Evaluating the Effects of Incentive Programs on Residential Solar Panel Adoption in Massachusetts *

Andrew Kearns †

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Abstract

How effective are demand-side incentive programs at encouraging households to adopt solar panels? I use data on residential solar panel installations in Massachusetts to estimate a dynamic model of solar panel adoption (or demand) that accounts for both current and future savings. The model allows me to evaluate several solar incentive programs implemented in Massachusetts in terms of their impacts on adoption rates, consumer welfare, and contribution to the reduction of CO_2 emissions. In addition, I analyze each program's cost effectiveness by comparing the social benefit generated due to displaced CO_2 emissions to the government's expenditure on each program. My estimates suggest that the social benefits generated are modest relative to the magnitude of public spending.

Keywords: solar panel demand estimation, technological adoption, dynamic discrete choice, environmental and energy policy

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†Department of Economics, Northeastern University, email: kearns.an@northeastern.edu. Thank you to James Dana, John Kwoka, and Imke Reimers for many helpful comments and suggestions.

1 Introduction

Federal and state governments in the United States have experimented with a variety of policies designed to encourage the adoption of green technologies. In particular, over the past two decades policymakers, across the U.S. and abroad, have championed the development of the photovoltaic (PV) solar industry, in large part as a response to increasing alarm about the impact of climate change on the environment and world economy. Many policymakers view the expansion of the renewable energy sector as a promising means to curb greenhouse gas emissions, especially carbon dioxide emissions, and increasingly PV solar makes up a significant portion of renewable energy generated in the U.S. (according to the U.S. Energy Information Administration (EIA), renewables accounted for 12% of total energy consumption in 2020 of which 11% was generated by solar).[1]

In an effort to incentivize residential and commercial adoption of solar panels, a patchwork of demand-side policies aimed at reducing the price of PV solar systems was legislated in the U.S. beginning in the mid-2000s. These programs include federal and state solar tax credits, state rebates and grants (usually capacity-based subsidies), net metering by electric utilities (mechanisms by which renewable owners are compensated by their local utilities for clean energy generation), and the introduction of renewable energy certificate (REC) markets (tradeable certificates supported by electric utility renewable portfolio standards; quotas for utilities' energy supply), a form of production-based subsidies. Each policy instrument has different characteristics including the mechanism by which funds are distributed (e.g. top-down versus market-based) and the time-horizon over which funds are distributed. Thus policymakers seeking to design the optimal subsidy policy must consider their financial constraints, as well as households' behavioral responses to different policy instruments. Determining how effective different incentives are at increasing the diffusion of PV solar systems is key to evaluating their relative cost-effectiveness and more generally key to assessing the extent to which adoption of renewables contributes to the reduction of greenhouse gas emissions.

In this paper, I investigate the efficacy of several of these programs on residential PV system adoption in Massachusetts. Specifically, using household-level data from the Massachusetts Clean Energy Center (MassCEC) from 2008 to 2018 I analyze the effect of three types of incentives: (1) upfront subsidies (federal and state tax credits and grants), (2) solar renewable energy certificates (SRECs), and (3) net metering. In order to disentangle the effect of each of incentive program, as well as distinguish between upfront and future incentives in a coherent economic framework, I estimate

[1]https://www.eia.gov/energyexplained/renewable-sources/

aggregate residential demand for solar PV systems using a dynamic discrete choice model following De Groote and Verboven (2019). Their model allows me to separately capture the effect of each program on demand and thus determine its contribution to cumulative adoption by simulating counterfactual scenarios. The model also allows me to investigate how the effectiveness of these subsidies depends upon various aspects of consumer behavior, including the extent to which households are forward looking and the degree of heterogeneity among households.

Given that solar incentives in Massachusetts were quite substantial during the period I study, on average about $32,000 per residential installation, unsurprisingly I find that each program had a substantial impact on residential adoption; upfront subsidies by increased adoption by 5-fold and SRECs increased adoption by 4.6-fold. Quantifying the impact of net metering on adoptions is more subjective due to lack of micro-data on households' electricity consumption, however, relying upon my most conservative estimate I find a 16% increase in PV system adoption as a result of net metering. Like De Groote and Verboven (2019), my estimates suggest that dollar for dollar upfront incentives are more efficient than long-term incentives because households significantly discount the future benefits of adoption.

In addition to estimating the effect of each incentive on household adoption, I undertake several welfare analyses. First, I quantify the amount of consumer surplus generated by each program. Second, using a recent estimate of the social cost of carbon from the climate literature, I approximate the social value of avoided CO_2 emissions due to each program. I find that the value of avoided CO_2 emissions is two orders of magnitude smaller than the amount of government support. For example, upfront subsidies resulted in a reduction in CO_2 emissions during the 2008-2017 period valued at only $5.25 million, while on the order of $280 million was invested in upfront subsidies. These findings beg the question are there more efficient policies in which governments should invest to curb CO_2 emissions?

1.1 Related Literature

This paper adds to the literature on residential solar incentives and is related to several strands of the economic literature including energy and environmental policy, consumer adoption of durable goods and the diffusion of new technologies in industrial organization, and the application of dynamic discrete choice models in econometrics.

To my knowledge, this is the first empirical study of the effects of Massachusetts' solar incentives on PV system adoption. Several authors including Burr (2014), Borenstein (2017), and Langer and Lemoine (2018) study the effects of government subsidies on PV adoption in California, and Bollinger and Gillingham (2012), Gillingham and

Tsvetanov (2019), Bollinger, Gillingham, Kirkpatrick, and Sexton (2020) use data from Connecticut to study the impact of subsidies and peer effects on solar adoption. However, each state has slightly different policies, which provides a unique opportunity to investigate the effectiveness of such policies. The policy that most distinguishes Massachusetts from other states is the design of its SREC market, which incorporates a price ceiling and a price floor as mechanisms to support prices. This design resulted in a relatively robust REC market compared to other states where prices tended to collapse. Therefore, Massachusetts provides a unique case study of the role of market design in public policy, as well as the effect of relatively generous, sustained production-based subsidies on PV system adoption.

Given the range of findings in the literature, as well as differences in policies across jurisdictions, there is no clear consensus as to the design of "optimal" solar subsidies, however, what seems clear is that policymakers have committed a lot of resources to solar without fully understanding how different policies influence households' incentives. Burr (2014) compares the capacity-based subsidies implemented in California to production-based subsidies and finds they are equally effective but that production-based subsidies are more efficient. Langer and Lemoine (2018) show that the optimal government subsidy in a dynamic technology adoption setting depends on the regulator's preferences in addition to household behavior and find that the most efficient policy for California would have been an increasing subsidy schedule as opposed to the declining schedule that was enacted.

My study most closely resembles De Groote and Verboven (2019) who use household-level data from Belgium to compare the efficiency of upfront subsidies, namely tax credits, relative to future subsidies, production-based subsidies in the form of SRECs distributed by the government. Consistent with my empirical findings, they find that upfront subsidies are more efficient given that households sufficiently undervalue future benefits. Borenstein (2017) shows that California's usage-based electricity rate structure increased high-usage customers' financial incentive to adopt solar relative to low-usage customers by perhaps as much as the 30% federal solar tax credit, highlighting the importance of accounting for the distributional effects of increasing electricity prices and net metering policies. Finally in a different set of studies, Bollinger and Gillingham (2012) and Bollinger, Gillingham, Kirkpatrick, and Sexton (2020) emphasize the importance of local peer effects on adoption behavior, which implies that government investment in solar may have a multiplier effect.

The primary contribution of this paper to the environmental and energy policy literature is the comparison of three policy instruments commonly applied to incentivize the adoption of renewables: tax credits (and other upfront subsidies), RECs, and net metering. A secondary contribution is that I directly approximate the amount of CO_2

emissions displaced by PV systems in my sample (because I observe estimated annual generation) and undertake a cost-benefit analysis of these programs using my estimates.

2 Industry Background

2.1 Technology and Supply

Photovoltaic solar systems convert sunlight into electrical energy. The fundamental component of PV systems are solar cells fabricated from semiconductor material, generally silicon, which absorb sunlight, transfer the light's energy to electrons, thus generating an electrical current. In a residential system, which typically consists of several chained modules or panels of solar cells, this current then flows through metal conductors on each cell to electrical wires that carry the electricity either to the local utility's grid or to the home (see Figure 1). The other major component of a PV system is the inverter which converts direct current (DC) to alternating current (AC) for home use. The amount of energy a system generates, or its efficiency, largely depends upon the material of its solar cells, as well as the system's exposure to sunlight, where the number of sunlight hours in a location and panel placement and tilt (angle relative to the ground) are important factors. The average residential system included in my sample has a capacity of 7.5 kW and produces about 8,800 kWh of electricity annually, which accounts for 118% of the 7,430 kWh of energy the average Massachusetts household consumes each year.

When solar panels were first introduced, low energy efficiency and high cost prevented their widespread use for all but the most specialized applications (for example in the aerospace industry), however, as efficiency has increased and manufacturing costs have decreased over time, PV solar has become increasingly viable for commercial and residential use. The energy industry carefully tracks the decline in the manufacturing cost of solar modules over time, and there is a large body of academic work that decomposes this trend into various factors (see Figure 2). For example, Kavlak, McNerney, and Trancik (2018) document that "PV module costs [have fallen] by about 20% with every doubling of cumulative capacity since the 1970s" and emphasize increased module efficiency, R&D funding, and scale economies as the major contributing factors over different periods. Louwen and van Sark (2020) find a structural break in this trend beginning in 2008 which is at least partially explained by economies of scale and learning-by-doing by Chinese manufactures entering the module market. Data from the National Renewables Energy Laboratory (NREL) shows that costs of components other than modules, and even some soft costs like labor, have also fallen over time. This decline in cost is reflected in prices too; according to data from the Lawrence Berkley

National Laboratory (2019), over the past two decades PV system installation prices in the U.S. have declined at a rate of 5-7% per year, largely due to reductions in manufacturing costs. As I explain in greater detail in the estimation section, this secular decline in module prices gives me a source of exogenous variation in local installation prices with which to identify households' price elasticity of demand for solar panels.

The PV system industry consists of module, inverter, and other component manufacturers, system installers that sell to end-users, and electric utilities which set electricity prices and control connectivity of renewables to the grid. Massachusetts has four large "utility markets" served by investor-owned utilities (IOUs), which cover 303 of Massachusetts' 351 municipalities; the remaining 48 are served individually by small municipal electric companies (see Figure 3). Electricity prices are set subject to rate of return regulation and tend to be set higher for IOUs than municipal utilities.

During my sample period, there were over 600 PV system installers operating in Massachusetts. The majority appear to be local electricians or construction companies, and the median number of installations by firms is two. However, the two largest installers SolarCity (acquired by Tesla in 2016) and Vivint (acquired by Sunrun in 2020) together account for 43% of all installations, 24% and 19% respectively. SolarCity and Vivant started selling in Massachusetts in 2011 and 2012, respectively. Both companies engaged in aggressive marketing campaigns, including door-to-door sales tactics, and promoted solar lease agreements to lower-income customers with much success.

In this paper, I focus on the demand-side of the market rather than the supply-side for several reasons. First, my primary focus is quantifying the effect of government subsidies on demand; second, incorporating a dynamic model of supply into my analysis would be quite challenging; and third, given the number of installers in Massachusetts it appears that the market, for installation at least, is relatively competitive which reduces the importance of firms' price setting behavior. Gerarden (2018) analyzes the supply-side of the market but focuses on competition between solar panel manufacturers rather than installers.

2.2 Tax Incentives and Subsides

Since the early 2000s both the federal government and several state governments have introduced relatively generous tax credits to support the development of the solar industry in the United States. Significant federal support for solar investment began during the Bush administration. The Energy Policy Act of 2005 established a 30% federal tax credit for residential and commercial investment beginning in early 2006. The Solar Investment Tax Credit (ITC) was extended by the Tax Relief and Health Care Act of 2006 and then extended several more times in the wake of the 2008 financial crisis under the Obama administration. The most recent version of the solar ITC (as of December 2020) offers declining support for solar investment through the end of 2023: 30% from 2006 to 2019, 26% from 2020 to 2022, and 22% during 2023.[2]

Along with several other states (Arizona, California, Maryland, and New Jersey), Massachusetts has been a leader in supporting the development of the solar industry in the United States. Massachusetts offers several tax incentives, as well as direct subsidies to encourage the adoption of solar. The most significant, longstanding tax benefit is the Residential Renewable Energy Income Tax Credit (RETC). Introduced in 1979, the RETC instituted a state tax credit of 15% net expenditure (installation price net any rebates) on renewable energy source property, up to a maximum $1,000 credit.[3] Other tax benefits include the Solar Installation Property Tax Exemption, which precludes increases in property taxes as a result of PV system installations, and the Home Solar System Sales Tax Exemption, which exempts residential installations from sales tax (6.25% in MA). For purposes of my analysis, I focus on the effect of the RETC on households' adoption behavior because the benefit of the property tax exemption to adopters is difficult to measure.

Massachusetts also directly subsidized the installation of residential and commercial solar systems through two major rebate programs, Commonwealth Solar I and II, from 2008 to 2015. These programs offered solar adopters upfront rebates proportional to system capacity (or capacity-based subsidies). These rebates decreased over time as installation prices declined and were more or less phased out entirely by the end of 2016. Using installation data from MassCEC, I am able to observe the amount of rebates credited to each system installation transaction, which allows me to measure the aggregate effect of upfront rebates on adoption behavior.

2.3 Net Metering Program

In addition to tax credits and rebates, Massachusetts allows renewable energy system owners to net meter. Net metering enables residential and commercial utility customers that generate their own electricity to offset their usage as well as receive compensation for excess production over and above their consumption. For example, suppose a residential utility customer owns solar panels. Energy generated by his/her solar panels (after being converted from DC to AC) is either consumed or transferred to the grid via a bi-directional meter. This meter keeps track of the net amount of electricity consumed by the household, equal to total electricity transferred from the utility to the household minus total electricity generated by the solar panel and transferred to the grid. Under

[2] https://www.seia.org/initiatives/solar-investment-tax-credit-itc
[3] https://www.mass.gov/regulations/830-CMR-6261-residential-energy-credit

a net metering program, the utility tracks the household's monthly consumption and production. When net consumption is positive, the household pays a bill for net usage. When consumption is negative, the household receives a credit, which can accumulate over a finite period.

Net metering has been practiced to some extent in Massachusetts since 1981, but the Green Communities Act of 2008 significantly expanded the scope of net metering in order to encourage investment in renewables. In particular, it allowed credit from on-site generation to accumulate over time, which substantially increased the value of net metering to solar panel owners. Customers of both IOUs and municipal utilities in Massachusetts are allowed to net meter, however, municipal utilities are not obligated to offer net metering. Privately owned solar systems (and other renewables such wind) of 2MW capacity or less are eligible for net metering (if capacity is 60kW or less any energy generating technology is eligible).[4] As I explain in the model section, the benefit of net metering to households is similar to but distinct from the benefit of avoiding future electricity costs by adopting a PV system.

2.4 SREC Programs

In order to increase the proportion of electricity generated by renewables in the energy sector, several state governments including Massachusetts have introduced renewable portfolio standards (RPS) for public utilities. RPS require utilities to purchase a certain portion of the energy they distribute from renewable suppliers or face financial penalties. In Massachusetts, RPS were first introduced in 2003 and required that 1% of utilities' total energy supply come from renewables. This share was ratcheted up by half a percentage point per year until 2009 (4%), then revised to increase one percentage point per year thereafter (13% in 2018).[5]

To support the expansion of the solar industry and allow utilities to have more flexibility to meet their RPS targets, Massachusetts and other states introduced renewable energy certificate (REC) programs, which allow utilities to purchase certificates ("rights" to renewable energy production) from households that own renewable energy system owners in certificate markets. These certificate programs encourage solar panel adoption by giving residential and commercial renewable owners the opportunity to sell their certificates in these markets; in Massachusetts renewable owners earn one certificate for every MWh of energy they produce. Massachusetts introduced its first SREC (solar REC) program in 2010 and has introduced three separate programs thus far. PV systems installed from 2010 to 2013 were eligible for the SREC I program, systems

[4]https://www.mass.gov/guides/net-metering-guide

[5]https://www.mass.gov/service-details/program-summaries

installed from 2014 to 2018 were eligible SREC II program, and systems installed from 2019 onward are eligible for the Solar Massachusetts Renewable Target (SMART) program.[6] My period of analysis is 2008 to 2018, therefore, I measure the benefits derived from SREC I and II. Both of these programs allow solar system owners to earn SRECs for up to 16 years. As I will discuss in more detail, the main difference between the programs is the rate at which owners are compensated for their certificates (SREC I certificates are more valuable than SREC II certificates).

Certificate prices in Massachusetts' SREC markets are determined by the supply of and demand for certificates subject to regulatory constraints. Based on the mixed success of REC programs in other states, the Department of Energy Resources (DOER) designed a price support mechanism to stabilize SREC prices and ensure sustained investment in solar over a number of years. Specifically, DOER introduced financial penalties for utilities that failed to meet their RPS, as well as a quantity auction mechanism to sell off excess certificates in periods of low demand. Utilities that fail to meet their RPS are required to pay a penalty equal to the shortfall of renewable energy times an alternative compliance price (ACP) predetermined by DOER. DOER also sets fixed auction prices, at which SREC owners are (almost) guaranteed to sell their certificates.[7] Schedules of ACPs and auction prices are published years in advance to reduce uncertainty about the future value of certificates. As illustrated in Figure 4, SREC prices are determined by the supply of certificates from solar system owners and demand for certificates by utilities, where the ACP acts as a price ceiling and the auction price acts as a price floor. SREC I certificates are more valuable than SREC II certificates because both ACPs and auction prices were initially set higher to encourage early adoption.

The fact that SREC prices are bounded by ACPs and auction prices is important in my empirical application, because I do not observe equilibrium certificate prices, however, I do observe these bounds. Therefore, when I estimate the future benefits of the SREC programs to adopters, I use the midpoint of the bounds as an approximation of expected equilibrium prices.

2.5 Other Benefits

In addition to the aforementioned benefits, Massachusetts has also incentivized residential solar panel adoption by increasing access to financial markets. In particular, the Mass Solar Loan Program enables eligible low income households access to low-interest

[6] https://www.mass.gov/guides/solar-carve-out-and-solar-carve-out-ii-program-information

[7] The auction mechanism is quantity auction in which utilities bid for an amount of SRECs a fixed price. If the market doesn't clear i.e. not all certificates are sold, then the auction is conducted again with the same fixed prices but the lifetime of the certificates is extended (increasing the certificates' value). This process is iterated until the market clears.

loans in order to finance PV system purchases.[8] Unfortunately, I am unable to observe whether or not installations were financed in my data, therefore, while the increased financialization of residential solar may partially explain household adoption behavior, I do not attempt to model it in my analysis. Table 1 summarizes the future incentives that I consider in my analysis.

3 Model

3.1 Overview

The dynamic adoption, or demand, model I specify closely follows De Groote and Verboven (2019). In the model, households choose among a discrete set of PV systems to maximize their expected discounted utility. PV systems are differentiated on the basis of capacity or energy production and price or the net present cost of installation. The net present cost of installation of a system depends upon the upfront installation price net of the upfront and long-term or future incentives offered by the government. Because upfront installation prices are falling over time, and government subsidies vary over time, the household faces an intertemporal tradeoff between adopting a system in the current period or waiting until a future period when the net present cost of installation may be lower. Recall that the ultimate goal of my analysis is to quantify the effects of different incentive programs on adoption; in the model these incentives enter into the net present cost of installation. Therefore, the most policy relevant parameters of the model are households' price sensitivity and discount factor.

The main difference between my implementation of the model and De Groote and Verboven (2019) is that when it comes to estimation, I exploit cross-sectional variation across geographic markets in my data, in addition to time-series variation, to help identify the key parameters of the model. This cross-sectional variation also allows me to use a different instrumental variable strategy to account for endogenous prices in the model.

The estimating equation I specify is derived from recent econometric work by Scott (2014) and Kalouptsidi, Scott, and Souza-Rodrigues (2021) who develop methods for estimating structural dynamic discrete choice models using linear regression techniques, which they dub "Euler Equations in Conditional Choice Probabilities" (ECCP) estimators. The advantage of their approach is that it does not require the researcher to specify the evolution of market-level state variables in the model, unlike previous full information approaches in the dynamic discrete choice literature (for example, Rust 1987 and Gowrisankaran and Rysman 2011). This aspect of their estimation approach

[8] https://www.masssolarloan.com/

is crucial in my application, because, as noted by De Groote and Verboven (2019), it would be unrealistic to credibly model households' expectations about the evolution of government incentives for residential PV systems over time. However, by making the relatively limited assumption that households have rational expectations, Kalouptsidi, Scott, and Souza-Rodrigues (2021) show that it is possible to estimate dynamic discrete choice models using the ECCP method without imposing other assumptions.

3.2 Adoption Decision

I model households' PV adoption decisions using a dynamic discrete choice model. Where $j = 1, ..., J$ indexes solar systems by capacity, $t = 1, ..., T$ indexes time, and $m = 1, ..., M$ indexes geographic markets defined by electric utilities' service areas. To simplify the discussion that follows I drop the market index.

At each time t, household i decides whether to adopt a PV system $j = 1, ..., J$ now or wait until later to adopt, which I denote by $j = 0$. If the household purchases at time t, it exits the market, otherwise it has the option to purchase a system at a later date. In the meantime, a household that waits to adopt continues to pay its local provider for electricity usage. Note that for simplicity the model ignores that households' adoption behavior may reflect a joint adoption/electricity consumption decision. Also for simplicity, I assume that households do not have the option to replace their systems later; this assumption seems reasonable given that I observe households adoption decisions over a ten year period and the likelihood of a household requiring a system replacement during that period is de minimis. The household makes its adoption decision given its utility from adopting a system today and its expected discounted utility from adopting a system in the future.

3.2.1 Households' Utility from Adoption

The indirect flow utility of household i from adopting system j at time t is a function of the system's capacity (captured by a product specific constant β_j), net present cost of installation $p_{jt}(\delta)$, an unobserved product characteristic ξ_{jt}, and an idiosyncratic error ϵ_{ijt},

$$u_{ijt} = \beta_j - \alpha p_{jt} + \xi_{jt} + \epsilon_{ijt} = \bar{u}_{jt} + \epsilon_{ijt}. \tag{1}$$

Here I assume households have homogeneous preferences for product characteristics, in which case $\bar{u}_{jt}$ represents the mean utility households obtain from adoption. Later on in the paper, I relax this assumption and allow households to have heterogenous preferences that vary across observable demographic characteristics.

3.2.2 Net Present Cost of Installation

The "price" term in the households' utility function p_{jt}, the net present cost of installation, depends upon the upfront installation cost p^I_{jt}, the household's discount factor δ (which is also homogenous), and both federal and state upfront and long-term incentives,

$$p_{jt} = p^I_{jt} - \underbrace{(0.3 \cdot p^I_{jt})}_{\text{Fed. Tax Credit}} - R_{jt} - \underbrace{(1-0.22) \cdot \min\left\{[0.15 \cdot (p^I_{jt} - R_{jt})], 1000\right\}}_{\text{MA Tax Credit}} \tag{2}$$

$$- \underbrace{\sum_{\tau=0}^{24} \delta^\tau \cdot (1-d)^\tau \cdot g^e_{jt} \cdot p^e_{t+\tau}}_{\text{Net Metering}} - \underbrace{\sum_{\tau=0}^{24} \delta^\tau \cdot (1-d)^\tau \cdot g^e_{jt} \cdot p^{sc}_{t+\tau}}_{\text{SREC Revenue}} .$$

During the period of analysis 2008–2018, the federal solar investment tax credit reduces PV system owners' taxes by 30% of the upfront installation cost. Through various rebate programs, Massachusetts state offers capacity subsidies to residential adopters R_{jt}, as well as the RETC which accounts for 15% of the upfront installation cost (net of capacity subsidies) up to a maximum of \$1,000 (this tax credit is subject to federal income tax, which I assume is 22%). The upfront installation cost minus the sum of federal and state tax credits as well as capacity subsidies reflects the upfront installation cost net of upfront incentives.

As previously described, in addition to upfront incentives, Massachusetts implemented two long-term incentive programs to encourage residential solar adoption; the net metering program and the creation of a market for SRECs. In order to calculate the net present value of each incentive program to adopters, I assume that all PV systems have a 25-year lifespan, all systems' electricity generation depreciates at a rate of d each year (which I set equal to 1%), and households discount future benefits at a rate δ.[9]

The present value of the net metering program and avoided future electricity costs to a household adopting system j at time t is given by,

$$\text{PV}^{nm}_{jt} = \sum_{\tau=0}^{24} \delta^\tau \cdot (1-d)^\tau \cdot g^e_{jt} \cdot p^e_{t+\tau}, \tag{3}$$

where g^e_{jt} is the estimated production of electricity (kWh) by system j at time t and $p^e_{t+\tau}$ is the estimated real price of electricity (\$/kWh) at time $t+\tau$. Recall that the household's outside option includes paying its utility for electricity, which is why the

[9]Burr (2014) and several industry sources suggest that 25 years is an appropriate assumption for the lifespan of a solar system. Additionally, MassCEC Residential Guide to Solar Energy suggests that by year 20 a solar system should generate at least 80% of its original electricity output. At $d = 1\%$ after 25 years, generation is approximately 80% of its original output.

expression above represents both the present value of net metering and the present value of avoided future electricity costs.

The present value of the SREC program to a household adopting system j at time t is given by,

$$\mathrm{PV}^{sc}_{jt} = \sum_{\tau=0}^{24} \delta^{\tau} \cdot (1-d)^{\tau} \cdot g^{e}_{jt} \cdot p^{sc}_{t+\tau}, \tag{4}$$

where again g^e_{jt} is the estimated production of electricity (kWh) by system j at time t and $p^{sc}_{t+\tau}$ is the estimated real price of solar renewable energy certificates ($/kWh) at time $t+\tau$.

Taking all incentives into account p_{jt}, the net present cost of installation, is the upfront installation price net of all upfront and future incentives.

3.2.3 Households' Utility from Waiting to Adopt

The household's option value of waiting to adopt at time t,

$$v_{i0t} = u_{0t} + \delta E_t \max\left\{v_{i0t+1}, u_{i1t+1}, ..., u_{iJt+1}\right\} = u_{0t} + \delta E_t[V_{it+1}], \tag{5}$$

is the sum of u_{0t}, the flow utility from not adopting this period, and $\delta E_t[V_{it+1}]$, the discounted expected value of delaying the adoption decision until next period.

Assuming that ϵ_{ijt} is i.i.d. extreme value type I, the ex-ante value of waiting is the closed-form logsum expression,

$$\bar{V}_{t+1} = 0.577 + \log\Big(\exp\left(\bar{v}_{0t+1}\right) + \sum_{j=1}^{J} \exp\left(\bar{u}_{jt+1}\right)\Big) \tag{6}$$

where 0.577 is Euler's gamma, the mean of the standard extreme value type I distribution.

3.2.4 Households' Choice Probabilities

Assuming households maximize their utility, the probability that a household adopts system j at time t is given by,

$$s_{jt} = \frac{\exp\left(\bar{u}_{jt}\right)}{\exp\left(\bar{v}_{0t}\right) + \sum_{j=1}^{J} \exp\left(\bar{u}_{jt}\right)}, \tag{7}$$

the standard multinomial logit probability formula. In order to take the model to the data, following Berry (1994), I equate these probabilities to the aggregate market shares of PV systems in each year.

3.3 Estimating Equation

In order to derive a closed-form estimating equation, I use techniques developed in Scott (2014), De Groote and Verboven (2019), and Kalouptsidi, Scott, and Souza-Rodrigues (2021).

Following Scott (2014), I assume that households have rational expectations about the future benefits of adopting PV. Specifically, I assume the ex-ante value function $\bar{V}_{t+1}$ equals the expected value function $E_t[\bar{V}_{t+1}]$ plus a prediction error η_t. Rearranging this relationship, I represent the expected value of delaying the adoption decision as,

$$E_t[\bar{V}_{t+1}] = \bar{V}_{t+1} - \eta_t. \tag{8}$$

Then, assuming that households' one-period-ahead predictions about the value of waiting are on average correct ($E_t[\eta_t] = 0$ i.e. that households have rational expectations), the option value of waiting to adopt at time t can be written as,

$$\bar{v}_{0t} = u_{0t} + \delta\big(0.577 + \log\big(\exp(\bar{v}_{0t+1}) + \sum_{j=1}^{J}\exp(\bar{u}_{jt+1})\big) - \eta_t\big). \tag{9}$$

Hotz and Miller (1993) show how to write $\bar{V}_{t+1}$ in terms of conditional choice probabilities (CCPs), which yields a convenient closed-form estimating equation.

Take the CCP of a household adopting any arbitrary system j at time $t+1$, say $j = 1$,

$$s_{1t+1} = \frac{\exp(\bar{u}_{1t+1})}{\exp(\bar{v}_{0t+1}) + \sum_{j=1}^{J}\exp(\bar{u}_{jt+1})}. \tag{10}$$

Taking the log of both sides and rearranging, the logsum expression is equal to the flow utility from adopting system $j = 1$ minus the log share of adopting system $j = 1$,

$$\log\big(\exp(\bar{v}_{0t+1}) + \sum_{j=1}^{J}\exp(\bar{u}_{jt+1})\big) = \bar{u}_{1t+1} - \log(s_{1t+1}). \tag{11}$$

Substituting this expression into equation (9) and normalizing $u_{0t} + \delta 0.577 = 0$, the option value of waiting to adopt becomes,

$$\bar{v}_{0t} = \delta\big(\bar{u}_{1t+1} - \log(s_{1t+1}) - \eta_t\big). \tag{12}$$

One can think about this expression as essentially proxying the value of the waiting to adopt as the discounted utility the household receives from adopting system $j = 1$ in the following period minus the household's prediction error, η_t, and an additional term, $\log(s_{1t+1})$, that adjusts for the fact that adopting $j = 1$ in the next period may not be optimal. It should be noted here that it is possible to use any terminal adoption decision $j = 2, ..., J$ in place of $j = 1$ as a "proxy" for the value of the outside option.

Now using Berry's (1994) market share inversion to formulate a discrete choice model of aggregate demand, we can derive an estimating equation based on aggregate market shares,

$$\log\left(\frac{s_{jt}}{s_{0t}}\right) = \bar{u}_{jt} - \bar{v}_{0t}, \tag{13}$$

$$\log\left(\frac{s_{jt}}{s_{0t}}\right) = \big(\beta_j - \alpha p_{jt} + \xi_{jt}\big) - \delta\big(\beta_1 - \alpha p_{1t+1} + \xi_{1t+1} - \log\left(s_{1t+1}\right) - \eta_t\big). \tag{14}$$

In the standard static multinomial logit demand model, the indirect utility from the the outside option is typically normalized to zero, $\bar{v}_{0t} = 0$, and so the second term in equations (13 and 14) disappears. However, in this case because the household faces a dynamic choice we subtract the option of waiting to adopt.

Grouping like terms and defining the econometric error term $e_{jt} = \xi_{jt} - \delta\xi_{1t+1} + \delta\eta_t$, the estimating equation becomes,

$$\log\left(\frac{s_{jt}}{s_{0t}}\right) = \big(\beta_j - \delta\beta_1\big) - \alpha\big(p_{jt} - \delta p_{1t+1}\big) + \delta\log\left(s_{1t+1}\right) + e_{jt}. \tag{15}$$

This equation, which looks somewhat like a first-difference equation, is my main estimating equation.

When $\delta = 0$, this equation becomes the standard static demand model, which can be estimated using OLS or linear IV,

$$\log\left(\frac{s_{jt}}{s_{0t}}\right) = \beta_j - \alpha p_{jt} + \xi_{jt}.$$

When δ is known, one can construct a new dependent variable and estimate the following equation using OLS or linear IV,

$$\log\left(\frac{s_{jt}}{s_{0t}}\right) - \delta\log\left(s_{1t+1}\right) = \big(\beta_j - \delta\beta_1\big) - \alpha\big(p_{jt} - \delta p_{1t+1}\big) + e_{jt}.$$

When δ is unknown, because demand is now a nonlinear function of δ, one can estimate the following equation using nonlinear least squares (NLLS) or nonlinear IV (NLIV),

$$\log\left(\frac{s_{jt}}{s_{0t}}\right) = \big(\beta_j - \delta\beta_1\big) - \alpha\big(p_{jt} - \delta p_{1t+1}\big) + \delta\log\left(s_{1t+1}\right) + e_{jt}.$$

In the estimation section, I estimate versions of the model in which I specify households' discount factor prior to estimation and versions where I estimate δ jointly with the other parameters.

4 Data

To analyze household adoption behavior and measure their responses to solar incentives, I combine data on PV system installations from the Massachusetts Clean Energy Center (MassCEC)[10] with market size and electricity price data from the U.S. Energy Information Administration (EIA).[11] I also refer to the Massachusetts Department of Energy Resources (DOER) website[12] for data related to SREC prices and other regulatory information.

4.1 Solar Adoption Data and Sample Selection

MassCEC collects data on the installation and production of renewable energy systems across the state in its Production Tracking System (PTS).[13] The PTS database is used to evaluate the development of solar industry as well as to track energy production by systems for SREC reporting purposes (only registered systems are SREC eligible). I use this data as the basis of my empirical analysis.

The data consists of system-level records including the date the system was installed, the location (county, city, zip code) of installation, the total upfront installation cost of the system, the value of any rebates received, and limited information about the owner, installer and system manufacturer. Importantly for my analysis, the data indicates whether a system is host owned or third-party owned, whether the owner is a residential, commercial, industrial, or governmental entity, and which electric utility the owner is served by.

I focus my analysis on residential, host owned solar system adoption during the 2008–2018 period. My sample consists of 31,637 solar installations of a possible 90,003 installations in Massachusetts from 2001–2018. There are several reasons to restrict my sample. First, both federal and state solar support changed significantly in 2008. The federal ITC was extended as part of the governments' response to the financial crisis, and Massachusetts greatly expanded net metering with the passage of the Green Communities Act. Figure 5 shows that solar adoption pre-2008 was relatively limited, therefore, given the lack of installations before 2008 and the change in the regulatory regime I find it reasonable to limit the scope of my analysis on the 2008–2018 period.

Of the four major groups of electric utility customers included in the data: (1) residential, (2) commercial, (3) industrial, and (4) governmental, the residential sector accounts for over 94% of all installations (approximately 24% of estimated annual solar

[10] https://www.masscec.com
[11] https://www.eia.gov/
[12] https://www.mass.gov/orgs/massachusetts-department-of-energy-resources
[13] https://www.masscec.com/about-pts

generation). While residential customers' incentives for adoption are arguably similar to other customers (the purpose is to offset their electricity bills by generating their own electricity), residential customers face a different set of institutional and regulatory constraints. For example, individual households' ability to finance their systems is potentially limited compared to larger customers, however, residential customers actually receive more favorable support from the state because eligibility for the SREC and net metering programs is limited to smaller capacity PV systems.

During the 2008-2018 period, as rooftop solar gained popularity, installers including Vivant and SolarCity introduced third-party ownership agreements to further expand the market to more financially constrained households. These companies offered customers the option to rent PV systems for an extended period through solar lease agreements, rather than purchase them outright. Typically these agreements are structured such that the lease-holders own the system and the rights to any incentives derived from energy generation until the lease is paid off at which point the household owns the system. Of the 83,958 residential installations from 2008-2018, 52,321 (62%) are third-party owned systems. Figure 6 shows the number of host owned and third-party owned installations and installation cost per kW over time.

While third-party ownership is increasingly common during my period of study, and measuring the consumer and environmental benefits of the introduction of such agreements would be interesting to study from a policy perspective, there is no publicly available data on third-party ownership contracts that I can exploit to incorporate third-party owners into my analysis. Additionally, as with commercial, industrial, and governmental owners the behavior of third-party owners is likely to differ from host owners, therefore, I exclude them from my analysis. However, exclusion of third-party owners potentially introduces sample selection bias due to likely demographic differences between households that are host owners and households that sign contracts with third-party owners. I hypothesize that the major difference between these households is that host owners are likely to be wealthier, and as a result demand for solar panels may be more elastic than I find in my analysis.

In addition to my sample selection criteria, as part of processing the installation data for analysis, I rely on some guidelines recommended by the Lawerence Berkley National Laboratory (LBNL) for analyzing the residential solar PV market. Specifically, LBNL (2019) uses 20kW capacity as a threshold for delineating residential and non-residential installations and suggests that systems with installation cost per kW of less than $1,000 or greater than $20,000 (in 2018 dollars) are unlikely to be representative of PV solar prices. Therefore, I exclude any potential "outliers" on these bases.

Table 2 below displays mean and median system capacity, estimated production, upfront installation cost, and grants/rebates by system size for my final sample of solar installations. To estimate demand I discretize households' adoption choices by categorizing PV systems into five groups by system capacity and aggregate price and capacity data based on sample medians. Estimated production and installation costs increase monotonically with system capacity as expected. Also means and median are very close for all variables except rebates (this is because rebates are not distributed uniformly over time).

Figure 7 displays adoptions, cumulative adoptions, average and median installation prices, median capacity, and median estimated production by system size over time. In terms of adoption, initially the smallest capacity [0,4) kW systems are most popular, however, as installation prices fall more rapidly for larger systems, demand for medium and large-sized system increases. By 2018 cumulative adoption is largest for [4,6) kW capacity systems, closely followed by [6,8) kW. Upfront installation prices fall most rapidly for the largest capacity systems. Time series plots of median capacity and median estimated production show that capacity-group composition remains quite constant over time. Figure 8 displays the percentage of installations that receive rebates and median rebate amounts over time by capacity, which shows that a high percentage of projects (over 80%) received direct subsidies until 2015. From 2016 onwards almost no installations received direct subsidies from the state.

4.2 Electricity Price Data

To measure average annual electricity prices for households' net metering revenues and avoided electricity costs I rely upon Form EIA-861 data for Massachusetts utilities.[14] I collect data from 2008-2018 and calculate the annual average price per kWh for residential customers by dividing total revenues by total sales for each utility f,

$$p^e_{ft} = \frac{\text{Revenue}_{ft}}{\text{Sales (kWh)}_{ft}}.$$

Because the net present cost of installation depends on current and future electricity prices, I forecast future electricity prices for each utility using a simple log-linear regression on time, where I include utility-specific time trends γ_f and utility fixed effects ρ_f,

$$\log\left(p^e_{ft}\right) = \sum_f^F \gamma_f (Utility_f \times Time_t) + \sum_f^F \rho_f + \upsilon_{ft}.$$

In order to forecast real as opposed to nominal electricity prices, however, I also need to forecast future inflation, which I do using 2008-2018 urban CPI data and again a simple log-linear regression on time. My forecast of real electricity prices runs from

[14] https://www.eia.gov/electricity/data/eia861/

2019 through 2042, because I assume a PV system lifespan of 25 years, therefore, a household adopting in 2018 can accumulate net metering revenue and avoid electricity costs through 2042. After predicting future CPI, I convert nominal average residential electricity prices from 2008–2018 (calculated above) into real 2018 prices and regress log prices on utility-specific time trends; regression results are shown Table 3. Figure 9 displays actual and forecasted electricity prices from 2008–2042. The coefficients show that on average CPI grew approximately 1.7% per year, and real electricity prices in Massachusetts grew between 1.9-6.1% per year from 2008 to 2018, depending on the electric utility. My forecast suggests that, on average, real electricity prices will increase by over 3.5-fold in the next 30 years. Whether or not this forecast is realistic is certainly debatable, however, what this projection implies for my analysis is clear; depending on the degree to which households discount the future, the net present value of net metering and avoided electricity costs will likely increase over time because real electricity prices rise at a substantial rate.

4.3 SREC Incentive Data

To measure households' current and future benefits from Massachusetts SREC programs, I refer to the schedule of alternative compliance prices (ACPs) and auction prices posted on DOER's website.[15] Recall that a household earns a solar certificate for every 1,000 kWh of energy it generates. Benefits for the SREC I program span from 2010 to 2025 with 2013 being the last year of enrollment, while benefits for the SREC II program span from 2014 to 2029 with 2018 being the last year of enrollment. As previously discussed, SREC market prices are bounded by utilities' ACPs and fixed auction prices, which were determined and announced by DOER prior to the introduction of the programs. I estimate the market price of SRECs, for purposes of calculating the net present value of SRECs to households', as the midpoint of the auction price (price floor) and ACP (price ceiling),

$$p_t^{sc} = \frac{\text{ACP}_t + \text{Auction Price}_t}{2}.$$

In Figure 10 I plot the schedule of SREC I and II ACPs and auction prices determined by DOER, as well as p_t^{sc}. As with average electricity prices, I adjust SREC prices for inflation; plotted in Figure 11.

[15]https://www.mass.gov/service-details/solar-carve-out-and-solar-carve-out-ii-minimum-standards-and-market-information

4.4 Net Present Installation Costs

Having explained all of the empirical inputs of the "price" equation, I calculate the average net present installation cost for each system size over time using average annual installation prices and incentives, a discount factor $\delta = 0.9$, and a depreciation rate $d = 0.01$ to illustrate how the effective prices households face evolve over time. In Figure 12 I plot average discounted net metering revenue and average discounted SREC revenue over time by system size, and in Figure 13 I plot average net present installation cost over time by system size, as well as the breakdown of the net present installation cost for a [4,6) kW capacity system.

From 2008 to 2013 generally the net present installation cost for all systems is declining. There's a large discontinuity from 2008 to 2010 due to the introduction of the first SREC program, followed by a gradual decrease due to declining installation costs until 2013. As the rate of decline in upfront installation costs slows, net present installation costs flatten out from 2013 onwards. Note that prior to the introduction of the SREC I program, the net present cost of installation for most systems was greater than zero, indicating that on average early solar adopters could expect a net loss over the lifespan of their systems, however, from 2010 onwards, on the average adopting household could expect a net profit over the lifespan of its system due to the combination of SREC revenue and net metering revenue/avoided electricity costs.

Focusing on the breakdown of the average net present installation cost for a [4,6) kW capacity system, notice that SREC revenues are the largest incentive for system owners, followed by net metering revenues/avoided electricity costs which increase over time (driven by the assumption of real electricity price growth). Capacity subsidies by the state are initially large but decline quickly, the federal tax credit declines proportionally to upfront installation prices, and the Massachusetts tax credit remains fixed since 15% of the average upfront installation price almost always exceeds the $1,000 maximum state tax credit.

4.5 Aggregate Data

In order to estimate my model I aggregate my installation-level data within markets and years. I define markets as utility service areas, where I group municipal utilities together (see Figure 3). While not always geographically contiguous in Massachusetts, utilities' services areas constitute appropriately defined markets because electric utilities are regulated firms that earn rate of return revenues and charge uniform prices to specified classes of consumers i.e. residential, commercial, etc. Moreover each IOU in Massachusetts has varying capacity for solar PV connections to the grid based on its specific RPS, therefore, aggregating installations across "utility markets" seems reasonable in my application given the utility-specific rules governing solar installations. I aggregate installations for each year because a finer time period would result in zero adoptions in many periods due to sparsity of adoptions over time, across markets; De Groote and Verboven (2019) likewise deal with relatively sparse data. Table 4 displays the number of residential, host owned solar installations during the 2008–2018 period by utility, as well as the number of residential customers in 2008.

The aggregate market share for each solar system j in year t for market m is defined as,

$$s_{jtm} = \frac{q_{jtm}}{M_{tm}},$$

where q_{jtm} is the number of installations and M_{tm} is the size of market m in year t. Because I assume adoption is a terminal choice, the market size evolves over time according to,

$$M_{tm} = M_{t-1m}\Big(1 - \sum_{j=1}^{J} s_{jt-1m}\Big).$$

To compute market size and shares using my data, I define M_{1m} as the number of residential customers in 2008 in each "utility market" m. Due to the sparsity of installation data, for some market-years $q_{jtm} = 0$; in these cases I set $q_{jtm} = 1e^{-6}$ to avoid the common zero market share problem in logit demand models.

I calculate prices in each market-year using median upfront installation costs and median incentives. Similar to the zero market share problem, when I aggregate prices across markets, if the are no installations in a given market-year, then I don't observe price. Like De Groote and Verboven's (2019) in these instances I replace missing prices with average installation prices across other markets; this interpolation introduces measurement error into my econometric model and potentially leads to attenuation bias with respect to the price coefficient. Another measurement concern is that installation prices are household-specific as opposed to fixed prices offered by installers; again this may bias the price coefficient towards zero. Finally, I also use median estimated production as an estimate for aggregate energy generation in each year-market (again missing data is replace with the average across other markets). Table 5 displays summary statistics for the data I use in my estimation.

5 Identification

5.1 Price Endogeneity

The installation price of PV systems is endogenous in the estimating equation because prices are determined in equilibrium by supply and demand, $E[p_{jtm}e_{jtm}] \neq 0$. As a result estimation of the demand equation using OLS or NLLS will ignore any unobservable quality correlated with price resulting in a downward biased estimate of α, implying that demand is less elastic than in reality. To address this source of endogeneity, I use an instrumental variable for price that plausibly satisfies the orthogonality condition $E[z_{jtm}e_{jtm}] = 0$. Following Hausman (1996) and Nevo (2000), I use average prices (in this case average upfront installation prices) across other markets ($n \neq m$) to instrument for p_{jtm}.

While this instrument has been criticized because common variation in prices may be driven by demand-side factors such as advertising (see Bresnahan 1996), I argue that in this case common variation in prices is mostly explained by variation in supply as opposed to demand. As discussed previously, solar PV prices have fallen dramatically over time due to technological change that has made the cost of producing panels much cheaper. Therefore, variation in prices over time mostly reflects decreases in the cost of production. To the extent that prices are correlated across markets, I hypothesize that most of this correlation is due to common shifts in supply. Furthermore, since the markets I study are geographically close and served by the same firms, variation in transportation costs and other factor prices are likely limited. It follows then that differences in price *across* markets are mostly explained by differences in demand.

However, it is possible that a portion of the correlation in prices is due to common shocks to demand as a result of increasing awareness of solar panels across Massachusetts over my period of study. Because I suspect variation in prices over time is more likely driven by supply than demand and variation in prices across markets is more likely driven by demand than supply, I test which source of variation in prices is larger by decomposing this variation into between market variation and within market variation. If costs are similar across markets but falling over time and common supply shocks explain the majority of variation in price, then within market variation in price should be greater than across market variation. Price statistics are displayed in Table 6.

As expected, within market variation is larger than between market variation, meaning that most of the overall variation in price is due to changes over time, which I argue is most plausibly explained by shifts in supply. This exercise certainly doesn't prove that my instrument satisfies the exogeneity condition, but it does give me some confidence that the correlation in prices across markets is more likely explained by common supply shocks than by common demand shocks.

5.2 Discount Factor

Since demand for solar systems depends on households' discount factor δ, in addition to instrumenting for price in the nonlinear IV estimator, it is also necessary to include an instrument to identify δ (otherwise the number of parameters would exceed the number of instruments). Other applications of dynamic discrete choice models have found that it is difficult to identify δ, so most studies typically end up specifying a particular value (e.g. $\delta = 0.9$). For example, in his seminal study on bus engine replacement Rust (1987) compares how his model fits the data using different values for the discount factor. Estimating δ is empirically challenging because identification requires data on individuals' future payoffs that varies independently from current payoffs, which usually isn't available. To illustrate the point, imagine designing the ideal experiment to identify the degree to which individuals discount future income. In such an experiment one would want to hold constant current payoffs while randomizing future payoffs. One could also randomize current payoffs, however, the relevant variation in the data that would allow the researcher to identify individuals' discount factors is the relative difference between current payoffs and future payoffs.

As De Groote and Verboven (2019) point out, because solar subsidies vary across time independently from upfront installation costs, it is possible to identify δ in this context by using variation in the difference between upfront installation costs and future subsidies across time (and in my case markets) in the data. In addition to using this variation in the data to identify the discount factor, De Groote and Verboven (2019) use the price of green energy certificates in future periods as an instrument. Because future REC prices should be uncorrelated with upfront installation prices but are correlated with the future benefits of adopting solar, they are plausibly an appropriate instrument for households' discount factor. Similarly, in my application I can use variation in the difference between upfront installation costs and future subsidies across time (as well as across markets) and use the price of SRECs in future periods to identify δ.

6 Estimation

In this section, I estimate demand for PV systems using the dynamic adoption model previously outlined under several different assumptions and discuss the results. First, I estimate the model taking households' discount factor as given using linear regression techniques. I show (1) how different assumptions about δ affect the estimates and (2) the importance of treating price as endogenous in the model. Second, I estimate δ along with the other demand parameters with nonlinear methods and use variation in the difference between households' current and future payoffs in the data, as well as future SREC prices as an instrument to identify δ. Third, I perform some robustness checks to test the sensitivity of households' discount factor in the estimation. Forth, following De Groote and Verboven (2019) I extend the model to allow for observable heterogeneity among households located in different municipalities. Using demographic data on local municipalities I construct and add micro-moments to the model, which I estimate using generalized method of moments (GMM).

6.1 Linear Results

As described in the model section, when δ is known it is straightforward to estimate the following regression equation using OLS or linear IV,

$$\log\left(\frac{s_{jtm}}{s_{0tm}}\right) - \delta \log\left(s_{1t+1m}\right) = \underbrace{\left(\beta_j - \delta\beta_1\right)}_{\tilde{\beta}_0 + \mathbb{1}(j\neq 1)\tilde{\beta}_j} - \alpha\left(p_{jtm} - \delta p_{1t+1m}\right) + e_{jtm},$$

where in practice I estimate the above equation using a constant term $\tilde{\beta}_0$ and alternative-specific constants $\tilde{\beta}_2, ..., \tilde{\beta}_5$, which can then be manipulated to back out what I call the "normalized estimates" $\beta_1, ..., \beta_5$.

I estimate the above equation using OLS and 2SLS under two assumptions about household behavior. First, I assume households are completely myopic $\delta = 0$ (in which case the equation reduces to the standard static demand model). Second, I assume that households are relatively forward-looking $\delta = 0.9$; this discount factor is equivalent to an annual interest rate $r \approx 11\%$ which still implies a substantial degree of myopia when compared with the average rate at which households can borrow (perhaps 3%).

In the first-stage of the linear IV estimator, I estimate the following regression equation,

$$p^I_{jtm} = \phi_0 + \phi_1 p^I_{jtn} + \rho_j + \omega_{jtm},$$

where p^I_{jtn} is the average upfront installation price of system j at time t across markets $n \neq m$ and ρ_j are capacity dummies. Table 7 displays the results of the first-stage regression. Because I regress installation prices on average installation prices across other markets, as expected instrument power isn't an issue here (F-Statistic > 10).

Table 8 reports the linear demand equation estimates. Comparing the OLS and IV estimates, the Hausman-Nevo instrument shifts the price coefficient α in the expected direction. However, as δ increases demand becomes less elastic, which appears to be counter Gowrisankaran and Rysman's (2012) interpretation that applying static demand to durable goods will tend to lead to biased estimates of the price coefficient toward zero. But in this case, the price, or net present cost of installation depends on δ, so as δ rises, p_{jtm} shrinks, therefore, in fact my results are consistent with Gowrisankaran and Rysman's (2012) theory-based intuition that accounting for dynamics should yield more elastic demand estimates. Finally, the R-squared statistics show that the dynamic demand model rationalizes households' adoption behavior slightly better than the static model.

6.2 Nonlinear Results

When δ is unknown, demand is a nonlinear function of δ, therefore, I use nonlinear least squares (NLLS) and nonlinear IV (NLIV) to estimate,

$$\log\left(\frac{s_{jtm}}{s_{0tm}}\right) = \big(\beta_j - \delta\beta_1\big) - \alpha\big(p_{jtm} - \delta p_{1t+1m}\big) + \delta \log\left(s_{1t+1m}\right) + e_{jtm}.$$

To estimate the demand equation using NLLS, I search for the vector of parameters $\theta = (\beta_j, \alpha, \delta)$ that minimizes the objective function,

$$\mathbf{Q}(\theta) = \frac{1}{N}(\mathbf{e}'\mathbf{e}),$$

where $\mathbf{e}$ is the vector of residuals from the demand equation.

To estimate the demand equation using NLIV (or GMM in the just-identified case), I search for the vector of parameters θ that minimizes the objective function,

$$\mathbf{Q}(\theta) = (\mathbf{e}'\mathbf{Z})\mathbf{W}(\mathbf{Z}'\mathbf{e}),$$

where again $\mathbf{e}$ is the vector of residuals from the demand equation, $\mathbf{Z}$ is a matrix of instruments, and $\mathbf{W} = (\mathbf{Z}'\mathbf{Z})^{-\mathbf{1}}$ is the optimal GMM weighting matrix in the just-identified case.

In both procedures I search for the optimal θ using Newton's method (I derive analytical expressions for the gradient of each objective function in the appendix). The main complication in estimation is that the net present cost of installation depends on the value of δ (here I drop the market subscript for convenience),

$$\begin{aligned} p_{jt} = p^I_{jt} - \underbrace{(0.3 \cdot p^I_{jt})}_{\text{Fed. Tax Credit}} - R_{jt} - \underbrace{(1-0.22)\cdot \min\left\{[0.15\cdot(p^I_{jt} - R_{jt})], 1000\right\}}_{\text{MA Tax Credit}} \\ - \underbrace{\sum_{\tau=0}^{24} \delta^\tau \cdot (1-d)^\tau \cdot g^e_{jt} \cdot p^e_{t+\tau}}_{\text{Net Metering}} - \underbrace{\sum_{\tau=0}^{24} \delta^\tau \cdot (1-d)^\tau \cdot g^e_{jt} \cdot p^{sc}_{t+\tau}}_{\text{SREC Revenue}}. \end{aligned}$$

Because p_{jt} is a function of δ, I need to find a convenient way to calculate p_{jt} as δ changes. Defining the upfront installation price net of upfront incentives as,

$$\tilde{p}^I_{1t} \equiv p^I_{jt} - (0.3\cdot p^I_{jt}) - R_{jt} - (1-0.22)\cdot\min\left\{[0.15\cdot(p^I_{jt} - R_{jt})], 1000\right\}$$

a compact way to calculate the net present installation costs of systems $j \in \{1, ..., 5\}$, at time t is,

$$\begin{bmatrix} p_{1t} \\ p_{2t} \\ p_{3t} \\ p_{4t} \\ p_{5t} \end{bmatrix} = \begin{bmatrix} \tilde{p}^I_{1t} \\ \tilde{p}^I_{2t} \\ \tilde{p}^I_{3t} \\ \tilde{p}^I_{4t} \\ \tilde{p}^I_{5t} \end{bmatrix} - \begin{bmatrix} g^e_{1t} \\ g^e_{2t} \\ g^e_{3t} \\ g^e_{4t} \\ g^e_{5t} \end{bmatrix} \circ \begin{bmatrix} p^e_t & p^e_{t+1} & \cdots & p^e_{t+24} \\ p^e_t & p^e_{t+1} & \cdots & p^e_{t+24} \\ p^e_t & p^e_{t+1} & \cdots & p^e_{t+24} \\ p^e_t & p^e_{t+1} & \cdots & p^e_{t+24} \\ p^e_t & p^e_{t+1} & \cdots & p^e_{t+24} \end{bmatrix} \begin{bmatrix} 1 \\ \delta(1-d) \\ \delta^2(1-d)^2 \\ \vdots \\ \delta^{24}(1-d)^{24} \end{bmatrix} - \begin{bmatrix} g^e_{1t} \\ g^e_{2t} \\ g^e_{3t} \\ g^e_{4t} \\ g^e_{5t} \end{bmatrix} \circ \begin{bmatrix} p^{sc}_t & p^{sc}_{t+1} & \cdots & p^{sc}_{t+24} \\ p^{sc}_t & p^{sc}_{t+1} & \cdots & p^{sc}_{t+24} \\ p^{sc}_t & p^{sc}_{t+1} & \cdots & p^{sc}_{t+24} \\ p^{sc}_t & p^{sc}_{t+1} & \cdots & p^{sc}_{t+24} \\ p^{sc}_t & p^{sc}_{t+1} & \cdots & p^{sc}_{t+24} \end{bmatrix} \begin{bmatrix} 1 \\ \delta(1-d) \\ \delta^2(1-d)^2 \\ \vdots \\ \delta^{24}(1-d)^{24} \end{bmatrix}$$

where $\circ$ represents element-wise multiplication (Hadamard product).

Table 9 reports the nonlinear demand equation estimates. The major difference between the NLLS and NLIV results is the estimate of the discount factor, which is relatively low for NLLS and relatively high for NLIV. Recall that δ is identified using variation in the difference between households' current and future payoffs in the data, as well as future SREC prices in the case of NLIV. The NLLS estimates suggest that variation in the data can somewhat help identify δ, but the instrument increases the estimate of households' discount factor significantly. Correcting for price endogeneity using NLIV yields a similar estimate of the price coefficient (in fact demand actually appears to be less elastic using NLLS), however, again recall that as δ increases in the linear estimation the price coefficient shrinks, therefore, without holding δ constant it is difficult to compare coefficients across models. Taken altogether, the baseline linear and nonlinear estimates suggest that households' PV adoption behavior is better characterized by a dynamic rather than a static model.

6.3 Robustness Checks

6.3.1 Market Size Robustness Check

One potential concern in estimation is that identification of the discount factor in the empirical model partially depends on the difference in the number of households who choose the outside option and those who choose to adopt PV (or the difference between the aggregate share of households waiting to adopt and the shares of those who adopt). Therefore, poor estimation of the market size for PV systems will potentially lead to biased estimates of households' discount factor. Since I use the total number of residential electric utility customers in 2008 as an estimate of the initial market size in each geographic market, it is likely that I overstate the market size for PV systems, because some households may not have the ability to install solar panels depending upon their living situation (for example if they rent an apartment) or due to local zoning regulations or solar panel restrictions. If the market size is overstated, then it is possible that estimates of the discount factor are biased downwards, since in order to rationalize the number of households who choose the outside option, the estimated discount factor will decrease thus suggesting that households are less forward looking about the future benefits of adopting solar than is actually true.

To test the sensitivity of my main empirical results to the potential overstatement of market size, I re-estimate the NLIV specification using different initial estimates of the market size in each geographic market; specifically, I use 10% of the total number of residential electric utility customers in 2008 (see Table 10). The results show that neither the discount factor nor any of the other parameters of the model are meaningfully impacted by the reduction in market size.

6.3.2 Alternative Outside Options Robustness Check

As discussed in the model section, Hotz and Miller (1993) show that it is possible to represent the value of the outside option in dynamic discrete choice models in terms of CCPs. Specifically, in this model it is possible to use any arbitrary future terminal adoption decision as a "proxy" for the value of the outside option. In my main estimation I use $j = 1$, however, in practice I could have chosen any other alternative $j \neq 0$. De Groote and Verboven (2019) acknowledge this issue and develop a creative robustness check, which I employ here as well. Because any one of the terminal adoption decisions could be used to "proxy" for the value of the outside option, De Groote and Verboven (2019) suggest using all alternatives to estimate the model in a GMM framework. In this framework each parameter of the model is over-identified.

More specifically, if k corresponds to the terminal alternative used in the model to "proxy" for the value of waiting to adopt, a more general estimating equation is,

$$\log\left(\frac{s_{jtm}}{s_{0tm}}\right) = \left(\beta_j - \delta\beta_k\right) - \alpha\left(p_{jtm} - \delta p_{kt+1m}\right) + \delta\log\left(s_{kt+1m}\right) + e_{jtm}.$$

In a GMM framework it is possible to estimate the model using all 5 terminal adoption decisions $k = \{1, ..., 5\}$ by forming moment conditions for each alternative and stacking them together,

$$\mathbf{g}(\delta, \beta, \alpha) = \begin{bmatrix} \mathbf{Z}_1'\mathbf{e}_1(\delta, \beta, \alpha) \\ \mathbf{Z}_2'\mathbf{e}_2(\delta, \beta, \alpha) \\ \mathbf{Z}_3'\mathbf{e}_3(\delta, \beta, \alpha) \\ \mathbf{Z}_4'\mathbf{e}_4(\delta, \beta, \alpha) \\ \mathbf{Z}_5'\mathbf{e}_5(\delta, \beta, \alpha) \end{bmatrix},$$

where $\mathbf{Z}_k$ and $\mathbf{e}_k$ represent the set of instruments and errors that correspond to alternative k.

Then to find the optimal parameter values, minimize the GMM objective function,

$$\mathbf{Q}(\theta) = \mathbf{g}(\theta)'\mathbf{W}\mathbf{g}(\theta),$$

where $\mathbf{W}$ is a block diagonal matrix, where each block contains the matrix $(\mathbf{Z_k'Z_k})^{-1}$.

The results of this robustness check are displayed in Table 11. First, notice that the estimated discount factor is smaller (0.676) but still reasonably close to my main estimate (0.811). Second, the estimated price coefficient is almost identical to the main results. Finally, the parameters are more precisely estimated because of the inclusion of additional moment conditions.

6.4 Heterogeneity Among Households

In this section I extend the model to allow for heterogenous preferences among households. Modeling heterogeneity among households is potentially important for two main reasons in this setting. First, the standard multinomial logit model may generate unrealistic substitution patterns within PV system choices due to the IIA property, whereas a mixed logit can generate more realistic substitution patterns. Second, allowing for heterogeneity among households can help explain why many households choose not to adopt solar panels during my period of study. If households have homogenous preferences, then all variation among households must be rationalized by variation in ϵ_{ijt}. However, if certain types of households are unlikely to ever adopt solar panels and these types are correlated with observable characteristics, then the inclusion of demographic data can allow the model to better explain adoption behavior. Additionally, if certain households are likely to be "never adopters", then ignoring heterogeneity among households may lead to an estimate of the discount factor that is downward biased.

Following De Groote and Verboven (2019), I allow households located in different submarkets, in this case across Massachusetts' 351 municipalities, to have differing preferences for PV systems. The model is similar to adding micro-moments to the "BLP" demand system, as in Berry, Levinsohn, and Pakes (2004) and Petrin (2002), however, in this case I rely only on demographic data to identify heterogeneity among households, as opposed to using random coefficients to model unobservable heterogeneity as well as demographics to model observable heterogeneity. Although it is possible to include random coefficients in a dynamic demand model, for example see Gowrisankaran and Rysman (2012) and Conlon (2012), the researcher must specify how consumer preferences evolve over time in the model, which requires specifying the entire state space of the model. Instead, relying upon only demographic data to identify heterogeneity avoids having to make assumptions about the evolution of preferences and other state variables in the model such as PV prices and subsidies, allowing me to estimate the model using the ECCP method (Kalouptsidi, Scott, and Souza-Rodrigues 2021).

Suppose household h's flow utility from adopting system j at time t is given by,

$$u_{hjt} = \bar{u}_{jt} + \mu_{hjt} + \epsilon_{hjt} \tag{16}$$

where $\bar{u}_{jt}$ corresponds to the mean utility each household receives from adopting and μ_{hjt} represents the component of utility that varies over each household.

Assuming that households located in the same municipality i have similar demographic characteristics, let u_{ijt} be the flow utility each household $h \in i$ obtains from adopting system j in time t, where variation in preferences across municipalities depends upon certain demographic characteristics; in this case, average income, population density, and voting share for the democratic party,

$$u_{ijt} = \underbrace{\beta_j - \alpha p_{jt} + \xi_{jt}}_{\bar{u}_{jt}} + \underbrace{\lambda_j^I inc_i + \lambda_j^P pop_i + \lambda_j^V vote_i}_{\mu_{ijt}} + \epsilon_{ijt}. \tag{17}$$

Each demographic characteristic is interacted with system capacity to flexibly capture heterogeneity among households. I choose these particular demographic characteristics based on the existing residential solar literature and given the likely importance of each characteristic to households' choice of PV system. First, residential PV systems are a new, relatively expensive technology that are more likely to be adopted by high-income households. Second, households in more densely populated urban areas are less likely to adopt large capacity systems due to property size constraints. Third, given the politicization of climate policy in the U.S., I expect PV systems to be more popular in democratic-leaning municipalities, and moreover, peer effects may be stronger among more politically homogenous households.

Using the ECCP methodology as before to represent the household's value of waiting to adopt at time t in terms of the utility of adopting system $j = 1$ at time $t + 1$, the household's flow utility from the outside option at time t can be written as,

$$v_{i0t} = \delta\big(\underbrace{\beta_1 - \alpha p_{1t+1} + \xi_{jt+1} - \eta_t}_{\bar{u}_{1t+1}} + \underbrace{\lambda_1^I inc_i + \lambda_1^P pop_i + \lambda_1^V vote_i}_{\mu_{i1t+1}} - \log\left(s_{i1t+1}\right)\big), \tag{18}$$

then, normalizing the utility from adopting system j at time t relative to the value of outside option at time t,

$$u_{ijt} - v_{i0t} = \left(\bar{u}_{jt} - \delta\bar{u}_{1t+1}\right) + \left(\mu_{ijt} - \delta\mu_{i1t+1}\right) + \delta\log\left(s_{i1t+1}\right),$$

and defining the differences in the mean and variance components of utility as,

$$\tilde{u}_{jt} \equiv \bar{u}_{jt} - \delta \bar{u}_{1t+1} = \big(\beta_j - \delta\beta_1\big) - \alpha\big(p_{jt} - \delta p_{1t+1}\big) + e_{jt},$$

$$\tilde{\mu}_{ijt} \equiv \mu_{ijt} - \delta\mu_{i1t+1} = \underbrace{(\lambda_j^I - \delta\lambda_1^I)}_{\tilde{\lambda}_j^I} inc_i + \underbrace{(\lambda_j^P - \delta\lambda_1^P)}_{\tilde{\lambda}_j^P} pop_i + \underbrace{(\lambda_j^V - \delta\lambda_1^V)}_{\tilde{\lambda}_j^V} vote_i,$$

the probability that household i adopts system j at time t is,

$$s_{ijt}(\tilde{u}, \tilde{\lambda}) = \frac{\exp\left(\tilde{u}_{jt} + \tilde{\lambda}_j^I inc_i + \tilde{\lambda}_j^P pop_i + \tilde{\lambda}_j^V vote_i + \delta \log\left(s_{i1t+1}\right)\right)}{1 + \sum_k^J \exp\left(\tilde{u}_{kt} + \tilde{\lambda}_k^I inc_i + \tilde{\lambda}_k^P pop_i + \tilde{\lambda}_k^V vote_i + \delta \log\left(s_{i1t+1}\right)\right)}. \tag{19}$$

With these probabilities, it is now possible to write a log-likelihood function in terms of the probabilities of adoption s_{ijt} and number of adoptions q_{ijt} (and non-adoptions q_{i0t}) of each system j at time t in municipality i,

$$\log\left[\mathcal{L}(\tilde{u}, \tilde{\lambda}, \delta)\right] = \sum_{i=1}^{I}\sum_{t=1}^{T}\sum_{t=0}^{J}\left[q_{ijt}\log\left(s_{ijt}\right)\right], \tag{20}$$

where the mean utilities $\tilde{u}$, demographic-capacity interactions $\tilde{\lambda}$, and discount factor δ are parameters to be estimated. A technical detail here is that s_{i1t+1} also needs to be estimated since it is not directly observed. Following De Groote and Verboven (2019) I pre-estimate these probabilities in a first-stage regression using a logit model that includes product-time fixed effects and demographic-capacity interactions.

As in the BLP (1995) demand framework, with estimates of households' mean utilities $\tilde{u}_{jt}$ in hand it is possible to recover preferences for product characteristics by projecting characteristics onto mean utilities,

$$\tilde{u}_{jt} = \big(\beta_j - \delta\beta_1\big) - \alpha\big(p_{jt} - \delta p_{1t+1}\big) + e_{jt}. \tag{21}$$

This equation can be estimated using OLS if prices are thought to be exogenous or by linear IV when prices are assumed to be endogenous.

In order to estimate correct standard errors for the parameters of the model, and to estimate δ (because δ appears in both estimating equations), it is necessary to jointly estimate equations (19 and 21) using GMM. To obtain moments for equation (19) I derive the first-order conditions (or scores) of the log-likelihood function with respect to the parameters; these are "micro"-moments since they are sampled from household-level data. In a GMM framework, setting the expected scores of the log-likelihood function equal to zero is equivalent to MLE (see Train 2003). The moment conditions associated with equation (21) are formed as usual by interacting the instruments with the error term; these are "macro"-moments since they are sampled from aggregate market-level data.

Stacking all of the moment conditions together,

$$\mathbf{g}(\tilde{u}, \tilde{\lambda}, \delta, \beta, \alpha) = \begin{bmatrix} \frac{\partial \log[\mathcal{L}(\tilde{u},\tilde{\lambda},\delta)]}{\partial \tilde{u}} \\ \frac{\partial \log[\mathcal{L}(\tilde{u},\tilde{\lambda},\delta)]}{\partial \tilde{\lambda}} \\ \mathbf{Z}'\mathbf{e}(\tilde{u}, \delta, \beta, \alpha) \end{bmatrix},$$

I form the GMM objective function,

$$\mathbf{Q}(\theta) = \mathbf{g}(\theta)'\mathbf{W}\mathbf{g}(\theta),$$

where the weight matrix $\mathbf{W}$ is a block diagonal matrix, where the first block contains weights for the micro-moments, and the second block contains weights for the macro-moments.

In practice, I form the micro-moments using household-level data from 349 municipalities (the two municipalities excluded had no adoptions), for a total of 17,450 micro-moments. I form the macro-moments using market-level data aggregated over the 5 utility service areas, for a total of 50 macro-moments. Technically with aggregate data from each of the 5 "utility markets" I could sample from 250 macro-moments, representing a market-system-year rather than a system-year. This would require me to estimate 250 parameters, which moreover are only uniquely identified if there's at least one adoption for each market-system-year. However, due to the sparsity of adoptions in the data (I observe zero adoptions especially early on in my sample) I must aggregate the data over geographic markets.

While this aggregation reduces the number of parameters I have to estimate, the cost is that I am no longer able to exploit cross-market variation in prices to identify the parameters. Because price no longer varies across markets, I also have to use a different instrumental variable for price in equation (21). Instead of using average prices in other Massachusetts utility service areas, I use average prices in California as an instrument. This identification strategy is again based on the idea that common variation in prices across different markets should be mostly explained by common supply shocks rather than common demand shocks. Finally, to simplify the optimization routine, rather than estimating δ, I set $\delta = 0.8$.

The results of the heterogenous demand estimates are displayed in Table 12. First note that the estimated price coefficient here suggests that consumers are significantly less price sensitive than the estimate from the homogenous demand model. This difference may be driven by a number of factors including the absence of cross-market variation in price, a change in the price instrument, or the inclusion of heterogenous effects; in any case, the difference is large. Also unlike the homogenous model, capacity fixed effects increase monotonically with system size. Of the parameters capturing household heterogeneity, the set of population density-capacity interactions appear to be the most economically relevant and statistically significant. The coefficients show that as municipal population density increases, households are less likely to install larger capacity systems. This is intuitive because property sizes in less-dense or rural areas tend to be larger than property sizes in more-dense or urban areas, and homes are further apart allowing sunlight to reach them unobstructed for more hours per day. Furthermore, urban areas are likely to have a larger proportion of renters who don't have the ability to install PV systems. The income-capacity interactions generally show that as average household income rises, the more likely household is to purchase a larger capacity system, which is again an intuitive result. Finally, the vote share-capacity interactions show that households in municipalities with a larger democratic vote share are more likely to purchase PV systems, however, this effect declines with system size. Again the direction of these effects seem reasonable given the polarization of climate policy in the U.S. and given that the role politics plays in households' financial decisions is likely to shrink as upfront investment rises.

7 Counterfactual Analysis

In this section, I assess how different solar incentive programs affected households' decisions to adopt PV systems. Specifically, I use the homogenous and heterogenous demand estimates to predict adoptions in the absence of (1) upfront subsidies, (2) SREC revenues, and (3) net metering revenues. I also calculate the amount of consumer welfare generated by each program. I find that removing upfront subsidies (federal and state tax credits and grants/rebates) would result in the largest decrease in solar adoption followed by the establishment of SREC market and net metering policy, which makes sense given that households significantly discount the long-term benefits of adoption.

One complication in the counterfactual analysis is determining the degree to which preventing households from net metering affects their demand. In what follows, I describe the implementation of each counterfactual, describe the calculation of consumer welfare generated by each program, and discuss the results.

7.1 Implementation

Each counterfactual scenario I simulate only affects demand for PV systems through changes to the price term $\left(p_{jt} - \delta p_{1t+1}\right)$ in the estimating equation. To streamline the discussion of implementing each counterfactual, recall each component of the net present cost of installation,

(1) upfront subsidies;

$$\mathrm{UF}_{jt} = (0.3 \cdot p^I_{jt}) - R_{jt} - (1 - 0.22) \cdot \min\left\{[0.15 \cdot (p^I_{jt} - R_{jt})], 1000\right\},$$

(2) net metering revenue;

$$\mathrm{PV}^{nm}_{jt} = \sum_{\tau=0}^{24} \delta^\tau \cdot (1-d)^\tau \cdot g^e_{jt} \cdot p^e_{t+\tau},$$

(3) and SREC revenue;

$$\mathrm{PV}^{sc}_{jt} = \sum_{\tau=0}^{24} \delta^\tau \cdot (1-d)^\tau \cdot g^e_{jt} \cdot p^{sc}_{t+\tau},$$

where the net present cost of installation is the upfront installation cost minus the above terms,

$$p_{jt} = p^I_{jt} - \mathrm{UF}_{jt} - \mathrm{PV}^{nm}_{jt} - \mathrm{PV}^{sc}_{jt}.$$

To measure the effect of each incentive on overall residential adoption, I remove each one at a time and simulate counterfactual demand. It should be noted here that to generate counterfactual predictions using my estimates, in each model I set the structural error term, $e_{jt} = 0$.

7.2 Removal of Upfront Subsidies

When upfront subsidies are removed p_{jt} and p_{1t+1} become,

$$p_{jt} = p^I_{jt} - \mathrm{PV}^{nm}_{jt} - \mathrm{PV}^{sc}_{jt},$$

$$p_{1t+1} = p^I_{1t+1} - \mathrm{PV}^{nm}_{1t+1} - \mathrm{PV}^{sc}_{1t+1},$$

and $\left(p_{jt} - \delta p_{1t+1}\right)$ becomes,

$$\left(p_{jt} - \delta p_{1t+1}\right) = \left(p^I_{jt} - \delta p^I_{1t+1}\right) - \left(\mathrm{PV}^{nm}_{jt} - \delta \mathrm{PV}^{nm}_{1t+1}\right) - \left(\mathrm{PV}^{sc}_{jt} - \delta \mathrm{PV}^{sc}_{1t+1}\right).$$

7.3 Removal of SREC Revenue

When SREC revenue is removed p_{jt} and p_{1t+1} become,

$$p_{jt} = p^I_{jt} - \mathrm{UF}_{jt} - \mathrm{PV}^{nm}_{jt},$$

$$p_{1t+1} = p^I_{1t+1} - \mathrm{UF}_{1t+1} - \mathrm{PV}^{nm}_{1t+1},$$

and $\left(p_{jt} - \delta p_{1t+1}\right)$ becomes,

$$\left(p_{jt} - \delta p_{1t+1}\right) = \left(p^I_{jt} - \delta p^I_{1t+1}\right) - \left(\mathrm{UF}_{jt} - \delta \mathrm{UF}_{1t+1}\right) - \left(\mathrm{PV}^{nm}_{jt} - \delta \mathrm{PV}^{nm}_{1t+1}\right).$$

7.4 Removal of Net Metering Revenue

The case of net metering is more complicated than the other policies because rather than directly affecting demand, preventing net metering indirectly affects a household's choice of PV system through its effect on the household's electricity bill. Not allowing households to net meter prevents them from balancing periods of net energy consumption with periods of net energy generation, which will lead them to purchase smaller capacity systems.

To see this, suppose each household chooses its system capacity optimally so that the estimated annual generation of the system exactly equals the household's annual consumption. Because household energy consumption fluctuates throughout the year and the efficiency of solar panels fluctuates throughout the year, a net metering policy enables the household to compensate for periods of net consumption with periods of net generation. Under such a policy, assume that households will purchase systems such that total system generation equals total their consumption,

$$\sum_{m=1}^{12} g_m = \sum_{m=1}^{12} c_m,$$

or equivalently such that average monthly generation equals average monthly consumption,

$$12 \cdot \bar{g} = 12 \cdot \bar{c}.$$

If this net metering policy were removed, then households wouldn't purchase the same sized system because they wouldn't be able to compensate for periods of net consumption with periods of net generation. Instead, perhaps each household would choose a system with average generation $\bar{g}^*$ such that average generation is a fraction $F \in (0, 1)$ of its average consumption,

$$\bar{g}^* = F \cdot \bar{c}.$$

That is, when the policy is removed, each household chooses a system that generates only enough electricity to cover a portion of its monthly consumption in order to avoid excess generation for which it is no longer compensated.

Determining how large an impact preventing net metering would have on households' choice of system capacity is difficult without household-level data on energy consumption. Therefore, in the absence of such data, I choose a range of values for the fraction of generation impacted by the loss of net metering $F = \{0.1, 0.25, 0.5, 0.75, 0.9\}$ and compare the differences of the effects on overall residential adoption. Values of F closer to 1 are likely to be more realistic, however, the range of effects is still informative as to the magnitude of the impact of removing the policy.

In the model F enters the net metering revenue portion of the price term,

$$\text{PV}_{jt}^{nm} = \sum_{\tau=0}^{24} \delta^{\tau} \cdot (1-d)^{\tau} \cdot F \cdot g_{jt}^{e} \cdot p_{t+\tau}^{e},$$

thus affecting demand by reducing the value of net metering and increasing the net present cost of installation.

7.5 Consumer Welfare

In order to calculate the change in consumer welfare attributable to each policy, I use the standard formula for computing welfare for discrete choice models (Train 2003). However, an important difference in my application is that changes in policies affect not only households' utility for PV systems u_{jt} but also their utility from the outside option v_{0t}, in this case the value of waiting to adopt.

Where $J^{\mathcal{S}}$, $J^{\mathcal{N}}$ denote the set of products with and without the subsidy or subsidies of interest, the change in consumer surplus due to the subsidy is given by,

$$\Delta E[CS_t] = \frac{M_t}{\alpha}\left[\log\left(\exp\left(\bar{v}_{0t}^{\mathcal{S}}\right) + \sum_{j=1}^{J^{\mathcal{S}}} \exp\left(\bar{u}_{jt}^{\mathcal{S}}\right)\right) - \log\left(\exp\left(\bar{v}_{0t}^{\mathcal{N}}\right) + \sum_{j=1}^{J^{\mathcal{N}}} \exp\left(\bar{u}_{jt}^{\mathcal{N}}\right)\right)\right].$$

Another important caveat of these welfare calculations is that my analysis is a partial equilibrium analysis, as opposed to a general equilibrium analysis, because for example if an increasingly large number of households in MA adopted PV systems eventually SREC prices would go to zero. Therefore, one might think of the average consumer surplus in this context as the amount of consumer welfare generated by the program for the marginal household or perhaps as an upper bound of average consumer welfare generated by the program.

7.6 Counterfactual Results

The results of the counterfactual simulations are displayed in Table 13 and Figures 14 and 15. The top panel of Table 13 displays cumulative adoptions during the 2008-2017 period by system capacity predicted using the homogenous demand estimates, while the bottom panel displays the predictions of the heterogenous demand estimates. Figures 14 and 15 display cumulative adoptions over time by system size using homogenous and heterogenous demand estimates, respectively. First, note that the homogenous demand model overpredicts total cumulative adoptions by just under 3,000 or about 11% (the model overpredicts adoptions for all capacities except the [10,20) kW category). While the model predicts the flow of adoptions in any given year poorly, its prediction for the stock of PV systems in 2017 is relatively good. The flexibility of the heterogenous model doesn't appear to improve its predictive power. There are several reasons why this might be the case including the smaller price coefficient, fewer macro-moments capturing cross market variation in price, and the fact that one-period ahead shares of adoption must be pre-estimated; in any case, for purposes of analysis I rely more upon the estimates of the simpler model.

Comparing the counterfactual outcomes of the model, elimination of upfront subsidies reduces adoptions the most, closely followed by the elimination of the SREC market. The impact of preventing households from net metering depends on the degree to which households' consumption varies during in a year, however, even at the extremes net metering has less of an effect on adoption rates than either of the other policies. Notice that the elimination of any one incentive program significantly impacts cumulative adoptions because (1) the elimination of any program substantially increases the net present cost of PV systems and (2) the probability of adoption is modeled as a nonlinear function of price.

Comparing the predicted to counterfactual outcomes, I estimate that elimination (1) the SREC market would have decreased cumulative adoptions by approximately 78%, (2) upfront subsidies by 80%, and (3) net metering, assuming a relatively small impact by 13%. Table 14 presents the change in consumer welfare generated by each program, where I measure the change as the difference between having all the programs and the elimination of the program of interest. Note that measuring the change in consumer welfare due to introduction of more than one program is indeed possible but onerous to present.

From the results we can see that upfront subsidies generated the largest amount of consumer surplus during the 2008-2017 period. Again recall that these estimates represent a partial equilibrium analysis and as such should be interpreted appropriately; the marginal household in MA benefitted most from upfront subsidies offered by federal and state governments. Another aspect of these welfare exercises to consider when interpreting the results is that setting aside the relative magnitude of upfront incentives and future incentives, all else equal, a household values a dollar today more than a dollar in the future. Therefore, the amount of future incentives received by households would necessarily have to be greater than upfront subsidies in order to achieve a commensurate increase in consumer surplus.

8 Estimating the Value of Avoided CO_2 Emissions

One particularly relevant question for energy and environmental policymakers is to what extent do incentive programs reduce carbon dioxide emissions? Also, given the negative externalities associated with CO_2 emissions what is the economic value of avoided emissions due the implementation of these programs? Using the homogenous demand parameter estimates, I approximate the reduction in CO_2 emissions attributable to each incentive program. Then with a recent estimate of the social cost of carbon (SCC) from Cai and Lontzek (2019), I quantify the value of avoided CO_2 emissions due to each program.

To approximate the reduction in CO_2 emissions given the implementation of each incentive program, for simplicity, I assume that in the absence of PV adoption, any electricity generated by residential solar panels would have been generated by an electric utility provider instead. Furthermore, I assume that this electricity would have been generated using natural gas power plants. The EIA's 2019 profile of Massachusetts indicates that 70.3% utility-scale net electricity generation is sourced from natural gas-fired power plants, while the almost all of the remainder is derived from renewables.[16] Correctly identifying the source of electricity generation is important for determining avoided CO_2 emissions because pollution varies substantially across fuels. According to EIA, on average coal, natural gas, and petroleum-fired power plants emit 2.21, 0.91, and 2.13 pounds of CO_2 per kWh of electricity generated, respectively.[17] Using EIA's estimate of pounds of CO_2 per kWh for natural gas-fired power plants, I approximate metric tons of CO_2 emitted per MWh of electricity generated as,[18]

$$\frac{\text{tCO}_2}{\text{MWh}} = 0.91 \times 1,000 \times \frac{1}{2,204.62} \approx 0.41276955.$$

The standard definition of the social cost of carbon in the economic literature is the monetized economic loss caused by an increase in atmospheric carbon. In their model, Cai and Lontzek (2019) define the SCC as the marginal rate of substitution between atmospheric carbon concentration and capital and express the SCC in dollars per (metric) tons of carbon. As they note, the SCC is a shadow price that fluctuates

[16] EIA, Massachusetts State Energy Profile, https://www.eia.gov/state/print.php?sid=MA

[17] EIA, How much carbon dioxide is produced per kilowatthour of U.S. electricity generation?, https://www.eia.gov/tools/faqs/faq.php?id=74&t=11

[18] The factor 1,000 converts $\frac{1}{\text{kWh}}$ to $\frac{1}{\text{MWh}}$. The factor $\frac{1}{2,204.62}$ converts lbs to metric tons

as the state of the economy and climate evolve over time. I use their mean estimate of the SCC in 2020, \$87, which I convert into dollars per tons of CO_2 by multiplying by a factor of $\frac{12}{44}$ (given in Cai and Lontzek 2019),

$$\frac{\$}{\mathrm{tCO_2}} = \frac{12}{44} \times \frac{\$87}{\mathrm{tC}} \approx \frac{\$23.73}{\mathrm{tC}}.$$

Combining the above equations, the social cost of CO_2 per MWh that I use in my analysis is,

$$\frac{\mathrm{SCCO_2}}{\mathrm{MWh}} = \frac{\mathrm{tCO_2}}{\mathrm{MWh}} \times \frac{\$}{\mathrm{tCO_2}} \approx \$9.79.$$

Next I quantify the value of the avoided CO_2 emissions due to each incentive program during the period 2008–2017. In order to perform this exercise, first I approximate the total amount of electricity generated by all residential solar panels in Massachusetts adopted during the period. I assume that every year each system generates an amount of electricity equal to the median estimated annual production of the discrete category to which it belongs: [0,4), [4,6), [6,8), [8,10), and [10,20). Where q_{jt} is the number of solar systems of capacity $j \in \{1, ..., 5\}$ installed at time t and $\bar{g}_j$ is the median estimated annual production of system j, total electricity generation is given by,

$$\text{Generation (MWh)} = \sum_{t=2008}^{2017} \Big(\bar{g}_1 \cdot q_{1t} + \bar{g}_2 \cdot q_{2t} + ... + \bar{g}_5 \cdot q_{5t} \Big).$$

(It may be appropriate to discount this quantity with the social planner's discount factor δ_{sp}, as well as account for depreciation here). Given the data I observe, the total amount of electricity generated by residential solar systems from 2008 to 2017 was approximately 625 thousand MWhs. To put this figure in perspective, total annual electricity generation for Massachusetts in 2019 was 1,334 thousand MWhs.[19]

Using my NLIV estimates I calculate total electricity predicted by the model, as well as in counterfactual scenarios where I remove either (1) SREC revenues, (2) upfront subsidies, or (3) net metering revenues; the results are displayed in Table 15 and Figure 16. Because the underlying demand model overpredicts the number of adoptions (see Table 13) it also overpredicts the amount of electricity generated, but in this case by 50% (as opposed to only 11%) because as the stock of installations increases the flow of annual generation increases. However despite this overprediction, by comparing predicted generation to counterfactual generation I can recover a rough estimate of the effect of removing each incentive program on actual generation. For example, removing households' SREC revenues would result in a $(1 - \frac{164{,}814}{944{,}249}) \approx 82.5\%$ decrease in total

[19] EIA, Massachusetts State Energy Profile, https://www.eia.gov/state/print.php?sid=MA

generation.

With estimates of total generation in hand, I can quantify the value of avoided CO_2 emissions by simply multiplying total generation by the social cost of CO_2 per MWh (\$9.79). Using the relative difference between predicted and counterfactual generation, I approximate the value of avoided CO_2 emissions due to each program as follows,

$$\text{Value of Avoided CO}_2\text{ Emissions} = \$9.79 \times \left(1 - \frac{\text{Counterfactual Generation}}{\text{Predicted Generation}}\right) \times \text{Actual Generation}.$$

The results displayed in Table 16 show that avoided CO_2 emissions during the 2008–2017 period attributable to upfront subsidies are worth approximately \$5.25 million to society. This is a relatively modest sum compared to the amount of upfront support given to PV system adopters, about \$280 million (see Table 17). More generally, the results show that the social value generated by each program is two orders of magnitude smaller than the government's investment in each. Stated another way, in order for the government to breakeven on its investment in upfront subsidies, the SCC would have to be approximately 53.5 times larger than Cai and Lontzek's estimate of \$87 per ton of carbon i.e. \$4,654.50 per ton of carbon. Therefore, if the government's main objective was to reduce CO_2 emissions via these policies, then my estimates suggest that investment in these programs was relatively inefficient. However, it is certainly possible that the state had other objectives besides reducing emissions.

8.1 Limitations

There are several limitations of the counterfactual analysis I undertake, which may impact my estimates of the effect each incentive program has on overall PV adoption rates as well as the implied social benefits generated by each incentive. While there may be others, I discuss four potential limitations here: (1) supply-side response to incentives, (2) households' responses to different incentives, (3) interactions between incentive programs, and (4) market expansion over time/peer effects.

8.1.1 Supply-side Response to Demand-side Incentives

As previously discussed, I do not attempt to model the supply side of the market in this paper to avoid the added complexity of modeling dynamic competition among firms. However, it is important to consider how the results of my counterfactual analysis might change in general equilibrium, taking into account the behavior of PV manufacturers. In particular, one relevant question with respect to supply is whether the rapid decline in PV module manufacturing costs abroad during the 2008-2018 period (see Figure 2) was partially driven by domestic solar subsidies. If federal and state demand-side incentives spurred PV manufacturers to scale up their operations and reduce module production costs in order to meet demand, it is possible that my counterfactual estimates understate the social benefit generated by the demand-side incentive programs I study due to spillover effects on the supply side of the market. Then the question is how much of the decline in manufacturing costs is attributable to demand-side incentives? Given the large differential in the estimated costs and benefits of the programs that I find, the supply-side response attributable to these programs would have to be substantial in order to lead to a net social benefit. However, further study may be needed to quantify the contribution of domestic demand-side incentives to the reduction in PV manufacturing costs abroad (for example see Gerarden 2018).

8.1.2 Households' Responses to Different Incentives

A potential limitation of the demand model is that the effect of different incentives on household adoption are treated the same in the sense that households' responses to different incentives are captured by only two parameters in the model, the household's sensitivity to price α and the household's discount factor δ. Therefore, the model assumes that households exhibit the same sensitivity to each incentive, which isn't necessarily the case. For example, of the upfront incentives households receive, it is possible that federal and state tax credits are more salient than the state rebate programs. Likewise in the case of future incentives, it is possible that the benefits of net metering are more evident to households than the benefits of the SREC programs. Furthermore, there may be differences in the design of the programs, other than time horizon, that affect their efficiency. For example, production subsidies such as net metering and SRECs may be more likely to target the marginal PV adopter at any given time, whereas large upfront subsidies may be more likely to encourage inframarginal adoption. In that case, my analysis may overstate the efficiency of upfront incentives relative to long-term incentives.

8.1.3 Interactions Between Incentive Programs

Another potential limitation related to the model of demand is that households' responses to changes in price, and therefore changes in incentives, are nonlinear. As a result, the sum of the marginal impacts of removing each incentive is larger than the combined impact of removing more than one incentive. While this may be a realistic way to model household behavior, it is important to recognize this assumption. Additionally, interactions between incentive programs in equilibrium are not captured in the model. For example, as more and more households adopt PV, electricity prices and SREC prices may change in response. For example, Borenstein (2017) found that PV adoption in California put upwards pressure on electricity prices as electric utilities' customer bases shrank. Similarly, increased PV adoption increases the supply of SRECs, decreasing equilibrium SREC prices. While it is possible for me to perform counterfactuals in which I remove more than one incentive at a time, it is not straightforward to model these potential spillover effects.

8.1.4 Market Expansion Over Time/Peer Effects

A final potential limitation of my analysis is that I do not account for the fact that market size may be growing over time for several reasons. First, it is likely that early on in my sample households' general awareness of solar panels as a viable alternative to conventional electricity provision was low relative to later on in my sample. Second, the entry of large firms such as SolarCity and Vivant into the market, as well as increased advertising is likely to have impacted households' awareness. Finally, other papers in the solar literature have identified the potential importance of peer effects on households' adoption decisions (Bollinger and Gillingham 2012, Bollinger, Gillingham, Kirkpatrick, and Sexton 2020). Signing the bias of market expansion over time is challenging because on the one hand, while overestimating the market size will lead to an understatement of the effects of incentives on adoption, on the other hand, if peer effects play a role in adoption behavior then presumably ignoring these effects would lead me to overstate the effects of incentives, all else equal. Modeling growing awareness over time, possibly through peer effects, is potentially a fruitful avenue for future work.

9 Conclusion

Determining cost effective policies to facilitate a transition to a greener and cleaner economy in the near future is a significant and increasingly salient challenge for policy-makers. My evaluation of demand-side incentives for adopters of residential PV systems in Massachusetts suggests that recent efforts to encourage the adoption of small scale renewables have indeed increased adoption rates, however, these policies appear to have been relatively inefficient. My empirical results also suggest that dollar for dollar up-front incentives are likely to be more cost effective than long-term incentives, because residential adopters significantly discount the future benefits of adopting solar panels.

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Appendices

A Tables

Table 1. Duration of PV System Future Incentives (return)

Installation Year	Net Metering Program Revenue/ Avoided Electricity Cost	SREC I Revenue	SREC II Revenue
2008	2008 – 2032	N/A	N/A
2009	2009 – 2033	N/A	N/A
2010	2010 – 2034	2010 – 2025	N/A
...	...	...	...
2013	2013 – 2037	2013 – 2025	N/A
2014	2014 – 2038	N/A	2014 – 2029
...	...	...	...
2017	2017 – 2041	N/A	2017 – 2029

Table 2. Means and Medians by System Capacity (return)

	System Capacity (kW)					
Means	[0,4)	[4,6)	[6,8)	[8,10)	[10,20)	Total
System Capacity (kW)	3.12	5.04	6.95	8.98	12.20	7.50
System Estimated Production (kWh)	3,747.93	5,951.05	8,238.79	10,494.49	14,152.89	8,803.53
Upfront Installation Cost	16,444.91	23,581.38	29,755.82	35,982.72	46,477.22	31,330.94
MA Grants/Rebates	2,181.62	1,889.99	774.59	528.57	276.96	1,058.83
Medians						
System Capacity (kW)	3.25	5.04	6.90	8.99	11.79	7.08
System Estimated Production (kWh)	3,785.00	5,918.00	8,153.00	10,493.00	13,753.50	8,242.00
Upfront Installation Cost	15,491.86	22,233.38	28,382.37	34,619.87	44,655.88	29,897.36
MA Grants/Rebates	0.00	0.00	0.00	0.00	0.00	0.00
Observations	3,417	7,933	7,836	6,089	6,362	31,637

Table 3. Electricity Price Trend Estimates (return)

Specification	Log Price per kWh	
Municipal Utilities × Time	0.0188***	(10.44)
NSTAR × Time	0.0374***	(4.03)
National Grid × Time	0.0610***	(4.31)
Unitil × Time	0.0419***	(6.42)
WMECO × Time	0.0384**	(3.28)
Municipal Utilities	0	(.)
NSTAR	-37.16	(-1.95)
National Grid	-84.68**	(-2.95)
Unitil	-46.09**	(-3.38)
WMECO	-39.12	(-1.64)
Constant	-39.96***	(-11.01)
R-Squared	0.851	
F-Statistic	114.77	
Observations	54	

Table 4. Distribution of Residential Solar Installations and Customers by Utility (return)

Utilities	Installations (2008–2018)		Customers (2008)	
Municipal Utilities	2,098	(6.63%)	333,506	(13.99%)
NSTAR (DBA EverSource)	12,320	(38.94%)	785,251	(32.95%)
National Grid	13,110	(41.44%)	1,062,277	(44.57%)
Unitil	453	(1.43%)	24,277	(1.02%)
WMECO (DBA EverSource)	3,656	(11.56%)	178,173	(7.48%)
Total	31,637		2,383,484	

Table 5. Aggregate Data Summary Statistics (2008–2017) (return)

Variables	Mean	Std. Dev.	Minimum	Median	Maximum	N
Adoptions	104	167	1.0e-06	30	766	250
System Market Share	.00024	.00028	1.3e-12	.00014	.0012	250
Upfront Installation Cost	35,280	16,646	7,092	32,859	103,671	250
Federal Tax Credit	10,584	4,994	2,128	9,858	31,101	250
MA Grants/Rebates	3,337	4,267	0	1,863	20,297	250
MA Tax Credit	778	33	262	780	780	250
System Capacity (kW)	7.2	3	2.1	6.9	14	250
System Estimated Production (kWh)	8,299	3,471	2,571	8,031	16,952	250

Table 6. Price Variance Decomposition (2008–2017) (return)

System	Mean	Std. Dev. (Overall)	Std. Dev. (Between)	Std. Dev. (Within)
Capacity [0,4) kW	7,846	3,537	1,863	3,111
Capacity [4,6) kW	12,094	3,791	1,655	3,484
Capacity [6,8) kW	19,532	3,221	1,518	2,915
Capacity [8,10) kW	27,448	7,769	1,080	7,707
Capacity [10,20) kW	34,891	6,518	861	6,471

Table 7. First-Stage Estimates for Demand (return)

Specification	Installation Cost	
Average Installation Cost (000)	0.375***	(8.14)
Capacity [4,6) kW	0.852	(0.89)
Capacity [6,8) kW	5.087***	(4.82)
Capacity [8,10) kW	9.002***	(7.77)
Capacity [10,20) kW	12.68***	(6.79)
Constant	1.837*	(2.03)
r2	0.871	
F	355.2	
N	250	

Table 8. Linear Demand Equation Estimates (return)

Parameters	OLS, $\delta = 0$ Estimates	OLS, $\delta = 0$ Standard Errors	IV, $\delta = 0$ Estimates	IV, $\delta = 0$ Standard Errors	OLS, $\delta = 0.9$ Estimates	OLS, $\delta = 0.9$ Standard Errors	IV, $\delta = 0.9$ Estimates	IV, $\delta = 0.9$ Standard Errors
α: Net Present Installation Cost (000)	-0.347	(0.083)	-0.829	(0.163)	-0.202	(0.033)	-0.251	(0.040)
$\tilde{\beta}_2$: Capacity [4,6) kW	2.375	(0.761)	4.428	(1.045)	0.107	(0.774)	-0.087	(0.799)
$\tilde{\beta}_3$: Capacity [6,8) kW	3.913	(1.199)	9.554	(1.954)	-1.074	(0.853)	-1.302	(0.863)
$\tilde{\beta}_4$: Capacity [8,10) kW	5.078	(1.471)	14.538	(2.863)	-3.009	(1.024)	-3.323	(1.056)
$\tilde{\beta}_5$: Capacity [10,20) kW	6.262	(2.347)	19.312	(4.231)	-5.073	(1.032)	-5.550	(1.116)
$\tilde{\beta}_0$: Constant	-6.961	(0.796)	-3.075	(1.419)	-1.025	(0.561)	-1.023	(0.564)
R^2	0.214		-0.042		0.305		0.290	
Markets	5		5		5		5	
Years	10		10		10		10	
Observations	250		250		250		250	

Table 9. Nonlinear Demand Equation Estimates (return)

Parameters	NLLS Estimates	NLLS Standard Errors	NLIV Estimates	NLIV Standard Errors	Normalized Estimates: Parameters	NLLS	NLIV
α: Net Present Installation Cost (000)	-0.3605	(0.0789)	-0.3197	(0.1547)	α	-0.3605	-0.3197
$\tilde{\beta}_2$: Capacity [4,6) kW	1.9169	(0.6869)	0.7142	(1.7066)	β_1	-7.7988	-9.6627
$\tilde{\beta}_3$: Capacity [6,8) kW	3.0411	(0.9827)	0.5104	(3.4594)	β_2	-5.8819	-8.9485
$\tilde{\beta}_4$: Capacity [8,10) kW	3.7068	(1.1833)	-0.3596	(5.2832)	β_3	-4.7577	-9.1524
$\tilde{\beta}_5$: Capacity [10,20) kW	4.3102	(1.8622)	-1.4140	(7.2409)	β_4	-4.0920	-10.0223
$\tilde{\beta}_0$: Constant	-5.1171	(0.8014)	-1.8267	(1.7682)	β_5	-3.4886	-11.0767
δ: Discount Factor	0.3439	(0.1058)	0.8110	(0.1936)	δ	0.3439	0.8110
Objective Value	8.6503		0.0000				
R^2	0.3089		0.2201				
Markets	5		5				
Years	10		10				
Observations	250		250				

Table 10. Reduction of Market Size to 10% (return)

Parameters	NLIV		Normalized Estimates	
	Estimates	Standard Errors	Parameters	NLIV
α: Net Present Installation Cost (000)	-0.3211	(0.1563)	α	-0.3211
$\tilde{\beta}_2$: Capacity [4,6) kW	0.7231	(1.7129)	β_1	-7.3129
$\tilde{\beta}_3$: Capacity [6,8) kW	0.5325	(3.4778)	β_2	-6.5898
$\tilde{\beta}_4$: Capacity [8,10) kW	-0.3229	(5.3143)	β_3	-6.7804
$\tilde{\beta}_5$: Capacity [10,20) kW	-1.3631	(7.2836)	β_4	-7.6358
$\tilde{\beta}_0$: Constant	-1.3920	(1.3455)	β_5	-8.6760
δ: Discount Factor	0.8097	(0.1955)	δ	0.8097
Objective Function	0.0000			
R^2	0.2251			
Markets	5			
Years	10			
Observations	250			

Table 11. Include Moment Conditions for All Terminal Adoption Decisions (return)

Parameters	NLIV Estimates	NLIV Standard Errors	Normalized Estimates Parameters	Normalized Estimates NLIV
α: Net Present Installation Cost (000)	-0.3244	(0.0308)	α	-0.3244
$\tilde{\beta}_2$: Capacity [4,6) kW	1.3430	(0.3417)	β_1	-12.1782
$\tilde{\beta}_3$: Capacity [6,8) kW	1.7792	(0.4534)	β_2	-10.8352
$\tilde{\beta}_4$: Capacity [8,10) kW	1.6650	(0.6120)	β_3	-10.3990
$\tilde{\beta}_5$: Capacity [10,20) kW	1.4451	(0.7816)	β_4	-10.5132
$\tilde{\beta}_0$: Constant	-3.9447	(0.4706)	β_5	-10.7331
δ: Discount Factor	0.6761	(0.0405)	δ	0.6761
Objective Function	1,103.2291			
R^2	0.2636			
Markets	5			
Years	10			
Moments	1,250			

Table 12. Heterogenous Demand Estimates (return)

Parameters	GMM, $\delta = 0.8$ Estimates	GMM, $\delta = 0.8$ Standard Errors	Normalized Estimates Parameters	Normalized Estimates Estimates
Mean Utility				
α: Net Present Installation Cost (000)	-0.1869	(0.0358)	α	-0.1869
$\tilde{\beta}_2$: Capacity [4,6) kW	1.6120	(1.8424)	β_1	-12.7386
$\tilde{\beta}_3$: Capacity [6,8) kW	2.0826	(2.3178)	β_2	-11.1266
$\tilde{\beta}_4$: Capacity [8,10) kW	2.4467	(2.7352)	β_3	-10.6560
$\tilde{\beta}_5$: Capacity [10,20) kW	2.7018	(2.8833)	β_4	-10.2920
$\tilde{\beta}_0$: Constant	-2.5477	(2.7749)	β_5	-10.0368
Income × Capacity				
$\tilde{\lambda}_1^I$	0.0012	(0.0027)	λ_1^I	0.0059
$\tilde{\lambda}_2^I$	0.0015	(0.0019)	λ_2^I	0.0062
$\tilde{\lambda}_3^I$	0.0008	(0.0018)	λ_3^I	0.0056
$\tilde{\lambda}_4^I$	0.0013	(0.0016)	λ_4^I	0.0060
$\tilde{\lambda}_5^I$	0.0028	(0.0014)	λ_5^I	0.0075
Population Density × Capacity				
$\tilde{\lambda}_1^P$	-0.0196	(0.0380)	λ_1^P	-0.0981
$\tilde{\lambda}_2^P$	-0.0333	(0.0318)	λ_2^P	-0.1117
$\tilde{\lambda}_3^P$	-0.0911	(0.0308)	λ_3^P	-0.1696
$\tilde{\lambda}_4^P$	-0.1795	(0.0298)	λ_4^P	-0.2579
$\tilde{\lambda}_5^P$	-0.2757	(0.0295)	λ_5^P	-0.3542
Democratic Vote Share × Capacity				
$\tilde{\lambda}_1^V$	0.0112	(0.0420)	λ_1^V	0.0561
$\tilde{\lambda}_2^V$	-0.0048	(0.0318)	λ_2^V	0.0401
$\tilde{\lambda}_3^V$	-0.0138	(0.0284)	λ_3^V	0.0311
$\tilde{\lambda}_4^V$	-0.0221	(0.0259)	λ_4^V	0.0228
$\tilde{\lambda}_5^V$	-0.0236	(0.0255)	λ_5^V	0.0213
Objective Value	0.0000			
R^2	0.5196			
Municipalities	349			
Years	10			
Macro Moments	50			
Micro Moments	17,450			

Table 13. Cumulative Adoptions by System Size (return)

	System Capacity (kW)					
Homogenous Demand	[0,4)	[4,6)	[6,8)	[8,10)	[10,20)	Total
Actual	3,077	6,921	6,494	4,834	4,581	25,907
Predicted	3,294	9,423	8,559	5,162	2,365	28,803
CF (1): SREC	2,665	2,686	713	145	15	6,225
CF (2): Upfront Subsidies	1,913	2,118	1,266	404	72	5,773
CF (3): Net Metering 10%	2,823	4,398	2,025	582	93	9,920
CF (3): Net Metering 25%	2,897	4,991	2,568	833	157	11,446
CF (3): Net Metering 50%	3,024	6,165	3,826	1,522	383	14,920
CF (3): Net Metering 75%	3,157	7,621	5,716	2,796	945	20,235
CF (3): Net Metering 90%	3,238	8,656	7,281	4,038	1,637	24,849
	System Capacity (kW)					
Heterogenous Demand	[0,4)	[4,6)	[6,8)	[8,10)	[10,20)	Total
Actual	3,077	6,921	6,494	4,834	4,581	25,907
Predicted	3,111	5,863	4,374	3,549	3,722	20,619
CF (1): SREC	2,683	2,926	1,093	467	214	7,383
CF (2): Upfront Subsidies	2,150	2,303	1,319	750	444	6,967
CF (3): Net Metering 10%	2,855	3,912	2,072	1,148	720	10,707
CF (3): Net Metering 25%	2,897	4,185	2,346	1,385	945	11,757
CF (3): Net Metering 50%	2,967	4,682	2,886	1,895	1,490	13,920
CF (3): Net Metering 75%	3,038	5,240	3,553	2,593	2,353	16,776
CF (3): Net Metering 90%	3,082	5,605	4,025	3,130	3,097	18,939

Table 14. Annual Consumer Surplus from Incentive Programs (return)

Homogenous Demand		SREC Programs		Upfront Subsidies		Net Metering (50%)	
Year	Market Size	Average ΔCS	Total ΔCS (000,000)	Average ΔCS	Total ΔCS (000,000)	Average ΔCS	Total ΔCS (000,000)
2008	2,383,484	0	0	12,155	28,970	1,097	2,614
2009	2,383,186	5,542	13,208	8,780	20,925	1,239	2,952
2010	2,382,601	5,297	12,621	6,977	16,623	1,272	3,030
2011	2,382,202	5,081	12,104	5,787	13,786	1,315	3,131
2012	2,381,422	5,315	12,658	5,133	12,225	1,494	3,559
2013	2,380,426	4,578	10,898	5,454	12,983	1,668	3,970
2014	2,378,610	4,593	10,925	5,071	12,062	1,787	4,251
2015	2,375,246	4,423	10,506	4,076	9,681	1,845	4,382
2016	2,369,684	4,218	9,995	3,925	9,301	1,898	4,497
2017	2,363,045	4,019	9,497	3,924	9,273	1,975	4,668
Heterogenous Demand		SREC Programs		Upfront Subsidies		Net Metering (50%)	
Year	Market Size	Average ΔCS	Total ΔCS (000,000)	Average ΔCS	Total ΔCS (000,000)	Average ΔCS	Total ΔCS (000,000)
2008	2,882,236	0	0	13,123	37,823	996	2,870
2009	2,881,651	5,157	14,861	9,313	26,837	1,102	3,177
2010	2,881,252	5,001	14,409	7,435	21,422	1,144	3,297
2011	2,880,472	4,779	13,765	6,134	17,668	1,169	3,367
2012	2,879,476	4,996	14,386	5,327	15,339	1,322	3,805
2013	2,877,660	4,392	12,640	5,523	15,894	1,489	4,285
2014	2,874,296	4,295	12,346	4,891	14,058	1,558	4,478
2015	2,868,734	4,159	11,930	4,232	12,141	1,595	4,577
2016	2,862,095	3,992	11,425	4,042	11,567	1,650	4,724
2017	2,856,627	3,804	10,866	3,978	11,363	1,702	4,863

Table 15. Generation (MWh) by System Size (2008-2017) (return)

	System Capacity (kW)					
	[0,4)	[4,6)	[6,8)	[8,10)	[10,20)	Total
Actual	50,587	148,762	148,942	131,557	145,459	625,308
Predicted	58,211	259,550	289,394	217,539	119,555	944,249
CF (1): SREC	52,960	83,703	22,227	5,294	630	164,814
CF (2): Upfront Subsidies	30,111	47,534	38,512	15,330	3,226	134,712
CF (3): Net Metering 10%	50,293	124,997	72,300	26,279	5,337	279,205
CF (3): Net Metering 25%	51,531	141,134	90,960	37,233	8,862	329,721
CF (3): Net Metering 50%	53,669	172,860	133,566	66,787	20,855	447,736
CF (3): Net Metering 75%	55,899	211,798	196,467	120,305	49,667	634,135
CF (3): Net Metering 90%	57,277	239,277	247,827	171,574	84,034	799,989

Table 16. Value of Avoided CO_2 Emissions (2008-2017) (return)

Program	Value
CF (1): SREC	5,055,248
CF (2): Upfront Subsidies	5,250,482
CF (3): Net Metering 10%	4,313,331
CF (3): Net Metering 25%	3,985,699
CF (3): Net Metering 50%	3,220,277
CF (3): Net Metering 75%	2,011,330
CF (3): Net Metering 90%	935,635

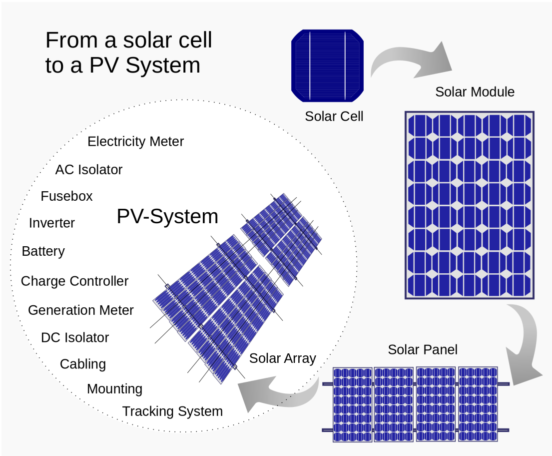
Table 17. Average Subsidies by System Capacity (return)

	System Capacity (kW)					
Means	[0,4)	[4,6)	[6,8)	[8,10)	[10,20)	Total
Av. Upfront Installation Cost	16,223	23,059	28,724	35,285	45,341	29,726
Av. Upfront Subsidies	7,874	9,725	10,036	11,812	14,670	10,823
Av. SREC Revenue	4,867	8,387	11,663	14,948	19,307	11,834
Av. Net Metering/Avoided Elec. Cost	3,963	6,429	9,221	11,991	16,053	9,531
Av. Total Subsidies	16,704	24,540	30,920	38,751	50,030	32,189
Totals						
Total Adoptions	3,077	6,921	6,494	4,834	4,581	25,907
Total Subsidies	51,398,447	169,842,768	200,797,131	187,324,520	229,188,608	838,551,474

B Figures

Figure 1. PV System Technology (return)

(a)



(b)

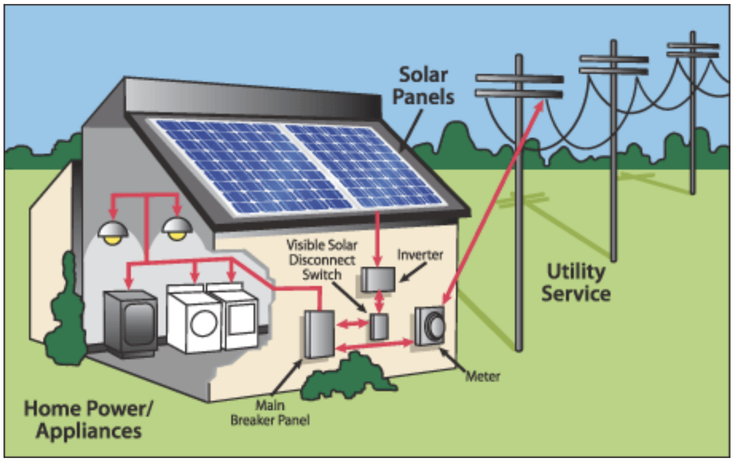
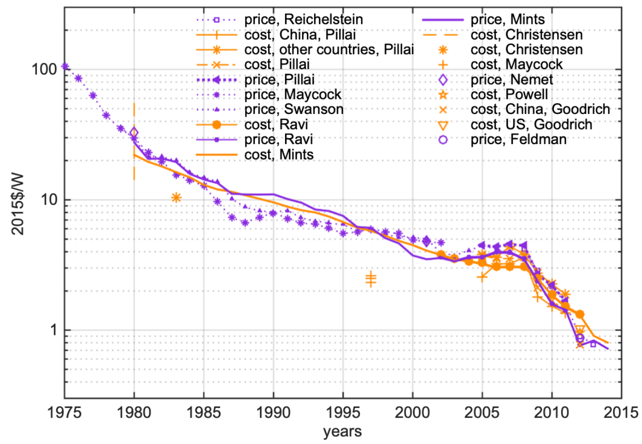
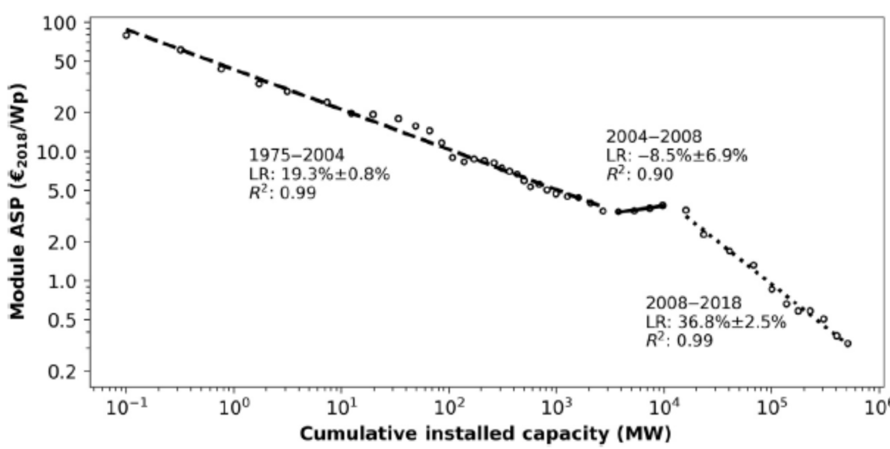


Figure 2. Declining Manufacturing Costs (return)

(a) Kavlak, McNerney, and Trancik (2018)



(b) Louwen and van Sark (2020)



(c) National Renewable Energy Laboratory

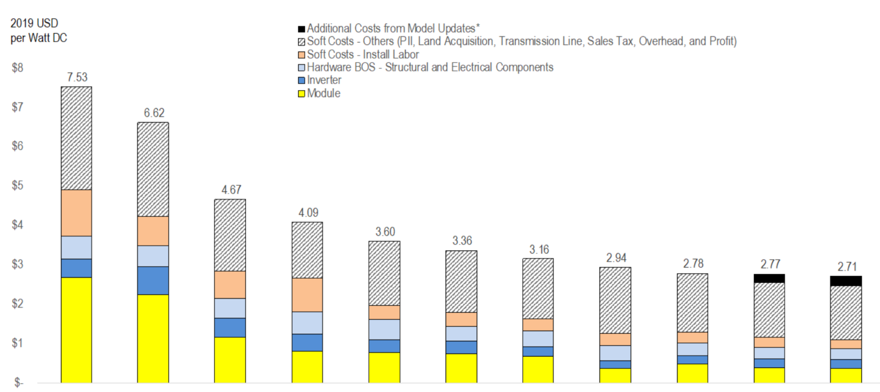


Figure 17. NREL residential PV system cost benchmark summary (inflation adjusted), 2010–2020

Figure 3. DPU Map of Utility Service Areas (return)

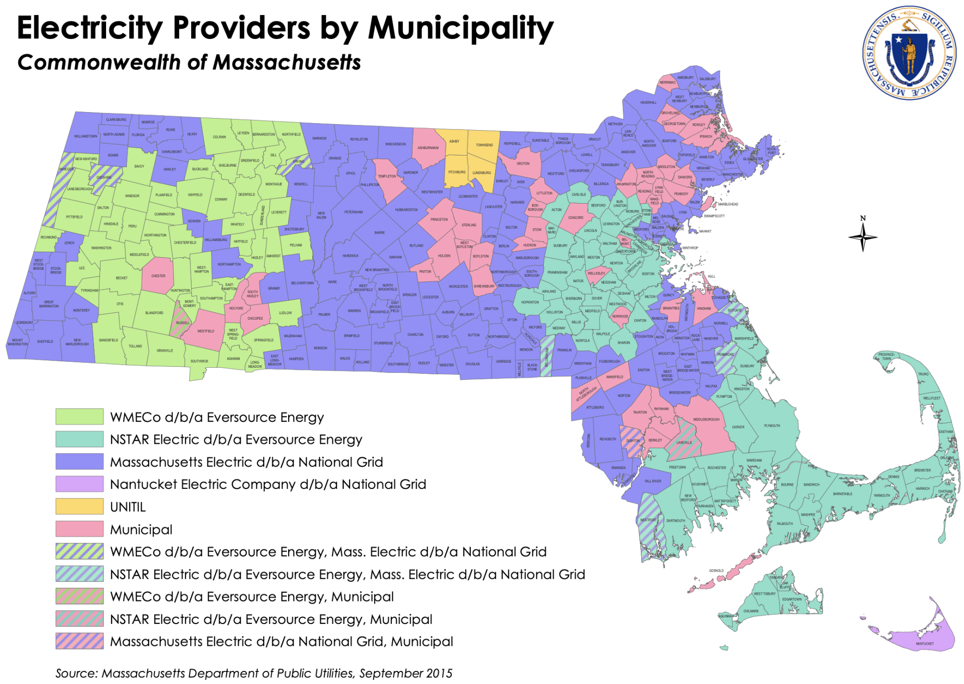


Figure 4. Market for SRECs (return)

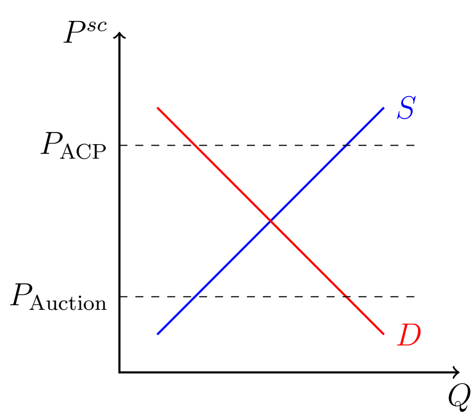


Figure 5. Residential Adoptions (return)

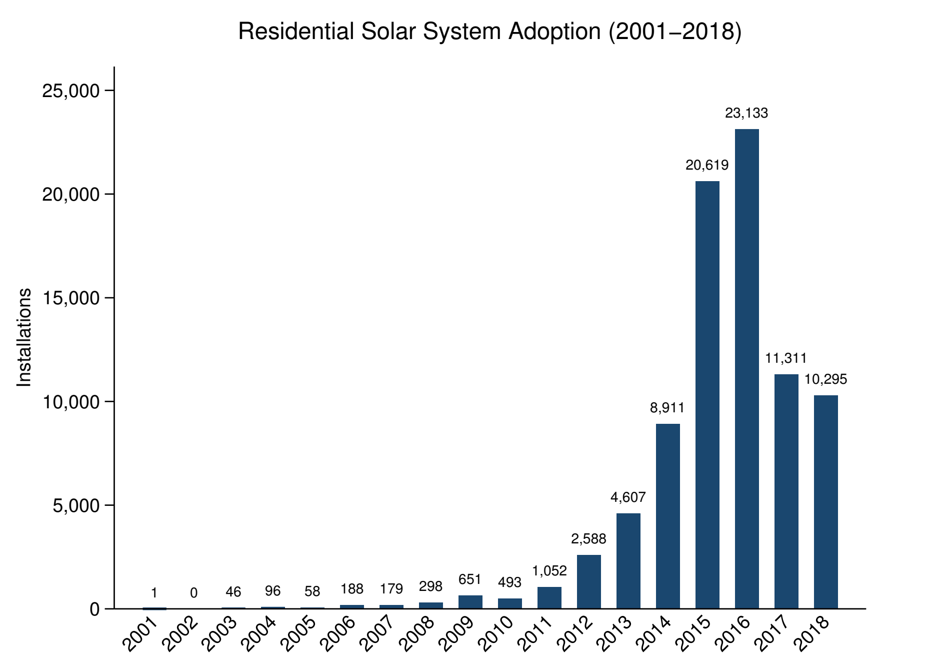
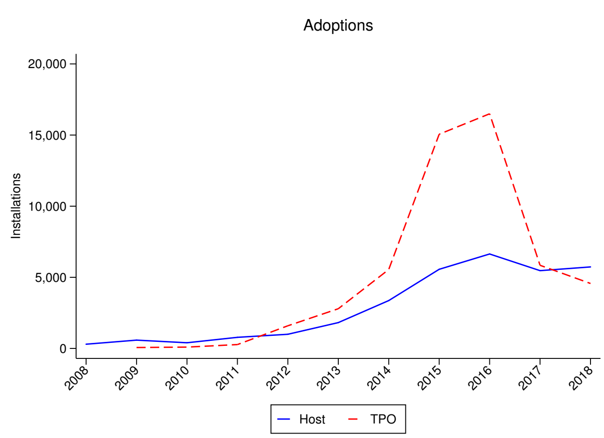


Figure 6. Host Owned vs. Third Party Owned Systems (return)

(a)



(b)

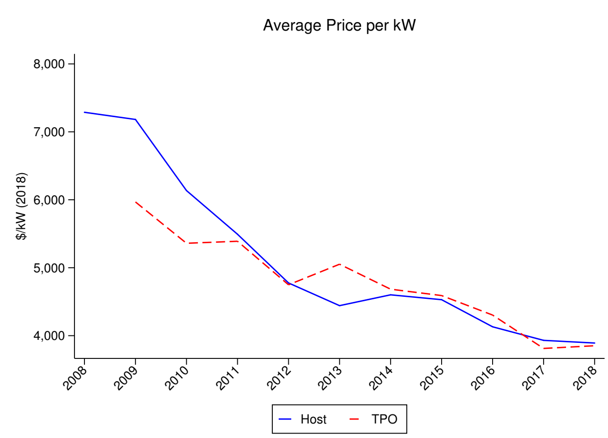
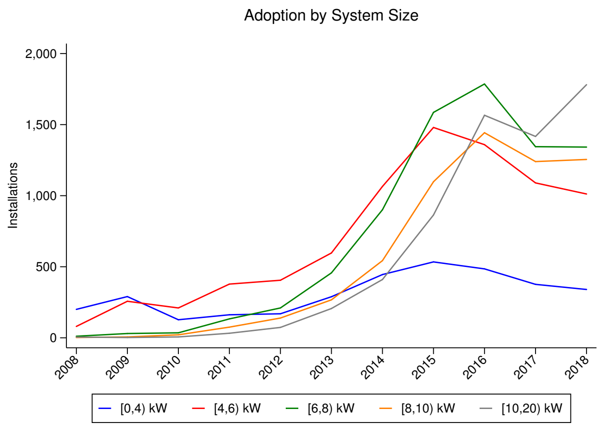
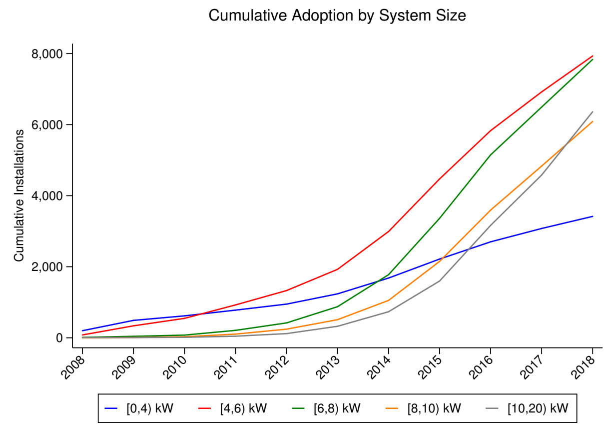


Figure 7. Adoptions, Cost, Capacity, and Production by Capacity (return)

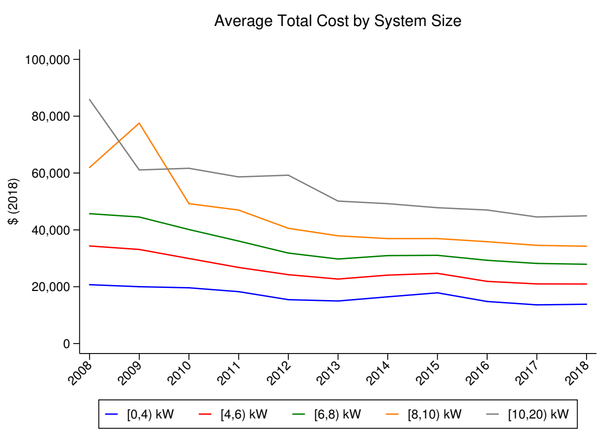
(a)



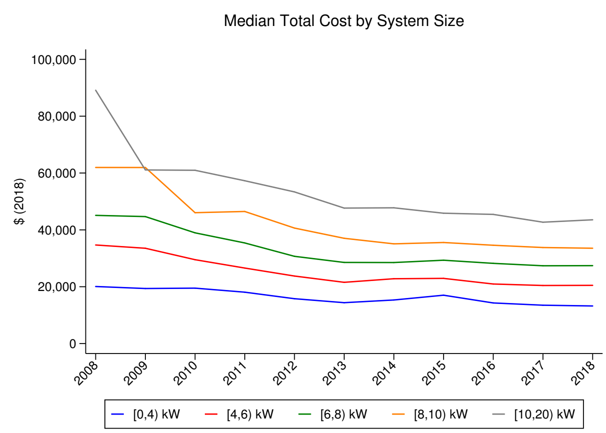
(b)



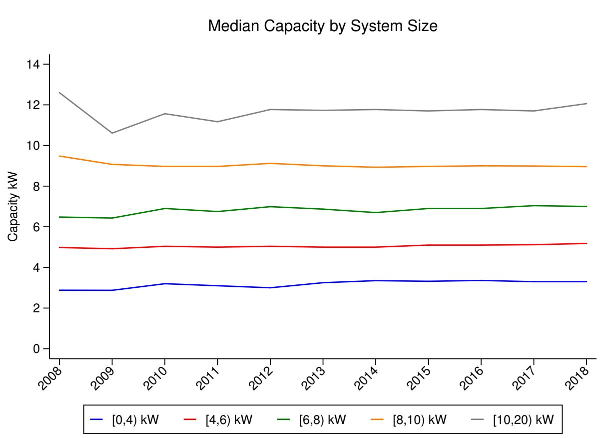
(c)



(d)



(e)



(f)

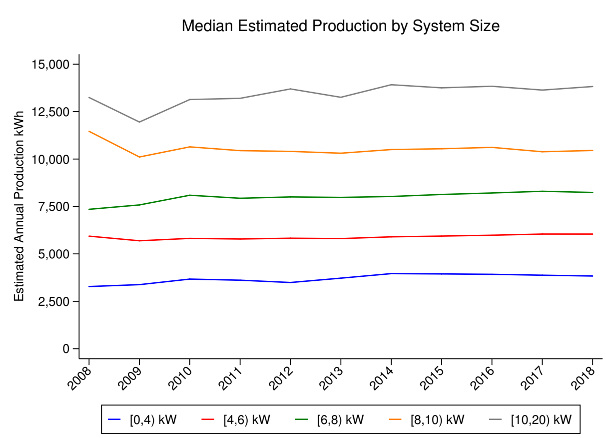
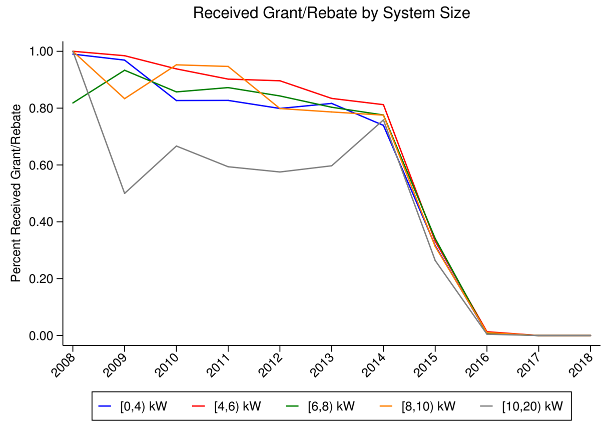


Figure 8. Rebates by Capacity (return)

(a)



(b)

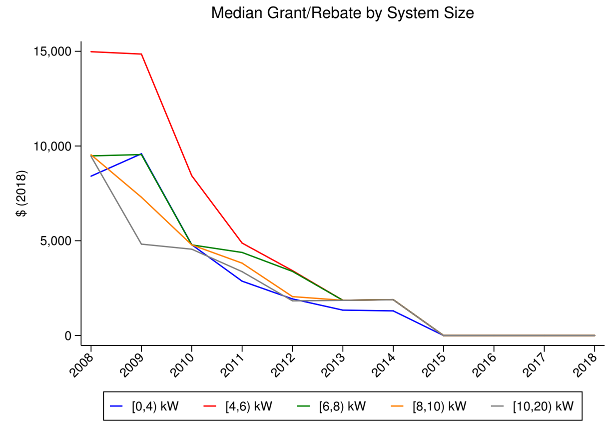
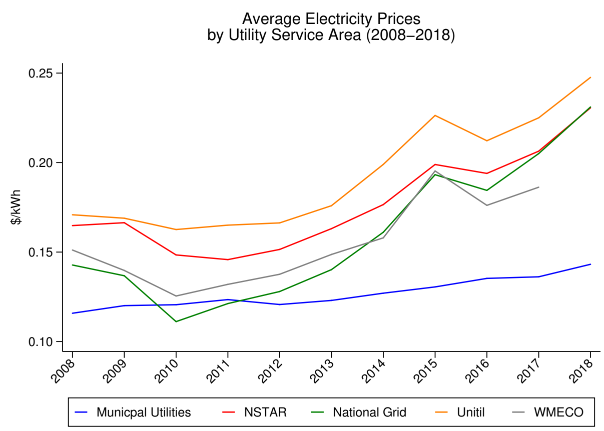


Figure 9. Actual and Forecasted Average Electricity Prices (return)

(a)



(b)

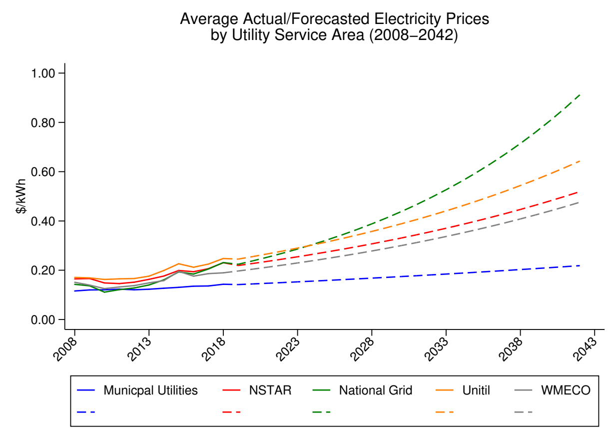
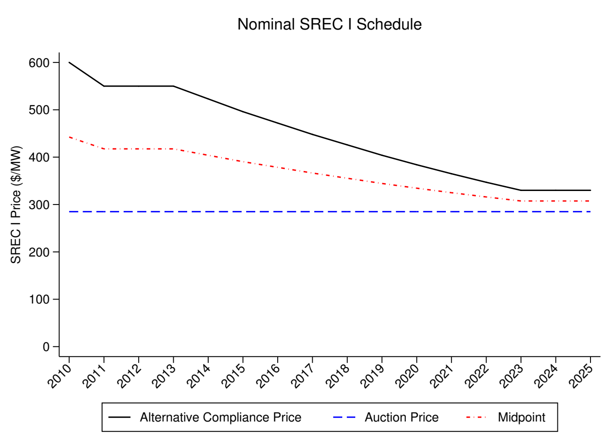


Figure 10. Nominal SREC Incentive Schedules (return)

(a)



(b)

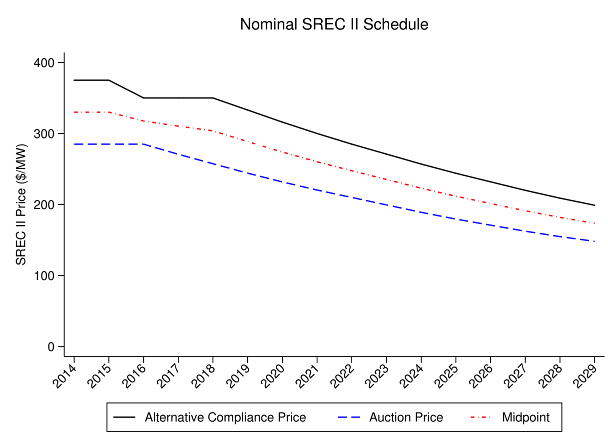


Figure 11. Real SREC Incentive Schedules (return)

(a) (b)

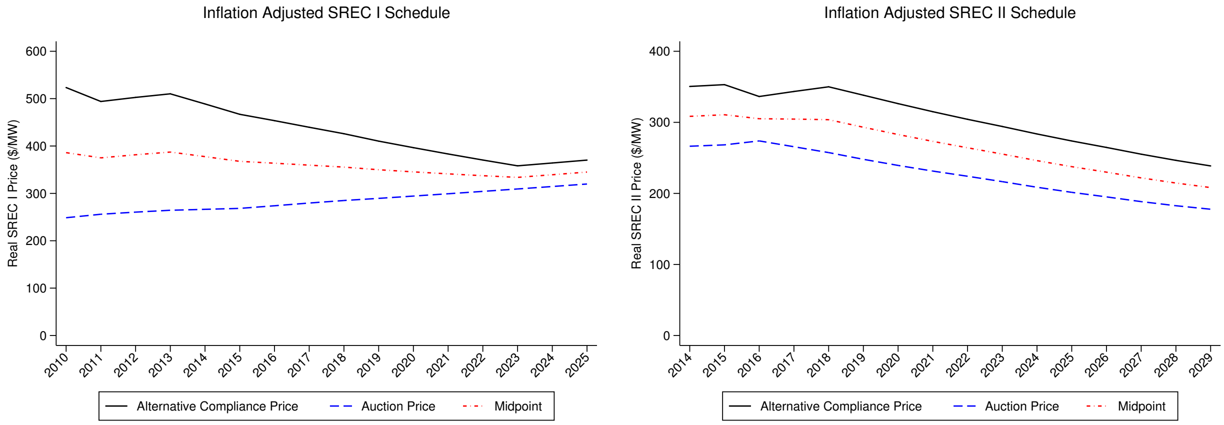


Figure 12. Adopter Revenue from Incentive Programs by Capacity (return)

(a) (b)

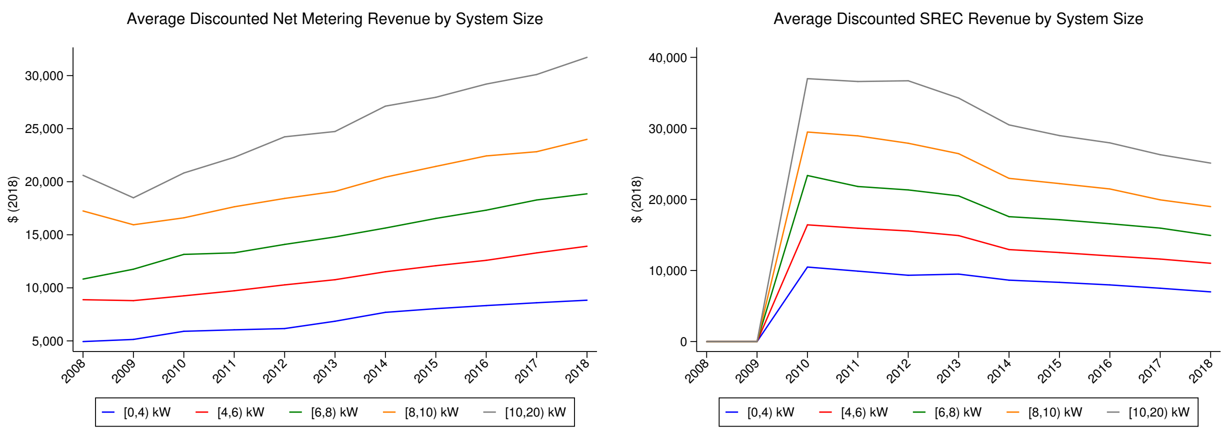


Figure 13. Installation Costs and Incentives (return)

(a) (b)

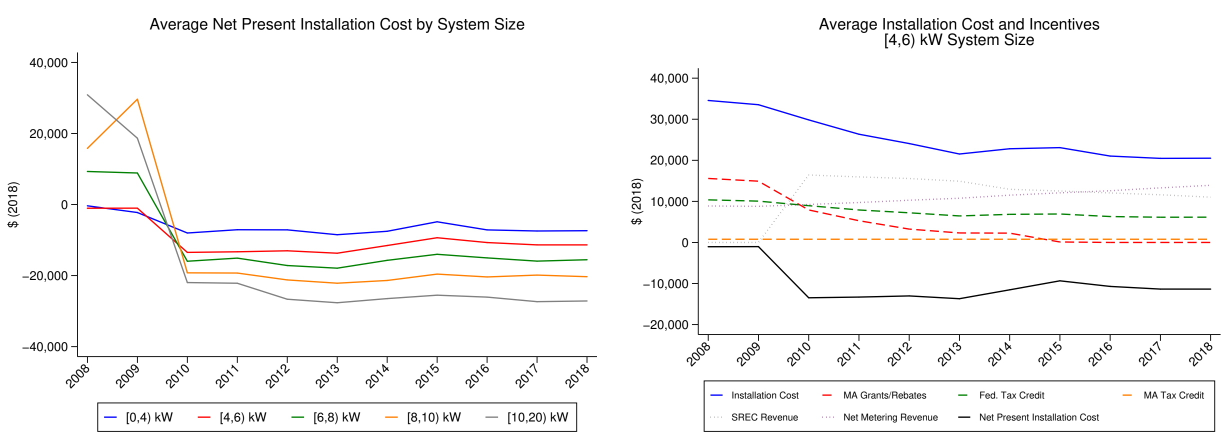


Figure 14. Homogenous Demand: Actual, Predicted, and Counterfactual Cumulative Adoption by Capacity (return)

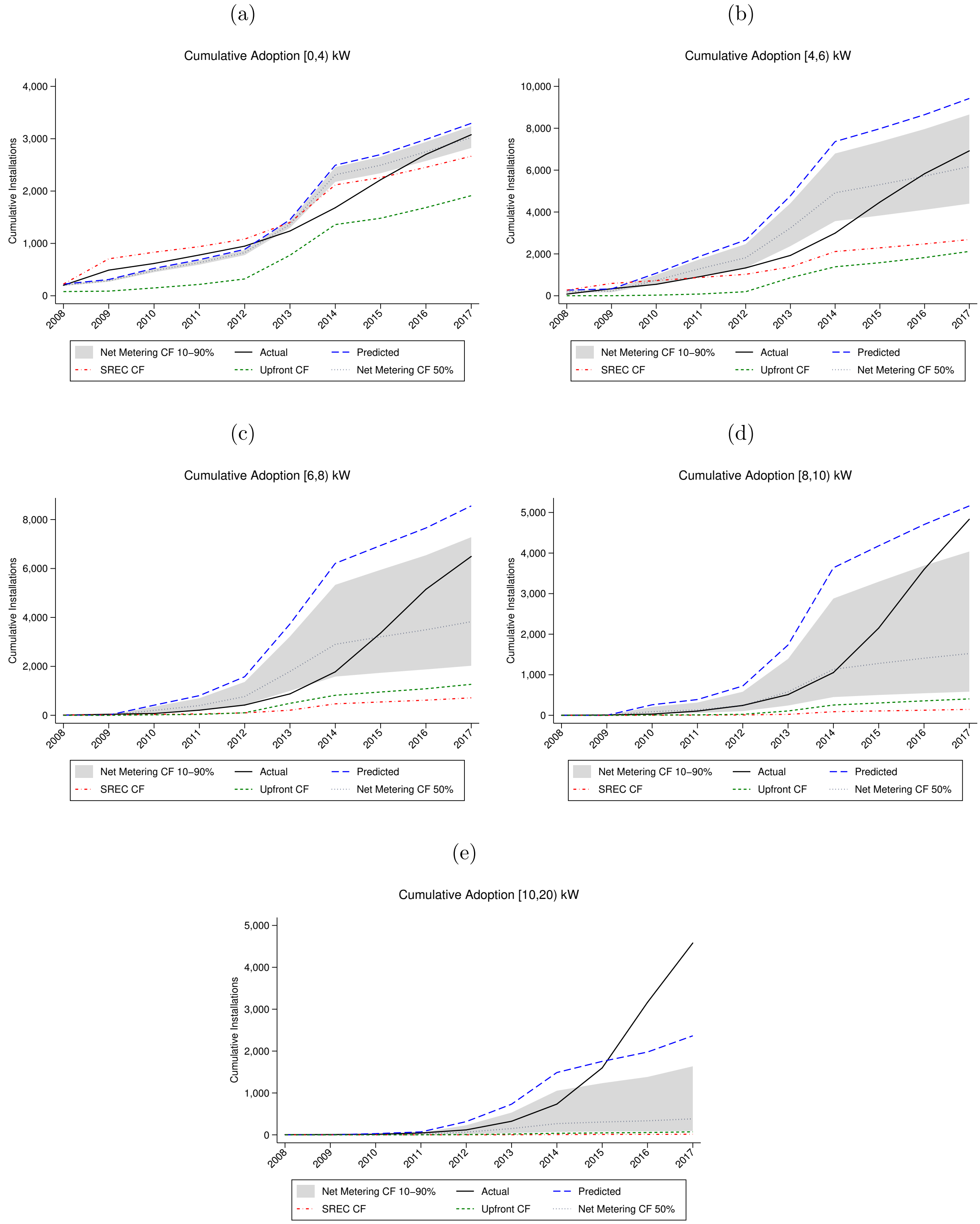
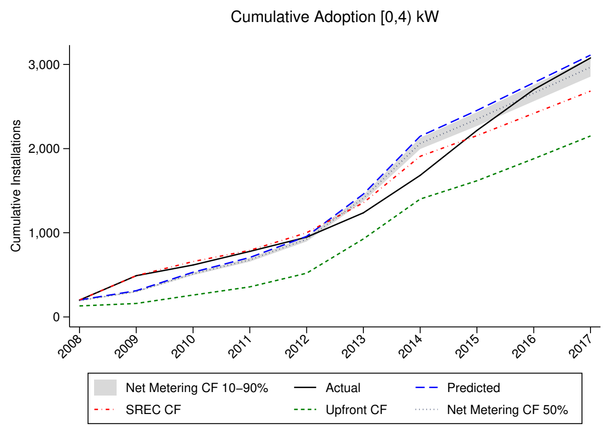
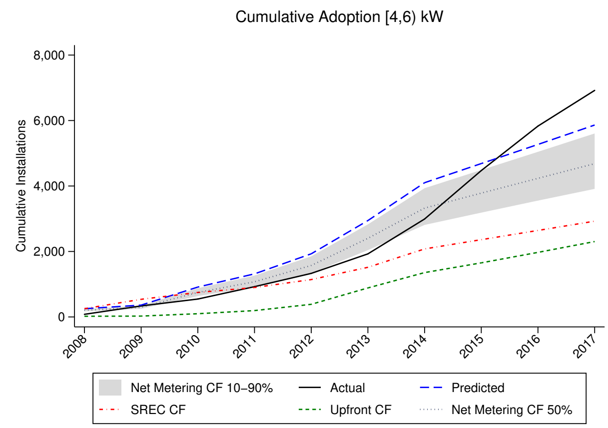


Figure 15. Heterogenous Demand: Actual, Predicted, and Counterfactual Cumulative Adoption by Capacity (return)

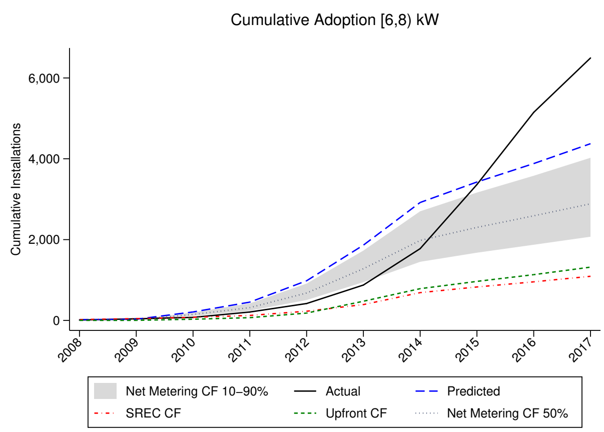
(a)



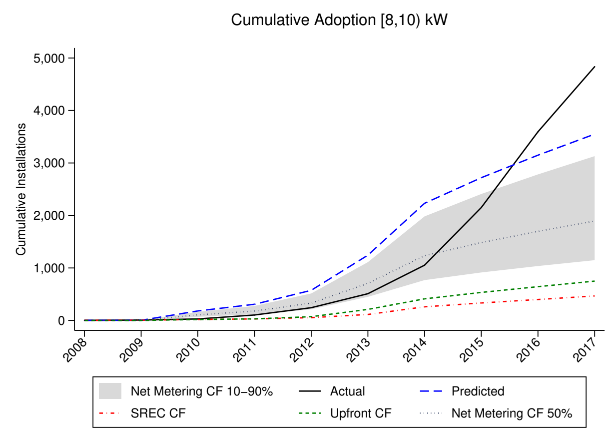
(b)



(c)



(d)



(e)

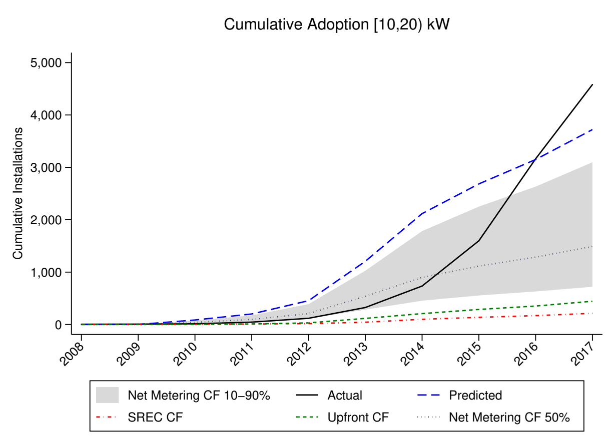
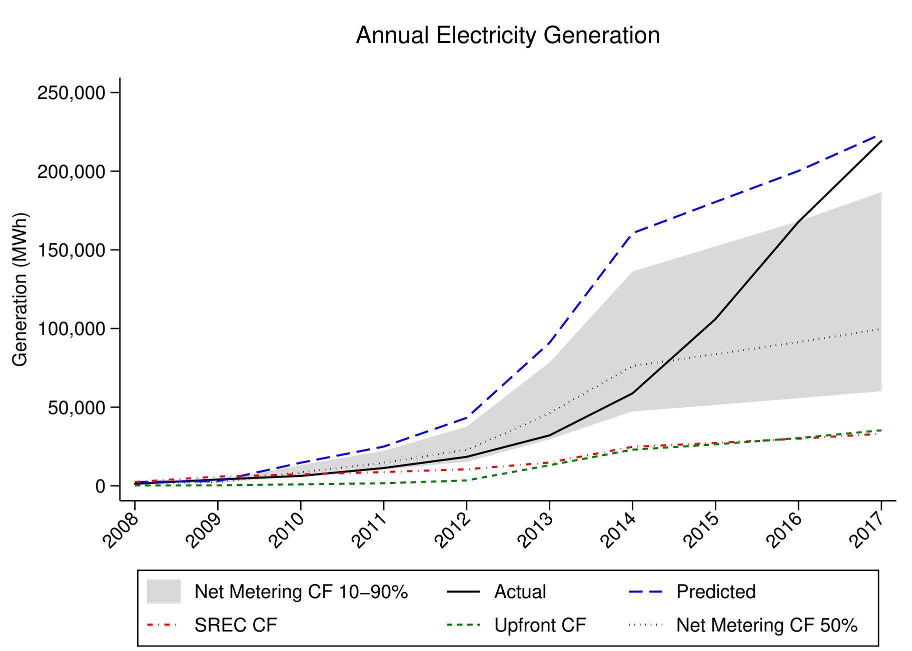


Figure 16. Actual, Predicted, and Counterfactual Annual Generation (return)



C NLLS Estimation

- Estimating Equation

$$\log\left(\frac{s_{jt}}{s_{0t}}\right) = \big(\beta_j - \delta\beta_1\big) - \alpha\big(p_{jt} - \delta p_{1t+1}\big) + \delta \log\left(s_{1t+1}\right) + e_{jt}$$

- Objective Function

$$Q(\theta) = \frac{1}{N}(\mathbf{e}'\mathbf{e})$$

- Gradient

$$g(\theta) = \begin{bmatrix} 1 & d_2 & d_3 & d_4 & d_5 \end{bmatrix} \begin{bmatrix} \tilde{\beta}_0 \\ \tilde{\beta}_2 \\ \tilde{\beta}_3 \\ \tilde{\beta}_4 \\ \tilde{\beta}_5 \end{bmatrix} - \alpha\big(p_{jt} - \delta p_{1t+1}\big) + \delta \log\left(s_{1t+1}\right)$$

$$\frac{\partial g(\theta)}{\partial \tilde{\beta}_0} = 1, \frac{\partial g(\theta)}{\partial \tilde{\beta}_j} = d_j, \frac{\partial g(\theta)}{\partial \alpha} = -\big(p_{jt} - \delta p_{1t+1}\big)$$

$$\frac{\partial g(\theta)}{\partial \delta} = -\alpha\Big(\frac{\partial p_{jt}}{\partial \delta} - p_{1t+1} - \delta\frac{\partial p_{1t+1}}{\partial \delta}\Big) + \log\left(s_{1t+1}\right)$$

$$\left.\frac{\partial g(\theta)}{\partial \theta}\right|_{\hat{\theta}} = \left[1, d_2, d_3, d_4, d_5, -\big(p_{jt} - \hat{\delta} p_{1t+1}\big), -\hat{\alpha}\Big(\left.\frac{\partial p_{jt}}{\partial \delta}\right|_{\hat{\delta}} - p_{1t+1} - \hat{\delta}\left.\frac{\partial p_{1t+1}}{\partial \delta}\right|_{\hat{\delta}}\Big) + \log\left(s_{1t+1}\right)\right]$$

$$\frac{\partial p_{jt}}{\partial \delta} = -g_{jt}\begin{bmatrix} p^e_{jt} & p^e_{jt+1} & p^e_{jt+2} & ... & p^e_{jt+24}\end{bmatrix}\begin{bmatrix} 0 \\ (1-d) \\ 2\delta(1-d)^2 \\ \vdots \\ 24\delta^{23}(1-d)^{24}\end{bmatrix} - g_{jt}\begin{bmatrix} p^{sc}_{jt} & p^{sc}_{jt+1} & p^{sc}_{jt+2} & ... & p^{sc}_{jt+24}\end{bmatrix}\begin{bmatrix} 0 \\ (1- \\ 2\delta(1- \\ \vdots \\ 24\delta^{23}(1 \end{bmatrix}$$

- White's Estimator of Asymptotic Variance

$$\hat{\mathbf{V}}(\hat{\theta}_{\mathbf{NLLS}}) = \Big(\frac{N}{N-K}\Big)(\hat{\mathbf{G}}'\hat{\mathbf{G}})^{-\mathbf{1}}\hat{\mathbf{G}}'\hat{\mathbf{\Omega}}\hat{\mathbf{G}}(\hat{\mathbf{G}}'\hat{\mathbf{G}})^{-\mathbf{1}}$$

$$\hat{\mathbf{G}} = -\left.\frac{\partial g(\theta)}{\partial \theta}\right|_{\hat{\theta}}$$

$$\hat{\mathbf{\Omega}} = Diag(\hat{e}_i^2)$$

D GMM Estimation

- Objective Function

$$\mathbf{Q}(\theta) = (\mathbf{e}'\mathbf{Z})\mathbf{W}(\mathbf{Z}'\mathbf{e})$$

- White's Estimator of Asymptotic Variance

$$\hat{\mathbf{V}}(\hat{\theta}_{\mathbf{GMM}}) = \left(\frac{N}{N-K}\right)[\hat{\mathbf{G}}'\mathbf{Z}\mathbf{W}\mathbf{Z}'\hat{\mathbf{G}}]^{-\mathbf{1}}[\hat{\mathbf{G}}'\mathbf{Z}\mathbf{W}\hat{\mathbf{S}}\mathbf{W}\mathbf{Z}'\hat{\mathbf{G}}][\hat{\mathbf{G}}'\mathbf{Z}\mathbf{W}\mathbf{Z}'\hat{\mathbf{G}}]^{-\mathbf{1}}$$

$$\hat{\mathbf{G}} = -\left.\frac{\partial g(\theta)}{\partial \theta}\right|_{\hat{\theta}}$$

$$\hat{\mathbf{S}} = \sum_i \hat{e}_i z_i z_i'$$

E Peer Effects

T.B.W.

Suppose households' utility depends upon the adoption behavior of other households i.e. there are peer effects. One proxy variable for the behavior of other households is the share of total adoption in the previous period,

$$S^a_{t-1} = \sum_{j=1}^{J} s_{jt-1}$$

Now households' flow utility from adopting system j at time t is,

$$u_{ijt} = \beta_j - \alpha p_{jt} + \gamma S^a_{t-1} + \xi_{jt} + \epsilon_{jt} = \bar{u}_{jt} + \epsilon_{ijt}$$

where γ measures the degree to which peer effects influence demand. The estimating equation becomes,

$$\log\left(\frac{s_{jt}}{s_{0t}}\right) = \bar{u}_{jt} - \bar{v}_{0t} = \big(\beta_j - \alpha p_{jt} + \gamma S^a_{t-1} + \xi_{jt} + \epsilon_{jt}\big) - \delta\big(\beta_1 - \alpha p_{1t+1} + \gamma S^a_t + \xi_{1t+1} - \log(s_{1t+1}) - \eta_{jt}\big)$$

$$\log\left(\frac{s_{jt}}{s_{0t}}\right) = \big(\beta_j - \delta\beta_1\big) - \alpha\big(p_{jt} - \delta p_{1t+1}\big) + \gamma\big(S^a_{t-1} - \delta S^a_t\big) + \delta \log(s_{1t+1}) + e_{jt}$$

Table. Linear Demand Equation Estimates

Specifications	OLS, $\delta = 0$		IV, $\delta = 0$		OLS, $\delta = 0.9$		IV, $\delta = 0.9$	
α: Net Present Installation Cost (000)	-0.286	(0.078)	-0.634	(0.139)	-0.186	(0.036)	-0.220	(0.041)
γ: S^a_{t-1}	5.205	(0.623)	4.069	(0.547)	-9.898	(2.775)	-8.245	(2.672)
β_2: Capacity [4,6) kW	2.113	(0.721)	3.596	(0.884)	0.195	(0.785)	0.063	(0.804)
β_3: Capacity [6,8) kW	3.195	(1.145)	7.268	(1.669)	-0.958	(0.863)	-1.111	(0.871)
β_4: Capacity [8,10) kW	3.875	(1.412)	10.703	(2.434)	-2.841	(1.027)	-3.049	(1.053)
β_5: Capacity [10,20) kW	4.602	(2.218)	14.023	(3.667)	-4.822	(1.014)	-5.139	(1.074)
β_0: Constant	-8.807	(0.793)	-5.707	(1.251)	-1.836	(0.681)	-1.699	(0.682)
R^2	0.317		0.189		0.323		0.317	
Markets	5		5		5		5	
Years	10		10		10		10	
N	250		250		250		250	