 2016 and “to transform the market for solar energy by reducing the cost of solar”
(CPUC 2009).

The CSI is a particularly interesting subsidy policy in that it counted on LBD bringing
down the cost of solar, for the subsidy declined in steps over time as the number of in-
stalled MW increases. 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).2 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 number of installa-
tions in California has exceeded expectations and the programs in all three utility regions
are closed or near-closed as of November 2014.

2.2 Solar Installations and Costs

By the end of 2012, California accounted for nearly 50 percent of total US residential
and commercial solar PV capacity installed in the U.S., making it the largest and most
important market for distributed generation solar PV.3 Over 80 percent of the systems
installed in both California and the U.S. by the end of 2012 were under 10 kW, which is a
common upper bound size for a small-scale residential or commercial system. This paper
focuses on these smaller systems, although it should be noted that these systems make

2SDG&E’s CSI program is run by the California Center for Sustainable Energy (CCSE)
3This estimate is based on the detailed 2013 “Tracking the Sun” report by Lawrence Berkeley National
Laboratory (LBNL), which includes roughly 72 percent of all grid-connected solar PV capacity from 1998 to
2012 (Barbose, Darghouth, Weaver, and Wiser 2013).
up less than 30 percent of the installed capacity, for there are a relatively number of very large-scale solar farms (Barbose, Darghouth, Weaver, and Wiser 2013).

The price of a solar installation can be broken down into several components. First, there is the cost of the PV module or panel and inverter. Until recently these two pieces of hardware made up 50 percent or more of the price of a solar installation, but the module and inverter costs have declined so significantly in price that they are currently a much smaller percentage. For convenience, we call the combined panel and inverter cost the “hardware cost.” Both modules and inverters are traded on a global market, with manufacturing in Asia, Europe, and North America for use anywhere in the world (IEA 2009). The remainder of the installation price is often called the “balance-of-system” (BOS), and is made up of non-hardware costs (e.g., overhead, labor costs, marketing costs, site visit costs) and a markup. These components of the price can be expected to differ based on localized factors, rather than at the global level.

Our dataset, based on Barbose, Darghouth, Weaver, and Wiser (2013), is unique in that it includes both the price and the hardware costs for most of installations in California through 2012. Our data includes all installations in California that received an incentive payment. For the three investor-owned utilities, it covers both the Emerging Renewables Program and the CSI. It also covers all municipal utility solar incentive programs. The data includes the type of installation (residential, commercial, government or nonprofit), price and size of the installation, whether the system is third-party owned or appraised value, the module and inverter costs, any financial incentives, PV installer and manufacturer information, average electricity rate in the zip code of the installation, and zip code of the installation. The raw dataset has 138,599 observations. Restricting the sample to installations for which module and inverter costs are reported, provides our sample for estimation of 94,109.

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4The inverter converts electricity from direct current (DC) to alternating current (AC) and accounts for roughly 6 to 15 percent of the total cost.
5Mounting or racking costs are also included in the BOS for convenience, as these are usually a small fraction of the cost.
6We also drop obviously miscoded installations, including installations with an installed price less than $1/W or greater than $12/W, hardware cost less than $0.30/W or greater than $12/W. Furthermore, we
Table 1 provides summary statistics for all of the key variables in our final dataset. All dollar-valued variables are converted to real 2012 dollars. As we hypothesize that LBD occurs with installations at different levels, we create variables for the cumulative number of installations, which we call the “installed base.”\(^7\) The installed base variables are calculated first for a given contractor at both the California-wide level and at the county level. Then, since LBD spillovers are most likely to occur between competing contractors, we create a variable for the cumulative installations by the contractor’s competitors, where we define a competitor to be any other contractor who has installations in a county in which the contractor operates in the year of the installation. 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. To control for potential economies of scale or capacity constraints, we also create a variable for the contractor’s on-going contracts, which is defined as the number of contacts that are in-progress between the contract signing and the actual installation.\(^8\)

We bring in monthly county-level data on roofing wages from the Bureau of Labor Statistics as a useful control that may influence prices. In addition, we bring in several potential demand shifters, such as daily county-level average solar radiation data from the UC IPM Online database (www.ipm.ucdavis.edu/weather) and monthly county-level data on housing prices from Zillow. The raw solar radiation data is at the daily weather-station level. We use a Gaussian Process regression, also known as kriging, to interpolate to the county-average level.

As the dataset contains both residential and non-residential installations, we provide summary statistics for key variables in each of these categories respectively in Tables 2 and 3. It is clear that most of the observations are residential systems, with only 2,402 non-residential systems. Residential systems tend to be significantly smaller, with a mean

\(^7\)We use the full raw dataset of 138,599 installations for calculating these cumulative installation variables. We also code up every merger and acquisition in the California solar PV market and develop alternative installed base variables that include all of the experience of both firms.

\(^8\)The average time between signing of the contract and installation is roughly 120 days.
size of 5.5 kW versus 20.38 kW, but slightly less expensive per watt on average than non-
residential systems ($7.27 per W versus $7.46 per W).

We plot the number of installations in both the full raw dataset and our final dataset
over time in Figure 2. During the period of the CSI, we see rapid acceleration of solar PV
adoption. Since 2002, the average installation price has declined from approximately ten
dollars per watt to under six dollars per watt, with much of this decline occurring after
2009 (Figure 3).9 Interestingly, while average solar PV prices have declined along with the
hard costs, it appears that the difference between the price and the non-hardware costs–
known as the “balance of system” (BOS)—has not experienced a corresponding drop, as
one might expect if there is LBD lowering non-hardware costs.

One hypothesis for the relatively constant BOS is that an increasing markup over time
may counteract the effect LBD. This may occur from dynamic pricing or if more experi-
enced firms can charge a higher markup through product differentiation, perhaps due to
perceived quality. Suggestive support for this hypothesis can be seen in Figure 4, which
illustrates the mean monthly 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 significantly over time for the smallest firms, which can be thought of
as a competitive fringe, while it actually increases over time for the largest firms, which
presumably have greater market power.

Figure 5 removes contractors who perform less than 10 installations and shows that
most firms in this market still fall into the competitive fringe. This competitive fringe
installs the majority of solar PV systems, but 31.2 percent are installed by the top 10 in-
stallers (over the full time period of the data), so there is some degree of concentration in

9For 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, Adelstein, del Cueto, Kroposki, Trudell, and
Moriarty 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 had a 2009 levelized cost in the range of
$0.05-$0.07.
the market. Table 4 provides summary statistics over the 2,991 contractors in the dataset (21 in 1998 and 1,184 in 2012). On average, contractors operate in 2.4 counties and have performed 33.2 installations.

3 Model of Installation Pricing

To account for the dynamic incentives that arise with appropriable LBD, we develop a model of forward-looking solar PV contractor pricing. 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 \( j \in J \) earns profits from installation \( i \) at time \( t \), as given by:

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

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 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 ac-
count 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 idiosyncrasies 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, our primary specification instruments 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 $\delta_{ijt}()$, 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 $w(S_{it}, q_{ijt}, c_{ijt}, W_{it})$ as $w_{ijt}$. Let $Q_t$ be the number of available potential installations at time $t$. The firm expected profits are:

$$\Pi_{jt} = \sum_{i=1}^{Q_t} \{ [p_{ijt} - c_{ijt} - w_{ijt}]S_{it}\delta_{ijt} \} - F_{jt}. \tag{2}$$

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 $j$ 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 $t$. 

11
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

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

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

### 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 \( e_{ijt}^{own} \) and installer \( j \)’s competitors’ experience by \( e_{ijt}^{comp} \). We can then define installer \( j \)’s total experience as its own experience plus any contribution from its competitors’ installations due to spillovers:

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

We now define each of these terms as a linear combination of the relevant depreciated installed base variables at each locality or geographic range \( l \):

\[
e_{ijt}^{own} = \sum_{l \in \mathcal{L}} \beta_{own,l} b_{ijtl}^{own},
\]

\[
e_{ijt}^{comp} = \sum_{l \in \mathcal{L}} \beta_{comp,l} b_{ijtl}^{comp}.
\]

Here \( b_{ijtl}^{own} \) is the depreciated cumulative previous installations surrounding installation \( i \) by firm \( j \) in geographic range \( l \in \mathcal{L} \). Similarly, \( b_{ijtl}^{comp} \) is the depreciated cumulative
previous installations surrounding installation $i$ by firm $j$’s competitors in geographic range $l \in \mathcal{L}$. For simplicity, we assume the set of potential geographic ranges of influence $\mathcal{L}$ is the same for both own and competitors’ depreciated installed base variables.

We can define these depreciated installed base variables as

\[
\begin{align*}
q_{ijtl}^{\text{own}} &= q_{ijtl}^{\text{own}} + \mu \sum_{s=0}^{t-1} q_{ijst}^{\text{own}} \\
q_{ijtl}^{\text{comp}} &= q_{ijtl}^{\text{comp}} + \mu \sum_{s=0}^{t-1} q_{ijst}^{\text{comp}},
\end{align*}
\]

where $q_{ijtl}^{\text{own}}$ is firm $j$’s completed installations at time $t$ that fall within the location or region $l \in \mathcal{L}$ that installation $i$ is situated in, and $q_{ijtl}^{\text{comp}}$ is firm $j$’s competitors’ completed installations at time $t$ that fall within the location $l \in \mathcal{L}$ 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. As mentioned above, we define a competitor as any competing firm in the same geographic area.

### 3.2 Static Profit Maximization

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

\[
\frac{d\Pi_{jt}}{dp_{ijt}} = \frac{\partial \Pi_{jt}}{\partial p_{ijt}} + \frac{\partial \Pi_{jt}}{\partial \delta_{ijt}} \frac{\partial \delta_{ijt}}{\partial p_{ijt}}.
\]
We can thus write the first order condition for each installation as:

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

Rearranging, we can solve for the optimal installation price:

\[ p^*_{ijt} = c_{ijt} + w_{ijt} - \frac{\delta_{ijt}}{\delta_{ijt}} \frac{\partial \delta_{ijt}}{\partial p_{ijt}}. \]

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 competitors 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:
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 $\delta_{ijt}^j$ 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 installation $i''$’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 effect, 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. We model this effect as working directly through installer experience, although it may also work as a different 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 condi-
tion, we can solve for the profit-maximizing price of installation \( i \) as follows:

\[
p_{ijt}^* = c_{ijt} + w_{ijt} - \frac{\delta_{ijt}}{\partial p_{ijt}} + \]

\[
- \frac{1}{S_{it}} \frac{1}{\partial p_{ijt}} \sum_{t'=1}^{Q_t} \rho^{(\tau-t)} \sum_{i' \in I} S_{i'\tau} \delta_{i'jt} \frac{\partial w_{i'jt}}{\partial q_{i'jt}} \frac{\partial q_{ijt}^{own}}{\partial b_{i'jt}^{own}} \frac{\partial \delta_{ijt}}{\partial p_{ijt}} +
\]

\[
- \frac{1}{S_{it}} \frac{1}{\partial p_{ijt}} \sum_{t'=1}^{Q_t} \rho^{(\tau-t)} \sum_{i' \in I} S_{i'\tau} \delta_{i'jt} \frac{\partial w_{i'jt}}{\partial q_{i'jt}} \frac{\partial q_{ijt}^{own}}{\partial q_{ijt}^{own}} \frac{\partial \delta_{ijt}}{\partial p_{ijt}} +
\]

\[
- \frac{1}{S_{it}} \frac{1}{\partial p_{ijt}} \sum_{t'=1}^{Q_t} \rho^{(\tau-t)} \sum_{i' \in I} S_{i'\tau} \delta_{i'jt} \left( p_{ijt}^* - c_{ijt} - w_{ijt} \right) S_{i'\tau} \frac{\partial \delta_{i'jt}}{\partial q_{ijt}^{own}} \frac{\partial q_{ijt}^{own}}{\partial q_{ijt}^{own}} \frac{\partial \delta_{ijt}}{\partial p_{ijt}}.
\]

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 pricing 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 6 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:

\[
w_{ijt} = h(e_{ijt})g(X_{ijt}^{mc}) + \xi_{j}^{w} + \eta_{m}^{w} + \zeta_{t}^{w} + \epsilon_{ijt}^{w}.
\]  

(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 \( (\xi_{j}^{w}) \), local market \( (\eta_{m}^{w}) \), and year-month \( (\zeta_{t}^{w}) \). 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 Appendix A. 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 (\(\xi_j^s\)), market (\(\eta_m^s\)), and year-month (\(\zeta_t^s\)):

\[
\delta_{ijt} \frac{\partial \delta_{ijt}}{\partial p_{ijt}} = \alpha_1^j c_{ijt} \phi_1^j(b_{ijt}^{own}, d_{ijt}^{own}) + \alpha_2^j c_{ijt} \phi_2^j(b_{ijt}^{comp}, \bar{d}_{ijt}^{comp}) + X_{ijt}^s \alpha^s + \xi_j^s + \eta_m^s + \zeta_t^s + \epsilon_{ijt}.
\]  

(11)

The functions \(\phi_j^1(\cdot)\) and \(\phi_j^2(\cdot)\) are functions of the vector of own installed base variables (\(b_{ijt}^{own}\)), competitors’ installed base variables (\(b_{ijt}^{comp}\)), the duration over which the firm has been installing (\(d_{ijt}^{own}\)), and the average duration the competitors have been installing (\(\bar{d}_{ijt}^{comp}\)). We assume that the derivatives 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 share of newly requested installations and the Herfindahl-Hirschman Index (HHI) for the number of new installations, both at the firm
level and at the county level.

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

$$\frac{\delta_{ijt}}{\partial \delta_{ijt}} = \alpha_1^{ij} c_{ijt} \phi^1(\epsilon_{ijt}^{own}) + \alpha_2^{ij} c_{ijt} \phi^2(\bar{\epsilon}_{ijt}) + X_{ijt}^s \alpha^s + \xi^s_j + \eta^s_m + \zeta^s_t + \epsilon_{ijt}^s,$$

(12)

where $\bar{\epsilon}_{int} = \sum_{l \in L} \beta_1^{own,l} \frac{1}{N_{ijt}} b_{ijt}^{comp}$. In this special case, the $\beta_1^{own,l}$ 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 $i$, $\frac{\partial w_{ijt}}{\partial q_{ijt}} = \frac{\partial g(X_{ijt}^{mc})}{\partial q_{ijt}} h(e_{ijt})$.\(^{10}\) 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

\(^{10}\)This 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 $\tau$.  

19
greatly simplify the expression as follows:

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

Moving on to the dynamic pricing term, we can note that  
\[
\frac{\partial w_{ij't}}{\partial q_{ij't}} = \mu^{(\tau-t)} \sum_{l \in L} \beta_{own,l}^{1}
\]  
(for \(\tau > t_c\), where \(t_c\) is the completion time of installations on-going at time \(t\)), and  
\[
\frac{\partial w_{ij't}}{\partial q_{ij't}} = \mu^{(\tau-t)} \beta^{s} \sum_{l \in L} \beta_{comp,l}^{1}
\]  
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:\textsuperscript{11}

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

The dynamic markup term can be addressed similarly. To begin, for firm \(j\), we have  
\[
\frac{\partial \delta_{ijt}}{\partial p_{ijt}} = \frac{\partial \delta_{ijt}}{\partial c_{ijt}} \alpha_{j}^{1} c_{ijt} \frac{\partial c_{ijt}}{\partial p_{ijt}} \frac{\partial \phi_{ijt}}{\partial q_{ijt}}
\]  
. For firms \(j' \neq j\), we have  
\[
\frac{\partial \delta_{ij't}}{\partial p_{ijt}} = \frac{\partial \delta_{ij't}}{\partial c_{ij't}} \alpha_{j}^{2} c_{ij't} \frac{\partial c_{ij't}}{\partial p_{ijt}} \frac{\partial \phi_{ij't}}{\partial q_{ij't}}
\]  
. We also have  
\[
\frac{\partial \phi_{ijt}}{\partial q_{ijt}} = \mu^{(\tau-t)}
\]  
, 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:

\[
-\frac{1}{S_{it}} \frac{1}{\partial p_{ijt}} \sum_{\tau=t+1}^{\infty} \rho^{(\tau-t)} \sum_{j' \in J} \sum_{i'v=1}^{Q_{\tau}} \sum_{l \in L} [p_{i'vjr} - c_{i'vjr} - w_{i'vjr} S_{i'vj'r'\tau} \frac{\partial \phi_{i'vj'r'\tau}}{\partial q_{i'vj'r'\tau}} \frac{\partial q_{i'vj'r'\tau}}{\partial \delta_{ij't}} \frac{\partial \delta_{ij't}}{\partial p_{ijt}} = \\
\sum_{l \in L} -\frac{1}{S_{it}} \left( \gamma_{j}^{c} \frac{\partial \phi_{ijt}}{\partial q_{ijt}} + \gamma_{j}^{d} \frac{\partial \phi_{ijt}}{\partial \delta_{ijt}} \right).\text{\textsuperscript{11}}
\]

\textsuperscript{11}Note \(\mu^{(\tau-t)} (\sum_{l \in L} \beta_{own,l} + \beta^{s} \sum_{l \in L} \beta_{comp,l})\) can be subsumed in \(\gamma_{j}^{b}\) since the \(\beta\) parameters are identified based on the other terms of the first-order condition.
In the special case described above, we have that:

\[
\sum_{l \in L} \left( -\frac{1}{S_{it}} \left( \gamma_c l \frac{\partial \phi^1_{ijl}}{\partial b^\text{own}_{ijl}} + \gamma_d l \frac{\partial \phi^2_{ijl}}{\partial b^\text{comp}_{ijl}} \right) \right) = -\frac{1}{S_{it}} \left( \gamma_c l \frac{\partial \phi^1_{ijl}}{\partial e^\text{own}_{ijl}} + \gamma_d l \frac{\partial \phi^2_{ijl}}{\partial e^\text{comp}_{ijl}} \right).
\]

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:

\[
p_{ijt} = c_{ijt} + \underbrace{h(e_{ijt})g(X_{ijt}^\text{mc}) + \alpha^1_j c_{ijt} \phi^1_j(b^\text{own}_{ijt}, d^\text{own}_{ijt}) + \alpha^2_j c_{ijt} \phi^2_j(b^\text{comp}_{ijt}, d^\text{comp}_{ijt}) + X_{ijt}^e \alpha^e}_{\text{static markup}} + \gamma^1_j \frac{1}{S_{it}} \frac{\partial g(X_{ijt}^\text{mc})}{\partial q_{ijt}} h(e_{ijt}) + \gamma^2_j \frac{1}{S_{it}} \frac{\partial h(e_{ijt})}{\partial e_{ijt}} g(X_{ijt}^\text{mc}) + \sum_{l \in L} \left( -\frac{1}{S_{it}} \left( \gamma^3_j \frac{\partial \phi^1_{ijl}}{\partial e^\text{own}_{ijl}} + \gamma^4_j \frac{\partial \phi^2_{ijl}}{\partial e^\text{comp}_{ijl}} \right) \right) + \xi_j + \eta_m + \zeta_t + \epsilon_{ijt}.
\]

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.\(^{12}\) 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 discusses our specification for \(h\).

\(^{12}\)This also removes the assumption that firms are indeed internalizing the dynamic pricing incentives while still allowing for this forward-looking behavior.
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, List, and Syverson 2013) or a high rate of forgetting (Benkard 2004; Levitt, List, and Syverson 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 7 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 \( e^{\nu - 1} \). 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:

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

(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 consistent 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 (our specification is convex, but closer to linear than the power law).

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 described above in the special cases, so we have:

$$
\begin{align*}
\phi_1^j(b_{ijt}^{own}, d_{ijt}^{own}) &= \phi(e_{ijt}^{own}) = \exp(e_{ijt}^{own}) \\
\phi_2^j(b_{ijt}^{comp}, d_{ijt}^{comp}) &= \phi(e_{ijt}^{comp}) = \exp(e_{ijt}^{comp})
\end{align*}
$$

(15)

3.6 Final Specification

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

$$
p_{ijt} = c_{ijt} + \beta_0 \exp(e_{ijt}) \exp(X_{ijt}^{mc}) + \alpha_1 c_{ijt} \phi_1^j(e_{ijt}^{own}) + \alpha_2 c_{ijt} \phi_2^j(e_{ijt}^{comp}) + X_{ijt}^s \alpha^s + \frac{1}{S_{it}} \frac{\partial \exp(X_{ijt}^{mc})}{\partial q_{ijt}} h(e_{ijt}) + \frac{\gamma_2}{S_{it}} \frac{\partial \exp(e_{ijt})}{\partial e_{ijt}} \exp(X_{ijt}^{mc}) + \frac{1}{S_{it}} \left( \gamma_3 \phi_1^j(e_{ijt}^{own}) + \gamma_4 \phi_2^j(e_{ijt}^{comp}) \right) + \xi_j + \eta_m + \zeta_t + \epsilon_{ijt}.
$$

(16)

In this expression, we redefine the $\gamma$ parameters in order to combine terms where possible. Note that we are most interested in the coefficients within $e_{ijt}$, and are not interested in the $\alpha$’s and $\gamma$’s. Thus, this specification can be thought of as a semi-parametric control function approach motivated by the first-order conditions of the firm’s profit maximization problem.
4 Estimation

4.1 Method

We do not generally expect that 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.\(^\text{13}\)

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 \(k\)th element of \(\beta^h\), and the first element is the derivative of \(h(\cdot)\) with respect to \(\beta_0\). Similarly, let \(g_{k^g}\) be a vector in which the \(k^g\)th element is the derivative of \(g(\cdot)\) with respect to the \(k\)th element of \(\beta^g\). Define \(h^0 = h(\beta^{h0})\) where \(\beta^{h0}\) is the starting value for the vector \(\beta^h\) and \(g^0 = g(\beta^{g0})\) where \(\beta^{g0}\) is the starting value for the vector \(\beta^g\). We can write:

\[
w_{ijt} = h(e_{ijt})g(X_{ijt}^{mc}) \approx h^0 g^0 + \sum_{k^h=1}^{K^h} g^0 h^0_{k^h} \beta^h - g^0 h^0_{k^h} \beta^{h0} + \sum_{k^g=1}^{K^g} h^0 g^0_{k^g} - h^0 g^0_{k^g} \beta^{g0} \beta^g. \tag{17}
\]

Let \(w^0 = h^0 g^0 = \beta_0 \exp(-b_{ijt} \beta^{h0} + X_{ijt}^{mc} \beta^{g0})\). Because the exponential form allows us to combine the \(h(\cdot)\) and \(g(\cdot)\) expressions with their first derivatives, our final estimation equation is then:

\(^{13}\)This is a simple modification of the procedure described in chapter 7 of Greene (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.
\[ p_{ijt} - c_{ijt} + \frac{w^0}{\beta_0} - w^0 b_{ijt} \beta^{h0} + w^0 X_{ijt}^{mc} \beta^{g0} = \beta_0 w^0 - w^0 b_{ijt} \beta^h + w^0 X_{ijt}^{mc} \beta^g \]

\[ + X_{ijt} \alpha + \alpha_j c_{ijt} h^0 + \gamma_j^1 \frac{1}{S_{it}} w^0 + \gamma_j^2 \frac{1}{S_{it}} + \xi_j + \eta_m + \zeta_t + \epsilon_{ijt}, \]

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

After we perform this linear regression, we can update our values of \( \beta_0, \beta^h, \) and \( \beta^g \) 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 (Greene 2008). Another advantage is that it can easily be extended to allow for instrumenting of possible endogenous variables in \( X_{ijt} \).

### 4.2 Monte Carlo Simulations

To demonstrate the effectiveness of our estimation method, we simulate data for a simple duopoly under different assumptions. These assumptions are:

1. Consumers make a discrete choice between both firms and the outside option. Firms are myopic, so the model is static.

2. Consumers make a discrete choice between one firm and the outside option (i.e. the other firm is not in the consideration set). Firms are myopic so the model is static.

3. Consumers make a discrete choice between both firms and the outside option. Firms are forward-looking.

Details of our approach are included in Appendix B. In short, we simulate data under these three scenarios with an additive, structural error on soft costs. We then attempt to estimate the learning parameters using our estimation method. We assume that the
installed base of both firms enter non-hardware costs and that consumer utility for an installer increases with that installers’ installed base, which is one of the challenges we face in estimating the learning effect. The results of our simulations are in Table 5. It is clear that our method can recover the economic primitives of interest under different data generating processes, underscoring our ability to identify learning with only mild structural assumptions.

4.3 Identification

As described earlier, separate identification of the LBD parameters from static markup and dynamic pricing incentives comes from two 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 of learning on pricing is reasonable, but the idea that size itself is exogenous to pricing may be questionable. This motivates our decision to restrict the main analysis to installations less that 100 kW to avoid large commercial and utility scale installations, and to exclude ground mounted systems, which do not have the roof size constraints that many typical installations have. However, this still may not address the endogeneity of size. So we also instrument for size. 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 in-
teraction variables using variation in mean solar radiation. 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 year indicator variables as an instrument for the on-going contracts interaction variables. Similarly, we use the mean daily radiation and the mean monthly radiation interacted with year indicator variables. As another demand shifter, we also use the county-level monthly housing prices, based on the idea that larger and more valuable houses tend to use more electricity and changes in housing values may influence solar PV demand. At the same time, we see no obvious reason for housing prices to directly influence solar PV supply.

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 test statistic, we find serial correlation of only a few periods, indicating that this is not a concern.

Fundamentally, our coefficients of interest are identified from within-installer, within-zip code, and within-year-month variation in the installed base variables and the BOS after controlling for a variety of covariates and instrumenting for potentially endogenous variables with valid demand-shifters. We can separately identify the effect of experience from economies of scale through the differing variation in the installed base variables and the on-going contracts variables.
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 6 presents these results with an OLS specification (column 1) and fixed effects specification (column 2). These descriptive results do not attempt to model changing markups or dynamic pricing behavior, and thus are likely to be mis-specified and inconsistently estimated. Despite this caveat, we find these results to be an illustrative benchmark.

We find statistically significant evidence suggestive of a moderate own-experience effect, both within the county where the installation occurs and outside of the county. Taking these results at face value, increasing the contractor’s 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). Increasing the contractor’s installed base inside the county by 1,000 installations would decrease by 21 cents per watt. None of the other installed base variables are statistically significant and the magnitude of the competitor coefficients is very small. However, this linear model utilizes primarily time-series variation to identify spillover effects, much of which is absorbed by the year-month indicator variables. Moreover, we do not consider these results to be causal.

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 7. Column 1 presents the results of an ordinary least squares estimation, while column 2 presents the results of an instrumental variables estimation. We instrument for the system size and the ongoing contracts variables in the non-hardware cost term, as well as for the other quantity variables (the market share and HHI the firm level and at the county level) using the following demand shifters: daily solar radiation, average monthly solar
radiation, monthly solar radiation deviations, electricity rates, house values, and interactions of each of these with year dummy variables.\textsuperscript{14}

In both sets of estimation results, we find significant evidence of both appropriable and non-appropriable LBD. Our preferred IV estimation results show statistically and economically significant installed base effects for the contractor’s own installations both within and outside of the county. 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 installations by a contractor within a county (first row), our estimate indicates that adding 100 installations decreases non-hardware costs by $0.036 per watt. For installations by a contractor outside of the county, our estimate indicates that adding 100 installations reduces non-hardware costs by $0.021 per watt. The coefficient on the competitor’s installed base outside of the county indicates that 1,000 installations outside of the county reduces non-hardware costs by $0.005 per watt.

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 100 installations is a decline in non-hardware costs of $0.023 for installations within the county and $0.013 outside the county. The analogous figures for increasing the competitors’ total installed base by the same absolute amount is $0.003 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 -0.049, -0.229, and -0.304 for a contractor’s own installations

\textsuperscript{14}Our first stage results indicate that we have strong instruments. For example, the F-statistics are 702.8, 81.9, 1103.5, and 109.60 for CA HHI, county HHI, CA market share, and county market share variables respectively.
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 installations is larger than its competitors’ installations, non-appropriable learning is larger in terms of elasticities simply because there are so many more installations performed by competitors than by a single installer. Similarly, because there are so many more installations outside of a county than within, we find a greater learning elasticity due to installations outside the county. The corresponding mean progress ratios (the percentage of the cost that remains after a doubling of the installed base) for own and competitor installations (aggregating the own-effects for installations inside and outside the county) are 0.64 and 0.81, respectively. It should be noted that the different functional form leads to a declining progress ratio as installed bases increase, making a direct comparison to progress ratios estimated with power law specifications somewhat inappropriate.

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 0.5 cents per watt. An increase in the roofing wage rate by $1,000 increases the non-hardware costs by $0.096 per watt. Increasing the contractor ongoing contracts by 1,000 increases the non-hardware costs by $1.09 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 monthly 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 and our IV estimation (Figure 8). 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 8 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

We run a series of further robustness checks. Our primary specification treats installers as new firms after mergers, but it assumes that none of experience stock from the acquired firm is transferred. At the other extreme one could assume that all experience is transferred to the acquirer. We thus run the IV analysis where we assume that all firm experience is transferred during an acquisition. The results for this robustness check is found in column 1 of Table 9. We find that the results are very robust to the assumption made on experience transfer.

Our primary specification also assumes no forgetting. A second robustness check assumes a quarterly forgetting rate of 11% (a similar order of magnitude to that used/found in Kellogg (2011) and Benkard (2004)). The marginal coefficients with the exception of the installed base coefficients of interest change only slightly. As expected, the coefficients on the four installed bases in the creation of experience are scaled up (by about a factor of 1.5) since forgetting pushes installers back down the learning curve. The relative sizes of the coefficients are about the same as in the primary results. In addition, the elasticities for own installations in the county, own installations outside the county, and competitor installations do not substantially change: they go from values of -0.049, -0.229, and -0.304 to -0.047, -0.236, and -0.205, respectively.
6 Pigouvian Subsidy

We perform a set of illustrative calculations to quantify what our estimated non-appropriable LBD implies for the Pigouvian subsidy to address the positive externality. A full counterfactual welfare analysis would require imposing many more assumptions. Indeed, an advantage of our approach is that we can estimate LBD without assuming a demand system or a specific model of competition. Without such assumptions a full welfare analysis is not possible, and thus we restrict our focus on the Pigouvian subsidy.

Our calculations follow a similar logic to those in Nordhaus (2014). The intuition for these is that if a firm installs one additional solar PV system at time $t$, it will decrease the marginal non-hardware cost ($w$) for all installations of all other firms both at time $t$ and in all future periods. Let $\Delta w$ be the change in marginal cost for all other firms at time $t$. Further, let $Q_t$ be the number of installations by all other firms in the market at time $t$. For the purposes of illustrative calculations, we approximate the social welfare ($SW$) benefits (i.e., learning premium) from adding one additional installation as follows:

$$\Delta SW_t = \sum_t \rho^t \Delta w_t Q_t,$$

where $\rho$ is again the discount factor. Note this simple equation is a slight overestimate in a perfectly competitive market, for it overestimates the consumer willingness to pay for any additional installations demanded due to the cost decline. Analogously, it is a slight underestimate in an imperfectly competitive market, for there would be additional benefits from increasing the number of installations in reducing the difference between the marginal revenue and willingness to pay (demand).

We use the estimated non-hardware costs over time (shown in Figure 8), along with the spillover cost decline from an additional installation implied by our coefficients, to calculate the $\Delta w_t$ for each month from 2002 through the end of 2012. We do not model changes in costs leading to changes in demand from this increase of one installation. Since benefits from the spillovers continue to accrue after 2012, we must assume a future time
path of installations and $\Delta w_t$. We make several assumptions about these future time paths. In our baseline assumption, we fit a quadratic function to each and zero out $\Delta w_t$ when it turns negative. Under these baseline assumptions, learning spillovers diminish to zero around 2020, so we extrapolate until 2020 for the baseline. We then solve (19) for each month over the historical time period 2002-2012.

Table 10 presents the annual average Pigouvian subsidy results from these calculations. In our baseline estimates, which use a 5 percent discount rate, we find that $\Delta SW_t$ begins in 2002 at $0.55/\text{W}$, peaks in 2007 at $0.61/\text{W}$, and by 2012 drops to $0.45/\text{W}$ (all in 2012$)$. This concave shape reveals a tension between the two dominant factors determining the magnitude of the Pigouvian subsidy: rate of learning, which declines over time, and the number of installations that receive the lower costs, which would be expected to increase over time following a classic S-shaped technology diffusion curve (Griliches 1957). In 2002, learning is rapid, but the number of installations that receive a benefit is small. This number increases more quickly than our estimated decrease in learning at first, but eventually the decrease in learning dominates. Columns (2) through (4) provide further insight by assuming different extrapolations of installations and future costs. Column (5) shows the result using our baseline assumptions and a 3 percent discount rate.

While the different columns show that the magnitude of the Pigouvian subsidy is sensitive to assumptions, none of the magnitudes are in line with the actual subsidies (column (6)) until 2012. In fact, between 2002 and 2012, the average residential subsidy provided by the state of California was $2.12/\text{W}$, while the average subsidy in our baseline is only $0.56$ (in 2012$). Thus, to justify this policy, and even more so, the Federal tax credit on top of this policy, there must be large environmental externalities not addressed by other policies. Borenstein (2008), van Benthem, Gillingham, and Sweeney (2008), and Burr (2014) all find that the optimal (second-best) subsidy to address environmental externalities through solar PV systems is likely to be an order of magnitude smaller than the CSI subsidies. Given this, these illustrative calculations suggest that the CSI likely
over-subsidized solar PV relative to the economically efficient level, even after including benefits from LBD spillovers.

7 Conclusions

This paper develops a model of solar PV installer pricing to examine evidence for both appropriable LBD and non-appropriable LBD in the California solar PV market. We leverage a rich dataset of solar installations in California from 2002 to 2012 and develop a semi-parametric control function approach based on the first-order conditions of a forward-looking firm in the context of LBD. This approach imposes a minimal amount of structure and can flexibly control for changing market power, economies of scale, capacity constraints, and firm dynamic pricing incentives. It is particularly useful in our setting for it allows us to separate the non-hardware costs from the markup in the firm’s BOS.

We find clear evidence of economically-significant appropriable and non-appropriable learning in the non-hardware costs of solar PV installations. Learning by contractors within a county can reduce non-hardware costs by $0.036/W with the addition of 100 installations. Outside of the county the same 100 installations can reduce non-hardware costs by $0.021/W. But even more interesting than internal learning, is the evidence of external learning or learning spillovers. We find that 1,000 installations by competitors outside of the county reduces non-hardware costs by $0.005/W.

These results are not directly comparable to any in the literature. Papineau (2004) finds the effect of cumulative experience on solar PV prices is be significant in some specifications, but is insignificant when a time trend is included. In addition, Nemet (2006) finds stronger evidence for economies of scale than LBD in solar panel manufacturing. Ours is the first study to estimate localized appropriable and non-appropriable LBD in solar PV installations.

These findings have important ramifications for solar PV policy. Absent other market failures, policy action is warranted if the benefit from correcting the LBD spillover positive externality is greater than the cost of administering the policy and the distortionary
cost of raising the revenue. Illustrative calculations based on the empirical estimates suggest that Pigouvian subsidy to address this positive externality is less than $0.60/W, which is a fraction of the state financial incentives provided by California’s Emerging Renewables Program and the CSI. While by no means definitive, the illustrative calculations along with recent literature on the environmental externalities suggest that California has over-subsidized solar PV. That said, the results indicate that a smaller subsidy program may have been economic efficiency-improving based on the non-appropriable learning that occurred.

Such targeted subsidies do raise deeper questions about the role of government in industrial policy. As is clear from the literature, LBD and learning spillovers are not unique to solar PV. Should policy only focus on technologies like solar PV that have learning spillovers at the same time as environmental benefits? Or should policymakers consider policies for any technology that exhibits learning spillovers? We save this question for future research.

References


Appendicies

Appendix A: Static Markup Depends on Non-hardware Costs

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

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

To see why this is the case we can begin by writing:

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

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

$$\frac{\partial}{\partial p_{ijt}} \left( -\frac{\delta_{ijt}}{\frac{\partial p_{ijt}}{\partial p_{ijt}}} \right) \neq 1.$$
We can simplify this to:

\[ \delta_{ijt} \frac{\partial^2 \delta_{ijt}}{\partial p_{ijt}^2} \neq 0. \]

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.

Consider the second assumption. Although not necessary to assume a discrete choice framework, the ramification of this assumption is easily seen in such a framework. 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 \( j \) as:

\[ \delta_{ijt} = F_{-j} (u_{ijt} \iota_J) \]

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 \( \delta_{ijt} \) is not linear in price in a random utility setting is the same as assuming that the cdf of the stochastic utility is not linear, which is a very reasonable assumption.

**Appendix B: Monte Carlo Simulations**

For our Monte Carlo simulations, we simulate the data using the installers’ Euler conditions. Static profits are given by:

\[ \Pi(p, b^1, b^2) = \sum_{i=1}^{Q_t} \left\{ [p_i - c_i - (w_i(b^1, b^2) - \epsilon^1_{it})] S_i \delta_i \right\} - F. \]

where \( p \) is the price vector over all new potential installations, indexed by \( i \), \( b^1 \) is the installed base of the firm, \( b^2 \) the installed base of its competitor, and \( \epsilon^1_{it} \) and \( \epsilon^2_{it} \) are the unobserved shock to non-hardware costs for the focal firm and competitor, respectively.
\( \epsilon_{it}^{1} \) enters the profit function directly but \( \epsilon_{it}^{1} \) only enters through \( \delta_{i} \), which depends on the prices set by both firms if the consumer chooses between them, but the price of the non-chosen installer is not observed, which depends on \( \epsilon_{it}^{2} \).

Without loss of generality we can say the contractor maximizes

\[
\mathbb{E} V_{it} = \sum_{\tau=t}^{\infty} \rho^{(\tau-t)} \Pi(p_{\tau}, b_{1,\tau}^{1}, b_{2,\tau}^{2}),
\]

since \( \rho = 0 \) is the same as assuming myopic installers.

The resultant Euler equations for the pricing of each installation are:

\[
\frac{d\Pi(p_{t}, b_{1,t}^{1}, b_{2,t}^{2})}{dp_{i}} = \rho \left[ \sum_{i} \frac{d\Pi(p_{t+1}, b_{1,t+1}^{1}, b_{2,t+1}^{2})}{dp_{i,t+1}} + \frac{d\Pi(p_{t+1}, b_{1,t+1}^{1}, b_{2,t+1}^{2})}{db_{1,t+1}^{i}} + \frac{d\Pi(p_{t+1}, b_{1,t+1}^{1}, b_{2,t+1}^{2})}{db_{2,t+1}^{i}} \right].
\]

Since the prices of installations do not affect each other in the same period we can write:

\[
\frac{d\Pi(p, b_{1,t}^{1}, b_{2,t}^{2})}{dp_{i}} = S_{i} \delta_{i} + \left[ p_{i} - c_{i} - w_{i}(b_{1}^{1}, b^{2}) + \epsilon_{it} \right] S_{i} \frac{d\delta_{i}}{dp_{i}}.
\]

By substitution we can write:

\[
\epsilon_{it} = \frac{\rho \left[ \sum_{i} \frac{d\Pi(p_{t+1}, b_{1,t+1}^{1}, b_{2,t+1}^{2})}{dp_{i,t+1}} + \frac{d\Pi(p_{t+1}, b_{1,t+1}^{1}, b_{2,t+1}^{2})}{db_{1,t+1}^{i}} + \frac{d\Pi(p_{t+1}, b_{1,t+1}^{1}, b_{2,t+1}^{2})}{db_{2,t+1}^{i}} \right]}{S_{i} \frac{d\delta_{i}}{dp_{i}}} - \left( p_{i} - c_{i} - w_{i}(b_{1}^{1}, b^{2}) \right)
\]

In our simulations we assume perfect foresight and independence of \( \epsilon_{it}^{1} \) and \( \epsilon_{it}^{2} \). We can estimate this equation using OLS, once we have expressions for \( \delta \) and \( \frac{d\delta_{i}}{dp_{i}} \).

To get these expressions, we need to make an assumption on the nature of demand. Let us assume a random utility model which allows utility for an installer to increase with the installer’s experience:

\[
u_{i}^{1}(b) = \alpha p_{i} + (1 - \exp(-\gamma b)) + \beta_{0} + \varepsilon_{ij}
\]
The probability of purchasing from installer 1 if both are considered is:

\[ \delta^1(b^1) = \frac{\exp(u(b^1))}{1 + \exp(u(b^1)) + \exp(u(b^2))} \]

The probability of purchasing from installer 1 if only installer 1 is considered is:

\[ \delta^1(b^1) = \frac{\exp(u(b^1))}{1 + \exp(u(b^1))} \]

In our simulation we set \( \alpha = -0.1, \gamma = 0.1, \) and \( \beta_0 = 2.0. \) For our specification of soft costs, we assume that:

\[ w_i(b^1, b^2) = \exp(w_0 + w_s S_i + \beta_{own} b^1 + \beta_{comp} b^2) \]

with \( w_0 = 1.5, w_s = -0.01, \beta_{own} = 1.0, \) and \( \beta_{comp} = 0.5. \) We assume that each period has 20 potential installations each of sizes 1, 2, 3, 4, and 5 kW for a total of 100 new potential installations each period. The installed base is measured in 1000s. Hard costs are stochastic and lie between $10/W and $4/W; they change at different rates for the two installers.

We simulate data for 500 periods assuming optimal pricing under both demand assumptions with \( \rho = 0, \) to test the importance of demand assumptions on estimation results using our methodology. We also simulate data for the first model of demand under the alternative assumption that installers price optimally and are forward looking with \( \rho = 0.9. \) For all three data generating processes, we successfully recover the economic primitives using our proposed approach which requires no assumption on the nature of demand of the discount rate.
Figure 1: The California Solar Initiative incentive steps.

Figure 2: Average requested installations per month
Figure 3: CA solar prices over time

Figure 4: Balance-of-System (BOS) over time by firm size
Figure 5: Distribution of firms by firm size

Sample restricted to firms with greater than 10 installs

Figure 6: Balance-of-System (BOS) over time by installation size

- Installations over 6 kW
- Installations less than 4 kW
Figure 7: Our LBD specification versus a common specification

![Graph showing normalized cost and cumulative installations for two specifications.]

Figure 8: BOS vs. non-hardware costs, OLS

![Graph showing BOS and total non-hardware costs over weeks from 2002 to 2012.]
Figure 9: Model comparison

BOS and total non-hardware costs

- BOS
- simple model
- no dynamics
- no markup
- full model
<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min.</th>
<th>Max.</th>
<th>N</th>
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<tbody>
<tr>
<td>hardware costs ($2012/W)</td>
<td>4.339</td>
<td>1.697</td>
<td>0.373</td>
<td>10.976</td>
<td>94,109</td>
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<td>residential rebate ($2012/W)</td>
<td>1.205</td>
<td>1.095</td>
<td>0</td>
<td>9.370</td>
<td>94,109</td>
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<tr>
<td>system size (kW&lt;sub&gt;DC&lt;/sub&gt;)</td>
<td>6.137</td>
<td>6.338</td>
<td>0.6</td>
<td>99.75</td>
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<td>CA installed base (1000s)</td>
<td>69.023</td>
<td>35.016</td>
<td>1.824</td>
<td>138.08</td>
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<td>contractor installed base (1000s)</td>
<td>1.156</td>
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<td>0.00</td>
<td>16.426</td>
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<td>contractor’s county installed base (1000s)</td>
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<td>0.259</td>
<td>0.00</td>
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<td>competitors’ county installed base (1000s)</td>
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<td>3.861</td>
<td>0.00</td>
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<td>contractor’s on-going contracts (1000s)</td>
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<td>0.517</td>
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<td>monthly market share in county</td>
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<td>0.158</td>
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<td>HHI in CA</td>
<td>0.046</td>
<td>0.049</td>
<td>0.012</td>
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<td>HHI in county</td>
<td>0.145</td>
<td>0.13</td>
<td>0.028</td>
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<td>roofing wage rate (1000s 2012$)</td>
<td>40.123</td>
<td>5.877</td>
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<td>third party-owned system</td>
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<td>appraised value system</td>
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<td>0.329</td>
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<td>1</td>
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<td>average electricity rate (2012$)</td>
<td>0.152</td>
<td>0.011</td>
<td>0.095</td>
<td>0.177</td>
<td>94,067</td>
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<tr>
<td>monthly average radiation (W/m&lt;sup&gt;2&lt;/sup&gt;)</td>
<td>5468.665</td>
<td>1849.59</td>
<td>1559.458</td>
<td>8457.046</td>
<td>94,109</td>
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<td>dev. from monthly avg radiation (W/m&lt;sup&gt;2&lt;/sup&gt;)</td>
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<td>324.363</td>
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<td>monthly housing prices (1000s 2012$)</td>
<td>494.785</td>
<td>344.536</td>
<td>57.00</td>
<td>3,807.60</td>
<td>93,748</td>
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Notes: an observation is an installation. The installed base is the cumulative number of installations by that point in time. The HHI refers to the Herfindahl-Hirschman Index.
Table 2: Installation price and size, residential

<table>
<thead>
<tr>
<th>Variable</th>
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<th>Std. Dev.</th>
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<td>1.413</td>
<td>11.997</td>
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<tr>
<td>hard costs (2012$ per W)</td>
<td>4.329</td>
<td>1.697</td>
<td>0.379</td>
<td>10.976</td>
<td>90,869</td>
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Table 3: Installation price and size, non-residential

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<th>Max.</th>
<th>N</th>
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<td>price (2012$ per W)</td>
<td>7.458</td>
<td>1.854</td>
<td>1.82</td>
<td>11.985</td>
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<td>hard costs (2012$ per W)</td>
<td>4.771</td>
<td>1.687</td>
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<td>10.275</td>
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Table 4: Installations by contractor

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<th>Min.</th>
<th>Max.</th>
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<td>Contractor number of installations</td>
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<td>282.089</td>
<td>1</td>
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<td>Contractor MW of installations</td>
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<td>1.67</td>
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<td>68.66</td>
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<td>Contractor number of counties</td>
<td>2.381</td>
<td>3.605</td>
<td>1</td>
<td>52</td>
<td></td>
</tr>
<tr>
<td>Number of contractors</td>
<td>2,909</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5: Monte Carlo Simulation Results

<table>
<thead>
<tr>
<th>Assumed Data Generating Process</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Installers: static</td>
<td>-0.963*** (0.013)</td>
<td>-0.981*** (0.038)</td>
<td>-0.940*** (0.014)</td>
</tr>
<tr>
<td>Consideration set: 2 firms</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Consideration set: 1 firm</td>
<td>-0.546*** (0.013)</td>
<td>-0.529*** (0.025)</td>
<td>-0.511*** (0.012)</td>
</tr>
<tr>
<td>Consideration set: 2 firms</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: The true value of the own experience is -1.0 and competitor’s experience is -0.5. Each column refers to the assumed data generating process, while the rows refer to the estimated coefficients from our model. The simulations are based on 500 periods and 100 new potential installations per period, of five different sizes (20 each). Robust standard errors clustered on county in parentheses. *** indicates significant at the 1% level, ** at the 5% level, * at the 10% level.
<table>
<thead>
<tr>
<th></th>
<th>(OLS)</th>
<th>(FE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>contractor installed base within county (1000s)</td>
<td>-0.83***</td>
<td>-0.21**</td>
</tr>
<tr>
<td></td>
<td>(0.15)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>contractor installed base outside county (1000s)</td>
<td>-0.20***</td>
<td>-0.32***</td>
</tr>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>competitor installed base within county (1000s)</td>
<td>0.01</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>installed base outside county (1000s)</td>
<td>0.00</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>third party owned</td>
<td>0.12*</td>
<td>-0.06*</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>size (kW)</td>
<td>-0.01***</td>
<td>-0.01***</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>contractor on-going contracts</td>
<td>-0.02</td>
<td>0.03</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>roofing wage rate (1000s 2012$)</td>
<td>0.00</td>
<td>0.00*</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
</tr>
<tr>
<td>appraised value system</td>
<td>3.12***</td>
<td>2.37***</td>
</tr>
<tr>
<td></td>
<td>(0.09)</td>
<td>(0.10)</td>
</tr>
<tr>
<td>contractor monthly CA mkt share</td>
<td>1.82**</td>
<td>-1.08*</td>
</tr>
<tr>
<td></td>
<td>(0.67)</td>
<td>(0.51)</td>
</tr>
<tr>
<td>contractor monthly county mkt share</td>
<td>0.36</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.14)</td>
</tr>
<tr>
<td>constant</td>
<td>2.42***</td>
<td>2.45***</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
<td>(0.24)</td>
</tr>
<tr>
<td>HHI in county &amp; state</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>year-month indicators</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>contractor indicators</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>zip code fixed effects</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.362</td>
<td>0.660</td>
</tr>
<tr>
<td>N</td>
<td>94,080</td>
<td>94,080</td>
</tr>
</tbody>
</table>

Notes: The dependent variable is the BOS (i.e., price - hard costs; mean=2.9). An observation is an installation. The installed base variables enter linearly. Robust standard errors clustered on county in parentheses. *** indicates significant at the 1% level, ** at the 5% level, * at the 10% level.
Table 7: Primary Results

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS</th>
<th>(2) IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>contractor installed base</td>
<td>-0.770***</td>
<td>-0.368***</td>
</tr>
<tr>
<td>within county (1000s)</td>
<td>(0.172)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>contractor installed base</td>
<td>-0.269***</td>
<td>-0.216***</td>
</tr>
<tr>
<td>outside county (1000s)</td>
<td>(0.044)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>competitor installed base</td>
<td>0.016</td>
<td>0.002</td>
</tr>
<tr>
<td>within county (1000s)</td>
<td>(0.009)</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>(0.001)</td>
</tr>
<tr>
<td>intercept in $X^{w1}$</td>
<td>0.106*</td>
<td>0.248***</td>
</tr>
<tr>
<td>roofing wage rate (1000s 2012$)</td>
<td>0.324</td>
<td>0.077***</td>
</tr>
<tr>
<td>(0.132)</td>
<td>(0.027)</td>
<td></td>
</tr>
<tr>
<td>size (kW)</td>
<td>-0.001</td>
<td>-0.005***</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.000)</td>
<td></td>
</tr>
<tr>
<td>contractor on-going contracts (1000s)</td>
<td>0.579***</td>
<td>1.146***</td>
</tr>
<tr>
<td>(0.109)</td>
<td>(0.012)</td>
<td></td>
</tr>
<tr>
<td>third party-owned/appraised value</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>mkt share/county mkt share</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>HHI in state &amp; county</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>zip code fixed effects</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>year-month indicators</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>static markup controls</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>forward-looking controls</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.751</td>
<td>0.783</td>
</tr>
<tr>
<td>N</td>
<td>94,058</td>
<td>93,714</td>
</tr>
</tbody>
</table>

Notes: This table contains the results from estimating (18) by iterating over values of the $\beta$ coefficients until convergence. Effectively, the dependent variable is the BOS. An observation is an installation. The IV estimation in column 2 instruments for the system size, on-going contracts, and market share variables with daily solar radiation, average monthly solar radiation, monthly solar radiation deviations, house values, and interactions with year indicator variables. Robust standard errors clustered on county in parentheses. *** indicates significant at the 1% level, ** at the 5% level, * at the 10% level.
Table 8: 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>
<th>all</th>
</tr>
</thead>
<tbody>
<tr>
<td>contractor installed base within county (1000s)</td>
<td>-2.236*</td>
<td>-2.496***</td>
<td>-0.418***</td>
<td>-0.770***</td>
</tr>
<tr>
<td></td>
<td>(0.850)</td>
<td>(0.530)</td>
<td>(0.077)</td>
<td>(0.172)</td>
</tr>
<tr>
<td>contractor installed base outside county (1000s)</td>
<td>-0.514*</td>
<td>-1.714***</td>
<td>-0.193***</td>
<td>-0.269***</td>
</tr>
<tr>
<td></td>
<td>(0.203)</td>
<td>(0.192)</td>
<td>(0.038)</td>
<td>(0.044)</td>
</tr>
<tr>
<td>competitor installed base within county (1000s)</td>
<td>0.044*</td>
<td>0.014**</td>
<td>-0.012***</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>competitor installed base outside county (1000s)</td>
<td>0.006</td>
<td>-0.003*</td>
<td>-0.007***</td>
<td>-0.006**</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>intercept in $w_{i1}$</td>
<td>-2.591*</td>
<td>1.000***</td>
<td>0.355</td>
<td>0.106*</td>
</tr>
<tr>
<td></td>
<td>(0.981)</td>
<td>(0.214)</td>
<td>(0.291)</td>
<td>(0.414)</td>
</tr>
<tr>
<td>roofing wage rate (1000s 2012$)</td>
<td>1.535*</td>
<td>0.134</td>
<td>0.216**</td>
<td>0.324</td>
</tr>
<tr>
<td></td>
<td>(0.577)</td>
<td>(0.122)</td>
<td>(0.069)</td>
<td>(0.132)</td>
</tr>
<tr>
<td>size (kW)</td>
<td>-0.178**</td>
<td>-0.039***</td>
<td>-0.000***</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.005)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>contractor on-going contracts (1000s)</td>
<td>1.222***</td>
<td>0.859***</td>
<td>0.563***</td>
<td>0.579***</td>
</tr>
<tr>
<td></td>
<td>(0.351)</td>
<td>(0.192)</td>
<td>(0.096)</td>
<td>(0.109)</td>
</tr>
<tr>
<td>third party-owned/appraised value</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>mkt share/county mkt share</td>
<td>X</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>
<td>X</td>
</tr>
<tr>
<td>zip code fixed effects</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>year-month indicators</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>static markup controls</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>forward-looking controls</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.428</td>
<td>0.567</td>
<td>0.819</td>
<td>0.751</td>
</tr>
</tbody>
</table>

Notes: This table contains the results from estimating (18) by iterating over values of the $\beta$ coefficients until convergence. Effectively, the dependent variable is the BOS. The first column estimates a simple model without any of the static markup or forward-looking controls. The second adds forward looking controls, but does not include dynamics. The third includes the static markup, but no forward looking terms. The last is the same as the first column in Table 7. Robust standard errors clustered on county in parentheses. *** indicates significant at the 1% level, ** at the 5% level, * at the 10% level.
Table 9: Robustness Checks

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Full transfer of experience</td>
<td>Depreciation of 11% per quarter</td>
</tr>
<tr>
<td>contractor installed base</td>
<td>-0.388***</td>
<td>-0.532***</td>
</tr>
<tr>
<td>within county (1000s)</td>
<td>(0.022)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>contractor installed base</td>
<td>-0.214***</td>
<td>-0.350***</td>
</tr>
<tr>
<td>outside county (1000s)</td>
<td>(0.010)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>competitor installed base</td>
<td>-0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>within county (1000s)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>competitor installed base</td>
<td>-0.005**</td>
<td>-0.007***</td>
</tr>
<tr>
<td>outside county (1000s)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>intercept in $X^{wi}$</td>
<td>0.233***</td>
<td>0.215***</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.058)</td>
</tr>
<tr>
<td>roofing wage rate (1000s 2012$)</td>
<td>0.097***</td>
<td>0.079***</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>size (kW)</td>
<td>-0.005***</td>
<td>-0.005***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>contractor on-going contracts (1000s)</td>
<td>1.133***</td>
<td>1.127***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>third party-owned/appraised value</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>mkt share/county mkt share</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>HHI in state &amp; county</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>zip code fixed effects</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>year-month indicators</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>static markup controls</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>forward-looking controls</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.786</td>
<td>0.787</td>
</tr>
<tr>
<td>N</td>
<td>93,714</td>
<td>93,714</td>
</tr>
</tbody>
</table>

Notes: This table contains the results from estimating (18) by iterating over values of the $\beta$ coefficients until convergence. Effectively, the dependent variable is the BOS. An observation is an installation. The IV estimations instrument for the system size, on-going contracts, and market share variables with daily solar radiation, average monthly solar radiation, monthly solar radiation deviations, house values, and interactions with year indicator variables. Robust standard errors clustered on county in parentheses. *** indicates significant at the 1% level, ** at the 5% level, * at the 10% level.
## Table 10: Illustrative Pigouvian Subsidy Estimates

<table>
<thead>
<tr>
<th>year</th>
<th>(1) baseline</th>
<th>(2) linear</th>
<th>(3) constant end installs</th>
<th>(4) Δ MC end</th>
<th>(5) 3% discount</th>
<th>(6) actual rebate</th>
</tr>
</thead>
<tbody>
<tr>
<td>2002</td>
<td>0.548</td>
<td>0.866</td>
<td>0.472</td>
<td>0.300</td>
<td>0.67</td>
<td>4.429</td>
</tr>
<tr>
<td>2003</td>
<td>0.564</td>
<td>0.898</td>
<td>0.484</td>
<td>0.304</td>
<td>0.67</td>
<td>3.838</td>
</tr>
<tr>
<td>2004</td>
<td>0.580</td>
<td>0.931</td>
<td>0.496</td>
<td>0.307</td>
<td>0.68</td>
<td>3.054</td>
</tr>
<tr>
<td>2005</td>
<td>0.593</td>
<td>0.962</td>
<td>0.505</td>
<td>0.306</td>
<td>0.69</td>
<td>2.686</td>
</tr>
<tr>
<td>2006</td>
<td>0.604</td>
<td>0.991</td>
<td>0.511</td>
<td>0.302</td>
<td>0.69</td>
<td>2.469</td>
</tr>
<tr>
<td>2007</td>
<td>0.608</td>
<td>1.014</td>
<td>0.511</td>
<td>0.291</td>
<td>0.68</td>
<td>2.045</td>
</tr>
<tr>
<td>2008</td>
<td>0.598</td>
<td>1.024</td>
<td>0.496</td>
<td>0.265</td>
<td>0.66</td>
<td>1.720</td>
</tr>
<tr>
<td>2009</td>
<td>0.585</td>
<td>1.032</td>
<td>0.477</td>
<td>0.234</td>
<td>0.64</td>
<td>1.365</td>
</tr>
<tr>
<td>2010</td>
<td>0.556</td>
<td>1.025</td>
<td>0.443</td>
<td>0.188</td>
<td>0.60</td>
<td>0.826</td>
</tr>
<tr>
<td>2011</td>
<td>0.509</td>
<td>1.000</td>
<td>0.390</td>
<td>0.122</td>
<td>0.54</td>
<td>0.521</td>
</tr>
<tr>
<td>2012</td>
<td>0.452</td>
<td>0.939</td>
<td>0.327</td>
<td>0.045</td>
<td>0.48</td>
<td>0.355</td>
</tr>
</tbody>
</table>

Notes: Columns (1)-(5) represent the results of calculations of the Pigouvian subsidy to address non-appropriable LBD. Column (1) is the baseline estimate, in which a quadratic extrapolation is used for both future installations and the change in marginal cost. Column (2) uses a linear extrapolation. Column (3) shows the results if the number of installations remains at the December 2012 level indefinitely but with a quadratic extrapolation of marginal cost. Column (4) shows the results if all learning spillovers end in Dec 2012. Column (5) uses a 3% rather than 5% discount rate. Column (6) shows the actual rebate schedule observed over time.