Are Solar Incentive Programs Effective at Reducing CO_2 Emissions? Evidence from Massachusetts *

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Abstract

How effective are demand-side incentive programs at reducing CO_2 emissions? 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 and abatement 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.

JEL Codes: L9, Q4
Keywords: solar panels, technological adoption, dynamic discrete choice, demand estimation, social cost of carbon, environmental and energy policy

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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.[1]

Further investment in renewables and other clean energies aimed at reducing CO_2 emissions is poised to continue with the recent passage of the 2021 Investment Infrastructure and Jobs Act (IIJA), which includes significant funding for new energy infrastructure.[2] Among the energy projects described in bill are upgrades to the power grid in order to integrate renewable energies, R&D funding for clean hydrogen, advanced nuclear reactors, and carbon capture technologies, investment in a national network of electric vehicle charging stations, and energy efficiency improvements for public facilities. Given the vast array of potential investments and uncertainty about their relative effectiveness at abating future CO_2 emissions, understanding where the marginal dollar might be spent most effectively is crucial for policymakers, and given the attention renewables in particular have received, an important policy question is to what extent should solar subsidies play a role in future energy policy?

In this paper, I examine the effects of demand-side incentive programs on households' decisions to adopt solar panels and on the abatement of CO_2 emissions. Specifically, I analyze the effects of three types of incentives introduced in Massachusetts, (1) upfront subsidies (federal and state tax credits and grants), (2) solar renewable energy certificates (SRECs), and (3) net metering, using a structural model of PV solar adoption. Then, I conduct a cost-benefit analysis of these programs to determine whether the social value of avoided emissions attributable to the programs outweighs their costs. Because the incentive programs I analyze vary in design, households receive some benefits upfront at the time of adoption, while other benefits accumulate over the lifespan of a PV system. A key feature of my analysis is that I model households' decisions to adopt PV as dynamic—that is households choose between adopting PV today or

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

[2]Of the $550 billion laid out in the bill $79 billion has been allocated for power and grid projects and $15 billion for electric vehicles and buses, https://www.congress.gov/bill/117th-congress/house-bill/3684/text

delaying adoption until a future date. The dynamic aspect of the model enables me to quantify the impact that households' discounting of future benefits has on adoption and the abatement of CO_2 emissions. Additionally, and crucially in this setting, rather than assuming households' discount factor, I am able to identify and estimate their discount factor directly from my data using variation in the difference between upfront installation prices and long-term incentives, which is generally not possible in other empirical studies (Magnac and Thesmar 2002, De Groote and Verboven 2019). My results are informative for environmental policy and more generally for public policy regarding investments in new technologies—particularly related to the design of subsidy programs.

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 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,[3] net metering by electric utilities,[4] and the introduction of renewable energy certificate (REC) markets,[5] a form of production-based subsidies. Massachusetts implemented its own version of each of these policies, which makes it a rich setting in which to study the effects of these programs. With household-level data on adoptions from the Massachusetts Clean Energy Center (MassCEC) spanning from 2008 to 2018 and additional information about the timing and implementation of Massachusetts' solar incentive programs, I estimate aggregate residential demand for PV systems using a dynamic discrete choice model (Rust 1987, Gowrisankaran and Rysman 2012). This model allows me to disentangle the effect of each program on overall demand and thus quantify its contribution to cumulative adoption and emission abatement by simulating counterfactual scenarios.

Given that solar incentives in Massachusetts were quite substantial during my sample period, on average about \$22,000 per residential installation,[6] unsurprisingly I find that each program had a substantial impact on residential adoption. I find that upfront subsidies by increased adoption by 5-fold and solar RECs 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. These findings are robust to a number of modeling specifications including allowing for heterogenous preferences correlated with observable household

[3] Usually capacity-based subsidies i.e. incentives increasing in the capacity of an energy generator.

[4] Mechanisms by which renewable owners are compensated by their local utilities for clean energy generation.

[5] Tradeable certificates supported by electric utility renewable portfolio standards; quotas for utilities' energy supply).

[6] Approximately \$103,000 per household accounting for total subsidies distributed over the lifespan of a PV system.

demographics.

Beyond quantifying 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 (SCC) from the climate literature (Cai and Lontzek 2019), I approximate the social value of avoided CO_2 emissions attributable 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. Put another way, in order for the government to breakeven on its investment in upfront subsidies, the social cost of carbon would have to be over \$1,269 per (metric) ton of CO_2 or almost 25 times larger than the current federal estimate of \$51 per ton of CO_2.[7]

This paper contributes to the energy and environmental policy literature on subsidies for renewables and is related to several other strands of the economic literature including the adoption of durable goods and diffusion of new technologies in industrial organization, the application of dynamic discrete choice models in econometrics, and time discounting in behavioral economics.

De Groote and Verboven (2019) is the closest paper to my work. Like me they estimate a dynamic model of PV adoption in which households' discount factor is identified by changes in future benefits relative to current prices. Consistent with my results they find that households discount the future benefits of adopting PV significantly, and as a result, find that upfront incentive programs are more effective than long-term incentive programs dollar-for-dollar due to this discounting. However, most distinctly from their paper, I use my estimates to quantify the effects of different incentive programs on adoption and abatement. Additionally, I find that households are even more myopic in my setting, which may be explained by institutional differences in Massachusetts and Belgium's renewable energy policies, as well as by differences in cultural attitudes towards renewables. In particular, SREC prices were determined by a market mechanism in Massachusetts but determined top-down by the government in Belgium, which may explain the difference in households' perception of investment risk across these settings.

Also, my identification strategy is different from their's. I use both cross-sectional variation across geographic markets and time series variation in the difference between upfront installation prices and future benefits to identify households' discount factor, while De Groote and Verboven (2019) rely on time series variation. And because

[7]See "Technical Support Document: Social Cost of Carbon, Methane, and Nitrous Oxide Interim Estimates under Executive Order 13990," Interagency Working Group on Social Cost of Greenhouse Gases, United States Government, February 2021. In my analysis, I use Cai and Lontzek's (2019) mean estimate for the SCC in 2020 of \$87 per ton of carbon or \$23.73 per ton of CO_2.

Massachusetts is segmented into distinct electric utility markets, the cross-sectional nature of my data allows me to use an alternative instrumental variable strategy to deal with price endogeneity (Kalouptsidi, Scott, and Souza-Rodrigues 2021). I use Hausman-Nevo instruments (Hausman 1996, Nevo 2000) to correct for price endogeneity, while they use input prices as cost shifters.

Other papers in the environmental literature have used dynamic adoption models to analyze the effect of subsidies on adoption and the abatement of CO_2 emissions. For example, Burr (2014) and Langer and Lemoine (2018) use similar models to study the effects of government subsidies on PV adoption in California. 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 households' behavior, including time discounting, 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. However, both studies take households' discount factor as given, which is a key parameter in measuring the efficacy of subsidies for new technologies. I bring empirical estimation of the discount factor to bear on the analysis of the effects of subsidies on emission abatement.

Gillingham and Tsvetanov (2019) also analyze solar incentives using data from Connecticut but treat households decisions to adopt PV as static. They find a much lower implied cost of abatement for Connecticut than I find for Massachusetts.

As previously described, many states across the US have implemented solar incentive programs, however, each state has slightly different policies, which provides a unique opportunity for researchers 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 certificate prices tended to collapse, and also stands in contrast to the SREC program that De Groote and Verboven (2019) study. 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 adoption. To my knowledge, mine is the first empirical study of the effects of Massachusetts' solar incentives on PV adoption and the first to analyze such a market mechanism.

Yet more papers have studied other aspects of the solar panel market that impact residential adoption. For, example Bollinger and Gillingham (2012), Bollinger, Gillingham, Kirkpatrick, and Sexton (2020) use data from California and Connecticut to study the impact of subsidies and peer effects on solar adoption. Their results suggest that peer influence can have a significant impact on solar panel adoption, which implies that government investment in solar may benefit from a multiplier effect.

Finally, other papers in the literature have analyzed challenges associated with the increased propagation of, and reliance upon, solar power. Using data from Arizona, Gowrisankaran, Reynolds, and Samano (2016) investigate the social costs of solar generation intermittency and find that these costs are substantial. 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 analyzing the distributional consequences of increasing electricity prices and net metering policies.

The primary contribution of this paper to the environmental and energy policy literature is the comparison of the effects three policy instruments commonly applied to incentivize the adoption of renewables, tax credits (and other upfront subsidies), RECs, and net metering, on adoption rates and the abatement CO_2 emissions. A secondary contribution is that I undertake a cost-benefit analysis of these programs using my estimates, and find that the social cost of carbon would have to be significantly larger in order to justify the programs' expenses. A third contribution is that I provide evidence on the value of market design in markets for new technologies—Massachusetts' distinct SREC market mechanism sets it apart from other SREC programs. Finally, this paper adds to a growing literature applying empirical methods developed in industrial organization to analyze environmental policies (see Kellogg and Reguant 2021 for an overview).

The rest of the paper is organized as follows. In Section 2, I outline the industry and background information on the residential solar energy policies established in Massachusetts. Section 3 discusses the economic model. Section 4 describes the data and other empirical inputs of the model. Section 5 discusses identification of the model. Section 6 discusses the estimation, empirical results, and robustness analyses. Sections 7 and 8 describe the implementation of different policy counterfactuals and discuss their results. Section 9 concludes.

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 increased 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 (see Figure 3 for this trend in Massachusetts). 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 4). Electricity prices are set subject to rate of return regulation and tend to be set higher in areas served by IOUs than those served by 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, estimating a dynamic model of supply would be a challenge in its own right; 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. While competition between manufacturers is potentially important, the size of the market for residential PV in Massachusetts is small enough relative to the world market that state policies are unlikely to have a meaningful impact on manufacturers.

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.[8]

Along with several other states (Arizona, California, Maryland, and New Jersey), Massachusetts has become a leader in supporting the development of the solar industry in the United States. Massachusetts offers several tax incentives, as well as direct

[8]https://www.seia.org/initiatives/solar-investment-tax-credit-itc

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.[9] 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 benefits of the property tax exemption are idiosyncratic and 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 their 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 PV system and transferred to the grid. Under 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

[9] https://www.mass.gov/regulations/830-CMR-6261-residential-energy-credit

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 PV 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).[10] 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).[11]

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 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.[12] My period of analysis is 2008 to 2018, therefore, I measure the benefits derived from SREC I and II. Both of these programs allow PV 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).

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

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

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

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.[13] Schedules of ACPs and auction prices are published years in advance to reduce uncertainty about the future value of certificates. As illustrated in Figure 5, 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 these bounds as an approximation for expected equilibrium prices.

2.5 Other Benefits

In addition to the aforementioned benefits, Massachusetts has also incentivized residential PV adoption by increasing access to financial markets. In particular, the Mass Solar Loan Program enables eligible low income households access to low-interest loans in order to finance PV system purchases.[14] 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 long-term incentives that I consider in my analysis.

[13]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.

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

3 Model

3.1 Overview

In this section, I specify a dynamic adoption, or demand, model for PV systems. 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 and abatement. 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.

A major difference between my application 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 over previous full information approaches in the dynamic discrete choice literature (for example, Rust 1987 and Gowrisankaran and Rysman 2011) is that it does not require the researcher to specify the evolution of market-level state variables in the model. This aspect of their estimation approach is crucial in my application, because 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 additional 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 households' utility function p_{jt}, the net present cost of installation, depends upon the upfront installation cost p^I_{jt}, households' 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.[15]

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 continuing to pay its utility for electricity, which is why the 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,

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

[15] 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.

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,

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

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,

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

where the constant, 0.577, Euler's gamma, is 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,

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

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 follow techniques developed in Scott (2014) and Kalouptsidi, Scott, and Souza-Rodrigues (2021).

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 (Arcidiacono and Miller 2011 refer to this as the "correction" term). 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 given the indifference condition,

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

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

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 others where I estimate δ jointly with the other parameters.

4 Data

To analyze households' adoption behavior and measure their responsiveness to solar incentives, I combine data on PV system installations from the Massachusetts Clean

Energy Center (MassCEC)[16] with market size and electricity price data from the U.S. Energy Information Administration (EIA).[17] I also refer to the Massachusetts Department of Energy Resources (DOER) website[18] 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).[19] 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 6 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 to 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 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 po-

[16]https://www.masscec.com
[17]https://www.eia.gov/
[18]https://www.mass.gov/orgs/massachusetts-department-of-energy-resources
[19]https://www.masscec.com/about-pts

tentially 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 7 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 use to explicitly model third-party ownership—particularly to capture the effective prices households' face. 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 primary 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 primary analysis. In a robustness check, I estimate a model that incorporates the decision to adopt third-party owned systems in a simple manner and obtain similar estimates to my main results.

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 8 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 9 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.[20] 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 real electricity prices (adjusting for inflation with the urban CPI) 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,

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

My forecast of real electricity prices runs from 2019 through 2042, because I assume a PV system lifespan of 25 years, therefore, a household adopting in 2018 can accumulate

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

net metering revenue and avoid electricity costs through 2042. Regression results are shown Table 3. Figure 10 displays actual and forecasted electricity prices from 2008–2042. The coefficients show that on average 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. In the estimation section, I specify alternative growth paths for electricity prices.

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.[21] 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 quantity 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 ACP (price ceiling, $\overline{p}_t^{sc}$) and the auction price (price floor, $\underline{p}_t^{sc}$),

$$p_t^{sc} = \frac{\overline{p}_t^{sc} + \underline{p}_t^{sc}}{2}.$$

In Figure 11, 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. These are plotted in Figure 12.

4.4 Net Present Installation Costs

Having explained all of the empirical components 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 of $\delta = 0.9$, and a depreciation

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

rate of $d = 0.01$ to illustrate how the effective prices households face evolve over time. In Figure 13, I plot average discounted net metering revenue and average discounted SREC revenue over time by system size, and in Figure 14, I plot the 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 4). 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.[22]

[22]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 aggregate 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. In these instances I replace missing prices with average aggregate 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. However, the inclusion of an instrument for price in the model should address this measurement error. Finally, I also use median estimated production as an estimate for aggregate energy generation in each year-market (again missing data is replaced with the average across other markets). Table 5 displays summary statistics of the sample 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 demand shocks 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. These variance 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' average discount factor 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' price sensitivity and discount factor to various assumptions in the estimation. Forth, 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 municipal-level moments to the model, which I estimate using generalized method of moments (GMM).

6.1 Linear Estimation and 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 identify what I call the "normalized estimates" $\beta_1, ..., \beta_5$, corresponding directly to the parameters in households' indirect utility function.

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 logit 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, holding δ constant, the Hausman-Nevo instrument shifts the price coefficient α in the expected direction. However, as δ increases demand seems to become less elastic, which is counter to previous results in the literature estimating dynamic demand systems. In particular, Gowrisankaran and Rysman's (2012) suggest that applying static demand to durable goods will tend to lead to estimates of the price coefficient biased toward zero. However, unlike in their application, 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) results and theoretical intuition that accounting for dynamic consumer behavior 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 Estimation and 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 θ using quasi-Newton optimization (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 update 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.

Compared to De Groote and Verboven (2019), I find that households are more myopic about the future benefits of solar in my setting. Converting my estimate of households' discount factor into the annual interest rate at which households' would need to be compensated in order to invest in long-term solar benefits, $\hat{r} = \frac{1}{\hat{\delta}} - 1 \approx 23\%$, I compare our results. They estimate an equivalent annual interest rate of approximately 15% (or an annual discount factor of 0.87), which implies that households in Belgium were more forward looking about the future benefits of solar than their Massachusetts counterparts. One plausible explanation for this result is that SREC prices in Belgium were set by the government in a top-down manner, whereas in Massachusetts SREC prices are determined by the market mechanism established by DOER. While this market mechanism may have generated efficiency in the allocation of SRECs, this may have come at the cost of increased uncertainty for households choosing whether or not to adopt PV. This increased uncertainty about the riskiness of PV as a long-term investment may be reflected in the lower estimate of households' discount factor. Another, potential explanation is that the relative pervasiveness of PV adoption in Belgium reflects a greater acceptance and awareness of green technologies both as a matter of public policy and culturally in Europe. Of course besides institutional and cultural differences across settings, differences in identification strategies may also explain why I find that Massachusetts households are more myopic.

6.3 Robustness Checks

In this section, I subject the NLIV estimates, my preferred specification of the structural model, to a series of robustness checks. The objective of these exercises is to test the sensitivity of the model, in particular the key parameters α and δ, to some of its underlying assumptions. Specifically, I investigate how my assumptions about market size, differences across geographic markets, the evolution of electricity prices and SREC prices over time, and specification of the outside option affect these parameters. I find that most of these assumptions have limited impact on these estimates and do not change my main results or the policy implications of these results. In an additional section in the appendix, I extend the model to allow households to adopt third-party owned PV systems—again, this extension has a limited impact on my main findings.

6.3.1 Market Size Robustness Check

One potential concern in the 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 in reality.

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 Utility Market Fixed Effects Robustness Check

Unobservable institutional differences in PV installation policies and norms across electric utilities, as well as demographic variation that might affect adoption behavior across utility markets, may be correlated with PV installation costs and electricity prices. As a result, omission of these factors could result in inconsistent estimates of households' price sensitivity and discount factor.

To test the sensitivity of my main specification to unobservable variation across utility service areas, I estimate NLLS and NLIV specifications that include utility market fixed effects. These results are displayed in Table 11. I find that the inclusion of utility market fixed effects has essentially no impact on the estimates of the key parameters of the model, suggesting that time invariant unobservable differences in PV installation policies and norms, as well as demographic differences, (at least *across* utility service areas) are not a threat to identification. Additionally, note that both the NLLS and NLIV estimates are essentially the same as their original counterparts, which suggests that the Hausman-Nevo IV strategy for identifying the price coefficient is not sensitive to the inclusion of market fixed effects.

6.3.3 Sensitivity to the Magnitude of Future Benefits

In the structural model, a household's decision to invest in PV today depends upon the net present cost of installation, which includes the upfront installation price and the present value of the future stream of benefits (including the avoided cost of electricity and revenues from the SREC program) over the lifespan of the system. In estimation the key parameters of the model, α and δ, are jointly identified by variation in the difference between current and future net installation costs i.e. the relative magnitude of p^I to both p^e and p^{sc}. As a result, these key parameters may be sensitive to assumptions about the magnitude of these benefits. Below, I analyze the robustness of my main specification to these assumptions.

6.3.4 Electricity Price Sensitivity

Because the dynamic PV adoption model takes into account households' future electricity costs, it is necessary to obtain data on the electricity prices that households face in each utility service area as well as estimates of these prices spanning into the future. In the data section, I describe the baseline log-linear regression I use to forecast future electricity prices, which results in annual growth rates in prices of 1.9–6.1%. Because the structural model relies upon a forecast of future electricity prices, a potential concern is that such a forecast may be unreliable and/or unrealistic and may not appropriately capture households' expectations of future prices when they are choosing whether or not to adopt solar panels, and this misspecification may lead to biased estimates of the model's key parameters. In order to assess the sensitivity of my main parameter estimates to the specification of future electricity prices, I specify two alternative growth paths—a "linear price path" and a "no growth price path." Figure 15 displays the two alternative price trajectories. The linear growth path, which is derived from a simple linear regression of price on utility-specific time trends, results in generally lower electricity prices than the log-linear forecast during the relevant period. The no growth path assumes that from 2018 onward, electricity prices remain constant at their 2018 levels.

Tables 12 and 13 display estimates of the main structural model under the "linear growth path" and "no growth path" scenarios, respectively. In each case, the key parameter estimates are extremely similar to the main specification, demonstrating a lack of sensitivity to a wide range of possible electricity price forecasts.

6.3.5 Solar REC Price Sensitivity

As previously discussed, I do not directly observe equilibrium prices in the market for solar renewable energy certificates (SRECs). Instead, I approximate these prices using the effective upper and lower bounds of prices (or effective price ceiling and price floor) in the market, set annually by DOER. The effective upper bound or price ceiling is electric utilities' alternative compliance price (ACP), and the effective lower bound or price floor is the SREC last chance quantity auction price. In my main specification, I use the midpoint of these prices as an estimate of market clearing SREC prices,

$$p_t^{sc} = \frac{\overline{p}_t^{sc} + \underline{p}_t^{sc}}{2}.$$

In order to test the sensitivity of my main specification to this approximation of equilibrium SREC prices, I re-estimate this specification using either the series of upper bound prices or lower bound prices as alternative approximations for the series of equilibrium prices. These results are displayed in Tables 14 and 15.

Using the lower bound, quantity auction price series, as an approximation of equilibrium SREC prices results in a price coefficient of -0.21 and a discount factor of 0.97. Using the upper bound, alternative compliance price series, an as approximation of equilibrium SREC prices results in a price coefficient of -0.52 and a discount factor of 0.30. Both price coefficient estimates are within the 95% confidence interval of the main specification's point estimate ([-0.62, -0.02]), while only the discount factor of the specification using the lower bound price series lies within the 95% confidence interval of the main specification's point estimate ([0.43, 1.19]).

This robustness analysis reveals more sensitivity to assumptions about the magnitude of SREC prices than assumptions about the magnitude of electricity prices, which is likely driven not only by the fact that SREC incentives are larger but also by differences in temporal variation. SREC prices are declining over time, while electricity prices are increasing. Moreover, SREC benefits in Massachusetts exhibit kinks or discontinuities as the different phases of the program begin and end, whereas electricity prices vary more continuously over time. These discontinuities in the SREC incentives are helpful in identifying households' price sensitivity and discount factor, because the variation in the difference between upfront costs and long-term benefits is large between periods when these discontinuities occur.

This exercise also sheds light on the identification of the key parameters of the model. With lower overall SREC prices, in order to rationalize households' observed adoption decisions, households must be less price sensitive and more forward looking (smaller α, larger δ), because they are paying relatively more upfront and receiving a smaller stream of future benefits. With higher overall SREC prices, the opposite is true, households must be more price sensitive and less forward looking (larger α, smaller δ) in order to rationalize their observed adoption decisions.

6.3.6 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, they 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,

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

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 residuals 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 $(\mathbf{Z_k'Z_k})^{\mathbf{-1}}$.

The results of this robustness check are displayed in Table 16. 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, notice that 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 inconsistent estimates of households' price sensitivity and discount factor.

I allow households located in different submarkets, in this case across 345 of 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 on municipal-level 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 (De Groote and Verboven (2019), Kalouptsidi, Scott, and Souza-Rodrigues 2021).

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

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

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

Assuming that households located in the same municipality ℓ have similar demographic characteristics, let u_{ijt} be the flow utility each household $i \in \ell$ 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,

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

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,

$$v_{i0t} = \delta\big(\underbrace{\beta_1 - \alpha p_{1t+1} + \xi_{jt+1} - \eta_t}_{\bar{u}_{1t+1}} + \underbrace{\lambda_1^I inc_\ell + \lambda_1^P pop_\ell + \lambda_1^V vote_\ell}_{\mu_{\ell 1t+1}} - \log\left(s_{\ell 1t+1}\right)\big), \quad (18)$$

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

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

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

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

$$\tilde{\mu}_{\ell jt} \equiv \mu_{\ell jt} - \delta\mu_{\ell 1t+1} = \underbrace{(\lambda_j^I - \delta\lambda_1^I)}_{\tilde{\lambda}_j^I} inc_\ell + \underbrace{(\lambda_j^P - \delta\lambda_1^P)}_{\tilde{\lambda}_j^P} pop_\ell + \underbrace{(\lambda_j^V - \delta\lambda_1^V)}_{\tilde{\lambda}_j^V} vote_\ell,$$

the probability that a household in municipality ℓ adopts system j at time t is,

$$s_{\ell jt}(\tilde{u}, \tilde{\lambda}) = \frac{\exp\left(\tilde{u}_{jt} + \tilde{\lambda}_j^I inc_\ell + \tilde{\lambda}_j^P pop_\ell + \tilde{\lambda}_j^V vote_\ell + \delta\log\left(s_{\ell 1t+1}\right)\right)}{1 + \sum_k^J \exp\left(\tilde{u}_{kt} + \tilde{\lambda}_k^I inc_\ell + \tilde{\lambda}_k^P pop_\ell + \tilde{\lambda}_k^V vote_\ell + \delta\log\left(s_{\ell 1t+1}\right)\right)}. \quad (19)$$

With these probabilities, it is now possible to write a log-likelihood function in terms of the probabilities of adoption $s_{\ell jt}$ and number of adoptions $q_{\ell jt}$ (and non-adoptions $q_{\ell 0t}$) of each system j at time t in municipality ℓ,

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

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 $s_{\ell 1t+1}$ also needs to be estimated since it is not directly observed. I pre-estimate these probabilities in a first-stage regression using a multinomial 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,

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

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 municipal-level moments since they are sampled from municipal-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 market-level 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 municipal-level moments, and the second block contains weights for the market-level moments.

In practice, I estimate the model with household heterogeneity using market-level data and municipal-level data from four of the five utility service areas in Massachusetts. I exclude data from Unitil because its service area consists of only four municipalities and this limited variation in adoptions across these municipalities means that many of the mean utility parameters, $\tilde{u}_{jtm}$, associated with Unitil's geographic market are not identified. Additionally, I exclude two other municipalities in which no households adopted PV during the sample period. With market-level data from four utility coverage areas and municipal-level data from 345 municipalities, I estimate the model by sampling over 200 market-level moments and 17,250 municipality-level moments. Also, in practice, rather than estimating δ, I set $\delta = 0.8$ based on the results of the main NLIV specification. While in principle it is possible to estimate households' discount factor with household heterogeneity, I find that the estimation routine has difficulty converging when δ is a free parameter.

The results of the heterogenous demand estimates are displayed in Table 17. 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 the inclusion of income-capacity interactions, and because δ is a fixed parameter in this model—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 political affiliation 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 affect households' decisions to adopt PV systems.

In a first counterfactual analysis, I use the homogenous and heterogenous demand estimates to measure the impact of (1) upfront subsidies, (2) SREC programs, and (3) net metering program on overall PV adoption in Massachusetts. I also calculate the amount of consumer welfare generated by each program. I find that upfront subsidies (federal and state tax credits and grants/rebates) had the largest impact on solar adoption followed closely by the establishment of SREC market and less closely by the net metering policy. While the benefits Massachusetts households receive through the long-term incentive programs outweigh the value of upfront subsidies, upfront incentives have a larger effect on adoption, because households discount these future benefits significantly.

In a second counterfactual analysis, I compare the efficacy of upfront and long-term solar incentives on a dollar-for-dollar basis by simulating the effects of two hypothetical incentive programs using my demand estimates. This exercise illustrates the importance of discounting behavior in the design of subsidy programs.

In what follows, I describe the implementation of the counterfactuals, describe the calculation of consumer welfare generated by each program, and discuss the results.

7.1 Implementation

In the first set of counterfactuals, in order to measure the effect of each incentive program on overall residential adoption, I remove each one at a time and simulate counterfactual demand. An alternative approach to evaluating the effectiveness of each incentive program would be to invert this exercise and ask: starting from a baseline of no incentives—how much would cumulative adoption increase given the introduction of different incentive programs? I take this alternative approach in the second set of counterfactuals where I simulate the effects of two hypothetical incentive programs. The first series of counterfactuals measure the marginal contribution of each actual incentive introduced holding the level of other incentives constant. The second series of counterfactuals measure the marginal contribution of two hypothetical incentive programs starting from a baseline of no incentives.

It should be noted here that in all counterfactuals, in order to make predictions with the model, I set the error term in the estimating equation, $e_{jt} = 0$. An alternative approach would be to use the demand parameter estimates to back out estimates of e_{jt}, which could themselves be treated as structural parameters to be held fixed in counterfactual analyses (such an approach is commonly used in merger simulation in the IO literature). These product-market-time specific estimates would then be held fixed in the counterfactual simulations I conduct. However, the issue with that approach here is that it obfuscates the performance of the model in predicting actual household adoption ($\hat{e}_{jt}$ *is* the difference between actual and predicted adoptions). By setting $e_{jt} = 0$ instead, I am able to transparently assess the predictive power of the structural model attributable to the main variables of interest. Additionally, the interpretation of $\hat{e}_{jt}$ is trickier in this dynamic context than in a (typically) static context like merger simulation, because $\hat{e}_{jt}$ could include, among other things, information about households' beliefs about future solar incentive programs, which would of course not remain fixed in response to changes in these programs. Therefore, I find it more reasonable not to treat the e_{jt}'s as structural parameters in my application.

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,

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

To streamline the discussion of implementing each counterfactual, recall each component of the net present cost of installation,

(1) upfront subsidies;

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

(2) net metering revenue;

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

(3) and SREC revenue;

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

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

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

7.1.1 Removal of Upfront Subsidies

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

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

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

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

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

7.1.2 Removal of SREC Revenue

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

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

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

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

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

7.1.3 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,

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

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

7.1.4 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_{ijt} but also their utility from the outside option v_{i0t}, in this case the value of waiting to adopt.

Where $J^{\mathcal{S}}$ and $J^{\mathcal{N}}$ 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,

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

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 Massachusetts 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.

7.2 First Counterfactual: Program Effects

The results of the first set of counterfactuals are displayed in Table 18 and Figures 16, 17, and 18. The top panel of Table 18 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 16, 17, and 18 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 slightly improves its predictive power, but does not change the overall results. Therefore, 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, and the marginal effect of each program is large holding the level of other incentives constant.

Comparing the predicted to counterfactual outcomes, I estimate that elimination (1) of upfront subsidies would have decreased cumulative adoptions by approximately 80%, (2) the SREC market by 78%, and (3) net metering, assuming a relatively small impact by 13%. Table 19 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 Massachusetts 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—the implication of this result is explored further in the second series of counterfactuals.

7.3 Second Counterfactual: Upfront vs. Long-term Incentives

In the first set of counterfactuals, I measure the effectiveness of each incentive program introduced in Massachusetts on aggregate adoption by predicting the change in cumulative adoption in the absence of the incentives households actually received. While useful for measuring the total effects of these programs on overall adoption, these simulations do not yield an apple-to-apples comparison of the efficacy of upfront and long-term incentive programs on a dollar-for-dollar basis, which would be useful to policymakers.

In this section, I perform such an exercise by comparing the effects of a $10,000 upfront subsidy to households and a $10,000 long-term subsidy distributed in equal amounts annually over 25 years ($400 per year for the lifespan of the system). I choose $10,000 as the total amount of each subsidy in these counterfactuals so as to roughly match the incentives Massachusetts households received through different programs. As reported in Table 24, Massachusetts households received approximately $10,000 in incentives through each program I account for (upfront subsidies, SREC revenue, and net metering revenue).

Unlike the previous set of counterfactuals, I do not differentiate between the mechanisms through which long-term incentives could be distributed (i.e. via a SREC program or via net metering), because the effect of *any* long-term incentive program in the structural model is determined by the parameters α and δ and the per period revenues of the incentive, *not* the mechanism through which an incentive is distributed.

Also, unlike the set of previous counterfactuals, rather than predicting the change in aggregate adoptions by removing incentives that households received, I invert this exercise and ask: starting from a baseline of no incentives—how much would cumulative adoption increase given the introduction of alternative incentive programs?

Essentially this counterfactual considers a scenario in which a policymaker is deciding whether to implement either an upfront or long-term solar incentive program of equal cost per adopting household.

As a baseline in the simulations, I first use my empirical estimates to predict adoption without any incentives, then I predict cumulative adoptions over time given the introduction of the upfront subsidy and long-term subsidy.

Figure 19 displays the counterfactual results. In the absence of any incentives, the model predicts 6,225 adoptions by 2017. From this baseline, I estimate that an upfront subsidy of $10,000 to each adopter would increase cumulative adoption by 83% to 11,376 households, whereas a long-run subsidy of $10,000 distributed evenly over 25 years would increase cumulative adoption by 13% to 7,032 households by 2017.

This exercise demonstrates the gap in efficacy of upfront and long-term subsidies driven by households' relatively low discount factor.

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.[23] 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.[24] 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,[25]

$$\frac{\text{tCO}_2}{\text{MWh}} = 0.91 \times 1,000 \times \frac{1}{2,204.62} \approx 0.41.$$

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 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

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

[24]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

[25]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

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 in my sample during this 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 a social planner's discount factor, 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.[26]

Using my NLIV estimates I calculate total electricity generation predicted by the model, as well as in counterfactual scenarios where I remove either (1) upfront subsidies, (2) SREC revenues, or (3) net metering revenues. These results are displayed in Table 20 and Figure 20. Because the underlying demand model overpredicts the number of adoptions (see Table 18) 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 incentives would result in a $(1 - \frac{164{,}814}{944{,}249}) \approx 82.5\%$ decrease in total 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

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

(\$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 21 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. 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 (\$4,655 per ton of carbon) or almost 25 times larger than the current federal estimate of \$51 per ton of CO_2 (\$1,269 per ton of CO_2). 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. For example, these objective could include increasing general awareness of green technologies or preparing current energy infrastructure for interoperability with small scale renewables in the future.

Table 21. Value of Avoided CO_2 Emissions (2008–2017) (return)

Program	Social Value	Cost Over 2008–2017	Cost Over Lifespan
CF (1): Upfront Subsidies	\$5.25 M	\$281.01 M	\$281.01 M
CF (2): SREC	\$5.06 M	\$188.17 M	\$785.38 M
CF (3): Net Metering 50%	\$3.22 M	\$113.32 M	\$1,613.98 M
Total		\$582.51 M	\$2,680.38 M

Notes: See Tables 22, 23, and 24 for more detailed information about the social value and costs attributable to each incentive program. "Cost Over 2008–2017" accounts for realized incentives distributed during the 2008–2017 period. "Cost Over Lifespan" accounts for all incentives distributed over the lifespan of PV systems adopted during 2008–2017. While "Cost Over 2008–2017" may make for a better comparison with the estimated value of avoided CO_2 emissions during this same period, as reflected in the structural model, a household's PV adoption decision is made on the basis of expected savings over the lifespan of the system. For comparison, I report both here.

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, putting downward pressure on 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 policymakers. In this article, I estimate a dynamic discrete choice model of residential PV adoption in Massachusetts in which households receive both upfront and long-term incentives and estimate households' price sensitivity and discount factor. I then use these results to conduct a cost-benefit analysis of three solar incentive programs established by the state. My empirical results suggest that dollar for dollar upfront incentives are likely to be more cost effective than long-term incentives, because residential adopters significantly discount the future benefits of adopting solar panels. Additionally, compared to previous work using data from Belgium, I find that Massachusetts households are more myopic about long-term solar incentives. Furthermore, this myopia may be at least partially attributable to the unique design of the SREC market in Massachusetts, through which households received a large fraction of their long-term incentives.

In terms of environmental and energy policy, my cost-benefit analysis of demand-side incentives for residential PV systems suggests that recent efforts to encourage the adoption of small scale renewables in Massachusetts have indeed increased adoption rates, however, these policies appear to have been relatively inefficient as a means of reducing CO_2 emissions. Based on my estimates, in order for the government to breakeven on its investment in upfront residential solar incentives, in terms of the social benefits of abatement, the social cost of carbon would have to be 25 times larger than the current federal estimate.

Despite this dim finding for Massachusetts' solar policy, designing a cost effective solar subsidy program aimed at reducing CO_2 emissions is fraught with perils given high uncertainty about the social cost of carbon, as well as uncertainty about future demand for solar. Ex-post, the costs of these programs seem out of proportion with their social benefits, however, ex-ante, they may have appeared like promising investments. An alternative policy approach for environmental and energy policymakers would be to impose a tax on carbon rather than subsidizing new technologies, as many economists have suggested (WSJ 2019). This would still require estimating the social cost of carbon but would avoid the challenge of calibrating incentives so as to stimulate demand in a cost effective manner, which, as this paper suggests, is likely difficult to get right in practice.

Additionally, my findings beg the question are there more cost effective alternatives in which society should invest to curb emissions? Other potential investments on the table include those on the cutting edge such as electric vehicles, next generation nuclear power plants, and hydrogen fuel, and those that are more conventional such as energy efficiency improvements to the grid and public facilities and substitution away from coal towards natural gas. An accounting of the marginal social benefits of potential abatement from these investments, similar to the exercise conducted in this paper, would be a useful tool for policymakers.

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Appendices

A Tables

Table 1. Duration of Long-term PV 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

Notes: This table summarizes the stream of future incentives a household receives on annual basis conditional on the year it adopts a PV system. A household adopting in 2008 receives the benefits of the net program/avoided electricity costs over the 25 lifespan of the system. A household adopting in 2010 receives benefits through net metering in addition to revenue through the first, more generous, phase of the SREC market until the end of phase I in 2025. A household adopting in 2014 receives benefits through net metering in addition to revenue through the second, less generous, phase of the SREC market until the end of phase II in 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

Notes: Number of observations 31,637 is the number of residential, host-owned installations during the 2008–2018 period. In the structural model, households' choice of PV system is discretized by system capacity into the five categories displayed above. Upfront installation costs, state grants and rebates, and estimated annual production are aggregated within these capacity categories, within utility service areas, and within years. Median values are used to estimate the model, however, as shown above mean values are similar.

Table 3. Electricity Price Trend Estimates (return)

Specification	Log Price per kWh	
	Estimates	Standard Errors
Municipal Utilities × Time	0.0188	(0.00180)
NSTAR × Time	0.0374	(0.00928)
National Grid × Time	0.0610	(0.0142)
Unitil × Time	0.0419	(0.00653)
WMECO × Time	0.0384	(0.0117)
NSTAR	0.212	(0.0731)
National Grid	-0.0479	(0.115)
Unitil	0.270	(0.0520)
WMECO	0.0939	(0.0834)
Constant	-2.179	(0.0117)
R^2	0.851	
F-Statistic	114.74	
Observations	54	

Notes: Observations are annual residential electricity prices by electric utility during the 2008–2018 period: 5×11 observations (missing price data for WMECO in 2018). Municipal utilities are grouped together. Heteroskedasticity-consistent standard errors are displayed in parentheses. Utility-specific time trends are used to forecast future electricity prices in order to calculate households' value of net metering/avoided electricity costs.

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	

Notes: 31,637 is the number of residential, host-owned PV installations during 2008–2018. 2,383,484 is the total number of residential electric utility customers in Massachusetts in 2008. The distribution of PV installations across electric utilities is similar to the distribution of residential customers. Municipal utilities are grouped together.

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

Notes: This table summarizes the aggregate sample of PV adoption data used to estimate the structural demand model. The number of observations is 250 = 5 capacities × 5 utility markets × 10 years (2008–2017). Adoptions are residential, host-owned PV installations summed within system-market-years. Median values of individual installation data are used to estimate aggregate prices, incentives, and estimated annual production within system-market-years.

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

Notes: Means are average upfront installation prices by capacity over utility markets and years. Overall standard deviations are calculated over markets and years, *between* standard deviations are calculated between markets, *within* standard deviations are calculated within markets. The number of observations for each statistic is 50 = 1 capacity × 5 utility markets × 10 years (2008–2017).

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

Specification	Installation Cost (000)	
	Estimates	Standard Errors
Average Installation Cost (000)	0.375	(0.0460)
Capacity [4,6) kW	0.852	(0.954)
Capacity [6,8) kW	5.087	(1.056)
Capacity [8,10) kW	9.002	(1.158)
Capacity [10,20) kW	12.68	(1.867)
Constant	1.837	(0.906)
R^2	0.871	
F-Statistic	355.17	
Observations	250	

Notes: The number of observations is 250 = 5 capacities × 5 utility markets × 10 years (2008–2017). Heteroskedasticity-consistent standard errors are displayed in parentheses. Average installation cost is the Hausman-Nevo instrument for price—mean installation prices across other utility service areas. The first-stage F-Statistic is greater than 10.

Table 8. Linear Demand Equation Estimates (return)

Parameters	OLS, $\delta = 0$		IV, $\delta = 0$		OLS, $\delta = 0.9$		IV, $\delta = 0.9$	
	Estimates	Standard Errors	Estimates	Standard Errors	Estimates	Standard Errors	Estimates	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	

Notes: The number of observations is 250 = 5 capacities × 5 utility markets × 10 years (2008–2017). Heteroskedasticity-consistent standard errors are displayed in parentheses. The first two specifications are static aggregate multinomial logit demand models, static because households' discount factor is set to 0. The second two specifications are dynamic aggregate multinomial logit demand models estimated using the ECCP approach, where households' discount factor is set to 0.9. Note that the net present cost of installation (price) is a function of δ in the model. IV specifications are estimated using average upfront installation cost across other markets as an instrument for price.

Table 9. Nonlinear Demand Equation Estimates (return)

Parameters	NLLS Estimates	NLLS Standard Errors	NLIV Estimates	NLIV Standard Errors	Normalized Estimates Parameters	Normalized Estimates NLLS	Normalized Estimates 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				

Notes: The number of observations is 250 = 5 capacities × 5 utility markets × 10 years (2008–2017). Heteroskedasticity-consistent standard errors are displayed in parentheses. Both specifications are dynamic aggregate multinomial logit demand models estimated using the ECCP approach, where δ is a parameter to be estimated. The NLLS specification does not instrument for price, whereas the NLIV specification uses average upfront installation costs across other markets as an instrument for price and one period ahead SREC prices as an instrument for the discount factor. Note that the net present installation cost (price) is a function of δ in the model. The normalized estimates report the capacity-specific constants in households' indirect utility function, $\beta_1, ..., \beta_5$, which can be separately identified by a transformation of the original estimates.

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			

Notes: The number of observations is 250 = 5 capacities $\times$ 5 utility markets $\times$ 10 years (2008–2017). Heteroskedasticity-consistent standard errors are displayed in parentheses. In this specification, the initial market size, number of residential utility customers in 2008, is reduced to 10% of its size. Average upfront installation costs across other markets is used as an instrument for price, and one period ahead SREC prices are used as an instrument for the discount factor. The normalized estimates report the capacity-specific constants in households' indirect utility function, $\beta_1, ..., \beta_5$, which can be separately identified by a transformation of the original estimates.

Table 11. Market Fixed Effects Robustness (return)

Parameters	NLLS		NLIV	
	Estimates	Standard Errors	Estimates	Standard Errors
α: Net Present Installation Cost (000)	-0.3637	(0.0785)	-0.3177	(0.1552)
$\tilde{\beta}_2$: Capacity [4,6) kW	1.9848	(0.7083)	0.6984	(1.7200)
$\tilde{\beta}_3$: Capacity [6,8) kW	3.1869	(0.9982)	0.4725	(3.4877)
$\tilde{\beta}_4$: Capacity [8,10) kW	3.9416	(1.2161)	-0.4220	(5.3227)
$\tilde{\beta}_5$: Capacity [10,20) kW	4.6404	(1.9153)	-1.5007	(7.3009)
NSTAR	0.6789	(0.8400)	0.0271	(0.7738)
National Grid	1.2508	(0.7969)	1.0466	(0.8291)
Unitil	-0.8105	(1.1575)	0.3570	(1.1810)
WMECO	0.7070	(0.8622)	0.3908	(0.7740)
Constant	-6.0344	(1.0867)	-2.1729	(1.8828)
δ: Discount Factor	0.2602	(0.1185)	0.8132	(0.1934)
Objective Function	8.4284		0.0000	
R^2	0.3266		0.2252	
Markets	5		5	
Years	10		10	
Observations	250		250	

Notes: The number of observations is 250 = 5 capacities × 5 utility markets × 10 years (2008–2017). Heteroskedasticity-consistent standard errors are displayed in parentheses. Both specifications include utility market fixed effects. The NLLS specification does not instrument for price, whereas the NLIV specification uses average upfront installation costs across other markets as an instrument for price and one period ahead SREC prices as an instrument for the discount factor. Note that the net present installation cost (price) is a function of δ in the model.

Table 12. Electricity Price Linear Robustness (return)

Parameters	NLIV		Normalized Estimates	
	Estimates	Standard Errors	Parameters	NLIV
α: Net Present Installation Cost (000)	-0.3262	(0.1439)	α	-0.3262
$\tilde{\beta}_2$: Capacity [4,6) kW	0.7718	(1.5887)	β_1	-9.6119
$\tilde{\beta}_3$: Capacity [6,8) kW	0.6458	(3.1708)	β_2	-8.8401
$\tilde{\beta}_4$: Capacity [8,10) kW	-0.1380	(4.8069)	β_3	-8.9661
$\tilde{\beta}_5$: Capacity [10,20) kW	-1.1039	(6.5704)	β_4	-9.7499
$\tilde{\beta}_0$: Constant	-1.8777	(1.6697)	β_5	-10.7159
δ: Discount Factor	0.8047	(0.1843)	δ	0.8047
Objective Function	0.0000			
R^2	0.2199			
Markets	5			
Years	10			
Observations	250			

Notes: The number of observations is 250 = 5 capacities × 5 utility markets × 10 years (2008–2017). Heteroskedasticity-consistent standard errors are displayed in parentheses. In this specification, I use an alternative forecast of future electricity prices, which affects the net present installation cost of PV systems through net metering/avoided electricity cost incentives. In this case, I assume future electricity prices follow a simple linear time. Average upfront installation costs across other markets is used as an instrument for price, and one period ahead SREC prices are used as an instrument for the discount factor. The normalized estimates report the capacity-specific constants in households' indirect utility function, $\beta_1, ..., \beta_5$, which can be separately identified by a transformation of the original estimates.

Table 13. Electricity Price No Growth Robustness (return)

Parameters	NLIV		Normalized Estimates	
	Estimates	Standard Errors	Parameters	NLIV
α: Net Present Installation Cost (000)	-0.3341	(0.1329)	α	-0.3341
$\tilde{\beta}_2$: Capacity [4,6) kW	0.8406	(1.4680)	β_1	-9.5468
$\tilde{\beta}_3$: Capacity [6,8) kW	0.8076	(2.8723)	β_2	-8.7062
$\tilde{\beta}_4$: Capacity [8,10) kW	0.1270	(4.3132)	β_3	-8.7392
$\tilde{\beta}_5$: Capacity [10,20) kW	-0.7337	(5.8762)	β_4	-9.4198
$\tilde{\beta}_0$: Constant	-1.9385	(1.5712)	β_5	-10.2805
δ: Discount Factor	0.7969	(0.1750)	δ	0.7969
Objective Function	0.0000			
R^2	0.2193			
Markets	5			
Years	10			
Observations	250			

Notes: The number of observations is 250 = 5 capacities × 5 utility markets × 10 years (2008–2017). Heteroskedasticity-consistent standard errors are displayed in parentheses. In this specification, I use an alternative forecast of future electricity prices, which affects the net present installation cost of PV systems through net metering/avoided electricity cost incentives. In this case, I assume future electricity prices remain constant at 2018 levels. Average upfront installation costs across other markets is used as an instrument for price, and one period ahead SREC prices are used as an instrument for the discount factor. The normalized estimates report the capacity-specific constants in households' indirect utility function, $\beta_1, ..., \beta_5$, which can be separately identified by a transformation of the original estimates.

Table 14. SREC Lower Bound Robustness (return)

Parameters	NLIV Estimates	NLIV Standard Errors	Normalized Estimates Parameters	Normalized Estimates NLIV
α: Net Present Installation Cost (000)	-0.2102	(0.1256)	α	-0.2102
$\tilde{\beta}_2$: Capacity [4,6) kW	-1.0308	(2.3631)	β_1	-6.9655
$\tilde{\beta}_3$: Capacity [6,8) kW	-3.2938	(4.7091)	β_2	-7.9963
$\tilde{\beta}_4$: Capacity [8,10) kW	-6.5706	(7.2904)	β_3	-10.2593
$\tilde{\beta}_5$: Capacity [10,20) kW	-10.0934	(10.1180)	β_4	-13.5360
$\tilde{\beta}_0$: Constant	-0.2206	(1.7137)	β_5	-17.0589
δ: Discount Factor	0.9683	(0.1103)	δ	0.9683
Objective Function	0.0000			
R^2	0.1349			
Markets	5			
Years	10			
Observations	250			

Notes: The number of observations is 250 = 5 capacities × 5 utility markets × 10 years (2008–2017). Heteroskedasticity-consistent standard errors are displayed in parentheses. In this specification, I use an alternative price series for equilibrium SREC prices, which affects the net present installation cost of PV systems through SREC incentives. In this case, I assume equilibrium SREC prices are equal to the price floor in the market set by DOER annually. Average upfront installation costs across other markets is used as an instrument for price, and one period ahead SREC prices are used as an instrument for the discount factor. The normalized estimates report the capacity-specific constants in households' indirect utility function, $\beta_1, ..., \beta_5$, which can be separately identified by a transformation of the original estimates.

Table 15. SREC Upper Bound Robustness (return)

Parameters	NLIV Estimates	NLIV Standard Errors	Normalized Estimates Parameters	Normalized Estimates NLIV
α: Net Present Installation Cost (000)	-0.5193	(0.0544)	α	-0.5193
$\tilde{\beta}_2$: Capacity [4,6) kW	2.3042	(0.6238)	β_1	-7.0094
$\tilde{\beta}_3$: Capacity [6,8) kW	4.3189	(0.6851)	β_2	-4.7052
$\tilde{\beta}_4$: Capacity [8,10) kW	5.9058	(0.9456)	β_3	-2.6905
$\tilde{\beta}_5$: Capacity [10,20) kW	7.3098	(0.0000)	β_4	-1.1036
$\tilde{\beta}_0$: Constant	-4.8761	(1.0046)	β_5	0.3004
δ: Discount Factor	0.3044	(0.1542)	δ	0.3044
Objective Function	2.7561			
R^2	0.2507			
Markets	5			
Years	10			
Observations	250			

Notes: The number of observations is 250 = 5 capacities × 5 utility markets × 10 years (2008–2017). Heteroskedasticity-consistent standard errors are displayed in parentheses. In this specification, I use an alternative price series for equilibrium SREC prices, which affects the net present installation cost of PV systems through SREC incentives. In this case, I assume equilibrium SREC prices are equal to the price ceiling in the market set by DOER annually. Average upfront installation costs across other markets is used as an instrument for price, and one period ahead SREC prices are used as an instrument for the discount factor. The normalized estimates report the capacity-specific constants in households' indirect utility function, $\beta_1, ..., \beta_5$, which can be separately identified by a transformation of the original estimates.

Table 16. Include Moment Conditions for All Terminal Adoption Decisions (return)

Parameters	NLIV		Normalized Estimates	
	Estimates	Standard Errors	Parameters	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			

Notes: The number of moments is 1,250 = (5 capacities × 5 utility markets × 10 years) × 5 alternative specifications of the outside option. Heteroskedasticity-consistent standard errors are displayed in parentheses. Average upfront installation costs across other markets is used as an instrument for price, and one period ahead SREC prices are used as an instrument for the discount factor. The normalized estimates report the capacity-specific constants in households' indirect utility function, $\beta_1, ..., \beta_5$, which can be separately identified by a transformation of the original estimates.

Table 17. 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)	-0.1778	(0.0253)	α	-0.1778
$\tilde{\beta}_2$: Capacity [4,6) kW	1.5899	(1.9727)	β_1	-13.0372
$\tilde{\beta}_3$: Capacity [6,8) kW	2.0435	(2.4083)	β_2	-11.4473
$\tilde{\beta}_4$: Capacity [8,10) kW	2.4617	(2.7450)	β_3	-10.9937
$\tilde{\beta}_5$: Capacity [10,20) kW	2.3441	(2.8637)	β_4	-10.5756
$\tilde{\beta}_0$: Constant	-2.6074	(2.6001)	β_5	-10.6932
Income × Capacity				
$\tilde{\lambda}_1^I$	0.0011	(0.0037)	λ_1^I	0.0056
$\tilde{\lambda}_2^I$	0.0030	(0.0023)	λ_2^I	0.0074
$\tilde{\lambda}_3^I$	0.0036	(0.0020)	λ_3^I	0.0081
$\tilde{\lambda}_4^I$	0.0053	(0.0015)	λ_4^I	0.0098
$\tilde{\lambda}_5^I$	0.0082	(0.0013)	λ_5^I	0.0126
Population Density × Capacity				
$\tilde{\lambda}_1^P$	-0.0216	(0.0352)	λ_1^P	-0.1080
$\tilde{\lambda}_2^P$	-0.0229	(0.0275)	λ_2^P	-0.1094
$\tilde{\lambda}_3^P$	-0.0574	(0.0248)	λ_3^P	-0.1438
$\tilde{\lambda}_4^P$	-0.1103	(0.0254)	λ_4^P	-0.1967
$\tilde{\lambda}_5^P$	-0.1762	(0.0248)	λ_5^P	-0.2626
Democratic Vote Share × Capacity				
$\tilde{\lambda}_1^V$	0.0122	(0.0391)	λ_1^V	0.0611
$\tilde{\lambda}_2^V$	-0.0056	(0.0274)	λ_2^V	0.0432
$\tilde{\lambda}_3^V$	-0.0146	(0.0234)	λ_3^V	0.0342
$\tilde{\lambda}_4^V$	-0.0254	(0.0221)	λ_4^V	0.0234
$\tilde{\lambda}_5^V$	-0.0259	(0.0218)	λ_5^V	0.0230
Objective Value	0.0000			
R^2	0.4686			
Municipalities	345			
Markets	4			
Years	10			
Market Moments	200			
Municipal Moments	17,250			

Notes: The number of market-level moments is 200 = 5 capacities × 4 utility markets × 10 years (2008–2017). The number of municipal-level moments is 17,250 = 345 municipalities × 5 capacities × 10 years (2008–2017). Heteroskedasticity-consistent standard errors are displayed in parentheses. Households' discount factor is set to 0.8 rather than estimated. Average upfront installation cost across other markets is used as an instrument for prices, and one period ahead SREC prices are used as an instrument for the discount factor. Note that the net present installation cost (price) is a function of δ in the model. The normalized estimates report the capacity-specific constants, $\beta_1, ..., \beta_5$, and capacity-specific demographic interactions, $\lambda_1, ..., \lambda_5$, in households' indirect utility function, which can be separately identified by a transformation of the original estimates.

Table 18. 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): Upfront Subsidies	1,913	2,118	1,266	404	72	5,773
CF (2): SREC	2,665	2,686	713	145	15	6,225
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	3,045	6,858	6,393	4,759	4,508	25,563
Predicted	2,965	5,701	4,721	4,150	3,979	21,515
CF (1): Upfront Subsidies	2,137	2,334	1,560	982	552	7,565
CF (2): SREC	2,571	2,921	1,275	601	260	7,629
CF (3): Net Metering 10%	2,723	3,792	2,207	1,325	741	10,787
CF (3): Net Metering 25%	2,762	4,058	2,503	1,600	977	11,900
CF (3): Net Metering 50%	2,829	4,545	3,090	2,195	1,553	14,211
CF (3): Net Metering 75%	2,896	5,090	3,818	3,016	2,480	17,301
CF (3): Net Metering 90%	2,937	5,448	4,336	3,652	3,292	19,665

Notes: The top panel displays cumulative adoptions (2008–2017) based on the homogenous preferences demand model, while the bottom panel displays cumulative adoptions (2008–2017) based on the heterogenous preferences demand model. "Actual" refers to observed residential, host-owned PV installations, "Predicted" refers to the number of adoptions predicted by the model, and "CF" refers to the number of adoptions predicted by the model under a counterfactual scenario where one of households' financial incentives is removed.

Table 19. **Annual Consumer Surplus from Incentive Programs** (return)

Homogenous Demand		Upfront Subsidies		SREC Programs		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	12,155	28,970	0	0	1,097	2,614
2009	2,383,186	8,780	20,925	5,542	13,208	1,239	2,952
2010	2,382,601	6,977	16,623	5,297	12,621	1,272	3,030
2011	2,382,202	5,787	13,786	5,081	12,104	1,315	3,131
2012	2,381,422	5,133	12,225	5,315	12,658	1,494	3,559
2013	2,380,426	5,454	12,983	4,578	10,898	1,668	3,970
2014	2,378,610	5,071	12,062	4,593	10,925	1,787	4,251
2015	2,375,246	4,076	9,681	4,423	10,506	1,845	4,382
2016	2,369,684	3,925	9,301	4,218	9,995	1,898	4,497
2017	2,363,045	3,924	9,273	4,019	9,497	1,975	4,668
Heterogenous Demand		Upfront Subsidies		SREC Programs		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	2,856,298	12,119	34,616	0	0	1,014	2,897
2009	2,855,726	8,600	24,559	5,205	14,863	1,144	3,267
2010	2,855,339	6,935	19,803	4,997	14,269	1,179	3,366
2011	2,854,571	5,733	16,364	4,807	13,721	1,220	3,483
2012	2,853,586	5,068	14,462	5,021	14,327	1,383	3,947
2013	2,851,785	5,406	15,418	4,330	12,349	1,548	4,414
2014	2,848,465	4,943	14,079	4,323	12,313	1,650	4,699
2015	2,842,967	4,043	11,493	4,204	11,953	1,717	4,881
2016	2,836,418	3,878	11,001	4,021	11,405	1,770	5,020
2017	2,831,024	3,854	10,909	3,811	10,789	1,827	5,172

Notes: The top panel displays the estimated annual consumer surplus attributable to each incentive program based on the homogenous preferences demand model, while the bottom panel displays the estimated annual consumer surplus attributable to each incentive program based on the heterogenous preferences demand model. Note that these changes in consumer surplus are marginal estimates holding the level of the other incentive programs fixed. The market size for the homogenous and heterogenous demand estimates differ because the estimated initial market size for the homogenous demand model is approximated using the number of residential electricity customers in each utility service area in 2008, while the initial market size for the heterogenous demand model is approximated using the number of households in each municipality in 2008. Notice, however, that the average change in consumer surplus is very similar across models.

Table 20. 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): Upfront Subsidies	30,111	47,534	38,512	15,330	3,226	134,712
CF (2): SREC	52,960	83,703	22,227	5,294	630	164,814
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

Notes: This table displays the estimated cumulative electricity generation in MWh (2008–2017) by residential, host-owned PV systems in Massachusetts. "Actual" refers to estimated cumulative generation based on the number of observed residential, host-owned PV installations, "Predicted" refers to estimated cumulative generation based on the number of adoptions predicted by the homogenous demand estimates, and "CF" refers to estimated cumulative generation based on number of adoptions predicted by the model under a counterfactual scenario where one of households' financial incentives is removed.

Table 22. Value of Avoided CO_2 Emissions (2008–2017) (return)

Program	Social Value
CF (1): Upfront Subsidies	5,250,482
CF (2): SREC	5,055,248
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

Notes: This table displays the social value attributable to each solar incentive program during the 2008–2017 period based on counterfactual avoided CO_2 emissions, where the social cost of CO_2 per MWh of electricity generated is \$9.79.

Table 23. Subsidies Distributed During 2008–2017 Period 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	3,811	6,226	7,177	8,579	9,884	7,135
Av. Net Metering/Avoided Elec. Cost	2,814	3,784	4,188	4,999	5,917	4,341
Av. Total Subsidies	14,498	19,735	21,402	25,390	30,472	22,299
Totals						
Total Adoptions	3,077	6,921	6,494	4,834	4,581	25,907
Total Upfront Subsidies	24,227,757	67,305,769	65,174,368	57,101,308	67,204,118	281,013,318
Total SREC Revenue	11,725,475	43,086,799	46,610,407	41,469,160	45,280,764	188,172,604
Total Net Metering/Avoided Elec. Cost	8,658,339	26,190,516	27,199,053	24,164,081	27,107,502	113,319,491
Total Subsidies	44,611,571	136,583,084	138,983,827	122,734,548	139,592,383	582,505,414

Notes: This table displays the average upfront installation cost, as well as, the average (and total) subsidies households received through each incentive program during the 2008–2017 period, broken down by system capacity. Unlike table 24, these estimates account only for realized incentives distributed during the 2008–2017 period. The average upfront installation cost during 2008–2017 is $29,726. The average upfront subsidy to households is $10,823. The average amount of SREC revenue distributed to households during this period is $7,135. The average amount of net metering/avoided electricity cost revenue distributed to households during this period is $4,341. Therefore, average total subsidies households adopting during 2008–2017 receive over the lifespan of their systems is $22,299.

Table 24. Subsidies Over System Lifespan by System Capacity (return)

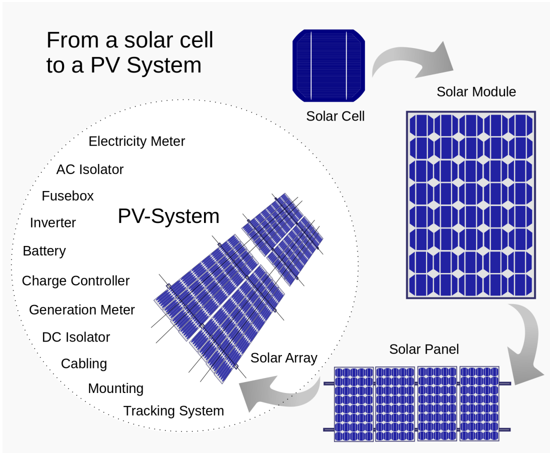
	System Capacity (kW)					
Means	[0,4)	[4,6)	[6,8)	[8,10)	[10,20)	Total
Av. Upfront Installation Cost	16,223	23,059	28,724	35,285	45,341	29,726
Av. Upfront Subsidies	7,874	9,725	10,036	11,812	14,670	10,823
Av. SREC Revenue	12,622	21,644	29,666	37,783	48,340	30,011
Av. Net Metering/Avoided Elec. Cost	25,420	41,499	59,963	78,144	105,088	62,023
Av. Total Subsidies	45,915	72,868	99,665	127,739	168,099	102,857
Totals						
Total Adoptions	3,077	6,921	6,494	4,834	4,581	25,907
Total Upfront Subsidies	24,227,757	67,305,769	65,174,368	57,101,308	67,204,118	281,013,318
Total SREC Revenue	38,837,102	149,800,797	192,654,078	182,644,966	221,447,812	785,384,754
Total Net Metering/Avoided Elec. Cost	78,216,904	287,212,249	389,398,729	377,745,895	481,408,103	1,613,981,881
Total Subsidies	141,281,763	504,318,814	647,227,174	617,492,168	770,060,033	2,680,379,953

Notes: This table displays the average upfront installation cost, as well as, the average (and total) subsidies households received through each incentive program over the (25 year) lifespan of their PV systems, broken down by system capacity. The average upfront installation cost during 2008–2017 is $29,726. The average upfront subsidy to households is $10,823. The average amount of SREC revenue a household could expect to receive over 25 years is $30,011. The average amount of net metering/avoided electricity cost revenue a household could expect to receive over 25 years is $62,023. Therefore, average total subsidies households adopting during 2008–2017 receive over the lifespan of their systems is $102,857.

B Figures

Figure 1. PV System Technology (return)

(a)



(b)

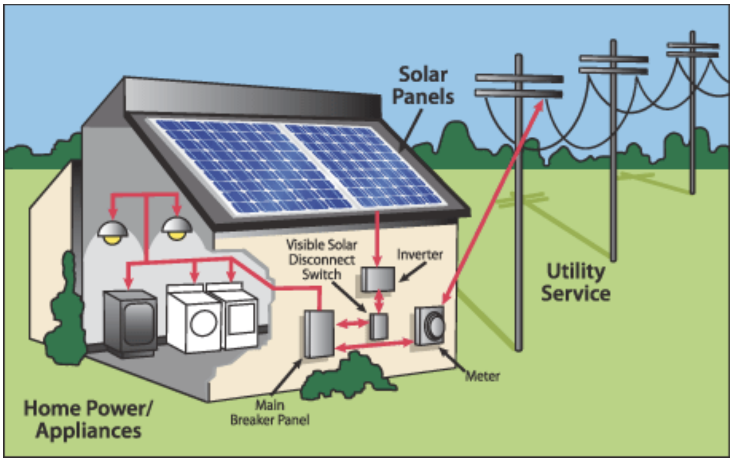
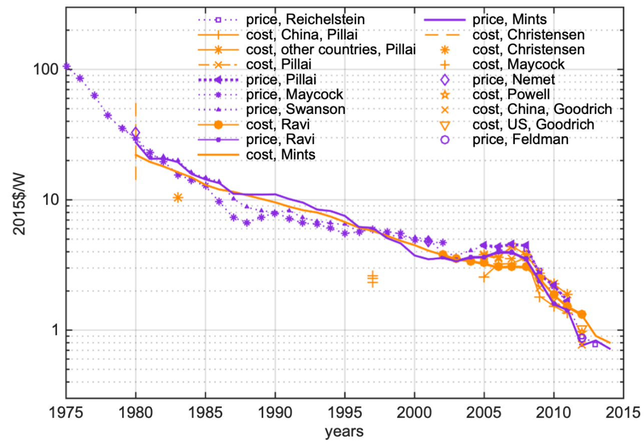
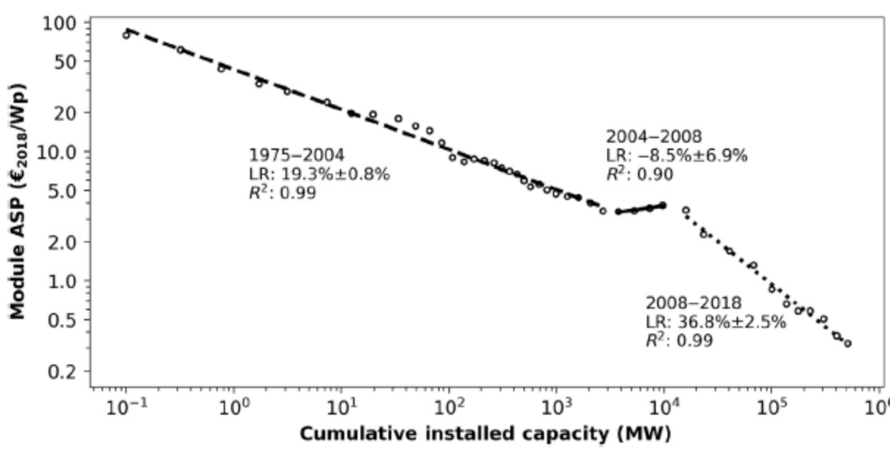


Figure 2. Declining Manufacturing Costs (return)

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



(b) Louwen and van Sark (2020)



(c) National Renewable Energy Laboratory

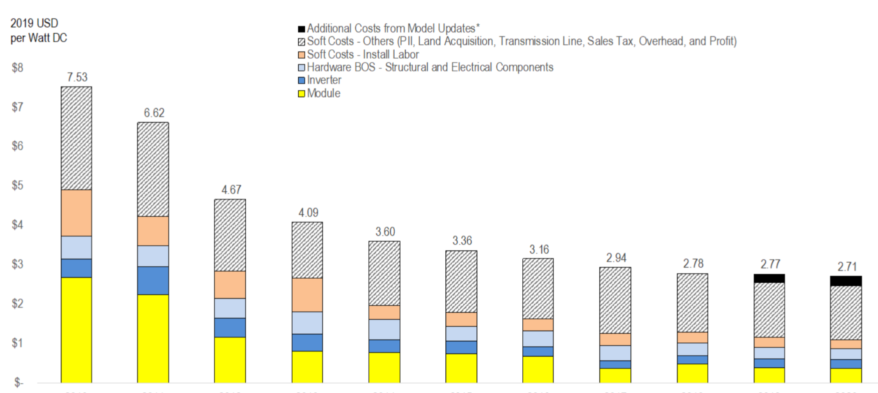
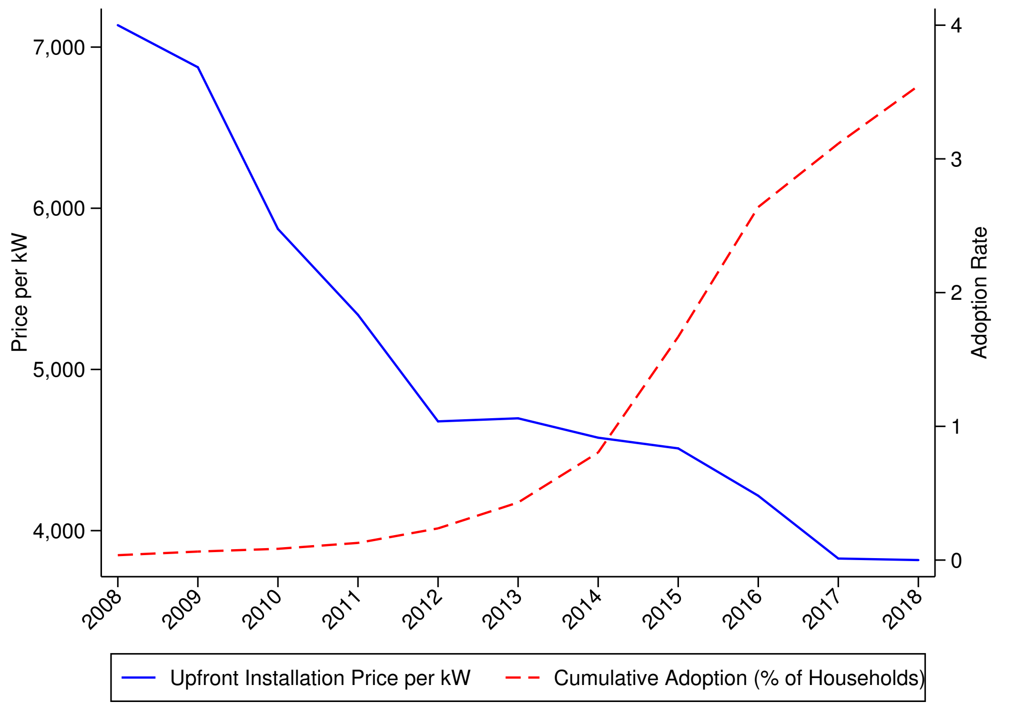


Figure 17. NREL residential PV system cost benchmark summary (inflation adjusted), 2010–2020

Figure 3. Overall PV Price and Adoption Rate in Massachusetts (return)



Notes: The denominator of cumulative adoption is the total number of residential electric utility customers in Massachusetts in 2008. Cumulative adoption includes all residential PV installations, both host owned and third-party owned. Annual upfront installation price per kW is weighted by annual capacity installed.

Figure 4. DPU Map of Utility Service Areas ([return](#))

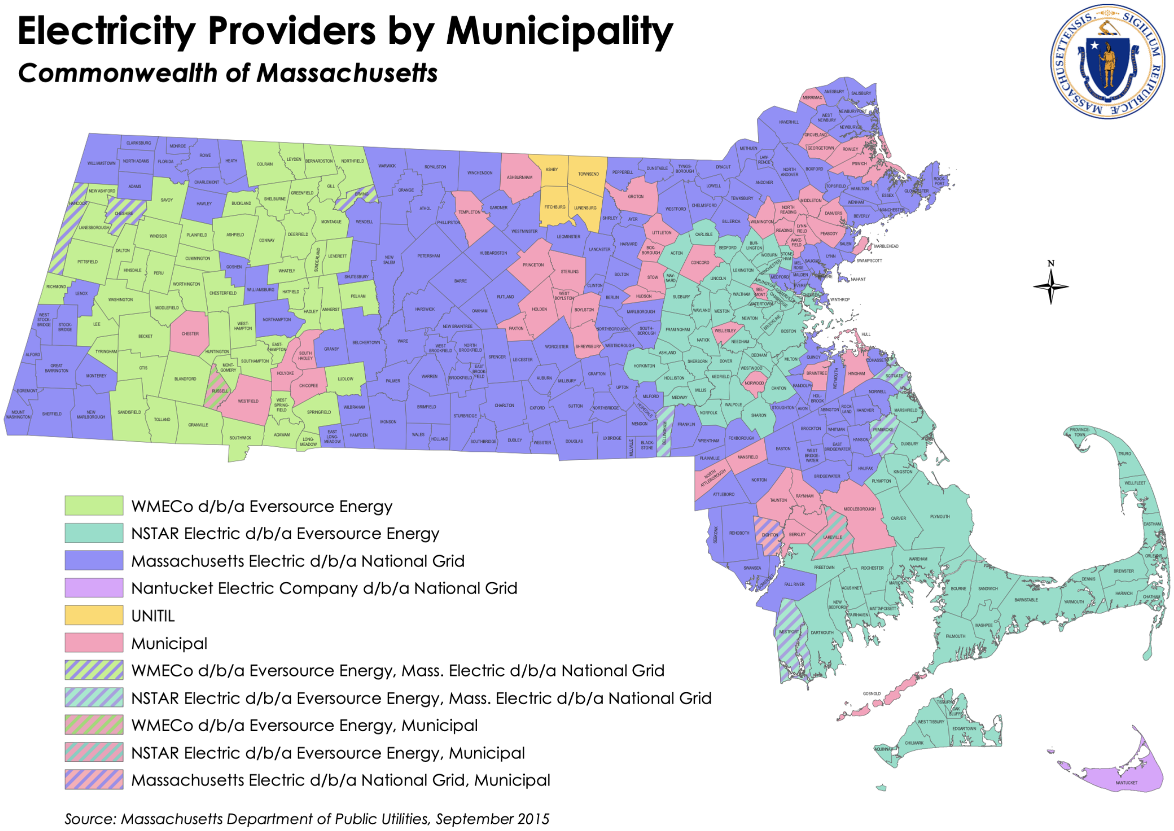
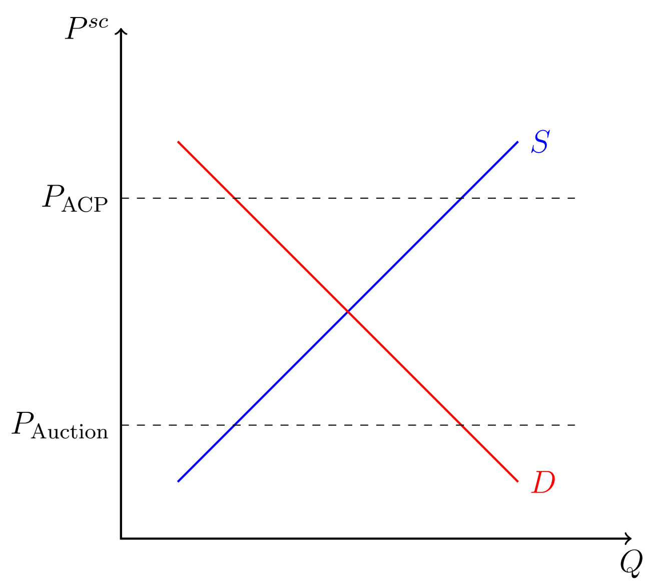
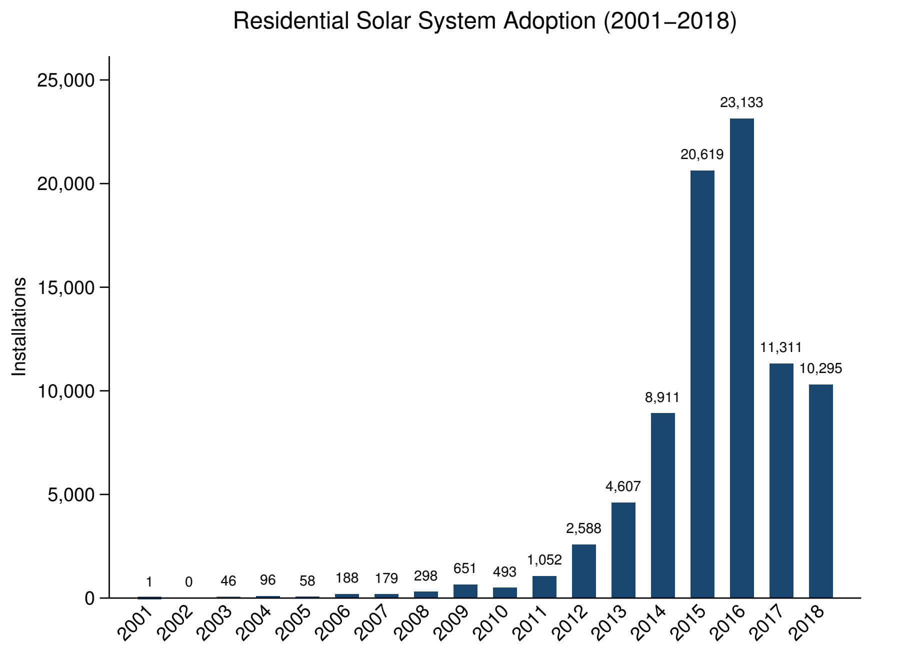


Figure 5. Market for SRECs ([return](#))



Notes: This figure illustrates how equilibrium certificate prices are bounded in the SREC market by a price ceiling and a price floor determined by DOER. The price ceiling is the alternative compliance price (ACP) an electric utility is required to pay (per kWh) if it violates its renewable portfolio standards (RPS). The price floor is a quantity auction price at which households earning SRECs are essentially guaranteed to sell their certificates for in the event that a surplus exists.

Figure 6. Residential Adoptions (return)

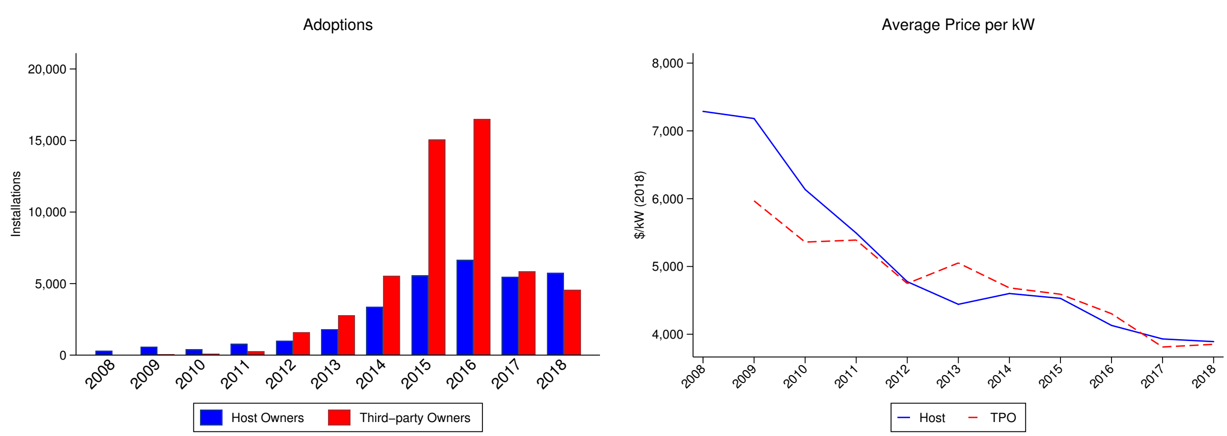


Notes: Installations includes all residential PV installations, both host owned and third-party owned. As illustrated, pre-2008 PV installations were relatively limited.

Figure 7. Host Owned vs. Third-party Owned Systems (return)

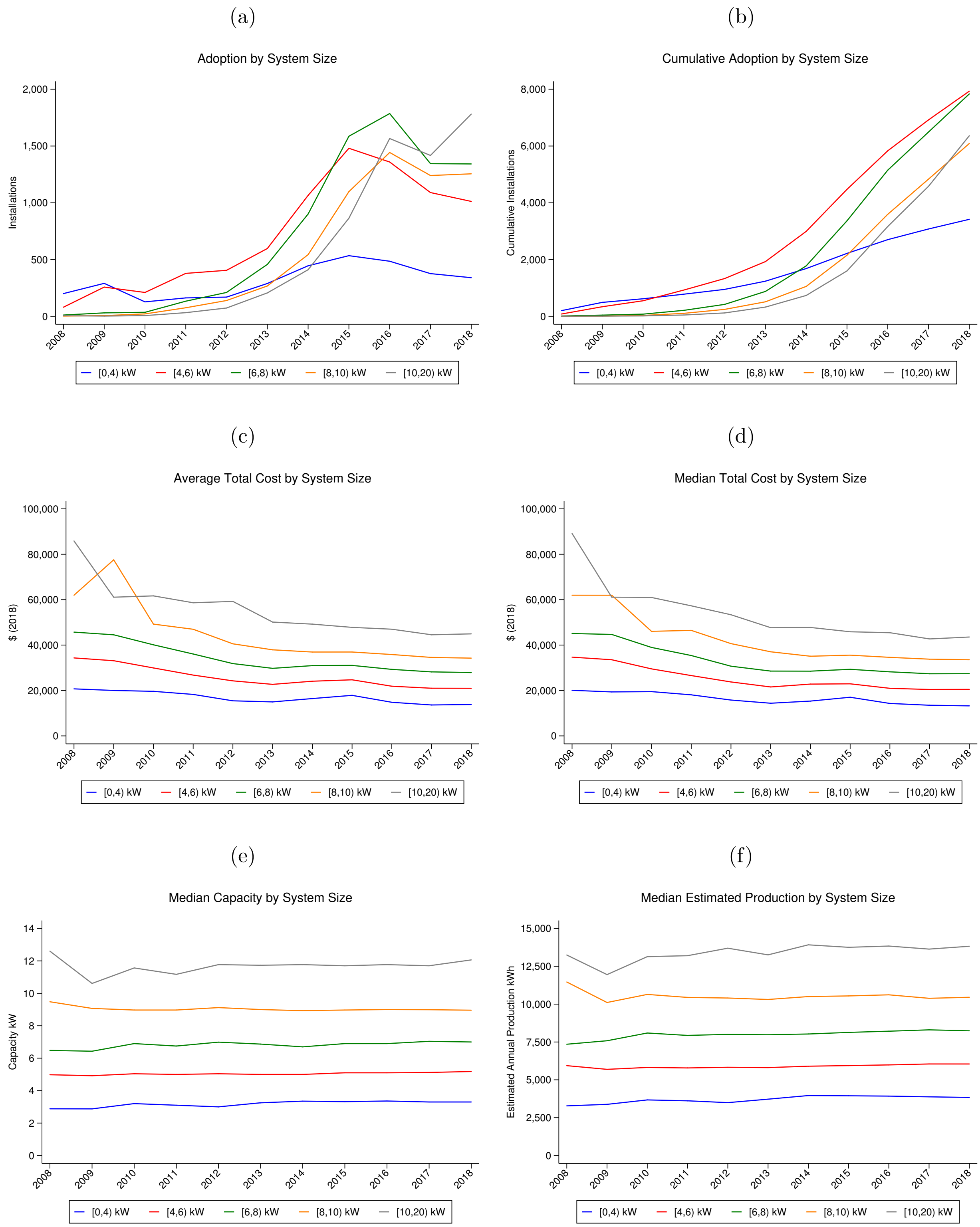
(a)

(b)



Notes: Third-party owned PV installations make up just under 2/3 of all residential installations with the rest being host owned installations. As discussed, the choice of host owned and third-party owned PV systems is quite different, therefore, I limited my analysis to host owned systems only. Notice there is little difference in the average upfront installation price of host owned and third-party owned systems during the sample period.

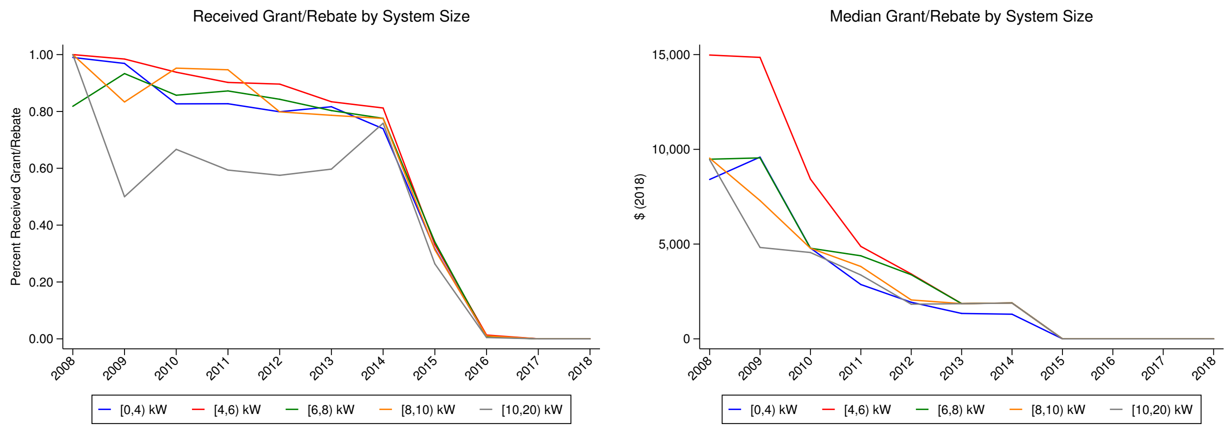
Figure 8. Adoptions, Cost, Capacity, and Production by Capacity (return)



Notes: This figure shows adoptions, cumulative adoptions, average and median installation costs, median capacity, and median estimated annual production of systems for my estimation sample by capacity group over time.

Figure 9. Rebates by Capacity (return)

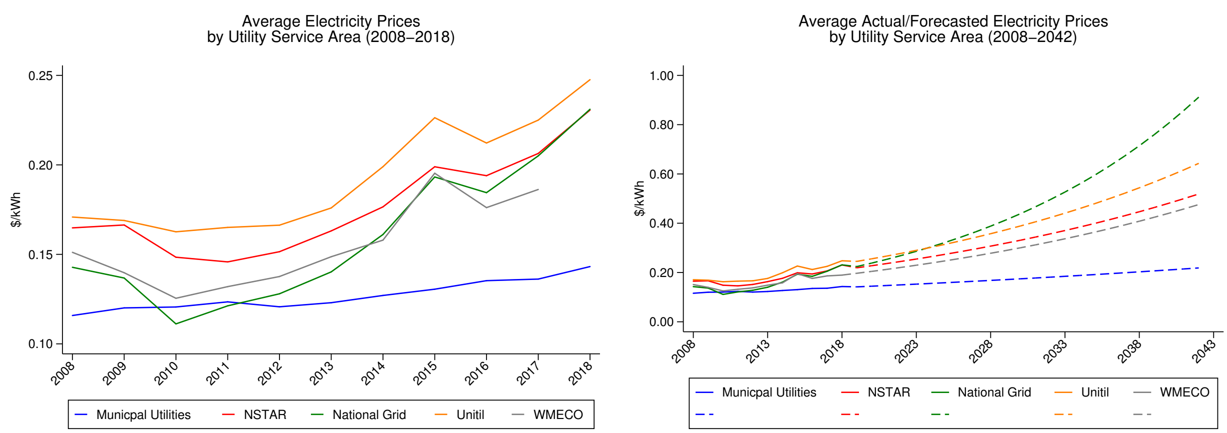
(a) (b)



Notes: This figure shows the percent of installations that received a state grant/rebate and the median state grant/rebate given for my estimation sample by capacity group over time.

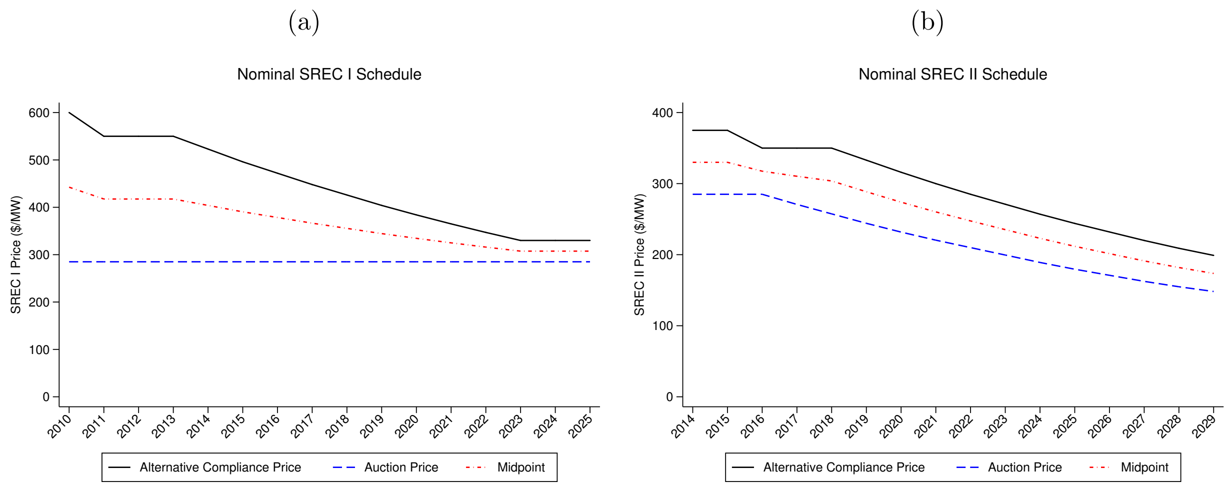
Figure 10. Actual and Forecasted Average Electricity Prices (return)

(a) (b)



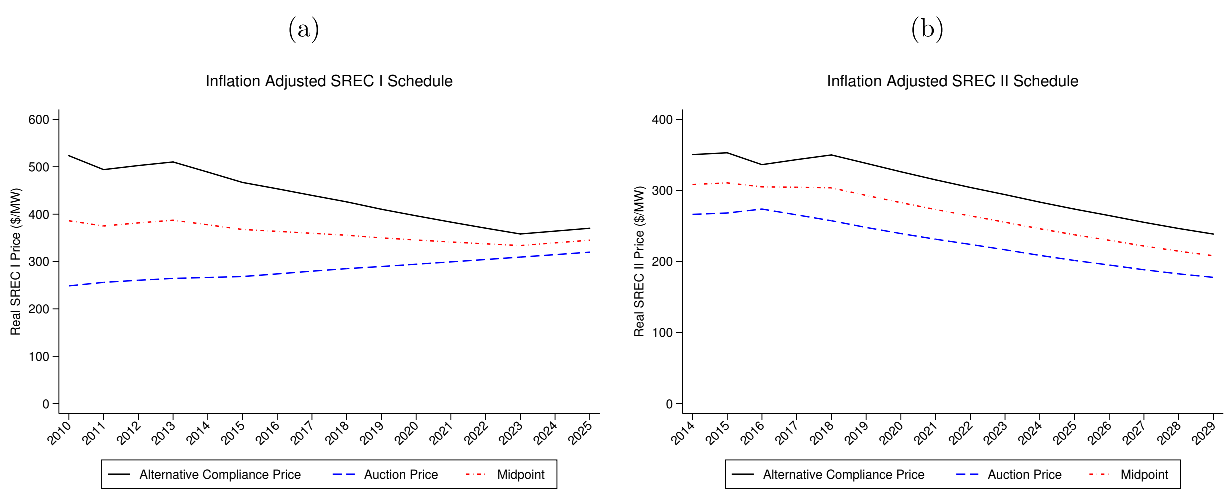
Notes: Panel (a) shows average residential electricity prices over time in each utility service area in Massachusetts during the sample period, where municipal utilities are grouped together. Panel (b) shows actual and forecasted electricity prices over time in each utility service area, where the forecast is a utility-specific log-linear trend. These forecasts are an input into the present value of net metering in the empirical model.

Figure 11. Nominal SREC Incentive Schedules (return)



Notes: This figure shows the schedule of SREC prices over time in nominal dollars, where panel (a) shows the prices of SREC I certificates and panel (b) shows the prices of SREC II certificates. The alternative compliance prices and quantity auction prices are set by DOER and bound equilibrium SREC prices in the market. I use the midpoint of these prices to represent the equilibrium price of SRECs in the empirical model.

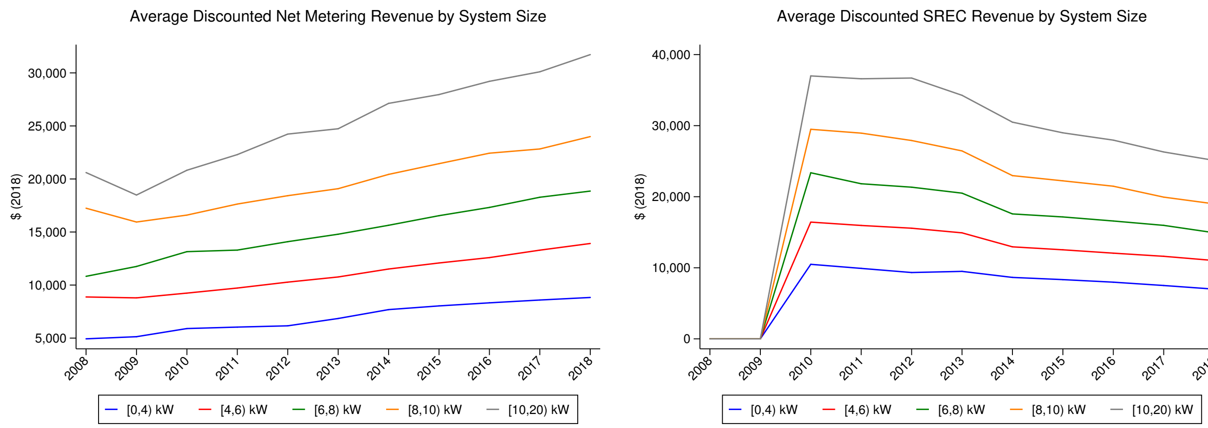
Figure 12. Real SREC Incentive Schedules (return)



Notes: This figure shows the schedule of SREC prices over time adjusted for inflation, where panel (a) shows the prices of SREC I certificates and panel (b) shows the prices of SREC II certificates. The alternative compliance prices and quantity auction prices are set by DOER and bound equilibrium SREC prices in the market. I use the midpoint of these prices to represent the equilibrium price of SRECs in the empirical model.

Figure 13. Revenue from Long-term Incentive Programs by Capacity (return)

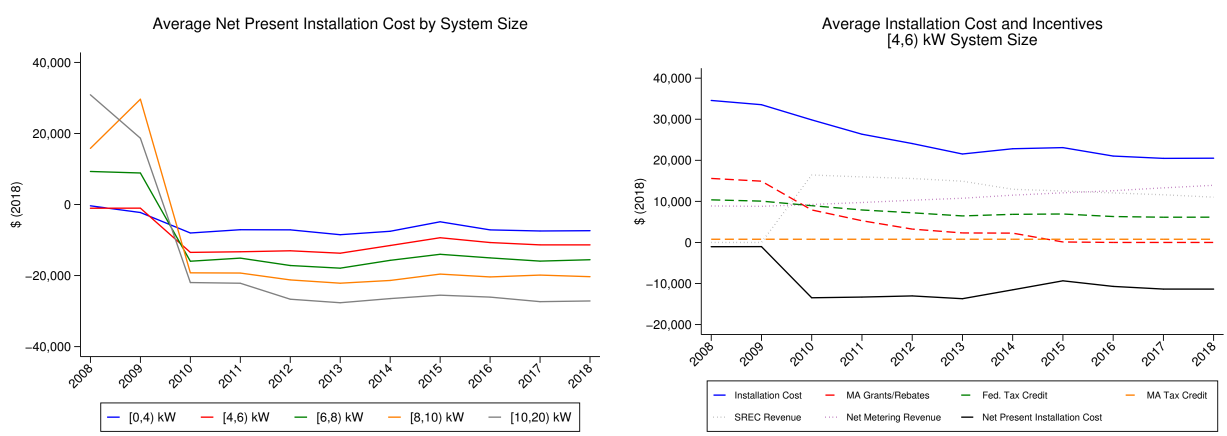
(a) (b)



Notes: This figure shows the present value of revenues generated from both long-term incentive programs over time by capacity when households' discount factor, $\delta = 0.9$. Panel (a) shows the present value of revenues from the net metering program, and panel (b) shows the present value of revenues from the SREC programs.

Figure 14. Installation Costs and Incentives (return)

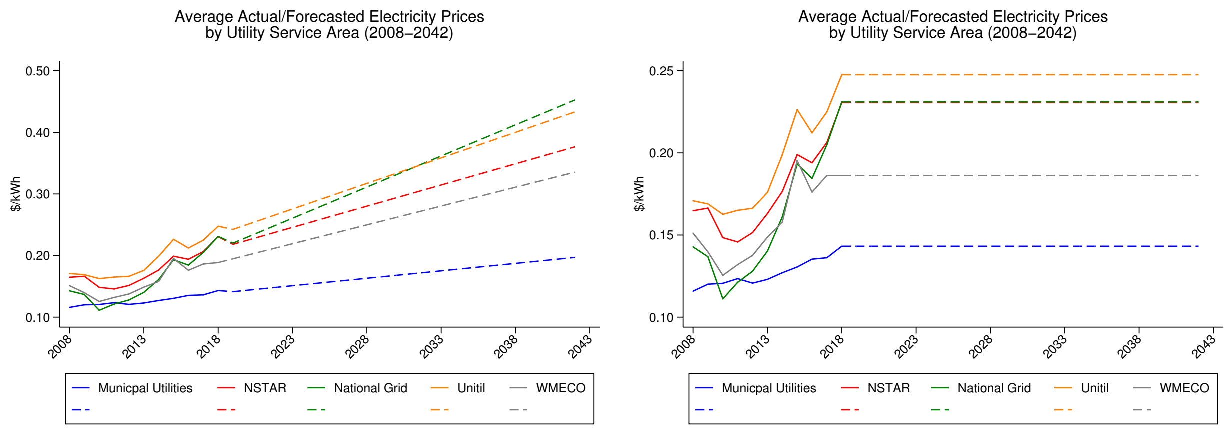
(a) (b)



Notes: Panel (a) shows the net present installation cost over time by system capacity when households' discount factor, $\delta = 0.9$. Panel (b) shows the breakdown of the net present installation cost over time for a [4,6) kW capacity system into its various components.

Figure 15. Electricity Price Robustness (return)

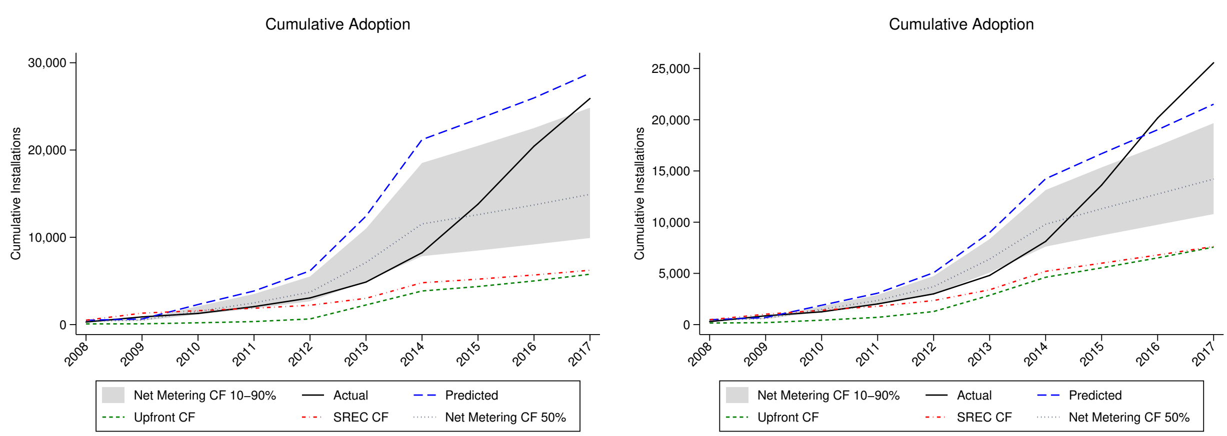
(a) (b)



Notes: This figure show the alternative electricity price trajectories I use to assess the sensitivity of my model to assumptions about the future growth of electricity prices. Panel (a) shows the "linear price path," and panel (b) shows the "no growth price path."

Figure 16. Actual, Predicted, and Counterfactual Cumulative Adoption (return)

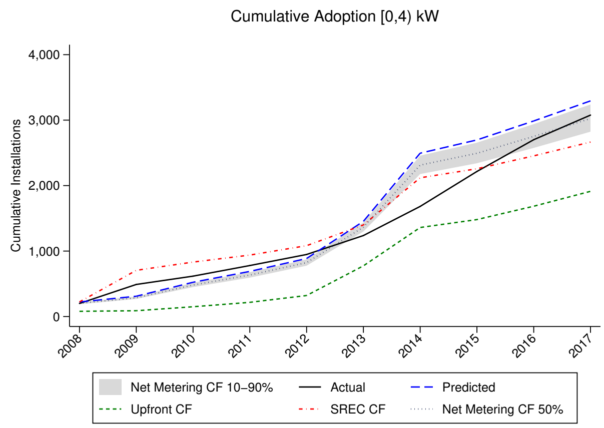
(a) (b)



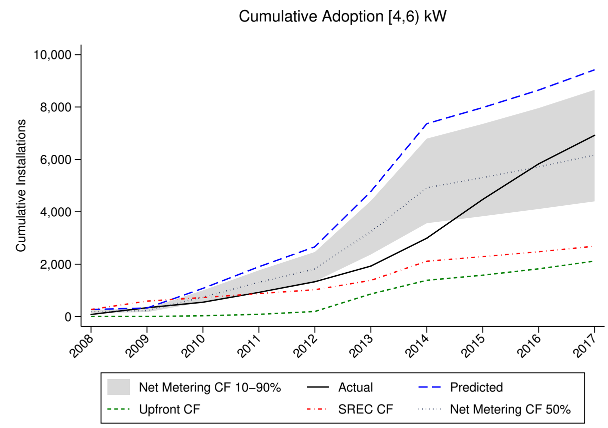
Notes: This figure shows actual, predicted, and counterfactual cumulative adoptions based on my demand estimates. Panel (a) shows predictions based on the homogeneous demand model and panel (b) shows predictions based on the heterogenous demand model.

Figure 17. Homogenous Demand: Actual, Predicted, and Counterfactual Cumulative Adoption by Capacity (return)

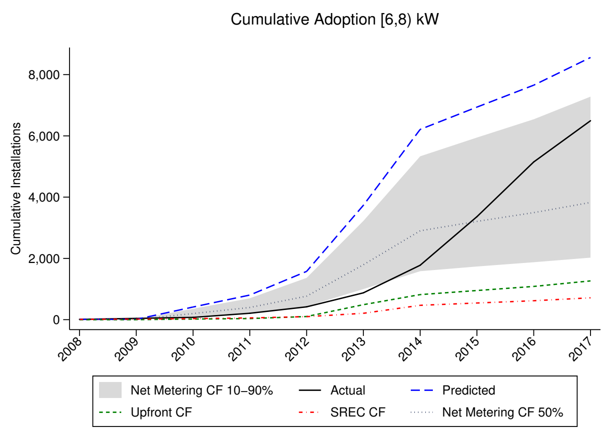
(a)



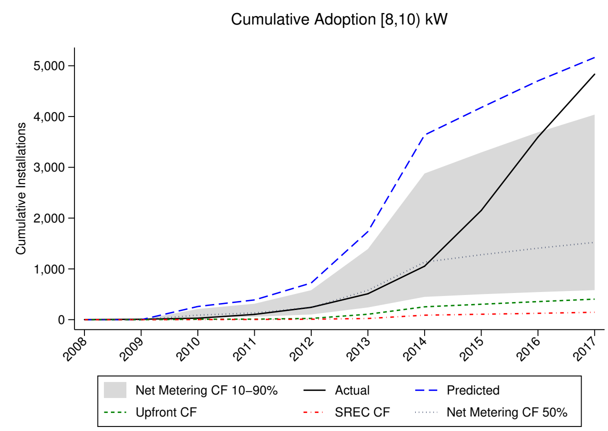
(b)



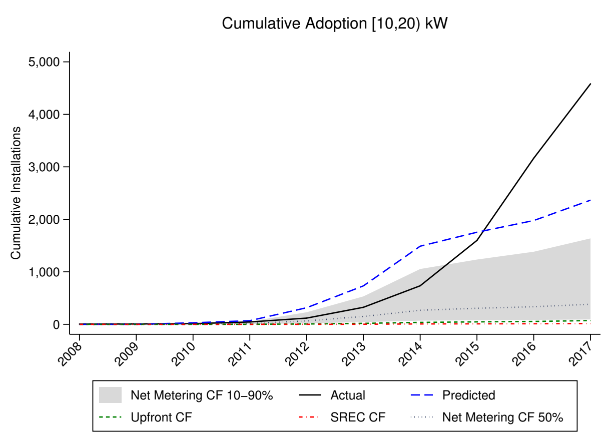
(c)



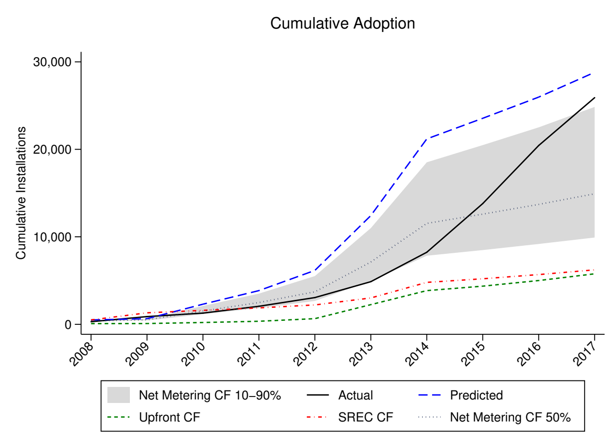
(d)



(e)

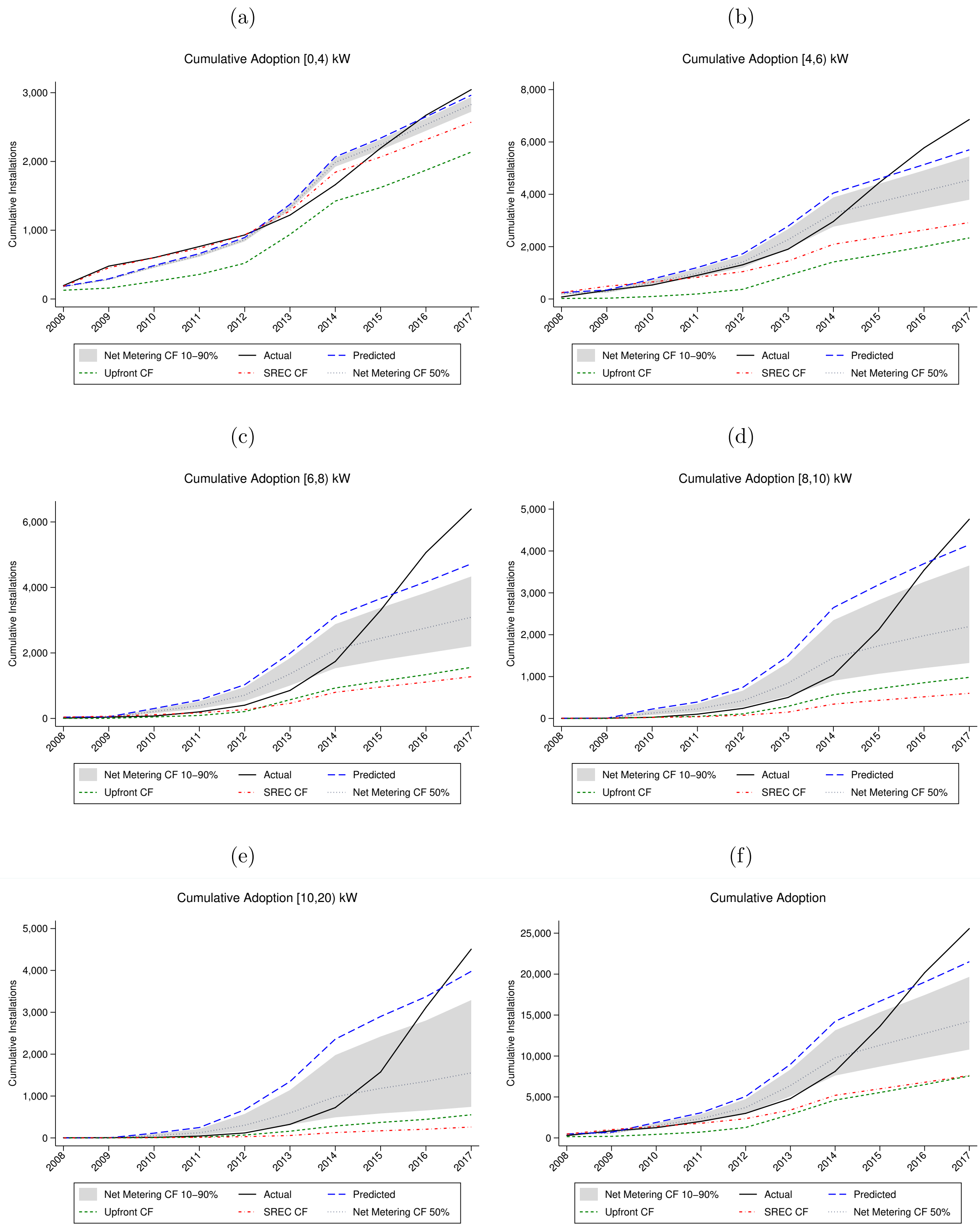


(f)



Notes: This figure shows actual, predicted, and counterfactual cumulative adoptions by system capacity based on the homogeneous demand model estimates.

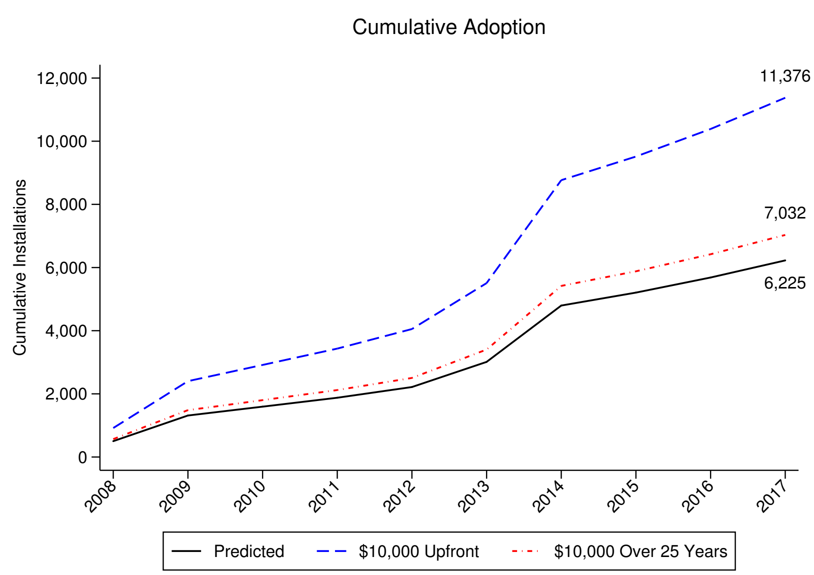
Figure 18. Heterogenous Demand: Actual, Predicted, and Counterfactual Cumulative Adoption by Capacity (return)



Notes: This figure shows actual, predicted, and counterfactual cumulative adoptions by system capacity based on the heterogenous demand model estimates.

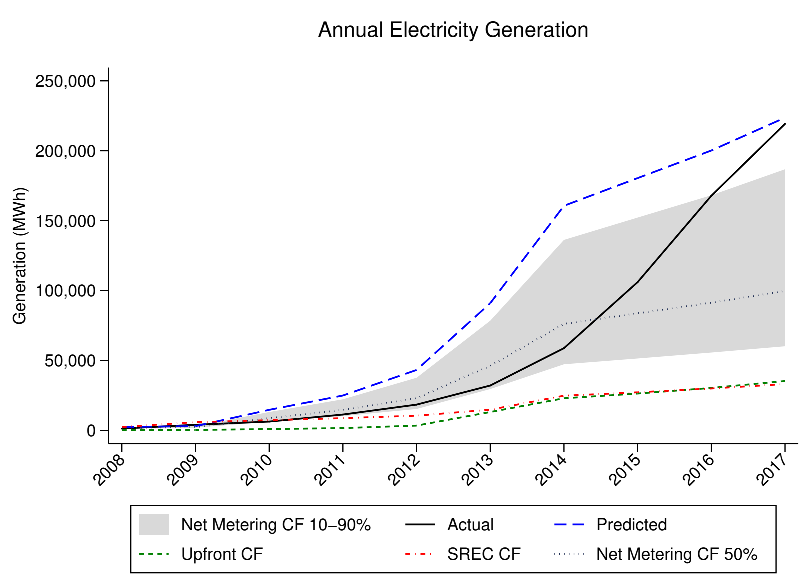
Figure 19. Upfront vs. Future Incentives Counterfactual (return)

(a)



Notes: This figure shows predicted cumulative adoptions in the case of no incentives compared with two counterfactual scenarios: (1) where households are given $10,000 in upfront incentives and (2) where households are given $10,000 in long-term incentives over a period of 25 years. This demonstrates the impact of discounting behavior on the efficacy of long-term incentives.

Figure 20. Actual, Predicted, and Counterfactual Annual Generation (return)



Notes: This figure shows actual, predicted, and counterfactual annual electricity generation based on my homogenous demand estimates.

C Third-Party Adoption

In this section, I extend my model of PV adoption to allow households' the option to adopt third-party owned PV systems. A concern with my main economic model is that it does not account for third-party owned PV systems, which may lead me to over predict host owned PV adoption using the model if households substitute away from host owned to third-party owned PV as this option becomes more widely available. As discussed in section 4, third-party ownership agreements or solar lease agreements whereby households' lease solar panels from companies such as SolarCity is an increasingly popular option during my sample period—eventually making up just under $\frac{2}{3}$ of all residential installations in Massachusetts (see Figure 6). However, without data on the terms of these agreements, I am unable to measure the effective prices that households face when they are choosing whether to enter into these contracts. In my main analysis, the choice to lease PV is subsumed into the outside option—waiting until a future period to adopt. Below, I include third-party ownership explicitly in the model.

I specify the model with household heterogeneity to allow for correlation between households' demographic characteristics and their alternatives. Without this flexibility, including third-party owned PV as another alternative in the model would result in substitution away from host owned PV and waiting to adopt directly proportional to their market shares due to the IIA property of logit.

At each time t, suppose that in addition to having the option to adopt a PV system $j = 1, ..., J$ now or wait until later to adopt $j = 0$, a household i now has the option to adopt a third-party owned system, denoted $j = \varnothing$. Household i's indirect utility from adopting $j = \varnothing$ at time t is given by,

$$u_{i\varnothing t} = \bar{u}_{\varnothing t} + \mu_{i\varnothing t} + \epsilon_{i\varnothing t},$$

Assuming that households located in the same municipality ℓ have similar demographic characteristics, let $u_{i\varnothing t}$ be the flow utility each household $i \in \ell$ obtains from adopting system $j = \varnothing$ in time t, where variation in preferences across municipalities depends upon certain demographic characteristics,

$$u_{i\varnothing t} = \underbrace{\beta_{\varnothing,t} + \xi_{\varnothing t}}_{\bar{u}_{\varnothing t}} + \underbrace{\lambda^I_{\varnothing} inc_\ell + \lambda^P_{\varnothing} pop_\ell + \lambda^V_{\varnothing} vote_\ell}_{\bar{\mu}_{\ell\varnothing t}} + \epsilon_{i\varnothing t},$$

Households' mean utility from third-party owned PV is modeled simply as a series of alternative-time specific constants $\beta_{\varnothing,t}$, which capture the evolution of households' preferences for third-party owned PV over time without any direct information about how the terms of solar lease agreements vary over time. The demographic interactions

$\lambda_{\varnothing}^{I}, \lambda_{\varnothing}^{P}$, and $\lambda_{\varnothing}^{V}$ allow households' preferences for third-party owned PV to vary across municipalities.

Including this alternative in my main model and estimating it using GMM, I report the results below in Table 25. Notice that the parameter estimates for host owned PV systems are very similar to those reported in table Table 17. The estimates of $\beta_{\varnothing,t}$ show the increasing popularity of third-party owned PV over time, and the demographic interactions show that solar leasing is negatively correlated with income, population density, and democratic vote share, which are intuitive results when compared relative to the demographic parameters interacted with host owned systems.

Given that the model appears to be picking up some substitution to third-party owned PV in the way one would expect, I compare the predictions of this model to the predictions of my main heterogenous demand model. In Figure 21, I plot predicted cumulative installations over time using both models and find that the model including the third-party option predicts only slightly less host owned PV adoption—this implies that the augmented model predicts more substitution from the outside option to third-party owned PV than from host owned to third-party owned PV, which makes the exclusion of third-party agreements from the main model less of a concern.

Figure 21. Third-Party Model Fit: Actual and Predicted Cumulative Adoption (return)

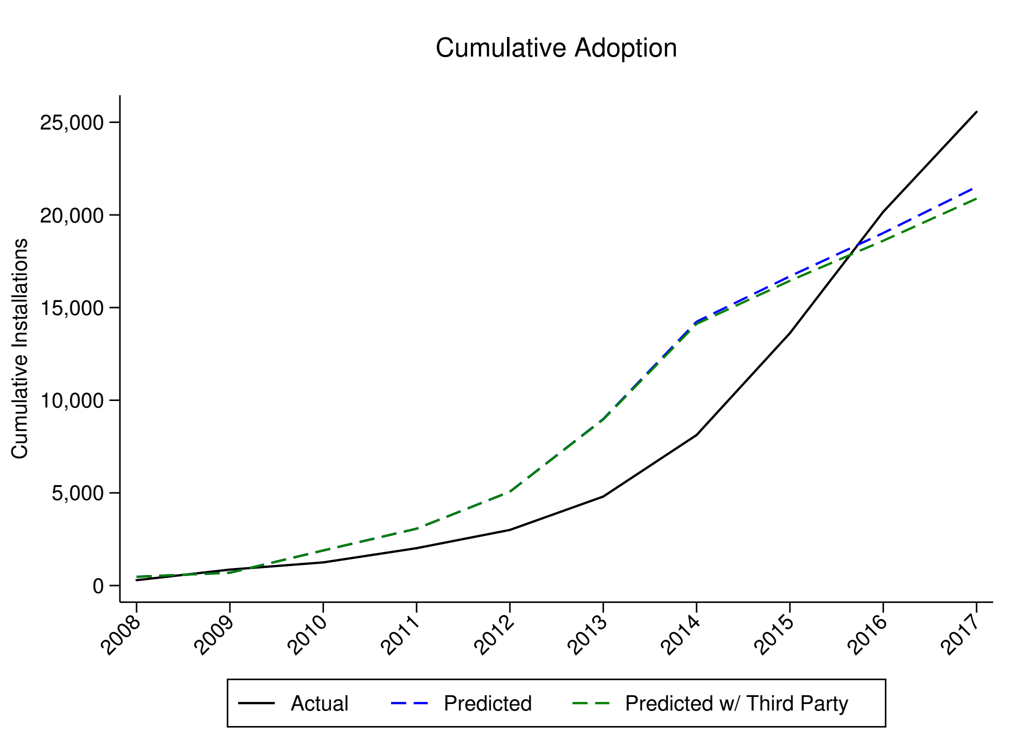


Table 25. Heterogenous Demand Estimates with Third-Party Option (return)

	GMM, $\delta = 0.8$		Normalized Estimates	
Parameters	Estimates	Standard Errors	Parameters	Estimates
Mean Utility				
α: Net Present Installation Cost (000)	-0.1791	(0.0259)	α	-0.1791
$\tilde{\beta}_2$: Capacity [4,6) kW	1.7020	(2.1508)	β_1	-12.9420
$\tilde{\beta}_3$: Capacity [6,8) kW	2.1988	(2.6341)	β_2	-11.2400
$\tilde{\beta}_4$: Capacity [8,10) kW	2.6443	(3.0190)	β_3	-10.7431
$\tilde{\beta}_5$: Capacity [10,20) kW	2.5504	(3.1469)	β_4	-10.2977
$\tilde{\beta}_0$: Constant	-2.5884	(3.0174)	β_5	-10.3916
$\tilde{\beta}_{\varnothing,1}$: Third-Party, 2008	-4.0226	(2.4808)	$\beta_{\varnothing,1}$	-14.3762
$\tilde{\beta}_{\varnothing,2}$: Third-Party, 2009	2.3650	(3.6695)	$\beta_{\varnothing,2}$	-7.9886
$\tilde{\beta}_{\varnothing,3}$: Third-Party, 2010	3.8752	(3.6097)	$\beta_{\varnothing,3}$	-6.4784
$\tilde{\beta}_{\varnothing,4}$: Third-Party, 2011	4.7349	(3.6573)	$\beta_{\varnothing,4}$	-5.6187
$\tilde{\beta}_{\varnothing,5}$: Third-Party, 2012	6.3850	(3.5841)	$\beta_{\varnothing,5}$	-3.9686
$\tilde{\beta}_{\varnothing,6}$: Third-Party, 2013	5.9807	(3.6605)	$\beta_{\varnothing,6}$	-4.3729
$\tilde{\beta}_{\varnothing,7}$: Third-Party, 2014	6.0992	(3.6312)	$\beta_{\varnothing,7}$	-4.2544
$\tilde{\beta}_{\varnothing,8}$: Third-Party, 2015	7.5486	(3.6738)	$\beta_{\varnothing,8}$	-2.8049
$\tilde{\beta}_{\varnothing,9}$: Third-Party, 2016	7.8323	(3.7131)	$\beta_{\varnothing,9}$	-2.5213
$\tilde{\beta}_{\varnothing,10}$: Third-Party, 2017	7.3857	(3.6183)	$\beta_{\varnothing,10}$	-2.9679
Income × Capacity				
$\tilde{\lambda}_1^I$	0.0011	(0.0030)	λ_1^I	0.0056
$\tilde{\lambda}_2^I$	0.0029	(0.0020)	λ_2^I	0.0074
$\tilde{\lambda}_3^I$	0.0035	(0.0017)	λ_3^I	0.0079
$\tilde{\lambda}_4^I$	0.0049	(0.0014)	λ_4^I	0.0094
$\tilde{\lambda}_5^I$	0.0074	(0.0012)	λ_5^I	0.0119
$\tilde{\lambda}_\varnothing^I$	-0.0118	(0.0044)	$\lambda_\varnothing^I$	-0.0074
Population Density × Capacity				
$\tilde{\lambda}_1^P$	-0.0237	(0.0439)	λ_1^P	-0.1185
$\tilde{\lambda}_2^P$	-0.0275	(0.0364)	λ_2^P	-0.1223
$\tilde{\lambda}_3^P$	-0.0742	(0.0336)	λ_3^P	-0.1690
$\tilde{\lambda}_4^P$	-0.1460	(0.0329)	λ_4^P	-0.2408
$\tilde{\lambda}_5^P$	-0.2321	(0.0310)	λ_5^P	-0.3268
$\tilde{\lambda}_\varnothing^P$	0.0438	(0.0299)	$\lambda_\varnothing^P$	-0.0510
Democratic Vote Share × Capacity				
$\tilde{\lambda}_1^V$	0.0118	(0.0464)	λ_1^V	0.0588
$\tilde{\lambda}_2^V$	-0.0077	(0.0343)	λ_2^V	0.0394
$\tilde{\lambda}_3^V$	-0.0168	(0.0294)	λ_3^V	0.0303
$\tilde{\lambda}_4^V$	-0.0273	(0.0263)	λ_4^V	0.0197
$\tilde{\lambda}_5^V$	-0.0274	(0.0245)	λ_5^V	0.0197
$\tilde{\lambda}_\varnothing^V$	-0.0615	(0.0240)	$\lambda_\varnothing^V$	-0.0145
Objective Value	0.0000			
R^2	0.6910			
Municipalities	345			
Markets	4			
Years	10			
Market Moments	240			
Municipal Moments	20,700			

Notes: The number of market-level moments is 240 = 6 choices × 4 utility markets × 10 years (2008–2017). The number of municipal-level moments is 20,700 = 345 municipalities × 6 choices × 10 years (2008–2017). Heteroskedasticity-consistent standard errors are displayed in parentheses. Households' discount factor is set to 0.8 rather than estimated. Average upfront installation cost across other markets is used as an instrument for prices, and one period ahead SREC prices are used as an instrument for the discount factor. Note that the net present installation cost (price) is a function of δ in the model. The normalized estimates report the capacity-specific constants, $\beta_1, ..., \beta_5$, and capacity-specific demographic interactions, $\lambda_1, ..., \lambda_5$, in households' indirect utility function, which can be separately identified by a transformation of the original estimates.

D 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

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

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

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

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

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

$$-g_{jt}\begin{bmatrix}p^{sc}_{jt} & p^{sc}_{jt+1} & p^{sc}_{jt+2} & \cdots & p^{sc}_{jt+24}\end{bmatrix}\begin{bmatrix}0\\ (1-d)\\ 2\delta(1-d)^2\\ \vdots\\ 24\delta^{23}(1-d)^{24}\end{bmatrix}$$

- White's Estimator of Asymptotic Variance

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

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

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

E NLIV/GMM Estimation

- Objective Function

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

- White's Estimator of Asymptotic Variance

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

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

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