Consumer Preferences and Policy Implications for Renewable Energy Adoption

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Abstract

In the first chapter of this dissertation, I study the relative advantages of investment (upfront) and output (production-based) subsidies for rooftop solar Photovoltaic (PV) adoption. While investment subsidies can be cost-effective due to adopters' inter-temporal discounting (impatience), output subsidies are better targeted to site quality. Using data from the California Solar Initiative, I estimate a dynamic discrete choice model of solar adoption, then simulate counterfactual subsidy policies to find an optimal balance of investment and output subsidy rates. The model estimates adopters' discounting factor and distribution of tastes, and hinges critically on the observed distribution of site quality as data. Considerable variation in personal taste (taste to be green) implies that the output subsidy can play a helpful role in incentivizing otherwise hesitant property owners with high production potential, while not overpaying eager adopters with lower potential.

The intertemporal discount factor, reflecting consumers' impatience, is a critical element in many models of consumer demand behavior. However, the discount factor must usually be calibrated (assumed) rather than estimated, and if calibrated incorrectly, may yield serious miscalculations in empirical results and policy implications. Therefore, in the second chapter of this dissertation, I estimate distinct values of

the discount factor for commercial and residential adopters of solar. In showing that commercial adopters are only about one third as impatient as residential adopters, this paper offers useful context for researchers seeking to make informed calibrations of the discount factor in related settings. In the setting of rooftop PV solar adoption, the difference in discount factors implies that the most cost-effective combination of investment and output subsidies involves relatively higher output subsidy rates for commercial properties, and relatively higher investment subsidy rates for residential properties.

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1 Optimizing investment Vs. Output Subsidies for Solar: Site Quality Vs. Personal Taste

1.1 Introduction

In order to reduce carbon emissions, governments around the world have instituted subsidies to encourage the adoption of renewable energy technologies. In this paper I examine the case of rooftop solar photovoltaic (PV) technology, with the goal of determining a government's most cost-effective allocation of budget between investment (upfront) and output (production-based) subsidies. The basic trade-off that the government faces is the following. On the one hand, investment subsidies are generally cost-effective due to the government's ability to borrow at minimal interest rates, and private entities' relatively more risk-averse or myopic dispositions.[1] On the other hand, investment subsidies may be poorly targeted to site quality [2]. Particularly, there are cases in which the investment subsidy offers more than necessary to adopters with low site quality, but high personal taste for solar (such as the desire to be green),[3] and less than necessary (to incentivize adoption) to potential adopters with high site quality, but low personal taste. Personal taste is especially relevant to the context of rooftop solar because the adopted technology is to be visibly present on property owners' homes - or on properties whose primary function is something other than electricity production.[4]

This paper explores the trade-off between investment and output subsidies for solar, with a special focus on the role played by the geographical distribution of personal taste for solar and its correlation with site quality. I develop a dynamic

[1]See De Groote and Verboven (2019).
[2]See Sexton et al. (2021), Talevi (2022).
[3]The situation in which the agent would adopt solar even without receiving a subsidy, known as "non-additionality," is a major concern with regard to reducing subsidy costs.
[4]If commercial adopters (firms) are less risk-averse or myopic than residential adopters (households) are, then the most cost-effective balance for firms may lean relatively more towards output subsidies because firms are relatively less enticed by upfront certainty.

discrete choice model of rooftop solar adoption, and an accompanying model of the government's policy objectives, to show how a few factors determine the relative cost-effectiveness of the investment and output subsidies. These key factors include potential adopters' discount factor (impatience), the correlation between taste and site quality, and how well the investment subsidy is targeted to site quality.

I estimate the model using detailed data on the rooftop solar market in California. Rich variation over time in the incentive rates offered by the California Solar Initiative for each subsidy type enable me to identify the key parameters of adopters' demand system. An estimated discount factor of 0.83, indicating that potential adopters of solar are highly impatient, strengthens the relative cost-effectiveness of the investment subsidy. At the same time, a negative correlation (-0.28) between taste and site quality in California strengthens the cost-effectiveness of the output subsidy. This negative correlation stems from the geographical divergence in California between the sun and populations most friendly to solar: while the sunniest areas to be inland, the higher educated and more politically left leaning populations tend to cluster along the coast. To weigh these countervailing factors against one another, I simulate counterfactual subsidy rates, seeking the most cost-effective[5] combination of investment and output subsidy rates. Each simulation computes the total distribution of rooftop solar adoption, electricity production and subsidy expenditure that would occur under each hypothetical combination of subsidy rates, and hence gauges the cost-effectiveness of each according to the model of the government's policy objectives.

I combine two major data sources to yield a comprehensive view of the rooftop solar market in California. First, the California Solar Initiative (CSI) program provides detailed information on each solar PV adoption that occurred from 2007-2014. This

[5]Cost-effectiveness may viewed either as maximizing production with a fixed subsidy budget, or as minimizing subsidy expenditure for a fixed production target. I build a model of the government's policy objectives in which the government has a willingness-to-pay parameter analogous to the social cost of carbon. This policy model nests both version of cost-effectiveness (production maximization and cost minimization), and also enables comparisons across a greater variety of outcomes. I evaluate outcomes according to this policy model, and also by cost minimization with assumed fixed production targets.

includes physical characteristics of each system adopted, the system installation price, and subsidy type and amount paid to each, amongst other details.[6] Second, because the CSI database includes only properties whose owners chose to adopt solar, I employ a powerful dataset from Google Project Sunroof[7] to get a sense of how non-adopters' production potential distribution differed from the adopters' distribution.

In the dynamic discrete choice model of rooftop solar adoption developed in this paper, individual potential adopters weigh their expected net financial benefit of adopting solar on the one hand, against their own personal taste for solar on the other. The net financial benefit is equal to the subsidy amount plus expected electricity cost savings, less the system installation price. If the net financial benefit is negative, then an individual needs an equally strong or stronger positive taste for solar (such as desire to be green) in order to adopt. And if the net financial benefit is positive, then the individual (excluding those waiting to adopt in a future time period) needs an equally strong negative taste in order to *not* adopt.

A changing structure of the net financial benefits over time gives rise to the dynamic aspect of the model. While the subsidy rates under the CSI program were declining in ten steps over time by design, system prices were also falling over time as a function technological change. As such, each potential adopter in the model may choose to adopt (with either of the two subsidy types) in any given time period, but must also consider the option value of waiting and potentially adopting in a future time period. On balance net financial benefits were typically increasing over time, as declining system installation prices outweighed the CSI program's declining subsidy rate steps.

The dynamic discrete choice model of rooftop solar adoption and accompanying model of the government's policy objectives show how two crucial mechanisms influ-

[6]Under the CSI program, each individual was given a choice between an investment and output subsidy. The investment subsidy (if chosen) was provided upfront, in an amount based on California's ex-ante approximation the system's lifetime expected solar production. The output subsidy was paid out on a rolling basis as a function of actual monthly production.

[7]Source: Google Project Sunroof data as of January 2023

ence the relative cost-effectiveness of the investment and output subsidies. First, if the intertemporal discounting factor is lower (individuals are more impatient), then the output subsidy becomes less attractive to potential adopters in utility terms, and therefore relatively less cost-effective as a subsidy. But second, as long as there is any variation in the distribution of site quality that is independent of the distribution of personal taste, then the output subsidy has at least some advantage over the investment subsidy in its ability to compensate potential adopters for their true site quality. A negative correlation between site quality and personal taste will bolster this relative advantage of the output subsidy, as higher quality sites will be less inclined to adopt in the absence of the better targeted subsidy. As such, the most cost-effective combination of investment and output subsidy rates is very much an empirical question.

The empirical results indicate that there are strong forces on both sides of the trade-off (between the investment and output subsidies). In agreement with many related studies, I find that residential rooftop solar adopters do discount the future heavily.[8] My estimated implicit annual discount factor at 0.83 is towards the lower end but very much within the range of comparable estimates.[9] It is well understood that a discount factor far below 1, implying that potential adopters are impatient with regards to benefits that will accrue in the future, strengthens the cost-effectiveness of the investment subsidy relative to that of the output subsidy. I add to this, however, both by showing the countervailing role of the correlation between taste and site quality in theory, and empirically in showing that this correlation is negative in the case of California at -0.28, implying a significant role for the output subsidy as well. This stems from the geographical divergence in California between sunlight intensity and populations most friendly to solar: while the sunniest areas to be inland, the higher educated and more politically left leaning populations tend to cluster along

[8]See Burr (2016), De Groote and Verboven (2019), Snashall-Woodhams (2019).

[9]De Groote and Verboven (2019) estimate a discount factor of 0.85 for residential consumers of solar PV in Flanders, Belgium. Snashall-Woodhams (2019) estimate a discount factor of 0.83 for residential consumers in CA, USA.

the coast.

To weigh the relative advantages of the investment and output subsidies against one another, I conduct counterfactual simulations that compute outcomes over a range of alternative subsidy rate policies.[10] The first set of counterfactuals takes the model estimation results as given, including the annual discounting factor of 0.83 and correlation between taste and site quality of -0.28. By passing counterfactual subsidy rates through the model with these parameter values, I find a cost-effective combination of investment and output subsidy rates for the actual setting of California. I then conduct a second set of counterfactual simulations that are meant to reach beyond the setting of California. That is, I repeat the first set of simulations, but with altered values of the key model parameter values, shedding further light on the role played by each parameter in influencing the cost-effectiveness of either subsidy.

The first set of counterfactual results show that the most cost-effective combination of rates for the setting of California is near to the rates actually offered by the CSI program, but with a roughly 20% higher investment rate and 30% lower output rate. Given the balance of the relative advantages between the investment and output subsidies as they manifest in California, it is cost-effective to rely mainly on the investment subsidy - as the CSI program did - offering a high enough investment rate that the vast majority of adopters opt for it. Yet, it is nonetheless helpful - as the CSI program also did - to offer a mild yet nonzero output subsidy that succeeds in incentivizing a small group of very high quality potential adopters who would not adopt otherwise.

Additional counterfactuals go beyond the setting of California by altering key parameter values, and examining how the cost-effective combination of investment and output subsidy rates shifts in response. First I increase the intertemporal discounting factor, representing a setting in which potential adopters are less impatient.

[10] The purpose of each simulation is to compute the distribution of rooftop solar adoption decisions, electricity production and subsidy expenditure that would occur under each hypothetical combination of subsidy rates, and hence to gauge the cost-effectiveness of each subsidy.

This increases the utility value of the output subsidy to potential adopters, yielding a higher cost-effective output subsidy rate. Because lower impatience increases the utility value of electricity cost savings as well, total adoption levels are considerably higher in this setting.

Finally, I alter what may be the most important factor of all. The CSI program's investment subsidy is superior to a conceptually pure, flat investment subsidy, in that it is adjusted for the state's ex-ante approximation of site quality (the CSI Rating). I examine the significance of this by replacing the CSI investment subsidy with a flat investment subsidy, representing a setting in which the government is completely unable to measure site quality ex-ante.[11] In this case the cost-effective output subsidy rate increases, as the output subsidy's advantage in targeting to site quality becomes more important. However, the total program cost needed to incentivize the same level of adoption and solar electricity production as in the CSI program increases considerably, as the investment subsidy no longer has the ability to incentivize higher quality sites to adopt in a cost-effective way.

Most closely related to this paper are several others that have evaluated cost-effective subsidy design for rooftop solar. My results concur with De Groote and Verboven (2019), Snashall-Woodhams (2019) and Talevi (2022) in finding that because potential adopters of rooftop solar discount the future heavily, an investment subsidy that is well-targeted to site quality is generally the most cost-effective option. I add to this however in showing that it may nonetheless yield mild gains to cost-effectiveness to offer an output subsidy option alongside the investment subsidy option, especially in settings such as California in which there is a negative correlation between site quality and personal taste. Langer and Lemoine (2022) study efficient subsidy design for rooftop solar with a focus on how the subsidy rate should be increased or decreased over time - an aspect of the subsidy design that I do not dissect in this paper.

[11]More abstractly, this can be thought of as decreasing the correlation between the CSI Rating (or the state's ex-ante approximation of site quality) and true site quality to zero.

The remainder of this paper is organized as follows. Section 1.2 covers the relevant industrial background, especially the most important details of the California Solar Initiative (CSI) subsidy program. Section 1.3 describes my data sources, including the CSI database and Google Project Sunroof, and the key variables contained in each. Section 1.4 presents some reduced-form evidence to motivate the central ideas in my model. Section 1.5, the longest section of the paper, defines and explains my dynamic discrete choice model of rooftop solar adoption behavior, and also my model of the government's policy objectives. This includes multiple simplified examples meant to help highlight key mechanisms that drive the relative cost-effectiveness of the investment and output subsidies. Section 1.6 estimates the model using the data described in Section 1.3, then presents counterfactual simulation results with hypothetical subsidy policies, and finally also with altered key parameter values. Section 1.7 concludes.

1.2 Industry Background

Subsidy programs for solar adoption in the US have been generous, both at the federal and state levels. In addition, the costs of solar Photovoltaic (PV)[12] systems have reduced substantially in recent decades. Preferential financing and leasing options are also common. Despite all of these benefits, solar adoption rates remain lower than most policy makers would like, as households and firms still face large upfront costs, and uncertain future benefits. Subsidies fall into two broad categories: upfront (investment) subsidies awarded at the time of adoption, and production-based (output) subsidies awarded on a rolling basis post-adoption.

I examine solar PV adoption behavior under the California Solar Initiative (CSI), a multi-billion-dollar program designed to incentivize solar adoption in CA. The CSI program was distinctive in two ways that make it a rich setting for analyzing adopters' demand behavior. First, CSI offered potential adopters a choice between either an

[12]PV systems are the most ubiquitous solar power harvesting technology.

investment subsidy or an output subsidy, with investment and output subsidy rates set as a function of region and time of adoption.[13] Second, the investment and output subsidy rates offered by the CSI program each declined in ten steps over time, providing rich exogenous price variation that can identify the parameters of adopters' demand model.

Taking effect in Jan 2007, the CSI program offered solar adopters a choice between an investment subsidy, called the Expected Performance-Based Buydown (EPBB), and an output subsidy called the Performance-Based Incentive (PBI). Both subsidies were designed to reward higher-producing adopters and their chosen systems: However, whereas the EPBB is a one-time, upfront payment based on a system's ex-ante expected performance; PBI payments are paid according to the system's actual performance, measured and paid out over the course of the five years following adoption. As such, although both subsidies offer more to properties with higher expected production, the output subsidy (PBI) is better-targeted in this goal, in so far as there is any error in the state's ex-ante estimate of expected production which informs the investment (EPBB) subsidy.

The CSI program's subsidy options were available to all customers of California's three major Investor-Owned Utilities (IOUs) from 2007-2014, but with subsidy rates that declined over time.[14] Particularly, 10 rate steps for each of the two subsidies were announced at the onset of the program: The highest rates were to be offered first - so that the earliest adopters would receive the largest subsidies - and the rates would decline monotonically thereafter. However, the timing of each rate change was not entirely predictable, but based on the aggregate amount of solar adoption achieved in each IOU region. As such, the rates changed at different times for each IOU, triggered

[13]Regardless of which CSI subsidy option is chosen, the adopter could also claim the federal Investment Tax Credit (ITC), a tax credit valued at 30% of the system installation price.

[14]Dollar amounts of subsidies are equal to the rates multiplied by production or expected production. In the case of the output subsidy (PBI), the rate (locked in at the time of adoption) is multiplied by actual solar electricity production measured on a rolling basis over the course of five years. In the case of the investment subsidy (EPBB), the rate is multiplied by the CSI Rating, which serves as the state's ex-ante estimate of an adopted system's lifetime expected production.

when each of the predetermined total adoption targets were achieved in each. Figure 17 plots the 10 EPBB subsidy rate steps ($/Watt) in red (right vertical axis),[15] and the corresponding cumulative solar capacity installed in blue (left vertical axis).

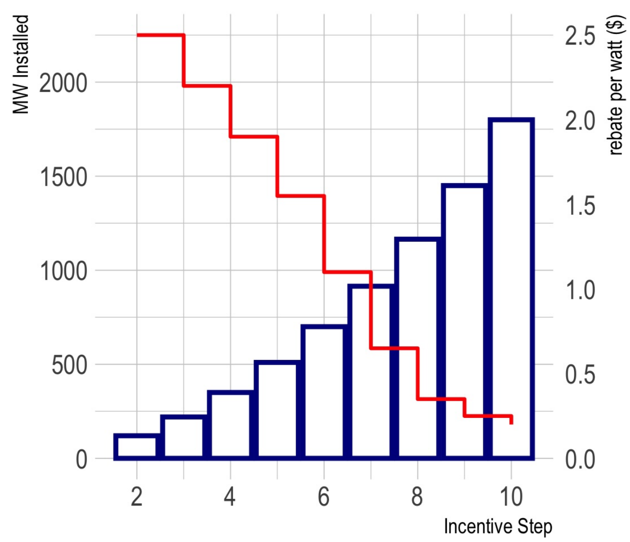


Figure 1: EPBB Subsidy Variation Over Time

A graph with the PBI rates in place of the EPBB rates in Figure 17 would look similar, as the former also decline in ten steps (from $0.39/KWh to $0.02/KWh).[16] More importantly with regards to analyzing adoption choices, Figure 18 displays how each of the subsidy rates evolved over time in each of the IOUs.

[15]The full schedule of rates can be found in Table 2.5 in Appendix.
[16]See Table 2.5 in Appendix.

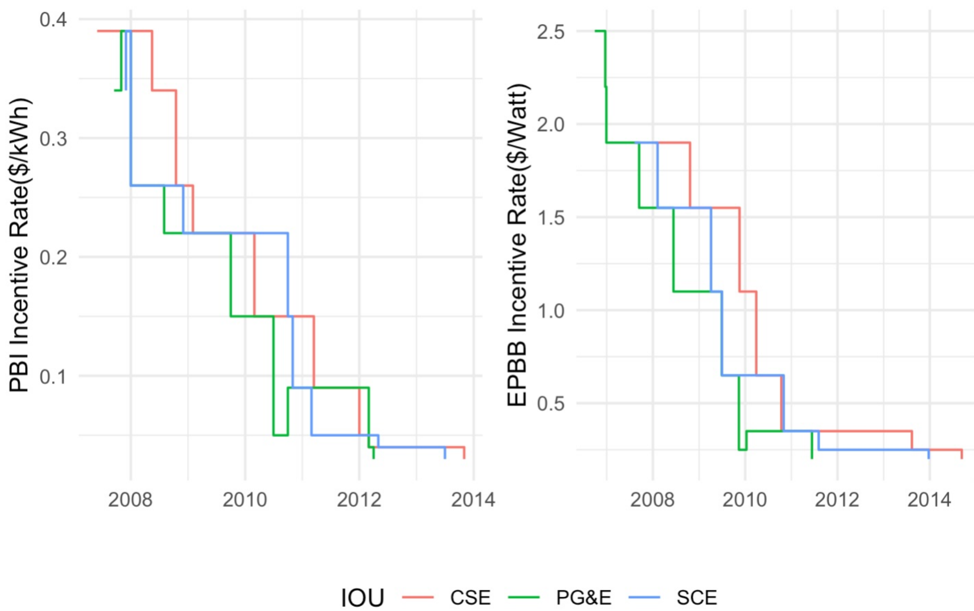


Figure 2: Cross-sectional Subsidy Variation

Because each of IOUs reached their aggregate capacity targets at different times, there is cross-sectional as well as time-series variation, that is, with rates differing across IOUs in any given time period. These sharp changes provide very useful price variation for evaluating adoption behavior.

That the subsidy rates were highest in the earliest years of the program begs the question as to why many adopters would wait until later periods to adopt. A countervailing factor, however, is that the prices of solar panels declined considerably over the same time span, implying potential profit for many adopters in waiting, despite the loss of subsidy. Furthermore, considerable idiosyncratic error must be at play in the context of rooftop solar, as many property owners may be unaware or insufficiently sold on the prospect of adopting solar in any given time period, regardless of pure financial primitives.

1.3 Data

This paper examines the effects of subsidies on property owners' choices of whether to adopt rooftop solar. The needed data must therefore include information on property owners' adoption decisions and the subsidies they were offered, as well as any property characteristics likely to influence adoption decisions alongside the subsidy offerings. The CSI database contains rich information on all of the above, so forms the backbone of my dataset for this paper. A limitation of the CSI database however is that it contains no information on properties whose owners refrained from adopting solar, which presumably are different on average than the included properties whose owners all did adopt. I therefore turn to Google Project Sunroof as second major data source. Relative to the CSI database, Google Project Sunroof contains less information per included property, but includes a much broader set of properties, particularly non-adopters of solar as well as adopters.

1.3.1 CSI Database

As a subsidizer, the CSI program collected detailed information on each property i to which it issued a subsidy. These include most importantly the investment subsidy rate $r^{\mathrm{u}}_{i,t}$ and the amount of the investment subsidy,

$$r^{\mathrm{u}}_{i,t} \cdot c_{i,t} \tag{1}$$

that was paid to each adopter who opted to receive the investment subsidy; the output subsidy rate $r^{\mathrm{q}}_{i,t}$ and the total amount of output subsidy,

$$r^{\mathrm{q}}_{i,t} \cdot \sum_{\tau=0}^{\text{5 years}} q_{i,t+\tau} \tag{2}$$

that was paid out over time to each adopter who opted to receive the output subsidy; and actual monthly solar electricity production $q_{i,t+\tau}$ for each output subsidy recipient. The CSI Rating $c_{i,t}$, which serves as the state's ex-ante estimate of expected production, is present in the data for both investment and output subsidy recipients (although actual production $q_{i,t+\tau}$ is present only for output subsidy recipients). Included also are the total installation price $p^{\mathrm{I}}_{i,t}$ of each system, and several component factor determinants of the CSI Rating, including system size s_i and number of inverters, roof tilt and azimuth, module characteristics, and the recipient's county and zip code.

In order to evaluate property owners' choices, it is necessary to quantify the options that each forwent, alongside the options that each chose. As such, a minor limitation of the CSI data is that it contains investment subsidy amounts only for investment subsidy recipients, and output subsidy amounts only for output subsidy recipients: It is necessary to quantify also the output subsidy amount that each investment subsidy recipient forwent, and the investment subsidy amount that each output subsidy recipient forwent. This can be remedied however, because of the known constitution of each subsidy as given in (33) and (34). As discussed in Section 1.2, the subsidy rates $r^{\mathrm{u}}_{i,t}$ and $r^{\mathrm{q}}_{i,t}$ do not vary per every individual property i, but rather per each i's utility provider (IOU), per time period t. I therefore recover the forgone output subsidy rates $r^{\mathrm{q}}_{z,t}$ for investment subsidy recipients, and the forgone investment subsidy rates $r^{\mathrm{u}}_{z,t}$ for output subsidy recipients, as a function of the county z in which each resides.[17]

The CSI database has two major limitations. First, although it has the CSI Rating c_i - that's is the state's ex-ante estimate of expected solar electricity production per property i - for both investment and output subsidy recipients, the CSI database has actual production $q_{i,t+\tau}$ only for output subsidy recipients. This in itself is not as severe a limitation as it may sound however, because property owners' choices in any case must hinge on (their own) ex-ante expected production, rather than on actual production per se. To arrive at a proxy y_i for property owners' ex-ante estimate of their own expected production (distinct from the state's estimate c_i of the same), I will fit actual production q_i as a nonlinear function of c_i and sunlight intensity ℓ_i, with slopes and intercepts varying by location z. Because the left hand side variable for

[17]Future period subsidy rates $r^{\mathrm{u}}_{i,t+\tau}$ and $r^{\mathrm{q}}_{i,t+\tau}$ likewise are not directly observed per individual i, yet recoverable given i's county of residence.

this function exists only for output subsidy recipients, this approach of course hinges on the assumption that the functional relationship between $y_i = \hat{q}_i$ and (c_i, l_i, z) for output subsidy recipients accurately reflects the same relationship for the broader population of properties. That is, given the function fit $y_i = \hat{q}_i$ from output subsidy recipients q_i data, I can impute y_i for investment subsidy recipients as well given their predictive data (c_i, l_i, z).

Second and most importantly, the CSI database contains no data at all on properties whose owners elected not to adopt solar. Because part of my goal is to make projections of adoption behavior under altered (counterfactual) subsidy policies and scenarios, it is necessary to model the distribution of properties whose owners in fact did not adopt, but might switch to adopting in the counterfactual. The distribution of non-adopters properties' could be assumed equal (in site quality measures c_i, y_i) to the distribution of adopters' properties. However this would be implausible in that higher quality sites must be more likely to have adopted. In order to approximate how adopters' site quality distribution differed from that of the broader population of properties, I therefore turn to Google Project Sunroof, which contains its own measures of rooftop solar production potential, for 80-90% of all rooftops in California.

1.3.2 Google Project Sunroof

Although the CSI database contains most of the key information needed for this study, it lacks one essential feature, that is the ability to compare the observed distribution of solar adopters to the broader distribution of potential adopters. Because higher quality sites stand to receive both higher subsidy amounts and greater electricity cost savings in the event of adopting solar, they must be more likely to adopt than lower quality sites are. Because the CSI database contains information only on adopters and none on non-adopters, any differences between these groups are completely unobservable. This is important particularly for counterfactual analysis. Although it may (arguably) be reasonable to estimate a model of adoption choice behavior using data on adopters alone, any counterfactual analysis must explicitly consider whether properties whose owners did not adopt would switch to adopting in the counterfactual.

Google Project Sunroof[18] contains its own measures of rooftop solar energy production potential, and unlike the CSI database covers (and identifies) non-adopters as well as adopters. I harness this data to obtain rough measurements of how the site quality distribution of adopters in California differs from the broader underlying distribution of potential adopters. I use these measurements to adjust the observed distribution of adopters from the CSI database, arriving at an imputed distribution which I take to represent the full spectrum of potential adopters for the purpose of my model estimation and counterfactuals. Because the CSI database and Google Project Sunroof do not contain exactly the same measures of site quality in common, this adjustment cannot be rigorous. However, it is an improvement over the most natural alternative, which would be to assume the distributions of adopters and non-adopters are either exactly the same, or differing by a calibrated (guessed) factor.

Project Sunroof uses aerial imagery and 3D modeling to derive estimates of maximum rooftop solar potential for each individual building, covering roughly 85% of all properties in California. The inputs to Google's maximum solar potential model include the roof space area (sq ft) suitable for installing solar panels, projections of shading on each point on the roof for each position of the sun in the sky, the compass orientation and vertical angle of each roof plane, and local weather data. Project Sunroof's web interface accommodates the entry of any individual address, as shown in Figure 19, returning various estimates related to the property's rooftop solar potential. I use an anonymized dataset of roughly 9 million such addresses, shared through a Data User Agreement.

[18]Source: Google Project Sunroof data as of January 2023

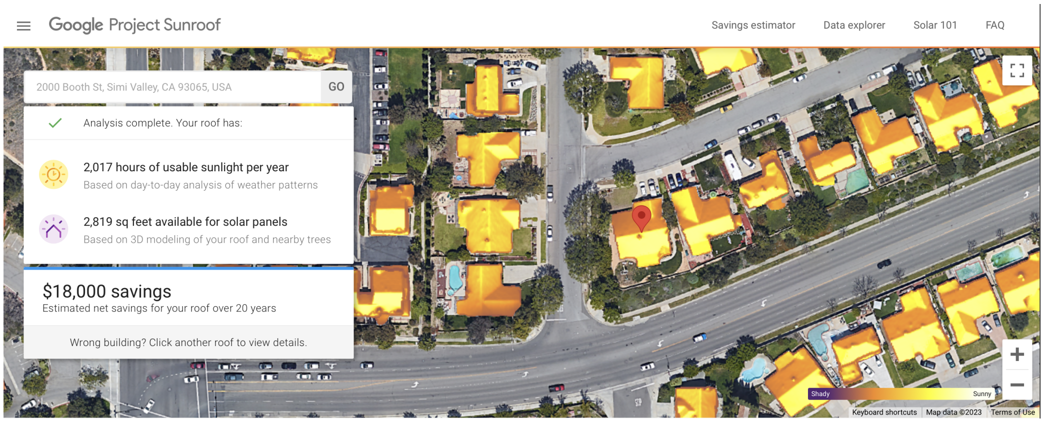


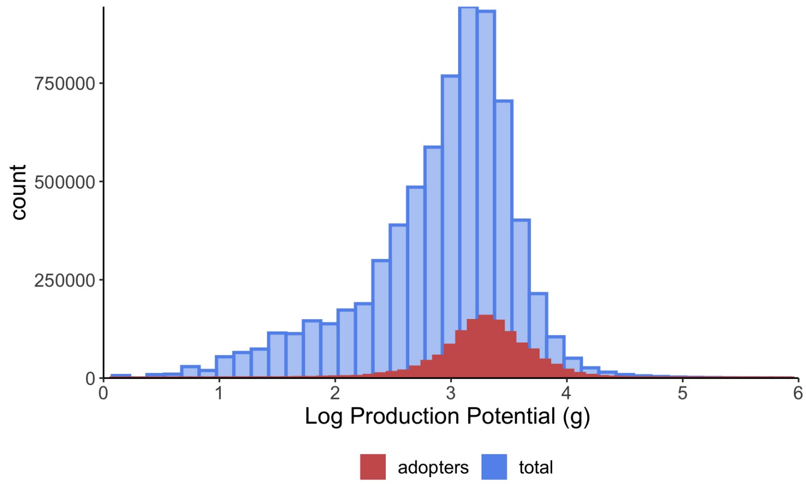
Figure 3: An Individual Property in Google Project Sunroof's Web Interface.

Because I use the Project Sunroof data to approximate how the distribution of rooftop solar adopters differs from the broader distribution of potential adopters, it is necessary to distinguish in some way between adopters and non-adopters within the Project Sunroof data itself. Fortunately, Project Sunroof's aerial imagery does identify properties with solar systems currently installed, enabling me to compare the distributions of adopters and non-adopters directly.[19] Figure 4 overlays the distribution of maximum solar potential for (residential)[20] adopters of solar (red) on the distribution of the same for the whole (residential) population of potential adopters (blue), with the height of each distribution reflecting total count.

[19]Because it is not known at what time each property in Project Sunroof with solar had its system installed, it is possible that adopters during the time of the California Solar Initiative program (2008-2014) have a different site quality distribution than that of the full set of adopters identified in Project Sunroof. However my interest for this data is with the (presumably) much larger distinction between adopters and non-adopters, not the presumably minor distinction between adopters during and after CSI.

[20]Although the Project Sunroof data identifies which properties have adopted solar, it does not identify which properties are residential. This is important because the distribution of commercial properties has a heavy right tail, that is of very large commercial properties with vast roof space. I isolate residential properties in the Project Sunroof data via a computationally intensive spatial matching with California Assessor data, described in the upcoming Section 2.3.3.

Figure 4: Google Project Sunroof Distribution of Maximum Production Potential (g_i) for Residential Properties in California.



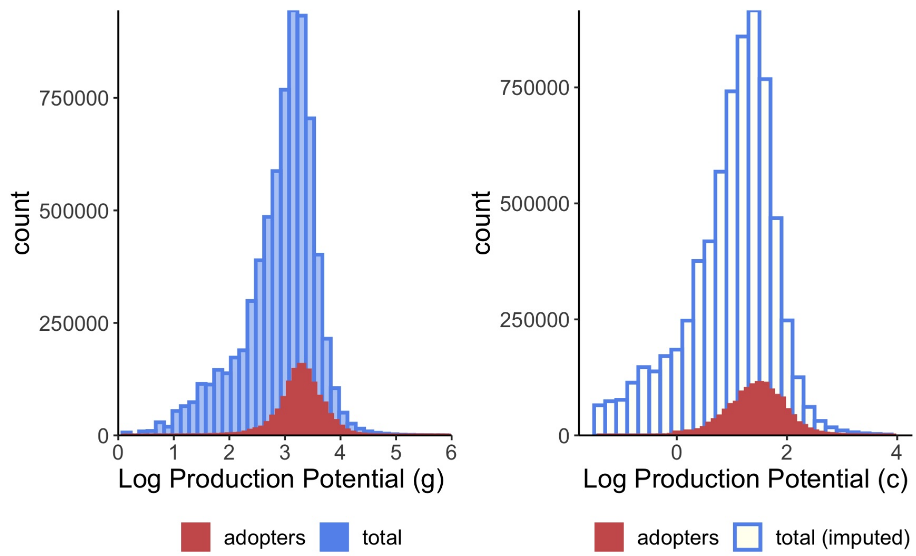
Notes: Google Project Sunroof distribution of maximum production potential (g_i) for residential properties in California. The red distribution is restricted to properties with solar PV systems currently installed (adopters), a subset of overall distribution (blue).

It is visible in Figure 4 that adopters tend toward the right of the total distribution, reflecting that properties with better site quality are more likely to adopt. But because the adopters are a relatively small subset of the total, there are nonetheless many non-adopters with comparable site quality across the whole distribution of adopters.

Although the maximum solar potential variable (g_i) present in the Project Sunroof data enables me to compare the distributions of adopters and non-adopters as displayed Figure 4, in order to make use of this comparison in my model estimation I will need to make a mathematical mapping between g_i and comparable site quality measures present in the CSI data, particularly the CSI Rating (c_i). Because there are no observations of g_i and c_i in common, this mapping cannot be rigorous, but is meant merely to adjust for the large average difference in site quality between adopters and non-adopters. Although different especially in their scale, g_i and c_i are both measures of site quality, and as such do share their most important elements in common.[21]

In order to impute the c_i distribution of non-adopters that I will use in my model estimation, I assume that adopters form a similarly shaped subset of the total distribution in c_i as they do in g_i. Three of the four distributions displayed in Figure 21 are observed data: the fourth is the imputed total c_i distribution.

Figure 5: Non-adopters' Site Quality Imputation



Notes: The left panel repeats Figure 4, showing the distribution of maximum solar production potential (g_i) for residential properties in blue, and the same restricted to adopters in red. The right panel shows the observed distribution of production potential (c_i) for adopters in the CSI database in red, and the imputed overall c_i distribution in hollow blue.

The left panel of Figure 21 is only a repeat of Figure 4, with the distribution of maximum solar potential (g_i) for adopters in red, and the distribution for all potential adopters (adopters and non-adopters together) in blue. The right panel displays the c_i distribution for adopters in red, and the imputed total c_i distribution in hollow blue. To arrive at the imputed distribution, I split each of the adopters' distributions

[21] An important difference between g_i and c_i is that the former is a measure of *maximum* solar production potential, whereas c_i is the expected production of systems being actually installed. g_i is the property's full ability to produce solar energy; c_i is a function of property's needs as well as its ability. Properties with lower energy usage needs will choose smaller system sizes than the maximum their roof can support, resulting in lower c_i relative to g_i. However larger properties will tend to have both more roof space and higher energy usage needs, and g_i and c_i share most other factors in common - roof angles, shading and local weather.

into 50 bins h, where each bin coincides with 2 percentile points, and fit a log-linear function of the bin cutoffs c_h of the adopters' c_i distribution on the bin cutoffs g_h of the adopters' g_i distribution. I then pass the g_i value for each non-adopter i through this fitted function, yielding the imputed distribution as shown. Each of these imputed values should not be viewed as the value of c_i per individual non-adopter i; but I take the distribution of these values to represent non-adopters' c_i distribution.

1.3.3 Additional Data Sources

While the CSI database and Google Project Sunroof together form the main bulk of my data, I use a few auxiliary data sources as well to fill in some additional needed variables. These auxiliary data are land use codes from California state assessor data, socioeconomic data from the US American Community Survey (ACS), political vote shares data from the MIT Election Data and Science Lab, and energy prices data from the US Energy Information Agency (EIA). I use the assessor data to identify residential properties, and the ACS and vote shares data to constitute proxies for personal taste for solar. Electricity prices are essential for calculating expected electricity cost savings, a key factor in the choice of whether to adopt solar.

I take land use codes from California state assessor data to identify residential properties in the Google Project Sunroof data. The Project Sunroof data critically enables me to compare the site quality distributions of adopters and non-adopters, but it does not identify which properties are residential. This is important because the site quality distribution of commercial properties has a particular right tail - of very large commercial properties with vast roof space for solar - which does not belong in the residential site quality distribution. I spatially match properties in Project Sunroof to properties in the assessor data using latitude and longitude by nearest neighbor matching with a distance error tolerance of 5 meters. Although there may be some degree of error in the latitude and longitude coordinates, the matches do not need to be exactly correct, because I am only interested in the land use codes from the assessor data - i.e. residential or commercial.

To proxy for personal taste for solar, I take socioeconomic variables from the ACS, and political vote shares data from the MIT Election Data and Science Lab. Personal taste is especially important for rooftop solar, and will play a central role in my model, because solar panels (if adopted) will become visibly present on one's home. Individuals may have a negative taste if they dislike the appearance of solar panels, or also a positive taste if they have a desire to be green or environmentally friendly. Unfortunately, both of these are unobservable, but I assume that the latter - the desire to be green - is correlated with observable covariates. Particularly I suppose that higher earning, higher educated, and more politically left-leaning populations are more likely to have positive taste for solar. From the ACS I take county level median income, and propensity to be college educated, to capture earnings and education, respectively. To capture political orientation, I calculate (from the MIT Election Data and Science Lab data) county level average vote shares for major left-leaning (Democrat and Green) party Presidential candidates, averaged over all elections from 2000 to 2016.

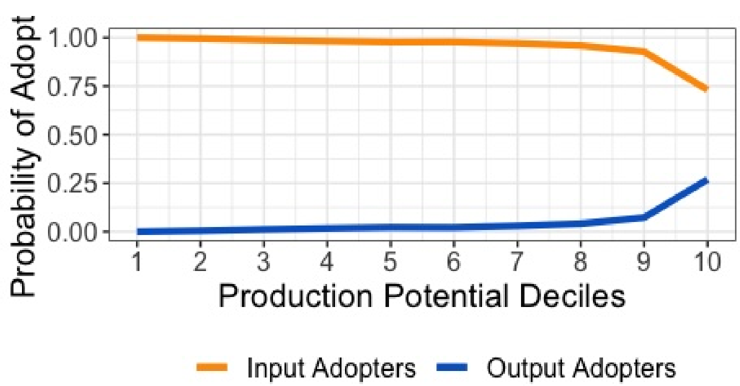
The choice of whether to adopt solar hinges in part on expected electricity cost savings, which depend on current and expected future electricity prices. Expected electricity cost savings are another component of the net financial benefit of adopting solar, that is, in addition to the chosen subsidy. As such, electricity prices data, which I take from the US Energy Information Agency (EIA), are essential for quantifying the value of each choice option faced by potential adopters in each time period. I follow De Groote and Verboven (2019) in assuming that each potential adopter conjectures future electricity prices in each time period from a linear trend on past prices in their respective region of residence.

1.4 Empirical Evidence

Potential adopters of solar in my setting face three basic choice options: to not adopt, to adopt with the investment subsidy, or to adopt with the output subsidy. In this section I examine patterns of which properties select into each choice option. Given that properties with higher solar production potential (site quality) stand to incur greater electricity cost savings in the event of adopting, the propensity to adopt should be increasing in site quality regardless of the choice of subsidy. But between the two subsidies - because the output subsidy is better targeted to site quality, and hence effectively offers something extra to the highest quality sites - the propensity to adopt with the output subsidy should be increasing in site quality at an especially steep rate. This section confirms that both of these patterns indeed occur in the data.

In addition to showing patterns of choice over the site quality distribution, this section can help to clarify the essential roles played by each of my two major data sources, that is the CSI database and Google Project Sunroof. While the CSI database identifies which adopters selected each type of subsidy, Google Project Sunroof identifies non-adopters in contrast to adopters. Figure 6 plots the propensity to select either subsidy type in the CSI data, for each decile of the site quality distribution.

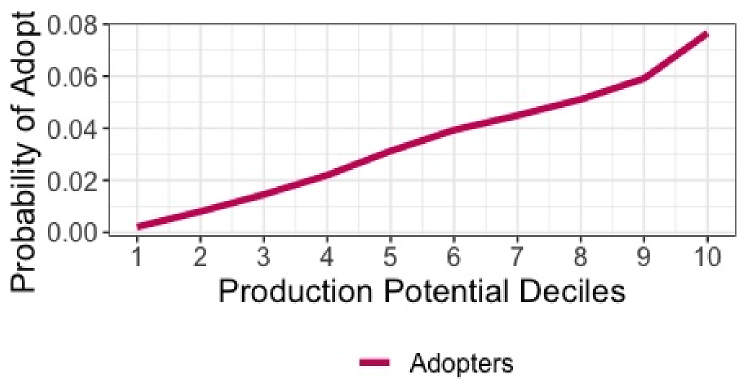
Figure 6: Conditional Propensity to Adopt With Either Subsidy Type by c_i Decile



Notes: c_i is the CSI Rating, CA's ex-ante estimate of each adopted system's lifetime expected production. The propensities are conditional on adoption, so sum to 1. The output adoption probabilities are scaled 10x.

Notice that because the CSI data does not contain non-adopters, the plotted probabilities cannot be unconditional, but instead are conditional on adoption. As the displayed (conditional) propensity to adopt with the output subsidy increases in site quality, the propensity to adopt with the investment subsidy must decrease as a mirror image of the former. This does not imply same for the unconditional propensity to adopt with the investment subsidy - that is, including the choice to not adopt at all. Figure 7 plots the unconditional probability of adoption for each site quality decile in the Google Project Sunroof data.

Figure 7: Propensity to Adopt by g_i Decile

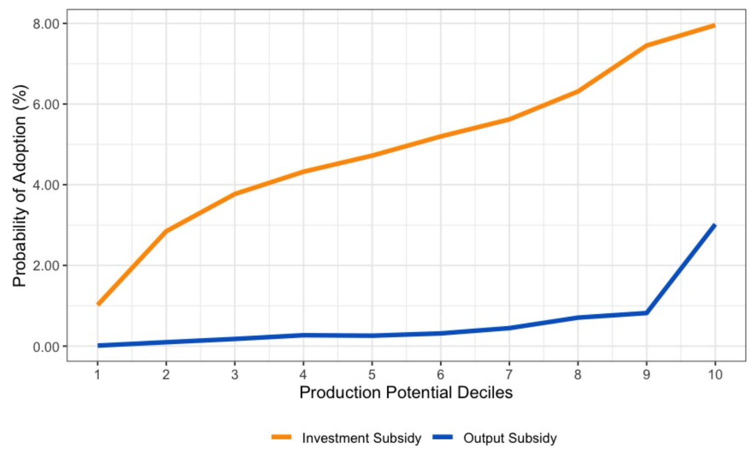


Notes: g_i is Google Project Sunroof's estimate of the property's maximum solar energy production potential.

It is visible in Figure 7 that the propensity to adopt solar is increasing steadily in site quality: but lacking any information on subsidy types, the Project Sunroof data cannot dissect these adopters further.

It is only in harnessing both the CSI data and the Project Sunroof data together that we can see the unconditional propensities to adopt with either subsidy. One can roughly think of multiplying each of the conditional probabilities in Figure 6 by the corresponding decile probability in Figure 7 to yield the unconditional probabilities in Figure 8 below.[22]

Figure 8: Unconditional Propensity to Adopt With Either Subsidy Type by c_i Decile



Notes: Non-adopters c_i values are imputed following the procedure given in Section 2.3.2. The output adoption probabilities are scaled 25x.

Although the probability of choosing the investment subsidy conditional on adopting is decreasing in site quality as shown in Figure 6, the probability of adopting as shown in Figure 7 is increasing to such an extent that the combination of these two is increasing. This is the unconditional probability of adopting with the investment subsidy, shown as the orange series in Figure 8. The probability of adopting with the output subsidy on the other hand is increasing through both channels - both conditionally as given in Figure 6, and in the absolute as given in Figure 7 - so is subject to an especially steep rise, visible particularly in the top decile. Each of these patterns will form an essential part of the identifying variation for the model: While adoption, regardless of subsidy type, increases in site quality due to electricity cost savings, adoption with the output subsidy in particular increases at an especially steep rate, due to the extra boost that it offers to the highest quality potential adopters.

[22]This is not exactly correct as the decile cutoffs in 6 are amongst adopters only, and hence higher than the true cutoffs in 7. To create Figure 8, the Project Sunroof non-adopters' production potential g_i values must first be translated into c_i terms following the procedure given in Section 2.3.2.

1.5 Model

This paper contains technically two models. The primary, Adoption Model is a dynamic discrete choice model of solar technology adoption.[23] I estimate the parameters of the Adoption Model assuming that potential adopters of solar are informed rational agents, and therefore that their observed choices identify their underlying tastes and objectives. The second, Policy Model parameterizes the government's tradeoff between the social benefit of increased solar energy production on the one hand, and the financial cost of associated subsidy payouts on the other. I use the Policy Model, in conjunction with the parameter estimates from the Adoption Model, to compute optimal investment and output subsidy rates under a variety of counterfactual scenarios.

1.5.1 Adoption Model

The success of any effort to promote rooftop solar energy production hinges on the distribution of individuals' choices of whether or not to adopt solar systems. I develop a dynamic discrete choice model to encapsulate the most essential elements of this choice. These essential elements comprise two main components: each individual's (1) net financial benefit in the event of adopting solar, and (2) personal taste for solar, such as the desire to be green. The net financial benefit in turn is composed of three sub-components: (1a) subsidies, (1b) electricity cost savings, and (negatively) (1c) the cost of the solar system. The balance of the net financial benefit and personal taste determines the adoption decision for each individual. If the net financial benefit is negative, an individual needs an equally strong positive taste for solar in order to adopt. And if the net financial benefit is positive, the individual needs an equally strong *negative* taste in order to *not* adopt.

The purpose of the Adoption Model is to clarify and quantify how the balance

[23] The Adoption Model is analogous to a typical discrete choice demand model in Industrial Organization.

of net financial benefit and personal taste resolves per individual - including, most importantly, how the investment and output subsidies may result in different resolutions of that balance for different individuals. As such, the model both theoretically defines, and provides the basis for estimating, a handful of key parameters that are crucial in determining the distribution of adoption decisions. On the net financial benefit side, the intertemporal discounting factor β adjusts the utility value of financial benefits that will accrue in the future. This is critical especially for determining the relative values of investment versus output subsidies, as investment subsidies are paid in the present, while output subsidies are paid in the future. On the personal taste side, both the mean and variance of the taste distribution are influential, but the covariance of taste with site quality also plays a particularly decisive role in determining the relative cost-effectiveness of investment versus output subsidies. As I show in section 1.5.7, a more negative correlation of taste with site quality increases the relative cost-effectiveness of the output subsidy, as the output subsidy's upside of offering more to better sites becomes more important.

Individuals i in the model are potential adopters of rooftop solar - that is, owners of properties with rooftops, whether residential or commercial.[24] In each time period t, the main choice d faced by each potential adopter i (who has not already adopted) can be written as:

$$d = \begin{cases} 0: & \text{do not adopt} \\ 1: & \text{adopt with investment subsidy} \\ 2: & \text{adopt with output subsidy} \end{cases}$$

The decision to adopt with either type of subsidy ($d > 0$) is a terminating action:[25] but not adopting ($d = 0$) preserves the option of adopting in a later time period. Conditional on the choice to adopt, i also chooses one of the available product contracts,

[24] I assume that only owner-occupied properties can consider adopting solar.

[25] The lifetime of a solar PV panel is about 20 years.

j. i's indirect utility is:

$$u^d_{i,j,t} = \nu^d_{i,j,t} + \xi^d_{z,j,t} + \epsilon^d_{i,j,t} \tag{3}$$

$$\nu^d_{i,j,t} = \begin{cases} \alpha \cdot R^{d>0}_{i,j,t} + \theta_i & \text{if } d > 0 \\ u^{d=0} + \beta \cdot E_t[\bar{V}_{i,t+1}] & \text{if } d = 0 \end{cases}$$

Commonly as in many demand models, the structural error term $\epsilon_{i,j,t}$ follows a type I extreme value distribution with respect to the choice options d, j, implying logit choice probabilities. The empirical error term $\xi^d_{z,j,t}$ will be absorbed via fixed effects, with z denoting i's county or region of residence. The conditional value of adoption $\nu^{d>0}_{i,j,t}$ is a balance (mediated by a willingness to pay parameter, α) between the net financial benefit $R^{d>0}_{i,j,t}$ (subsidy + electricity cost savings − system price) and i's personal (non-financial) taste θ_i for whether or not to have solar (including the desire to be green). The conditional value of not adopting is the baseline flow utility $u^{d=0}$ (this can be imagined as zero, with the value of adopting sometimes negative in comparison) plus the option value of waiting in order to potentially adopt solar in a future time period. The option value of waiting $\beta \cdot E_t[\bar{V}_{i,t+1}]$ is the expected value of i's best choice option in the next time period, discounted by β because that value is to realize one period hence.

1.5.2 Value of Adopting Solar

The conditional value of adopting solar, $\nu^{d>0}_{i,j,t} = \alpha \cdot R^{d>0}_{i,j,t} + \theta_i$, is relatively straightforward: because adoption is a terminating action, this value is equal to the expected discounted utility of the adopted solar system in the present time period (that in which the system is adopted). The intertemporal discount factor β critically weighs the sub-components of the net financial benefit $R^{d>0}_{i,j,t}$ against one another.

Because the system installation price $p^{\mathrm{I}}_{z,j,t}$ is due in the present,[26] it is *not* weighted by β in utility terms. The the same goes for the investment subsidy. But the output subsidy as well as electricity cost savings accrue in the future, so must be weighted by β in utility terms. For $d = 1$ (adoption with investment subsidy) and $d = 2$ (adoption with output subsidy) respectively, the net financial benefits are,

$$R^{d=1}_{i,j,t} = \underbrace{r^{\mathrm{u}}_{z,t} \cdot c_{i,j}}_{\text{Investment Subsidy}} + \underbrace{\sum_{\tau=0}^{20 \text{ years}} (\delta \cdot \beta)^{\tau} \cdot E_t[q_{i,j,t+\tau}] \cdot E_t[p^{\mathrm{E}}_{z,t+\tau}]}_{\text{Electricity Cost Savings}} - \underbrace{p^{\mathrm{I}}_{z,j,t}}_{\text{Installation Price}} \tag{4}$$

$$R^{d=2}_{i,j,t} = \underbrace{r^{\mathrm{q}}_{z,t} \cdot \sum_{\tau=0}^{5 \text{ years}} (\delta \cdot \beta)^{\tau} \cdot E_t[q_{i,j,t+\tau}]}_{\text{Output Subsidy}} + \underbrace{\sum_{\tau=0}^{20 \text{ years}} (\delta \cdot \beta)^{\tau} \cdot E_t[q_{i,j,t+\tau}] \cdot E_t[p^{\mathrm{E}}_{z,t+\tau}]}_{\text{Electricity Cost Savings}} - \underbrace{p^{\mathrm{I}}_{z,j,t}}_{\text{Installation Price}}$$

where $r^{\mathrm{u}}, r^{\mathrm{q}}, p^{\mathrm{E}}$, and p^{I} denote the upfront subsidy rate, output subsidy rate, electricity price, and system installation price, respectively. The calibrated parameter δ adjusts for solar panels depreciation as well as expected inflation of the US dollar.[27] The output subsidy is paid out over 5 years, whereas electricity cost savings accrue for an expectation of 20 years, reflecting the typical lifespan of solar panels. $c_{i,j}$ is the CSI Rating, which serves as the state's official estimate of the adopted system's expected lifetime total solar energy production, while $E_t[q_{i,j,t+\tau}]$ is the potential adopter's own expectation of their own solar energy production per period $t+\tau$. Because the choice of subsidy has no bearing on expected electricity cost savings, nor on system installation price, the net financial benefits $R^{d=1}_{i,j,t}$ and $R^{d=2}_{i,j,t}$ are identical except for the subsidy.

The net financial benefit $R^{d>0}_{i,j,t}$ of adopting solar may be either positive or negative, depending on whether the subsidy plus electricity cost savings outweigh the

[26] The system price is adjusted for the federal Investment Tax Credit (ITC).

[27] The time intervals $t + \tau$ may be either months or years, only δ and β need to be adjusted accordingly.

system price. The personal taste term θ_i may be either positive or negative, also, depending on whether the desire to be friendly to the environment outweighs one's aesthetic distaste for having solar panels on one's roof. However, unlike the net financial benefit which consists of mostly observed components, taste θ_i is primarily unobservable. Empirically, I proxy for θ_i with county (z) level socioeconomic indicators likely to correlated with taste for solar: political leaning, education, and median household income. That is,

$$\theta_i = \theta^{\text{pol}} \cdot P_{z,t}^{\text{pol}} + \theta^{\text{edu}} \cdot P_{z,t}^{\text{edu}} + \theta^{\text{inc}} \cdot X_{z,t}^{\text{inc}} + \tilde{\theta}_i \tag{5}$$

where $P_{z,t}^{\text{pol}}$ is the fraction of the local population in i's county z who are politically left-leaning, $P_{z,t}^{\text{edu}}$ is the fraction with at least four years of higher education, and $X_{z,t}^{\text{inc}}$ is median household income. I leave the remaining unobserved portion of taste $\tilde{\theta}_i$ to merge with the model's empirical error term $\xi_{z,j,t}$ (absorbed in fixed effects), and structural error term $\epsilon_{i,j,t}$.

1.5.3 System Characteristics and Site Quality

Multiple elements of the net financial benefit of adopting solar, $R_{i,j,t}^{d>0}$, depend on system size and other system j characteristics. A larger system will come with both higher expected production and higher installation price. The CSI rating $c_{i,j}$, which serves as the state's approximation of expected production, is equal exactly to the system size s_j multiplied by a Design Factor, $\tilde{c}_i$.

$$c_{i,j} = \tilde{c}_i \cdot s_j \tag{6}$$

The Design Factor $\tilde{c}_i$ is a unitless scalar that adjusts for local sunlight intensity, azimuth (compass orientation of the roof on which the system is to be installed), tilt (vertical angle of the roof), and shading. (The state's estimate of expected production is

$$c_{i,j} \cdot \sum_{\tau} \bar{h}$$

where $\bar{h}$ is a **constant** grand average number of hours of sun exposure per system per time period.) The potential adopter's own expectation of their own production $E_t[q_{i,j,t+\tau}]$, though not directly observed, should be closely related to $c_{i,j}$ and similarly constituted, as both are essentially estimates of the same expected production.

The system installation price $p^{\mathrm{I}}_{z,j,t}$ should also be a function of system characteristics j, particularly system size s_j. I model system price as a linear function of size, with both the slope and intercept varying by region z as well as time period t:

$$p^{\mathrm{I}}_{z,j,t} = p^{\mathrm{oI}}_{z,t} + p^{\mathrm{sI}}_{z,t} \cdot s_j \tag{7}$$

The intercept terms $p^{\mathrm{oI}}_{z,t}$ coincide with fixed costs. A $2kW$ system will be more than half as expensive as a $4kW$. Such decreasing average costs per kW size, implied by the presence of positive fixed costs, imply that optimal system sizes will be larger for properties i with higher site quality.

To reduce the complexity of the model, I assume that all factors driving the choice of system j characteristics are exogenous. This implies that all j subscripts in the model are superfluous: j characteristics are implications of the characteristics of properties i or their associated regions z. (Similarly, a z subscript would be superfluous wherever there is an i.) As a simplest example, the Design Factor $\tilde{c}_i$ should arguably be written as $\tilde{c}_{i,j}$ in theory, although it needn't be in empirical execution. The Design Factor includes system characteristics such as azimuth and tilt. My assumption is that a system's azimuth is not a free choice, but is instead implied by the property i's roof space and orientation. Each property has a predetermined set of roof spaces, one of which is best oriented for solar regardless of other factors in the model.

I assume that each chosen system size s_j, and all other system j characteristics, all are implied by their associated property i's exogenous characteristics, similarly as is each system's chosen azimuth. These exogenous i characteristics include the household's energy usage needs, roof space and orientation, sunlight intensity and shading. Although theoretically unappealing, this assumption of exogenous system characteristics helpfully simplifies the model, while preserving the vast bulk of what is likely to be important in practice for the question at hand. For example, although it is conceivable that optimal system sizes s_j may respond to subsidy rates on a very small margin, it is fair to assume that each property i's chosen system size - conditional on yes or no adoption - is (in the vast bulk) a function of its (exogenous) energy usage needs and roof space. I assume the parameters of the system pricing function, $p^{\mathrm{oI}}_{z,t}$ and $p^{\mathrm{sI}}_{z,t}$, likewise to be exogenous. This precludes any price setting behavior amongst solar supplier firms, but coincides with the vast bulk of what is likely to drive solar installation prices - namely, equipment and labor costs.

The assumption of exogenous system characteristics has, amongst other upsides, the benefit of simplifying the concept of site quality. Because expected production follows from site i characteristics (which are exogenous) and system j characteristics - and the j characteristics themselves follow from the i characteristics - expected production is to be viewed as following entirely from site i characteristics. Therefore expected production - conditional on yes or no adoption - is exogenous, and synonymous with site quality. As such the CSI rating $c_{i,j} = c_i$ which is the state's estimate of i's expected production, and i's own estimate of their own expected production $E_t[q_{i,j,t+\tau}] = E_t[q_{i,t+\tau}]$, both measures of expected production, serve as alternative measures of site quality. The extent to which these two measures disagree with one another is critical in the model, as the investment subsidy amount follows from the former, while the expected output subsidy amount follows from the latter.

1.5.4 Hidden Site Quality

In the model as it is written, the output subsidy can have no possible advantage over the investment subsidy unless the adopter i's estimate $E_t[q_{i,t+\tau}]$ of their own site quality is more accurate than the state's estimate c_i of the same. To proxy for $E_t[q_{i,t+\tau}]$, I fit ex-post actual production $q_{i,t}$ in hindsight as a function of ex-ante observable site and system characteristics, seeking maximal fit. I find in this empirical case that c_i does predict actual production $q_{i,t}$ (or q_i - averaged over t) very well,[28] but that the highest values of c_i underestimate the highest values of q_i. This is to say that q_i is an increasing function of c_i rather than a linear function. I therefore fit a nonlinear function of q_i on c_i, with intercepts c^{o} and slopes c^{q} varying by region z:

$$\begin{aligned} \log(q_i) &= c_z^{\mathrm{o}} + c_z^{\mathrm{q}} \cdot \log(c_i) + c^{\ell} \cdot \log(\ell_i) \\ y_i &= \exp(\widehat{\log(q_i)}) \end{aligned} \tag{8}$$

where ℓ_i is sunlight intensity data from Google Project Sunroof. The fitted values - which I call y_i - serve as an additional measure of site quality. Particularly y_i is the most accurate available estimate, such as adopters i might have given full knowledge of their own properties. I therefore use y_i (iterated over time periods $t + \tau$) to proxy for the adopters' i estimate $E_t[q_{i,t+\tau}]$ of their own expected production, that which is more accurate than the state's estimate c_i of the same.

[28] I find a correlation of c_i with q_i of 0.79.

$$R_{i,t}^{d=1} = \underbrace{r^{\mathrm{u}}_{z,t} \cdot c_i}_{\substack{\text{Investment}\\ \text{Subsidy}}} + \underbrace{\sum_{\tau=0}^{20 \text{ years}} (\delta \cdot \beta)^{\tau} \cdot y_i \cdot E_t[p^{\mathrm{E}}_{z,t+\tau}]}_{\text{Electricity Cost Savings}} - \underbrace{\left(p^{\mathrm{oI}}_{z,t} + p^{\mathrm{sI}}_{z,t} \cdot s_i\right)}_{\substack{\text{Installation}\\ \text{Price}}}$$

$$R_{i,t}^{d=2} = \underbrace{r^{\mathrm{q}}_{z,t} \cdot \sum_{\tau=0}^{5 \text{ years}} (\delta \cdot \beta)^{\tau} \cdot y_i}_{\substack{\text{Output}\\ \text{Subsidy}}} + \underbrace{\sum_{\tau=0}^{20 \text{ years}} (\delta \cdot \beta)^{\tau} \cdot y_i \cdot E_t[p^{\mathrm{E}}_{z,t+\tau}]}_{\text{Electricity Cost Savings}} - \underbrace{\left(p^{\mathrm{oI}}_{z,t} + p^{\mathrm{sI}}_{z,t} \cdot s_i\right)}_{\substack{\text{Installation}\\ \text{Price}}} \tag{9}$$

The use of the nonlinear function underlying y_i as hidden site quality - known to adopters but not to the state - begs the question as to why the state should not simply update its c_i measure to be equal to y_i. However, y_i should be thought of as an over-fitted function, harnessing information on actual production in hindsight such as should not be available to policy makers ex-ante in any practical setting. Thematically, the idea is that even with an investment subsidy program that is adjusted for site quality by the state ex-ante, the investment subsidy falls at least slightly short of the output subsidy in targeting to site quality for the reason that no ex-ante evaluation can be perfect. Granted, the adopter's evaluation of their own site quality is also ex-ante, but presumed to harness intimate knowledge that cannot be available to the state. This is to say that the output subsidy retains at least some small upside relative to the investment subsidy, though not necessarily that this upside is enough to overcome the output subsidy's relative downside of intertemporal discounting. The more accurate an investment subsidy program is in adjusting to site quality, the less scope there can be for the output subsidy to yield gains in cost-effectiveness.

1.5.5 Model Solution

Potential adopters i may choose to refrain from adopting solar, either in order to retain the option to adopt in a future time period, or to never adopt. The conditional value of not adopting $\nu_{i,t}^{d=0}$ is equal to the baseline flow utility $u^{d=0}$ plus the option value of waiting,

$$\nu_{i,t}^{d=0} = u^{d=0} + \beta \cdot E_t[\bar{V}_{i,t+1}] \tag{10}$$

where $\bar{V}_{i,t+1}$ is the value of behaving optimally from period $t+1$ onward, an aggregation of the values $\nu_{i,t+\tau}^{d>0}$ of all future options.

I follow De Groote and Verboven (2019), Scott et al. (2013) and Hotz and Miller (1993) in substituting out for $E_t[\bar{V}_{i,t+1}]$ in the Conditional Choice Probability (CCP) formulas. This will simplify the estimation of the dynamic discrete choice model. I will not need to specify whether the adoption decision is a finite or infinite time horizon problem, neither do I have to specify how agents believe the future states to evolve. I only need to assume rational expectations on state transitions. By the assumption that the structural error terms $\epsilon_{i,t}^{d}$ are EV1 distributed, the conditional choice probabilities $P_{i,t}^{d}$ for each choice option d take the logit forms,

$$\begin{aligned} P_{i,t}^{d} &= \exp(\nu_{i,t}^{d}) \Big/ \sum_{d'} \exp(\nu_{i,t}^{d'}) \\ P_{i,t}^{d} \Big/ P_{i,t}^{d'} &= \exp(\nu_{i,t}^{d}) \Big/ \exp(\nu_{i,t}^{d'}) \end{aligned} \tag{11}$$

and the continuation value $\bar{V}_{i,t+1}$ takes the form,

$$\bar{V}_{i,t+1} = \gamma + \log \sum_{d'} \exp(\nu_{i,t+1}^{d'}) \tag{12}$$

where γ is Euler's Constant. Following Scott et al. (2013), I assume that potential adopters i predict $\bar{V}_{i,t+1}$ accurately up to a mean-zero error $\eta_{i,t}$,

$$E_t[\bar{V}_{i,t+1}] = \bar{V}_{i,t+1} - \eta_{i,t} \tag{13}$$

Equations (42) - (45) can be combined to yield a non-recursive solution to the choice probabilities (43). To do this, first replace the $E_t[\bar{V}_{i,t+1}]$ in (42) with that in (45),

$$\nu_{i,t}^{d=0} = u^{d=0} + \beta \cdot (\bar{V}_{i,t+1} + \eta_{i,t})$$

then apply the $\bar{V}_{i,t+1}$ formula (44),

$$\nu_{i,t}^{d=0} = u^{d=0} + \beta \cdot (\gamma + \log \sum_{d'} \exp(\nu_{i,t+1}^{d'}) - \eta_{i,t})$$

normalize $u^{d=0} + \beta \cdot \gamma = 0$, and let $-\beta \cdot \eta_{i,t}$ merge into $\xi_{z,t}^{d=0}$ and $\epsilon_{i,t}^{d=0}$ in (35). This results in,

$$\nu_{i,t}^{d=0} = \beta \cdot \log \sum_{d'} \exp(\nu_{i,t+1}^{d'}) \tag{14}$$

Now notice that,

$$\sum_{d'} \exp(\nu_{i,t+1}^{d'})$$

is the denominator of the logit conditional choice probability formula (43) evaluated for $P_{i,t+1}^{d}$,

$$P_{i,t+1}^{d} = \exp(\nu_{i,t+1}^{d}) \Big/ \sum_{d'} \exp(\nu_{i,t+1}^{d'})$$

Inverted, this is,

$$\log \sum_{d'} \exp(\nu_{i,t+1}^{d'}) = \nu_{i,t+1}^{d} - \log P_{i,t+1}^{d}$$

which can applied in (46) to yield,

$$\nu_{i,t}^{d=0} = \beta \cdot (\nu_{i,t+1}^{d} - \log P_{i,t+1}^{d}) \tag{15}$$

This equation is valid when evaluated for any given d choice,

$$
\begin{aligned}
\nu_{i,t}^{d=0} &= \beta \cdot (\nu_{i,t+1}^{d=0} - \log P_{i,t+1}^{d=0}) \\
&= \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}) \\
&= \beta \cdot (\nu_{i,t+1}^{d=2} - \log P_{i,t+1}^{d=2})
\end{aligned}
$$

Evaluating at $d = 0$ is not helpful though, as this yields only a solution for $\nu_{i,t}^{d=0}$ in terms of $\nu_{i,t+1}^{d=0}$, which in turn is solved only in terms of $\nu_{i,t+2}^{d=0}$, and so on. However $\nu_{i,t+1}^{d=1}$ and $\nu_{i,t+1}^{d=2}$, as $\nu_{i,t}^{d=1}$ and $\nu_{i,t}^{d=2}$, have their own definitions as developed in 2.5.1 and 2.5.3,

$$
\begin{aligned}
\nu_{i,t}^{d=1} \;&=\; \alpha \cdot \Bigg(\underbrace{r_{z,t}^{\mathrm{u}} \cdot c_i}_{\substack{\text{Investment}\\\text{Subsidy}}} + \underbrace{\sum_{\tau=0}^{20\text{ years}} (\delta \cdot \beta)^{\tau} \cdot y_i \cdot E_t[p_{z,t+\tau}^{\mathrm{E}}]}_{\text{Electricity Cost Savings}} - \underbrace{\left(p_{z,t}^{\mathrm{oI}} + p_{z,t}^{\mathrm{sI}} \cdot s_i\right)}_{\substack{\text{Installation}\\\text{Price}}} \Bigg) \\
&\quad + \underbrace{\theta^{\mathrm{pol}} \cdot P_{z,t}^{\mathrm{pol}} + \theta^{\mathrm{edu}} \cdot P_{z,t}^{\mathrm{edu}} + \theta^{\mathrm{inc}} \cdot X_{z,t}^{\mathrm{inc}}}_{\text{Taste for Solar}} \\
\nu_{i,t}^{d=2} \;&=\; \alpha \cdot \Bigg(\underbrace{r_{z,t}^{\mathrm{q}} \cdot \sum_{\tau=0}^{5\text{ years}} (\delta \cdot \beta)^{\tau} \cdot y_i}_{\substack{\text{Output}\\\text{Subsidy}}} + \underbrace{\sum_{\tau=0}^{20\text{ years}} (\delta \cdot \beta)^{\tau} \cdot y_i \cdot E_t[p_{z,t+\tau}^{\mathrm{E}}]}_{\text{Electricity Cost Savings}} - \underbrace{\left(p_{z,t}^{\mathrm{oI}} + p_{z,t}^{\mathrm{sI}} \cdot s_i\right)}_{\substack{\text{Installation}\\\text{Price}}} \Bigg) \\
&\quad + \underbrace{\theta^{\mathrm{pol}} \cdot P_{z,t}^{\mathrm{pol}} + \theta^{\mathrm{edu}} \cdot P_{z,t}^{\mathrm{edu}} + \theta^{\mathrm{inc}} \cdot X_{z,t}^{\mathrm{inc}}}_{\text{Taste for Solar}}
\end{aligned} \tag{16}
$$

Therefore (47) evaluated at either $d = 1$ or $d = 2$ yields a non-recursive solution for $\nu_{i,t}^{d=0}$. Choosing $d = 1$, the solution

$$
\nu_{i,t}^{d=0} = \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}) \tag{17}
$$

joins the $\nu_{i,t}^{d>0}$ expressions (48) to complete the model. The conditional choice probabilities (43) resolve as,

$$
\begin{aligned}
P_{i,t}^{d=0} &= \frac{\exp(\beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}))}{\exp(\beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1})) + \exp(\nu_{i,t}^{d=1}) + \exp(\nu_{i,t}^{d=2})} \\
P_{i,t}^{d=1} &= \frac{\exp(\nu_{i,t}^{d=1})}{\exp(\beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1})) + \exp(\nu_{i,t}^{d=1}) + \exp(\nu_{i,t}^{d=2})} \\
P_{i,t}^{d=2} &= \frac{\exp(\nu_{i,t}^{d=2})}{\exp(\beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1})) + \exp(\nu_{i,t}^{d=1}) + \exp(\nu_{i,t}^{d=2})}
\end{aligned}
\tag{18}
$$

which alternatively can be written as,

$$
\begin{aligned}
P_{i,t}^{d=0} &= \frac{1}{1 + \exp(\nu_{i,t}^{d=1} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1})) + \exp(\nu_{i,t}^{d=2} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}))} \\
P_{i,t}^{d=1} &= \frac{\exp(\nu_{i,t}^{d=1} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}))}{1 + \exp(\nu_{i,t}^{d=1} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1})) + \exp(\nu_{i,t}^{d=2} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}))} \\
P_{i,t}^{d=2} &= \frac{\exp(\nu_{i,t}^{d=2} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}))}{1 + \exp(\nu_{i,t}^{d=1} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1})) + \exp(\nu_{i,t}^{d=2} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}))}
\end{aligned}
\tag{19}
$$

where each ν term is function of data and the parameters to be estimated $\{\alpha, \beta, \tilde{\theta}, \theta^{\text{pol}}, \theta^{\text{edu}}, \theta^{\text{inc}}\}$, as given by (48).[29] The choice probabilities P for each choice option d are essentially data, with the caveat that each individual potential adopter i may only realize one choice (per time period), so that probabilities at the level of individuals i are observed only indirectly.

I follow the approach of Arcidiacono and Miller (2011), that is of estimating (51)

[29]It should be noted that the choice probabilities (51) are conditional on having not already adopted, so in unconditional terms apply strictly as written only for the initial period. All subsequent t periods' probabilities are to be multiplied by the unconditional $d = 0$ probability from the previous period, iterated from the initial period.

in two steps.[30] In the first step, I approximate the right hand side probabilities $P_{i,t+1}^{d=1}$ via a flexible logit predictive model. This is analogous to the familiar use of observed market shares to approximate probabilities - but adjusted per individual i based on individual characteristics (c_i, y_i) as well as location z.[31] Taking the conditional choice probabilities as given in the second stage, the estimation then reduces to an essentially static multinomial logit criterion function with a precalculated offset term, as given by (51). That is, I take the approximated $P_{i,t+1}^{d=1}$ from the first step as data in the second (main) step of estimating (51) via simplex grid search Maximum Likelihood estimation. (As discussed earlier in this section, a few other components (y_i, $p_{z,t}^{\mathrm{oI}}$, $p_{z,t}^{\mathrm{sI}}$) of (51) are approximated as well in first steps of their own in parallel to $P_{i,t+1}^{d=1}$.) The resulting parameter estimates for $\{\alpha, \beta, \theta^{\mathrm{pol}}, \theta^{\mathrm{edu}}, \theta^{\mathrm{inc}}\}$ critically enable me to project the distribution of adoption decisions and subsidy payouts under alternative counterfactual policies and scenarios.

1.5.6 Policy Model

The Adoption Model of Section 1.5.1 determines the distribution of adoption decisions as a function of subsidy rates, site qualities, and electricity and system prices. Given estimates for the parameters of the Adoption Model, it is possible to quantify the extent to which altered subsidy policies would result in altered distributions of adoption decisions. However, more generous subsidy rates that would result in increased adoption would result in higher expenditure for the government as well. Is it worth it to increase subsidy expenditure by an amount B in order to increase adoption by an amount Q? The purpose of the Policy Model is to quantify the government's tradeoff between solar production and subsidy expenditure, thereby enabling evaluation of which counterfactual outcomes are better than others.

The Policy Model must weigh total solar production Q against total subsidy

[30] De Groote and Verboven (2019) conduct an analogous two step estimation in their Online Appendix

[31] The predictive model is a static analogue of (51) with added fixed effects and interaction terms, meant to maximize fit rather than identify parameters.

expenditure B. I model total solar production as,

$$Q = \sum_{i,t} (P_{i,t}^{d=1} + P_{i,t}^{d=2}) \cdot Y_i \tag{20}$$

where

$$Y_i = \sum_{\tau} y_i$$

is an individual property's lifetime solar production. That is, each potential adopter i produces Y_i if they adopt, but zero if they do not adopt. Therefore each i's contribution to total solar production is their probability of adopting $(P_{i,t}^{d=1} + P_{i,t}^{d=2})$ multiplied by their expected lifetime production Y_i conditional on adopting; and total solar production is the sum over individual i contributions. Whereas each i produces the same Y_i regardless of whether they adopt with the investment subsidy $(d = 1)$ or with the output subsidy $(d = 2)$, expenditure is slightly more involved in that the payout per individual depends on the choice of subsidy. Total subsidy expenditure is,

$$B = \sum_{i,t} (P_{i,t}^{d=1} \cdot r_{z,t}^{u} \cdot c_i + P_{i,t}^{d=2} \cdot r_{z,t}^{q} \cdot Y_i) \tag{21}$$

Because the adoption probabilities $P_{i,t}^{d=1}$ and $P_{i,t}^{d=2}$ are themselves functions of the subsidy rates $r_{z,t}^{u}$ and $r_{z,t}^{q}$ as given by (51), both production Q and expenditure B are increasing in the subsidy rates via the probabilities. But B is increasing in the subsidy rates more directly as shown in (21) as well, in that the government must pay the amount promised per individual who adopts.

The simplest version of the Policy Model would be to assume that the government's goal is to maximize solar production Q given a fixed subsidy budget target $B = \bar{B}$, or to minimize subsidy expenditure B given a fixed solar production target $Q = \bar{Q}$. However, because it is far from guaranteed that any given target will be met in this context, the use of fixed targets can fail to provide meaningful comparisons across many different outcomes. I assume instead that the government has a willingness to pay parameter α^{Gov}, analogous to the potential adopter's willingness to pay parameter α in (35), that translates expenditure dollars into the units of an indirect utility function:

$$
\begin{aligned}
u^{\text{Gov}} &= Q - \alpha^{\text{Gov}} \cdot B \\
&= \sum_{i,t} (P_{i,t}^{d=1} + P_{i,t}^{d=2}) \cdot Y_i - \alpha^{\text{Gov}} \cdot \sum_{i,t} (P_{i,t}^{d=1} \cdot r_{z,t}^{u} \cdot c_i + P_{i,t}^{d=2} \cdot r_{z,t}^{q} \cdot Y_i)
\end{aligned}
\tag{22}
$$

An appealing feature of (22) is that, although it is facially linear, it is fact concave in the subsidy rates $r_{z,t}^{u}$ and $r_{z,t}^{q}$, and thereby guaranteed to imply particular optimal values. This is because, as remarked in the previous paragraph, while both Q and B are increasing in the subsidy rates via the probabilities $P_{i,t}^{d=1}$ and $P_{i,t}^{d=2}$, B is additionally increasing in the rates via the subsidy payout per adoption. That is, as a subsidy rate becomes more generous, *both* the number of adopters *and* the payout per adopter increases. Thus subsidy expenditure B is a strictly steeper function of the subsidy rates than production Q is. This enables both a cogent analytical solution for the optimal subsidy rates under a linear approximation of the choice probabilities, and grid searched optimal rates under the full model, without need of imposing fixed targets.

A main challenge in making use of (22) it that it is of course sensitive to the value of α^{Gov}, which may be elusive or arbitrary (although the values of fixed targets $\bar{B}$ or $\bar{Q}$ would be no less arbitrary). However, we may look to the subsidy rates that were offered by the CSI program in fact to place bounds on the value of α^{Gov}. As the CSI program offered output subsidy rates of up to 0.39 $\$/kWh$, it follows the California government must value solar electricity production at 0.39 $\$/kWh$ or more. The government's willingness-to-pay parameter α^{Gov} would be the inverse of this rate, and as such is bounded above at 2.56 $kWh/\$$. Because estimates of the social marginal cost of carbon (via electricity production) usually fall below 0.39 $\$/kWh$,[32]

[32] Borenstein (2023) places the social marginal cost at 0.16 $\$/kWh$.

I assume that this bound holds, so that $\alpha^{\mathrm{Gov}} = 2.56\ kWh/\$$.

1.5.7 Analytical Solution under Linear Probabilities

Optimizing subsidy rates for the government's policy tradeoff (22) cannot be solved analytically under the full Adoption Model's logit choice probabilities (51), which instead require grid search optimization. However, a linear approximation of the choice probabilities does yield analytical solutions. Although lacking the full curvature of the logit model, this is nonetheless highly informative in demonstrating the key parameters' main impacts on the cost-effective values of the subsidy rates. Especially, it has the almost magical quality of yielding the correlation between taste and site quality explicitly in the optimal subsidy rate functions.

In order to arrive at the analytical solution to (22), I approximate the choice probabilities $P_i^{d=1}$ and $P_i^{d=2}$ as being proportional to their respective subsidy values per individual plus an individual taste θ_i. For ease of expression, I ignore the time t dimension as well system prices and electricity cost savings, and express the output subsidy as being paid in a single period in the future discounted by β. As such the value of the output subsidy to the adopter is $\alpha\beta r^{\mathrm{q}} y_i$,

$$
\begin{aligned}
P_i^{d=1} &= k_1(\alpha r^{\mathrm{u}} c_i + \theta_i) \\
P_i^{d=2} &= k_2(\alpha\beta r^{\mathrm{q}} y_i + \theta_i)
\end{aligned}
\tag{23}
$$

where k_1, k_2 are constants of proportionality. Thus (22) resolves as,

$$
\begin{aligned}
u^{\mathrm{Gov}} = & \sum_i (k_1 \alpha r^{\mathrm{u}} c_i y_i + k_2 \alpha\beta r^{\mathrm{q}} (y_i)^2 + (k_1 + k_2)\theta_i y_i) \\
& - \alpha^{\mathrm{Gov}} \sum_i (k_1 \alpha (r^{\mathrm{u}} c_i)^2 + k_2 \alpha\beta (r^{\mathrm{q}} y_i)^2 + (k_1 r^{\mathrm{u}} c_i + k_2 r^{\mathrm{q}} y_i)\theta_i)
\end{aligned}
\tag{24}
$$

As discussed earlier, it is necessarily the case that u^{Gov} is a steeper function of r^{u} and r^{q} in the negative (expenditure) part than it is in the positive (production) part, and therefore concave. In this case with linear probabilities, u^{Gov} is particularly linear in r^{u} and r^{q} in production, and quadratic in r^{u} and r^{q} in expenditure. The first order conditions,

$$\begin{aligned}\frac{\partial u^{\text{Gov}}}{\partial r^{\text{u}}} &= 0 \\ \frac{\partial u^{\text{Gov}}}{\partial r^{\text{q}}} &= 0\end{aligned} \tag{25}$$

solve as,[33]

$$\begin{aligned} r^{\text{u}*} &= \frac{1}{2}\left(\frac{1}{\alpha^{\text{Gov}}}\frac{\sum_i y_i c_i}{\sum_i c_i^2} - \frac{1}{\alpha}\frac{\sum_i \theta_i c_i}{\sum_i c_i^2}\right) \\ r^{\text{q}*} &= \frac{1}{2}\left(\frac{1}{\alpha^{\text{Gov}}} - \frac{1}{\alpha\beta}\frac{\sum_i \theta_i y_i}{\sum_i y_i^2}\right) \end{aligned} \tag{26}$$

Now because it is an accounting identity for any random variables x_i and z_i that,

$$\frac{\sum_i x_i z_i}{\sum_i z_i^2} = \frac{\bar{x}\cdot\bar{z}}{\sigma_z^2 + \bar{z}^2} + \frac{\sigma_x \cdot \sigma_z}{\sigma_z^2 + \bar{z}^2}\cdot \rho_{x,z} \tag{27}$$

the terms in (26) unpack into expressions involving the means ($\bar{c}$, $\bar{y}$, $\bar{\theta}$), variances (σ_c, σ_y, σ_θ) and correlations ($\rho_{y,c}$, $\rho_{\theta,c}$, $\rho_{\theta,y}$) characterizing the distributions of c_i, y_i and θ_i,

$$\begin{aligned} r^{\text{u}*} &= \frac{1}{2}\left(\frac{1}{\alpha^{\text{Gov}}}\left(\frac{\bar{y}\cdot\bar{c}}{\sigma_c^2+\bar{c}^2} + \frac{\sigma_y\cdot\sigma_c}{\sigma_c^2+\bar{c}^2}\cdot\rho_{y,c}\right) - \frac{1}{\alpha}\left(\frac{\bar{\theta}\cdot\bar{c}}{\sigma_c^2+\bar{c}^2} + \frac{\sigma_\theta\cdot\sigma_c}{\sigma_c^2+\bar{c}^2}\cdot\rho_{\theta,c}\right)\right) \\ r^{\text{q}*} &= \frac{1}{2}\left(\frac{1}{\alpha^{\text{Gov}}} - \frac{1}{\alpha\cdot\beta}\left(\frac{\bar{\theta}\cdot\bar{y}}{\sigma_y^2+\bar{y}^2} + \frac{\sigma_\theta\cdot\sigma_y}{\sigma_y^2+\bar{y}^2}\cdot\rho_{\theta,y}\right)\right) \end{aligned} \tag{28}$$

As such even under simple linear approximations of the choice probabilities, all model parameters as well as all aspects of all of the main variable distributions play roles in influencing the optimal subsidy rates.

The optimal subsidy rate formulas (29) indicate the direction of each parame-

[33] As subsidy rates must be bounded below at zero, a negative optimal rate implies that the optimal feasible rate is zero, or in other words that there is no useful subsidy to be offered.

ter's impact on each optimal rate. Although not fully representative of the complete model with logit choice probabilities, these can be viewed first order impacts. Most notably, under ordinary values of the means $\bar{\theta}$ and $\bar{y}$ and variances σ_θ and σ_y, the optimal output subsidy rate $r^{\mathrm{q}*}$ is increasing in the intertemporal discounting factor β and decreasing in the correlation between taste and site quality $\rho_{\theta,y}$. A higher β indicates that potential adopters are more patient with regards to the future. The downside of the output subsidy - that it is paid in the future - therefore diminishes with higher values of β.[34] A more negative correlation of taste with site quality $\rho_{\theta,y}$, on the other hand, strengthens the upside of the output subsidy. This is that the output subsidy is ideally targeted to site quality y_i, and thus more needed as taste θ_i is less aligned to the same end of incentivizing better sites to adopt.

The slightly more complex optimal investment subsidy rate $r^{\mathrm{u}*}$ formula nests a range of potential scenarios, as the state's ex-ante measure of site quality c_i may be more or less aligned with true site quality c_i. At one extreme the investment subsidy may be flat (constant), that is $c_i = \bar{c} = \bar{y}$ and $\rho_{y,c} = \rho_{\theta,c} = \sigma_c = 0$, then the formula simplifies to,

$$r^{\mathrm{u}*} = \frac{1}{2}\left(\frac{1}{\alpha^{\mathrm{Gov}}} - \frac{1}{\alpha} \cdot \frac{\bar{\theta}}{\bar{y}}\right) \tag{29}$$

At the other extreme where the investment subsidy is calibrated perfectly to site quality ($c_i = y_i$), the formula simplifies to the same as the optimal output subsidy rate formula except as if $\beta = 1$.

1.5.8 A Simplest Possible Example

Going beyond the simplified linear choice probabilities of section 1.5.7, the following example illustrates the relevance of the correlation between taste and site quality in perhaps the simplest possible setting. Suppose there are only two potential

[34] A countervailing effect of higher values of β is that adopters may be willing to accept *lower* output subsidy rates as they are thus less discounted in utility terms. Indeed there are relatively rare cases given by (26) in which this latter effect may dominate, such as if $\rho_{\theta,y} = -1$ and $\sigma_\theta \cdot \sigma_y > \bar{\theta} \cdot \bar{y}$. $\bar{\theta}$ and $\bar{y}$ themselves should be strictly positive given their construction in (23).

adopters in the economy, one with high site quality (i = Sonny) and the other with low site quality (i = Jett). The government's policy objective as given by (22) is to maximize total solar production minus total expenditure. As in 1.5.7, I ignore the time t dimension as well as electricity cost savings, and suppose that the output subsidy is paid in a single period in the future discounted by β. I suppose further that the investment subsidy r^{u} is flat (constant) - that is, not adjusted to site quality at all - representing the most extreme version of an investment subsidy. I replace choice probabilities with binary variables $1_i^{d=1}$ and $1_i^{d=2}$ indicating adoption with the investment subsidy and adoption with the output subsidy respectively. As such (22) can be rewritten as,

$$u^{Gov} = \sum_i (1_i^{d=1} + 1_i^{d=2}) \cdot y_i - \alpha^{Gov} \sum_i (1_i^{d=1} \cdot r^u + 1_i^{d=2} \cdot r^q \cdot y_i) \tag{30}$$

I let there be only two values of site quality y_i and two values of personal taste θ_i, that is 0 and 1 for both, and system price constant at $p = 2$. Each i chooses the d option that gives them the highest utility, which is given errorlessly as,

$$\begin{aligned} u_i^{d=0} &= 0 \\ u_i^{d=1} &= r^u - p + \theta_i \\ u_i^{d=2} &= \beta \cdot r^q \cdot y_i - p + \theta_i \end{aligned} \tag{31}$$

Given that,

$$\begin{aligned} y_{Sonny} &= 1 \\ y_{Jett} &= 0 \end{aligned} \tag{32}$$

I consider two scenarios regarding correlation between taste and site quality $\rho_{\theta,y}$. In the positive correlation case,

$$\begin{aligned} \theta_{Sonny} &= 1 \\ \theta_{Jett} &= 0 \end{aligned}$$

so $\rho_{\theta,y} = 1$. In the negative correlation case,

$$\theta_{Sonny} = 0$$
$$\theta_{Jett} = 1$$

so $\rho_{\theta,y} = -1$. In either case, because Jett's site quality is 0, it can be seen in (30) that the government can derive at most 0 utility from Jett. It follows that the only subsidy worth considering is the minimum needed to incentivize Sonny to adopt: If this does not yield positive u^{Gov} then the government's best choice to offer no subsidy at all. Because there can be only one minimum needed to incentivize Sonny to adopt, it follows furthermore that at least one of the subsidies should not be offered.

First consider the case of positive correlation. That is, suppose Sonny who has site quality $y_i = 1$ has taste $\theta_i = 1$; and Jett who has site quality 0 has taste 0. As discussed in the previous paragraph, the government need only consider the minimum needed to make Sonny adopt. The minimum investment subsidy amount needed to make Sonny adopt will be 1. With $r^{\mathrm{u}} = 1$,

$$u_{Sonny} = 1 - 2 + 1$$
$$u_{Jett} = 0 - 2 + 1$$

Sonny will adopt, and Jett will not. The government's utility follows as

$$u^{Gov} = 1 - \alpha^{Gov}$$

Offering the output subsidy instead, the minimum rate needed to make Sonny adopt will be $1/\beta$:

$$u_{Sonny} = \beta \cdot 1 \cdot \frac{1}{\beta} - 2 + 1$$
$$u_{Jett} = \beta \cdot 0 \cdot \frac{1}{\beta} - 2 + 0$$

Again Sonny will adopt, and Jett will not. The government's utility now will be

$$u^{\text{Gov}} = 1 - \alpha^{Gov} \frac{1}{\beta}$$

which is smaller than the utility from offering the investment subsidy,

$$u^{\text{Gov}} = 1 - \alpha^{Gov}$$

unless $\beta = 1$ (i.e. unless there is no intertemporal discounting). In this (positive correlation) case, the minimum subsidy to make Sonny adopt will not be enough to make Jett adopt, regardless of whether it is the investment or output subsidy. Thus the government's better option is the cheaper investment subsidy.

Consider now the case of negative correlation. That is, suppose Sonny who has site quality $y_i = 1$ has taste $\theta_i = 0$; and Jett who has site quality 0 has taste 1. The minimum investment subsidy amount needed to make Sonny adopt will be 2:

$$u_{Sonny} = 2 - 2 + 0$$

$$u_{Jett} = 2 - 2 + 1$$

In this case both Sonny and Jett will adopt solar, and the government's utility will be

$$u^{\text{Gov}} = 1 - \alpha^{\text{Gov}} 4$$

If instead the output subsidy is offered, the minimum rate needed to make Sonny adopt is $2/\beta$:

$$u_{Sonny} = \beta \cdot 1 \cdot \frac{2}{\beta} - 2 + 0$$

$$u_{Jett} = \beta \cdot 0 \cdot \frac{2}{\beta} - 2 + 1$$

Sonny adopts, and Jett does not. For the government,

$$u^{\text{Gov}} = 1 - \alpha^{\text{Gov}} \frac{2}{\beta}$$

which is larger than the utility from offering the investment subsidy,

$$u^{\text{Gov}} = 1 - \alpha^{\text{Gov}} 4$$

if $\beta > 0.5$. In other words, in the negative correlation case, only the output subsidy can make Sonny adopt without making Jett adopt also. Therefore the output subsidy is cost-effective to the government in order to avoid paying out to Jett.

1.6 Empirical Results

To concretely quantify the balance of motives underlying potential adopters' choices, I estimate the dynamic discrete choice Adoption Model (described in section 1.5.1). The estimation results both explain the factual pattern of adoption choices observed in the data, and enable me to forecast counterfactual choice patterns that would occur under different subsidy policies, or with some of the parameter values changed. In all cases, the Policy Model weighs the total social benefit of the distribution of solar adoptions against the total cost of the subsidy program. As such, the Policy Model critically evaluates which counterfactual outcomes are more desirable than others.

The upcoming section 1.6.1 presents and discusses the set of parameter estimates that result from fitting the Adoption Model to the data. These parameter estimates are "factual" in the sense that they represent the scenario that occurred in the data, as opposed to projected counterfactual scenarios that would occur under different subsidy rates or with some of the parameter values altered. Section 1.6.2 searches for cost-effective subsidy rates - conditional on the factual parameter values - by simulating a variety of possible counterfactual rates, forecasting the distribution of adoption decisions that would occur under each, and evaluating the corresponding total solar production and subsidy expenditure according to the Policy Model. Section 1.6.3 goes further, searching for cost-effective subsidy rates as in 1.6.2 - but conditional on counterfactual values of the key parameters rather than on the factual values. This enables me to evaluate how the cost-effective balance of rates may resolve differently under settings different than those in California.

1.6.1 Parameter Estimates

As discussed throughout Section 1.5, a few key parameters of the Adoption Model are critical both in driving the distribution of adoption decisions, and in determining the cost-effective balance of investment and output subsidy rates. While it can be seen from the theoretical structure of the model alone that both (i) a higher intertemporal discounting factor β and (ii) a more negative correlation of taste with site quality $\rho_{\theta,y}$ will strengthen the value of the output subsidy relative to that of the investment subsidy, concrete numerical values are needed in order to inform policy in practice. This section presents and discusses my estimates for these (and all other) parameters of the Adoption Model, obtained via simplex grid search Maximum Likelihood Estimation.

My estimates of β and $\rho_{\theta,y}$ - presented in Table 1.1 alongside my full set of Adoption Model parameter estimates - indicate that a robust trade-off between the relative upsides of the investment and output subsidies does exist empirically, as well as merely in theory. On the one hand, a considerably low value of $\beta = 0.82$ indicates that potential adopters of solar do discount the future substantially. This presents a strong case for the investment subsidy, as money that is to be paid out to adopters in the future via the output subsidy is somewhat wasted in utility terms. On the other hand, a solid negative value of $\rho_{\theta,y} = -0.28$ indicates that the investment subsidy may be wasted in its own way, strengthening the case for the output subsidy. That is, bluntly targeted investment subsidy money may be wasted on lower quality adopters who would have adopted regardless, while failing to sufficiently incentivize higher quality potential adopters with conservative leaning tastes.

My estimate for the discount factor β is on the lower side, but very much in the ballpark of estimates of the same in the related literature. As displayed in Table 1.1, I estimate a monthly discount factor (for residential potential adopters of solar) of 0.98, which translates to a yearly discount factor of 0.82. In comparison, De Groote and Verboven (2019) estimate a yearly discount factor of $\beta = 0.85$ for residential solar adopters in Flanders, while Snashall-Woodhams (2019) finds the same result as I do, $\beta = 0.82$ for residential adopters in California. As discussed in De Groote and Verboven (2019), the intertemporal discount rate of $1-0.85 = 15\%$ (or $1-0.82 = 18\%$ in the case of California) is considerably higher than most financial market interest rates. This suggests that potential adopters view their investments in solar to be considerably risky. But it also implies that the government stands much to gain by offering the investment subsidy rather than the output subsidy, as the former is riskless from adopters' point of view, while only the latter suffers from this heavy risk penalty.

Table 1.1: Adoption Model MLE (Residential)

	Parameter	Estimate
price sensitivity ($\$^{-1}10^{-5}$)	α	6.6424 (0.026)
monthly discount factor	β^{monthly}	0.9836 (0.004)
yearly discount factor	β^{yearly}	0.8209
mean taste for solar	$\bar{\theta}$	-4.9979 (0.007)
cov(taste, Democrat) (10^{-4})	θ^{pol}	8.3568 (0.234)
cov(taste, Income) ($\$^{-1}10^{-5}$)	θ^{inc}	1.8327 (0.028)
cov(taste, Educated) (10^{-4})	θ^{edu}	1.9871 (0.216)
corr(taste, site quality)	$\rho_{\theta,y}$	-0.2885

Notes: Parameter estimates from the dynamic discrete choice Adoption Model for residential solar adopters. Standard errors in parentheses.

Unlike the discount factor β, the taste factors θ are somewhat unique to this paper, so cannot be readily compared to corresponding estimates in the related literature. However, my results are intuitive: politically Left-leaning populations have higher taste for solar, as do higher earning and more educated populations.[35] Because the sunniest parts of the state tend to be inland while the more Left-leaning and educated populations tend to cluster along the coast, this implies a negative value of the correlation $\rho_{\theta,y}$. The negative mean taste for solar $\bar{\theta} = -4.99$ indicates that the default inclination of most residential properties is to not adopt solar. The decision to adopt requires either large positive net financial benefits, or unusually high idiosyncratic tastes. Given the value of $\alpha = 6.64 \cdot 10^{-5}$, the negative mean taste is equivalent to roughly $4.99/(6.64 \cdot 10^{-5}) = \$7,500$ worth of net financial benefit. This large negative mean taste may reflect the average person's visual distaste for the appearance of solar panels on their rooftop.

While the discount factor β may be function of setting to some extent (higher in Flanders than in California), the correlation $\rho_{\theta,y}$ between taste and site quality is likely to be even more so. My negative result for $\rho_{\theta,y}$ is a reflection of California's particular geography. To illustrate this point, Figure 28 displays a geographical plot of sunlight intensity (left) alongside a corresponding plot of political leaning (right). While politically Left leaning populations tend to cluster along the coast (e.g. San Francisco county), the sunniest areas in contrast tend to be more inland (e.g. San Bernardino county). Given that politically Right leaning populations tend to have lower taste for solar,[36] their relatively greater presence in the sunnier parts of the state (e.g. San Bernardino) coincides with the negative value of $\rho_{\theta,y}$.

The geographical plots of Figure 28 can be taken as a companion to the theoretical examples given in sections 1.5.7 and 1.5.8 in illustrating the advantage of the output subsidy. A potential adopter in San Bernardino, despite having outstanding

[35] Income refers to the median income per each potential adopter i's county, while Democrat and Educated refer to the fractions of the county population who are politically Left-leaning, and have at least 4 years of higher education, respectively.

[36] This is evident in my estimate for θ^{pol}, as well as in numerous surveys.

site quality, may be hesitant to adopt solar due to Conservative political leaning or related taste factors. He therefore may need an especially high subsidy in order tip his utility over the edge for making the decision to adopt: A high output subsidy rate is ideal for this task, as it compensates him directly for his site quality. A high investment subsidy could also tip the San Bernardinian over the edge to adopting, but at the expense of over-compensating others. That is, the higher investment subsidy would then also have to paid out to eager adopters in San Francisco with lower site quality, who would have adopted regardless.

It is worth noting that the negative correlation $\rho_{\theta,y}$ between taste and site quality does not necessarily imply that higher quality sites are less likely to adopt: rather, as shown in Section 1.4, the opposite is true. This is because the net financial benefit of adopting solar - another important component of the value of adopting solar, distinct from taste - is increasing in site quality y_i even while taste is decreasing in y_i. Furthermore, although the solid negative value of $\rho_{\theta,y}$ does strengthen the relative advantage of the output subsidy, this does not necessarily imply that it outweighs the relative advantages of the investment subsidy, which are themselves bolstered by the considerably low $\beta = 0.82$. Counterfactual simulations of altered rate policies - informed by the estimated values of β and $\rho_{\theta,y}$, and evaluated in cost-effectiveness terms according to the Policy Model - are needed to weigh the relative advantages of either subsidy against one another in arriving at optimal policy.

1.6.2 Counterfactual Policy Designs

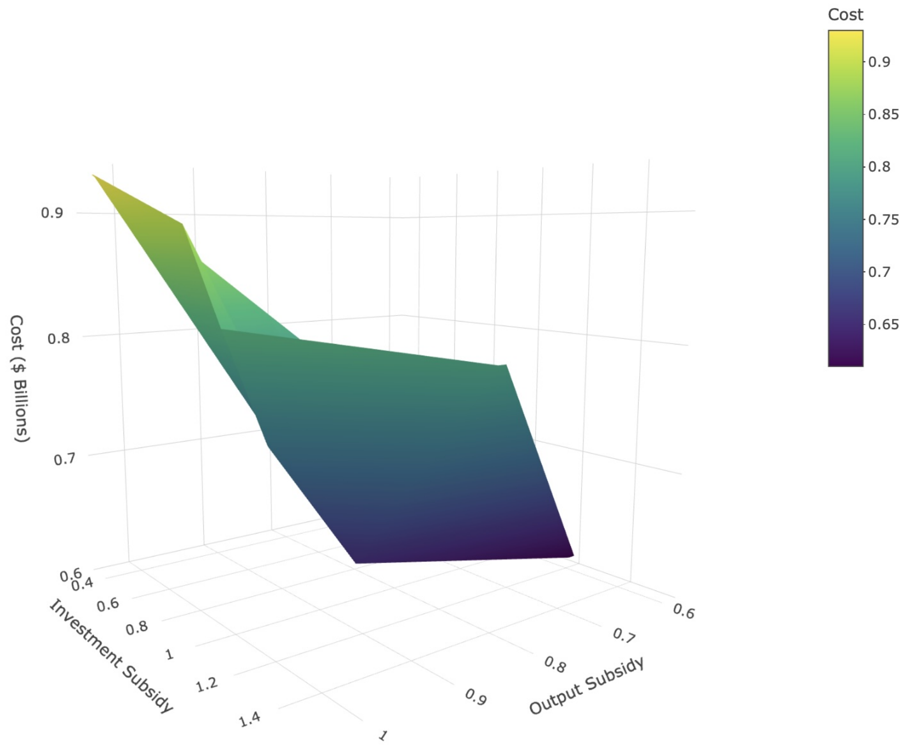
The California Solar Initiative paid out a total of roughly \$0.75 billion to subsidize residential rooftop solar systems that amounted to about 21.4 billion kWh in electricity production. A hypothetical subsidy policy that would result in the same production with lower expenditure, or higher production with the same expenditure, would undoubtedly be preferable to the government than the policy that was run. The Policy Model nests this consideration, while also enabling comparisons across sets of outcomes without exactly the same production or expenditure. Using the value of $\alpha^{\text{Gov}} = 2.56\ kWh/\$$ as described in Section 1.5.6, the factual outcomes coincide with $u^{\text{Gov}} = 21.4$ billion $kWh - \$0.75$ billion $\cdot\ 2.56\ kWh/\$ = 18.85$ billion kWh (or \$7.36 billion) in utility terms. It follows that a counterfactual subsidy policy that would result in $u^{\text{Gov}} > \$7.56$ billion would be preferable to the government than the policy that was offered, and vice versa.

First for conceptual simplicity, I search for a cost-minimizing combination of subsidy rates amongst those that meet a given, fixed production target.[37] I take as the production target that which was achieved under the CSI program, roughly 21.4 billion kWh. In the CSI program, each of the (investment and output) subsidy rates declined in ten steps over time:[38] To hold this feature constant in my counterfactuals, I multiply each of the original CSI rate schedules by a scalar ranging from 0 to 2. Figures 9 and 10 display the total program cost that I calculate would result from each combination of counterfactual subsidy rate schedules that meet the production target of 21.4 billion kWh.

[37]This can viewed as a special case of maximizing the government's objective function, as a lower cost total with the same production total must imply a higher value of u^{Gov} regardless of the value of α^{Gov}.

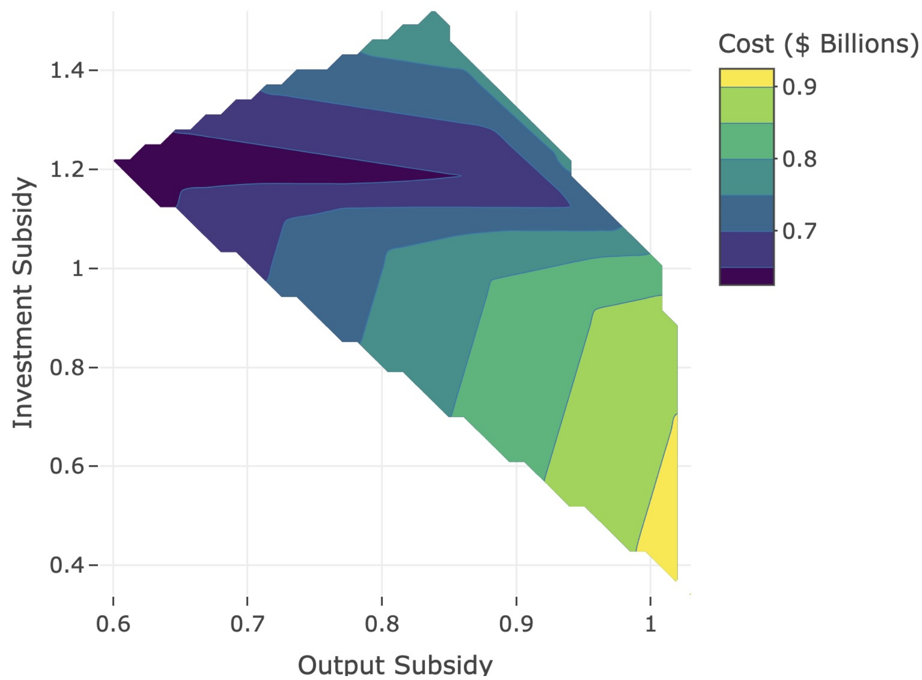
[38]See Table 2.5.

Figure 9: Total Subsidy Cost With Fixed Production Target (3D)



Notes: The investment and output subsidy rate axes plot the scalar by which the original CSI subsidy rate schedule is multiplied to yield each counterfactual rate schedule. The counterfactual subsidy program cost resulting from each rate schedule combination is plotted in color as well as on the vertical axis. All combinations included in the graph result in total solar electricity production roughly equal to 21.4 billion kWh, with a tolerance of 1% (21.2 - 21.6 billion kWh).

Figure 10: Total Subsidy Cost With Fixed Production Target



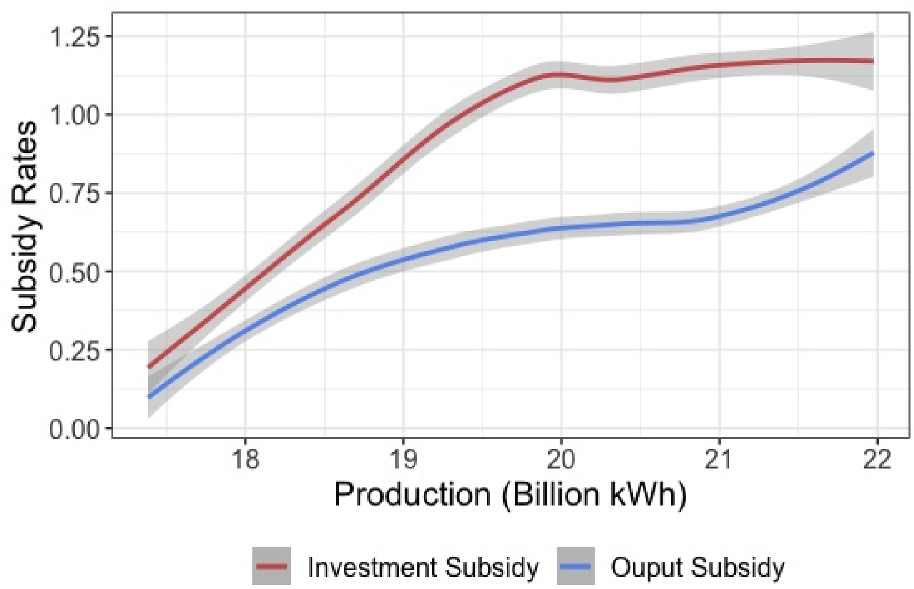
Notes: The investment and output subsidy rate axes plot the scalar by which the original CSI subsidy rate schedule is multiplied to yield each counterfactual rate schedule. The counterfactual subsidy program cost resulting from each rate schedule combination is plotted in color. All combinations included in the graph result in total solar electricity production roughly equal to 21.4 billion kWh, with a tolerance of 1% (21.2 - 21.6 billion kWh).

Amongst subsidy rate schedule combinations that result in roughly 21.4 billion kWh of solar electricity production, the lowest costing is visible in the left-most (dark blue) corner of the plot in Figure 10. This lowest costing (investment, output) combination is (1.21, 0.60) times the CSI schedule. Relative to the original CSI schedule (1, 1), the cost-minimizing combination (1.21, 0.60) delivers savings of about $140 million.

The investment subsidy rates in the original CSI program were already high enough that the vast majority adopters opted for the investment subsidy rather than the output subsidy. As such, these counterfactual results recommend an even more extreme prioritization of the investment subsidy. Because adopters are impatient with the low discount factor of 0.83, higher output subsidy rates are needed to achieve the same effect on utility as relatively more modest investment subsidy rates. This makes the investment subsidy generally more cost-effective, despite the output subsidy's advantage in targeting to site quality.

As the cost-effective combination of subsidy rates is not guaranteed to be similar across different production targets, I repeat the same exercise, and find the cost-effective combination of rate schedules across multiple production targets. These are displayed in Figure 11. Because lower subsidy rates cannot incentivize higher adoption and production, at least one of the subsidy rate schedule multipliers given on the vertical axis should be increasing for every higher value of production.

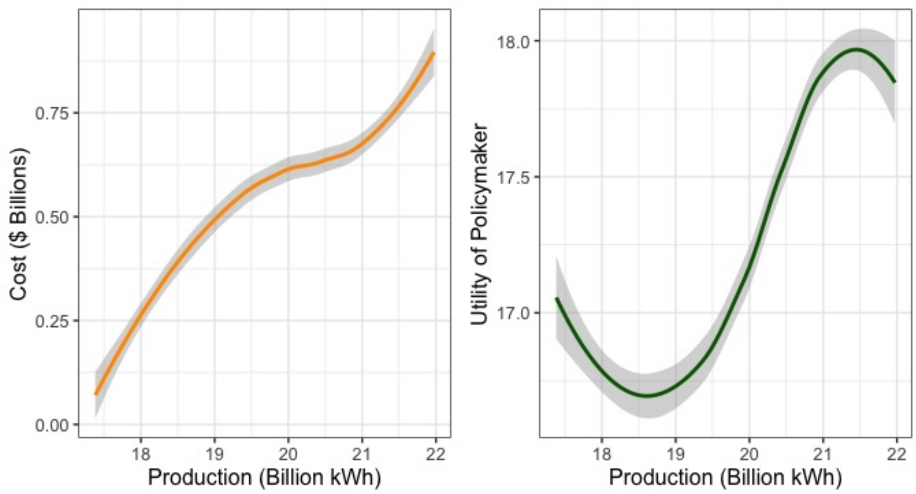
Figure 11: Cost-Minimizing Subsidy Rate Combinations



Notes: The vertical axis plots the scalar by which the original CSI subsidy rate schedule is multiplied to yield each counterfactual rate schedule. For each production target as given on the horizontal axis, the vertical axis plots the cost-minimizing combination of rate schedules amongst combinations that achieve the given production target.

It is visible in Figure 11 that although varying, the cost-effective combinations of rates are generally consistent across production targets, with investment subsidy rates somewhat higher (relative to their counterparts in the original CSI schedule) than the output subsidy rates. Figure 12 plots the minimum program cost - that which corresponds to the cost-minimizing combination of rates - for each production target in the left panel. The right panel then evaluates each set of outcomes in the left, assuming that the government values each additional 2.56 kWh of solar electricity production at \$1.

Figure 12: Minimum Subsidy Program Cost as a Function of Production Target



Notes: The left panel plots the minimum subsidy program cost needed to achieve each production target. The right panel evaluates each set of outcomes using the assumed value of $\alpha^{\text{Gov}} = 2.56\ kWh/\$$, that is assuming the government values each additional 2.56 kWh of solar electricity production at \$1.

1.6.3 Counterfactual Settings

While the above results show that the CSI program's offered subsidy were roughly well designed given the setting in California, it is possible that the same rates would not fare well in any other setting. In this section, I repeat the analysis of Section 1.6.2, but with key parameter values shifted, representing alternative settings. These key parameters are (1) the intertemporal discounting factor, which coincides with potential adopters' impatience and (2) the correlation between site quality and the CSI Rating - or how well the investment subsidy is targeted to site quality. Each of these should influence the relative advantages of the investment and output subsidies, and therefore may shift the cost-effective balance of subsidy rates.

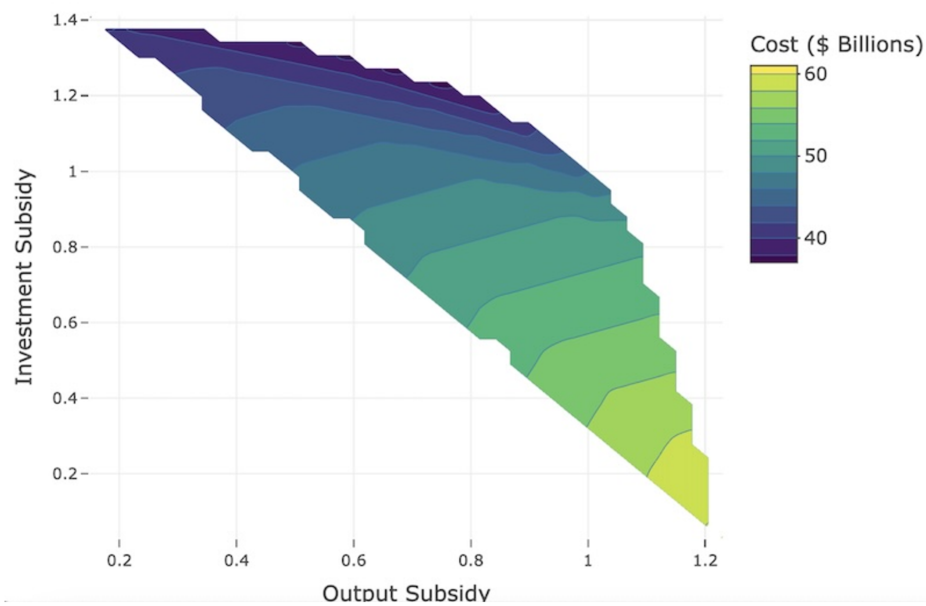
Because the output subsidy is to be paid out in the future, potential adopters' impatience (discount factor) critically influences the utility value of any given output subsidy. On the one hand, less impatience (encapsulated by a higher discount factor

β), by increasing the utility value of the output subsidy, increases its cost-effectiveness. On the other hand, a higher value of β needs to be compensated only by a lower output subsidy rate to achieve the same level of utility.

To gauge the importance of adopters' impatience in influencing the cost-effective balance of subsidies, I repeat the counterfactual simulation described in Figure 10, but now with a higher discount factor of $\beta = 0.90$. Figure 13 (like Figure 10 earlier) shows the contour plot for different combinations of investment and output subsidies that achieve the same production target, but vary in cost to the government. In this setting, solar adoption and electricity production are much higher than in the setting of $\beta = 0.83$, regardless of subsidies, because the higher discount factor increases the utility value of electricity cost savings as well. As the production target for the counterfactual simulations, I take the production that would occur in this setting under the subsidy rates offered in the CSI program.

In this setting with lower impatience among potential adopters, the cost-minimizing combination of investment and output subsidies is 1.24 and 0.77, respectively. This contrasts with the cost-minimization result in the main counterfactual using estimated demand parameters, where the cost-minimizing output subsidy is 0.60. A higher discount factor (lower impatience) boosts the cost-effectiveness of the output subsidy by increasing its utility value, thus resulting in an increased role for the output subsidy in the cost-effective balance of rates. Note that this effect is mitigated in that a higher discount factor also implies that the cost-effective output subsidy rate does not need to be as high to yield the same utility, and hence to incentivize adoption.

Figure 13: Outcomes under Alternative Subsidy Rates, with $\beta = 0.90$

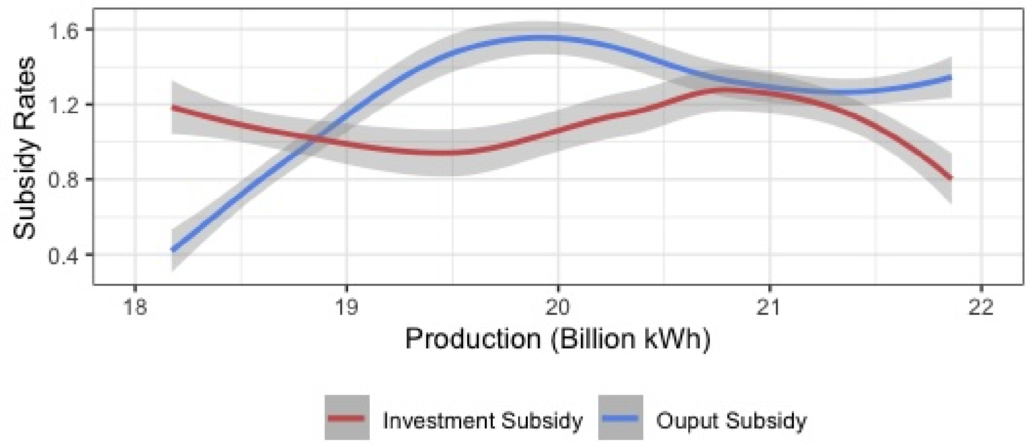


Notes: The investment and output subsidy rate axes plot the scalar by which the original CSI subsidy rate schedule is multiplied to yield each counterfactual rate schedule. The counterfactual subsidy program cost resulting from each rate schedule combination is plotted in color. All combinations included in the graph result in total solar electricity production roughly equal to 79.0 billion kWh, with a tolerance of 1% (78.2 - 79.8 billion kWh).

Because the advantage of the output subsidy is in its ability to target to site quality, perhaps the single most important factor influencing cost-effectiveness is the investment subsidy's ability to target to site quality. The CSI program's investment subsidy is not totally blind to site quality, as it is adjusted to each potential adopter's CSI Rating, which can be viewed as the state's ex ante estimate of expected production. The output subsidy retains an advantage over the investment subsidy in so far as there is any error in the state's estimate: but in the same sense, the accuracy of the state's estimate may limit the scope for the output subsidy to play a cost-effective role.

To demonstrate the importance of the CSI Rating in targeting the investment subsidy to site quality, I test the results of a conceptually pure, flat investment subsidy that cannot be targeted to site quality at all. In this setting, the investment subsidy is essentially equal to the investment subsidy rate: it is chosen freely by the state, but once chosen must be offered in the same amount to all potential adopters regardless of their CSI Rating or site quality.

Figure 14: Outcomes under Alternative Subsidy Rates, with Flat Investment Subsidy



Notes: The vertical axis plots the scalar by which the original CSI subsidy rate schedule is multiplied to yield each counterfactual rate schedule. For each production target as given on the horizontal axis, the vertical axis plots the cost-minimizing combination of rate schedules amongst combinations that achieve the given production target.

Figure 14, showing the cost-minimizing combination of investment and output subsidy rates for each given solar electricity production target, is different from the main counterfactual results in Figure 11 only in that the investment subsidy is now flat - that is to say, cannot be targeted to site quality at all. The results in Figure 14 show two important things. First, they show that the output subsidy becomes more important when the investment subsidy is not targeted to site quality. In contrast to Figure 11, the output subsidy now plays a more critical role in encouraging adoption and hence production. Second, to achieve the same production target of 21.4 Billion kWh as in the CSI program, the government has to offer higher rates for both subsidies, driving up the total cost considerably compared to the factual CSI program cost.

In this setting with a flat investment subsidy, the cost-minimizing combination of (investment, output) subsidy rate schedule multipliers needed to achieve the CSI program production target of 21.4 Billion kWh is (1.05, 1.39). The total cost to the government with this combination of rates is \$1.02 Billion - considerably higher than the CSI program cost of \$0.8 Billion for residential adopters of solar. Note that the investment subsidy rates here are not directly comparable to those in the main counterfactual, where the investment subsidy was targeted based on expected solar output via the CSI Rating. The output subsidy rate, on the other hand, is directly comparable, and shows that the cost-minimizing rate should be significantly higher than the factual rate offered under the CSI program (represented by the value 1).

1.7 Conclusion

In this paper, I find the most cost-effective allocation of the government's budget between investment subsidies which are paid at the time of adoption, and output subsidies which are paid in the future based on actual electricity production. In line with existing literature, I show that upfront subsidies are a more cost-effective subsidy design for incentivizing rooftop Photovoltaic (PV) solar adoption, as residential adopters of solar heavily discount future financial incentives. The upfront investment subsidies have a further advantage if they are adjusted to expected solar electricity production potential, that is, if they are well targeted. This paper has shown that it may nonetheless yield gains to cost-effectiveness to offer potential adopters an output subsidy option as an alternative. The cost-effective output subsidy option will be offered at a low rate - so that the vast majority of adopters opt for the generally more cost-effective investment subsidy - but succeeds in incentivizing a small handful of the highest quality sites to adopt who would not do so otherwise. The cost-effective combination of investment and output subsidy rates will be a function of setting, including potential adopters' impatience (discounting factor), the correlation between site quality and personal taste, and the accuracy at which the government can target the investment subsidy to site quality.

The analysis conducted in this paper may be extended in multiple ways. First, the adoption model is simplified so that the output subsidy's only advantage over the investment subsidy is in its superior targeting to site quality: But maintenance effort (cleaning) of solar PV systems, as well heterogeneous discounting rates or overconfidence, may provide additional mechanisms through which the output subsidy could yield gains to cost-effectiveness. Second, while I focus only on the relative values of the investment and output subsidy rates, without delving into the question of how either rate should be increasing or decreasing over time,[39] these two questions may be combined to yield a richer (albeit higher-dimensional) search for cost-effective subsidy policies. Third, it may be fruitful to consider still more creative subsidy designs, such as offering adopters a mix of investment and output subsides together, rather than requiring them to choose only one or the other.

[39] Langer and Lemoine (2022) focus on the latter question - how the subsidy rate should be increasing or decreasing over time - but with only an investment subsidy, and no output subsidy option.

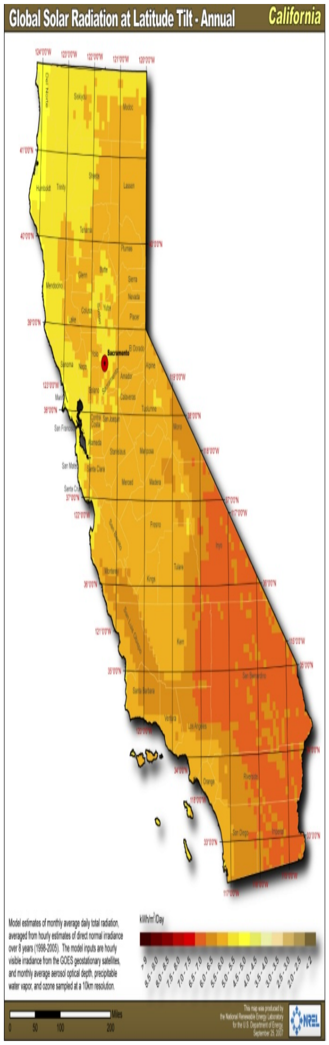
Appendix

Table 1.2: CSI Subsidy Schedule

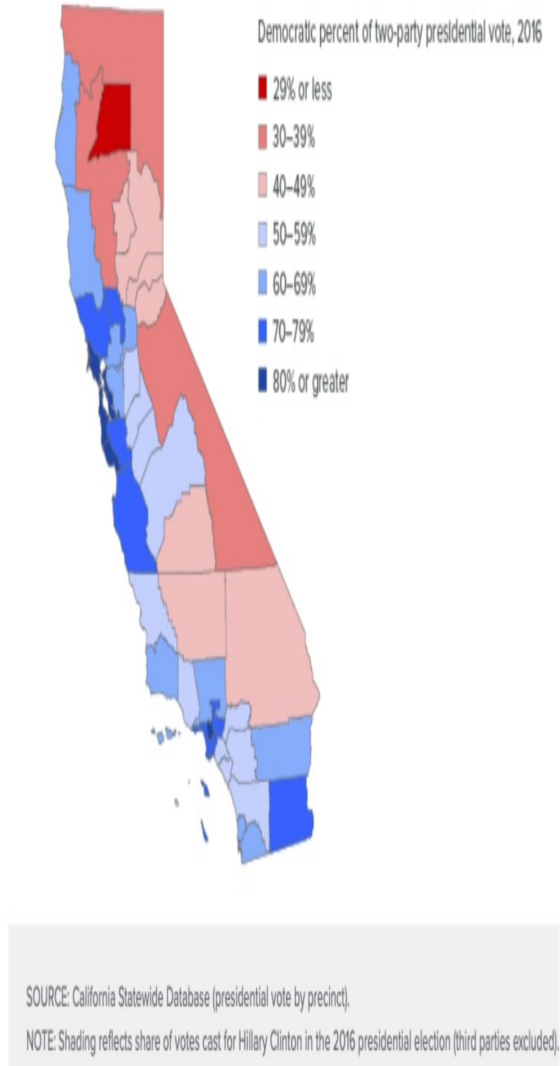
Step	Statewide MW in Step	EPBB Payments (per Watt)	PBI Payments (per kWh)
1	50	n/a	n/a
2	70	$2.50	$0.39
3	100	$2.20	$0.34
4	130	$1.90	$0.26
5	160	$1.55	$0.22
6	190	$1.10	$0.15
7	215	$0.65	$0.09
8	250	$0.35	$0.05
9	285	$0.25	$0.03
10	350	$0.20	$0.02

Notes: This schedule gives the pre-determined CSI subsidy rates. Both the EPBB (investment subsidy) and PBI (output subsidy) decline in 10 steps over time, based on the cumulative capacity installed in the state.

Figure 15: Sunlight Intensity and Political Leanings



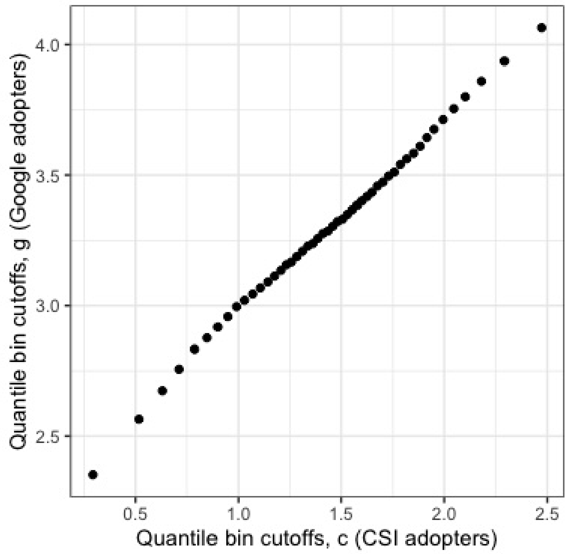
Sunlight Intensity



Political Leaning

Notes: The map on the left shows variation in sunlight intensity across different regions of California. The map on the right shows variation in the political leaning; regions in red are more Republican leaning, while those in blue are more Democratic leaning. Together, the maps show that in regions with higher sunlight intensity, and therefore with higher site quality, property owners are more likely to be more Republican, and therefore to have lower personal taste for solar.

Figure 16: Bin Cutoffs Mapping



Notes: This figure shows the relationship between bin cutoffs of the distribution of site quality (c_i) as measured by the CSI program on the horizontal axis, and the corresponding bin cutoffs of the distribution of site quality (g_i) of PV solar adopters in Google Project Sunroof.

2 Are Firms More Patient than Households? Evidence from Rooftop Solar Adoption in California

2.1 Introduction

Research on how consumers make choices over time has shown significant disparities between the estimated discount factor and commonly assumed benchmarks.[40] Incorrect assumptions of the discount factor will lead policy makers and businesses to over- or under-estimate consumers' willingness to make investments in the present for the sake of future payoffs. This is especially important in the area of green and energy efficient technology adoption, where large upfront investments are often needed in order to install expensive devices that yield financial savings only gradually over time.

[40]See Hausman (1979), Allcott and Greenstone (2012), De Groote and Verboven (2019).

While the vast bulk of studies involving intertemporal choice behavior must rely on calibrated (assumed) values of the discount factor, the rooftop solar adoption market in California offers an unusual opportunity for discount factor estimation. Under the California Solar Initiative (CSI), a state level subsidy program, potential adopters of rooftop solar were offered a choice between either an investment subsidy paid upfront at the time of adoption, or an output subsidy paid on a rolling basis per unit of electricity produced. Because these two subsidy options offer payment either in the present or in the future, adopters' observed choices between the two options identify their tradeoff between present and future financial benefits, and hence the discount factor. Furthermore, CSI offered the choice between subsidy options to commercial as well as residential adopters, enabling estimation of separate discount factors between these two important types of consumers.

I estimate a substantially higher discount factor for firms (commercial adopters) than for households (residential adopters), indicating that firms are more patient with respect to financial benefits that will accrue in the future. The discount factor may be defined in terms of pure impatience in a theoretical sense; but impatience per se is generally indistinguishable from the combined influence of multiple sub-factors, including myopia, uncertainty, risk aversion, and unobservable liquidity constraints.[41] Although all of the above factors are likely to affect firms as well as households, I reason that their impacts on firms should be less acute. Because this paper uses data from the rooftop solar PV adoption market in California to estimate households' and firms' discount factors, the empirical results are applicable strictly speaking only to the setting of rooftop solar, and only that in California. But they offer useful context wherever similar reasoning applies: And this paper's estimates, indicating that firms' are only about one third as impatient as households are in discount rate terms, may serve as a best guess where none other is available.

I estimate the model using detailed data on the rooftop solar market in Cali-

[41]See Branker et al. (2011) for a discussion of how the discount factor may vary with sub-factors and setting.

fornia. Rich variation over time in the incentive rates offered by the California Solar Initiative for each subsidy type enable me to identify the key parameters of adopters' demand system. I estimate, at $\beta = 0.94$, a much higher yearly discount factor for firms than for households ($\beta = 0.82$). These values of the discount factor, at 0.82 and 0.94, correspond to discount rate values of 0.22 and 0.06,[42] respectively. These indicate that firms are only about one third (29%) as impatient as households are in their valuation of the future financial benefits of adopting solar, implying that policy makers should treat firms and households very differently in seeking for cost-effective subsidy schedules.

This paper's results illustrate, in addition to the comparison of discount rates, the different roles played by subjective taste in motivating household and firm decision making. Subjective taste plays an out-sized role in the context of rooftop solar, particularly for residential adopters, because adopted solar systems will become visible on adopters' own homes. Solar systems adopted by commercial properties will become visible on business premises, however, and businesses may choose to internalize the tastes of local households in order to cultivate brand image. I find that the geographical correlation between subjective taste for solar and site quality is about the same for firms (-0.26) as for households (-0.29), suggesting that firms do indeed internalize local households' tastes.[43] However, because correlation does not have any bearing on magnitude, I also compare typical magnitudes of the subjective taste component in households' and firms' utility in relation to net financial benefits. I find that taste plays a smaller role in this sense for firms than it does for households, suggesting that the role of taste becomes diluted relative to that of objective financial gains in the group decision making processes of firms.

To assess the policy significance of the difference between in firms and households

[42] The discount rate is $1/\beta - 1$, where β is the discount factor. A lower discount factor (higher discount rate) indicates more impatience, and vice versa.

[43] This negative correlation stems from the geographical divergence in California between the sun and populations most friendly to solar: while the sunniest areas to be inland, the higher educated and more politically left leaning populations tend to cluster along the coast.

in their time preferences, I conduct counterfactual simulations that pass alternative hypothetical subsidy rate schedules through the model as estimated, for commercial and residential properties, respectively. I find that the cost-minimizing combination of investment and output subsidy rates for firms is very different than that for households, with that for firms leaning relatively more towards output subsidies, and vice versa. For residential properties, the cost-minimizing combination involves output subsidy rates roughly 40% lower than in the original CSI schedule, and investment subsidy rates 21% higher. For commercial properties, on the other hand, the cost-minimizing combination involves 4% higher output subsidy rates paired with 29% lower investment subsidy rates. That is, due to residential adopters' low discount factor at $\beta = 0.82$, money promised to adopters in the future in the form of output subsidies is to a large extent wasted in utility terms, implying that it is cost-effective to shift funds into the input subsidy instead: But the same is not true for commercial adopters, for whom $\beta = 0.94$.[44] These cost-minimizing subsidy schedules deliver savings to the government of about \$160 and \$140 million in commercial and residential subsidies, respectively.

Studies of rooftop solar adoption have found that residential adopters tend to be myopic, discounting future payoffs very heavily relative to financial market interest rates. De Groote and Verboven (2019) estimate an implicit discount factor of 0.86 in Belgium, while Snashall-Woodhams (2019) and Malhotra (2023) estimate a discount factor of 0.82 for the rooftop solar PV market in California. However, there have been very few attempts to estimate the intertemporal discount factor for commercial adopters.[45] Subsidy policies designed based on an assumption of a uniform discount factor between households and firms are unlikely to be as cost-effective as they could be.

[44]Because commercial adopters are not nearly as impatient the output subsidy's relative advantage of better targeting to site quality becomes more important than the input subsidy's relative advantage of being paid up front. See Malhotra (2023) for further discussion of the role of β and other parameters in influencing optimal subsidy rate combinations.

[45]See Qiu et al. (2015).

In addition to subsidy design, assumed values of the discount factor feature importantly in theoretical analysis of the energy-efficiency gap (EEG), that is the wedge caused by investment inefficiencies between the cost-minimizing level of energy efficiency and the level actually realized (Allcott and Greenstone (2012)). Gerarden et al. (2017) show that predictions founded on incorrect assumptions of the discount factor could misstate the size of the EEG.[46] While recent literature has shown that there might be little to no undervaluation in markets with more mature technologies, such as energy-efficient cars,[47] undervaluation or myopia seem to be present in markets for newer technologies such as solar PV systems.[48]

More broadly, this paper contributes to the literature on empirical intertemporal choice, which studies how consumers value future payoffs. Although of particular policy importance in the area of green technology adoption, assumed values of the discount factor may play critical roles in many other domains as well - ranging from land-use decisions[49] and cellphone pricing,[50] to valuations of real assets investments in emerging markets[51] and public project evaluation in developing countries.[52] Yao et al. (2012) for instance, who utilize consumers' cellphone usage data over time to infer the implicit discount rates they apply when making purchasing decisions, estimate a weekly discount factor (0.90) that is significantly lower than commonly assumed values in the literature (0.995). This leads to pricing recommendations that are generally too high, potentially reducing potential revenue gains by as much as 76%. In addition to Yao et al. (2012) and Malhotra (2023), estimations of the discount factor in a wide variety of settings have generally found it to be lower than commonly

[46]See Leskinen et al. (2020) and Branker et al. (2011) for discussions of how wrongly reported levelized cost of electricity (LCOE) values for new technologies can misguide policy initiatives. Reported LCOE values depend on assumed values of the discount rate.

[47]See Allcott and Wozny (2014), Busse et al. (2013).

[48]See De Groote and Verboven (2019), Snashall-Woodhams (2019), Talevi (2022), Malhotra (2023).

[49]Lloyd-Smith et al. (2021)

[50]Yao et al. (2012)

[51]Sabal (2004)

[52]Campos et al. (2015)

assumed benchmarks.[53]

The remainder of this paper is organized as follows. Section 2.2 covers the relevant industrial background, especially the most important details of the California Solar Initiative (CSI) subsidy program. Section 2.3 describes the data sources, including the CSI database and Google Project Sunroof, and the key variables contained in each. Section 2.4 presents some reduced-form evidence to motivate the central ideas in my model, and discusses how this evidence differs between firms and households. Section 2.5 defines and explains the dynamic discrete choice model of rooftop solar adoption demand. Section 2.6 estimates the model using the data described in Section 2.3. Section 2.7 presents counterfactual simulation results showing how the cost-effective combination of investment and output subsidies differs between households and firms, due to the difference in their estimated discount factors. Section 2.8 concludes.

2.2 Industry Background

I examine solar PV adoption behavior under the California Solar Initiative (CSI), a multi-billion-dollar program designed to incentivize solar adoption in CA. The CSI program was distinctive in two ways that make it a rich setting for analyzing adopters' demand behavior. First, CSI offered potential adopters a choice between either an investment subsidy (like a down payment awarded at the time of adoption) or an output subsidy (like a commission awarded on a rolling basis per unit of electricity produced), with investment and output subsidy rates set as a function of region and time of adoption.[54] Second, the investment and output subsidy rates offered by the CSI program each declined in ten steps over time, providing rich exogenous price variation that can identify the parameters of adopters' demand model.

Taking effect in Jan 2007, the CSI program offered solar adopters a choice

[53] Hausman (1979), Dubin and Mcfadden (1984), Gately (1980), Dube et al. (2009)

[54] Regardless of which CSI subsidy option is chosen, the adopter could also claim the federal Investment Tax Credit (ITC), a tax credit valued at 30% of the system installation price.

between either an investment subsidy, called the Expected Performance-Based Buydown (EPBB), and an output subsidy called the Performance-Based Incentive (PBI). Both subsidies were designed to reward higher-producing adopters and their chosen systems: However, whereas the EPBB is a one-time, upfront payment based on a system's ex-ante expected performance; PBI payments are paid according to the system's actual performance, measured and paid out over the course of the five years following adoption. As such, although both subsidies offer more to properties with higher expected production, the output subsidy (PBI) is better-targeted in this goal, in so far as there is any error in the state's ex-ante estimate of expected production which informs the investment (EPBB) subsidy.

The CSI program's subsidy options were available to all customers of California's three major Investor-Owned Utilities (IOUs) from 2007-2014, but with subsidy rates that declined over time.[55] Particularly, 10 rate steps for each of the two subsidies were announced at the onset of the program: The highest rates were to be offered first - so that the earliest adopters would receive the largest subsidies - and the rates would decline monotonically thereafter. However, the timing of each rate change was not entirely predictable, but based on the aggregate amount of solar adoption achieved in each IOU region. As such, the rates changed at different times for each IOU, triggered when each of the predetermined total adoption targets were achieved in each. Figure 17 plots the 10 EPBB subsidy rate steps ($/Watt) in red (right vertical axis),[56] and the corresponding cumulative solar capacity installed in blue (left vertical axis).

[55]Dollar amounts of subsidies are equal to the rates multiplied by production or expected production. In the case of the output subsidy (PBI), the rate (locked in at the time of adoption) is multiplied by actual solar electricity production measured on a rolling basis over the course of five years. In the case of the investment subsidy (EPBB), the rate is multiplied by the CSI Rating, which serves as the state's ex-ante estimate of an adopted system's lifetime expected production.

[56]The full schedule of rates can be found in Table 2.5 in Appendix.

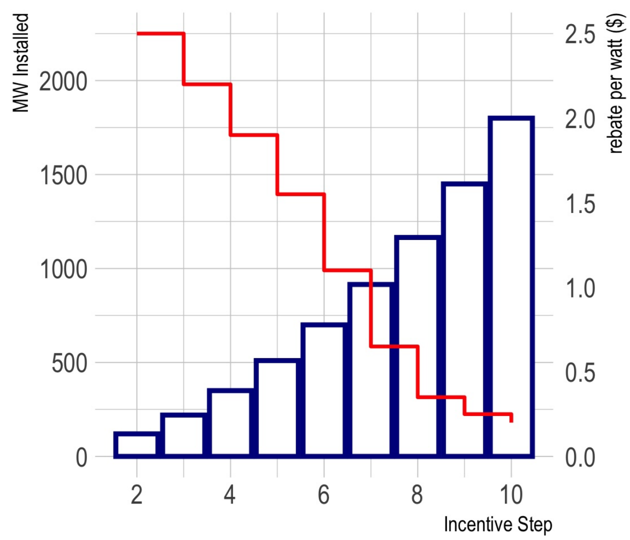


Figure 17: EPBB Subsidy Variation Over Time

A graph with the PBI rates in place of the EPBB rates in Figure 17 would look similar, as the former also decline in ten steps (from \$0.39/KWh to \$0.02/KWh).[57] More importantly with regards to analyzing adoption choices, Figure 18 displays how each of the subsidy rates evolved over time in each of the IOUs.

[57]See Table 2.5 in Appendix.

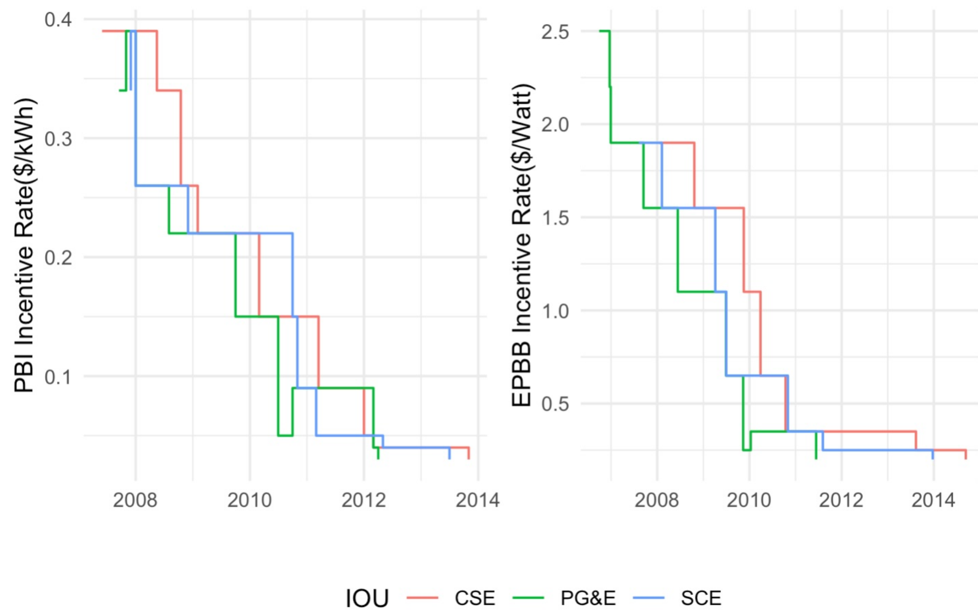


Figure 18: Cross-sectional Subsidy Variation

Because each of IOUs reached their aggregate capacity targets at different times, there is cross-sectional as well as time-series variation, that is, with rates differing across IOUs in any given time period. These sharp changes provide very useful price variation for evaluating adoption behavior.

That the subsidy rates were highest in the earliest years of the program begs the question as to why many adopters would wait until later periods to adopt. A countervailing factor, however, is that the prices of solar panels declined considerably over the same time span. This implies potential profit for many adopters in waiting, despite the loss of subsidy. Furthermore, considerable idiosyncratic error must be at play in the context of rooftop solar, as many property owners may be unaware or insufficiently sold on the prospect of adopting solar in any given time period, regardless of financial primitives.

2.3 Data

I combine two major data sources to yield a comprehensive view of the rooftop solar market in California. First, the California Solar Initiative (CSI) program provides detailed information on each solar PV adoption that occurred from 2007-2016. This includes physical characteristics of each system adopted, the system installation price, and subsidy type and amount paid to each, amongst other details.[58] Second, because the CSI database includes only properties whose owners chose to adopt solar, I employ a powerful dataset from Google Project Sunroof[59] to get a sense of how non-adopters' production potential distribution differed from the adopters' distribution.

2.3.1 CSI Database

The CSI program was distinctive in two ways that make it a rich setting for analyzing adopters' demand behavior. First, CSI offered potential adopters a choice between either an investment subsidy or an output subsidy, with investment and output subsidy rates set as a function of region and time of adoption.[60] Second, the investment and output subsidy rates offered by the CSI program each declined in ten steps over time, providing rich exogenous price variation that can identify the parameters of adopters' demand model.

As a subsidizer, the CSI program collected detailed information on each property i to which it issued a subsidy. These include, most importantly, the investment subsidy rate $r^{\mathrm{u}}_{i,t}$ and the amount of the investment subsidy,

$$r^{\mathrm{u}}_{i,t} \cdot c_{i,t} \tag{33}$$

that was paid to each adopter who opted to receive the investment subsidy; the output

[58]Under the CSI program, each property was given a choice between an investment and output subsidy. The investment subsidy (if chosen) was provided upfront, in an amount based on California's ex-ante approximation the system's lifetime expected solar production. The output subsidy was paid out on a rolling basis as a function of actual monthly production.

[59]Source: Google Project Sunroof data as of January 2023

[60]Regardless of which CSI subsidy option is chosen, the adopter could also claim the federal Investment Tax Credit (ITC), a tax credit valued at 30% of the system installation price.

subsidy rate $r^{\mathrm{q}}_{i,t}$ and the total amount of output subsidy,

$$r^{\mathrm{q}}_{i,t} \cdot \sum_{\tau=0}^{5\text{ years}} q_{i,t+\tau} \tag{34}$$

that was paid out over time to each adopter who opted to receive the output subsidy; and actual monthly solar electricity production $q_{i,t+\tau}$ for each output subsidy recipient. The CSI Rating $c_{i,t}$, which serves as the state's ex-ante estimate of expected production, is present in the data for both investment and output subsidy recipients (although actual production $q_{i,t+\tau}$ is present only for output subsidy recipients). Included also are the total installation price $p^{\mathrm{I}}_{i,t}$ of each system, and several component factor determinants of the CSI Rating, including system size s_i and number of inverters, roof tilt and azimuth, module characteristics, and the recipient's county and zip code.

In order to evaluate property owners' choices, it is necessary to quantify the options that each forwent, alongside the options that each chose. As such, a minor limitation of the CSI data is that it contains investment subsidy amounts only for investment subsidy recipients, and output subsidy amounts only for output subsidy recipients: It is necessary to quantify also the output subsidy amount that each investment subsidy recipient forwent, and the investment subsidy amount that each output subsidy recipient forwent. This can be remedied however, because of the known constitution of each subsidy as given in (33) and (34). As discussed in Section 2.2, the subsidy rates $r^{\mathrm{u}}_{i,t}$ and $r^{\mathrm{q}}_{i,t}$ do not vary per every individual property i, but rather per each i's utility provider (IOU), per time period t. I therefore recover the forgone output subsidy rates $r^{\mathrm{q}}_{z,t}$ for investment subsidy recipients, and the forgone investment subsidy rates $r^{\mathrm{u}}_{z,t}$ for output subsidy recipients, as a function of the county z in which each resides.[61]

The CSI database has two major limitations. First, although it has the CSI

[61]Future period subsidy rates $r^{\mathrm{u}}_{i,t+\tau}$ and $r^{\mathrm{q}}_{i,t+\tau}$ likewise are not directly observed per individual i, yet recoverable given i's county of residence.

Rating c_i - that's is the state's ex-ante estimate of expected solar electricity production per property i - for both investment and output subsidy recipients, the CSI database has actual production $q_{i,t+\tau}$ only for output subsidy recipients. This in itself is not as severe a limitation as it may sound however, because property owners' choices in any case must hinge on (their own) ex-ante expected production, rather than on actual production per se. To arrive at a proxy y_i for property owners' ex-ante estimate of their own expected production (distinct from the state's estimate c_i of the same), I will fit actual production q_i as a nonlinear function of c_i and sunlight intensity ℓ_i, with slopes and intercepts varying by location z. Because the left hand side variable for this function exists only for output subsidy recipients, this approach hinges on the assumption that the functional relationship between $y_i = \hat{q}_i$ and (c_i, l_i, z) for output subsidy recipients accurately reflects the same relationship for the broader population of properties. That is, given the function fit $y_i = \hat{q}_i$ from output subsidy recipients q_i data, I can impute y_i for investment subsidy recipients as well given their predictive data (c_i, l_i, z).

Second and most importantly, the CSI database contains no data at all on properties whose owners elected not to adopt solar. In order to make projections of adoption behavior under altered (counterfactual) subsidy policies and scenarios, it is necessary to model the distribution of properties whose owners in fact did not adopt, but might switch to adopting in the counterfactual. The distribution of non-adopters properties' could be assumed equal (in site quality measures c_i, y_i) to the distribution of adopters' properties. However, this would be implausible in that higher quality sites must be more likely to have adopted. In order to approximate how adopters' site quality distribution differed from that of the broader population of properties, I therefore turn to Google Project Sunroof, which contains its own measures of rooftop solar production potential, for 80-90% of all rooftops in California.

2.3.2 Google Project Sunroof

Although the CSI database contains most of the key information needed for this study, it lacks one essential feature, that is the ability to compare the observed distribution of solar adopters to the broader distribution of potential adopters. Because higher quality sites stand to receive both higher subsidy amounts and greater electricity cost savings in the event of adopting solar, they must be more likely to adopt than lower quality sites are. As the CSI database contains information only on adopters and none on non-adopters, any differences between these groups are completely unobservable. This is important particularly for counterfactual analysis. Although it may (arguably) be reasonable to estimate a model of adoption choice behavior using data on adopters alone, any counterfactual analysis must explicitly consider whether properties whose owners did not adopt would switch to adopting in the counterfactual.

Google Project Sunroof[62] contains its own measures of rooftop solar energy production potential, and unlike the CSI database covers (and identifies) non-adopters as well as adopters. I harness this data to obtain rough measurements of how the site quality distribution of adopters in California differs from the broader underlying distribution of potential adopters. I use these measurements to adjust the observed distribution of adopters from the CSI database, arriving at an imputed distribution which I take to represent the full spectrum of potential adopters. Because the CSI database and Google Project Sunroof do not contain exactly the same measures of site quality in common, this adjustment cannot be rigorous. However, it is an improvement over the most natural alternative, which would be to assume the distributions of adopters and non-adopters are either exactly the same, or differing by a calibrated (guessed) factor.

Project Sunroof uses aerial imagery and 3D modeling to derive estimates of maximum rooftop solar potential for each individual building, covering roughly 85%

[62]Source: Google Project Sunroof data as of January 2023

of all properties in California. The inputs to Google's maximum solar potential model include the roof space area (sq ft) suitable for installing solar panels, projections of shading on each point on the roof for each position of the sun in the sky, the compass orientation and vertical angle of each roof plane, and local weather data. Project Sunroof's web interface accommodates the entry of any individual address, as shown in Figure 19, returning various estimates related to the property's rooftop solar potential. I use an anonymized dataset of roughly 9 million such addresses, shared through a Data User Agreement.

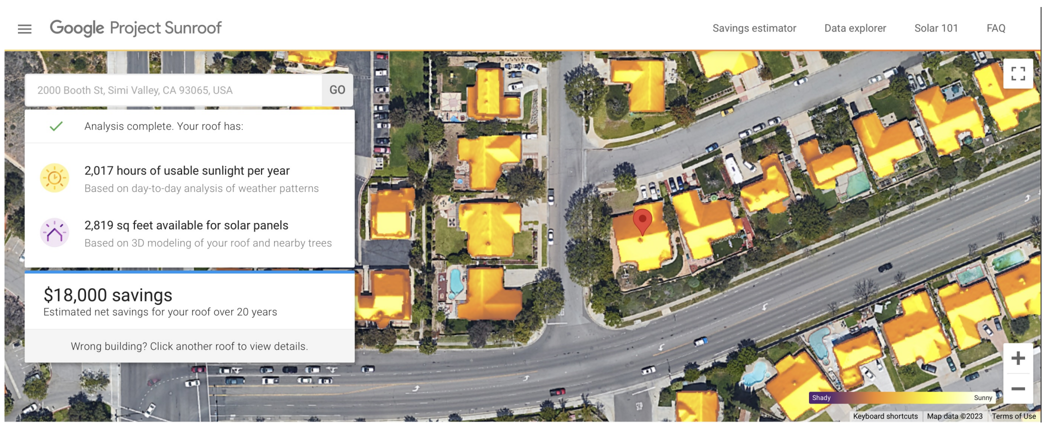


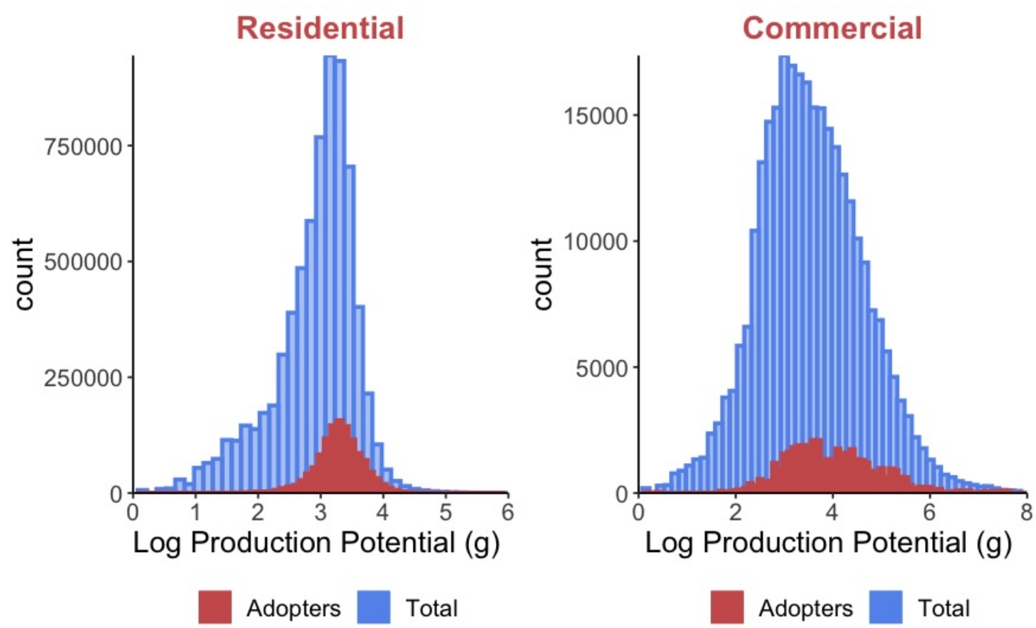
Figure 19: An Individual Commercial Property in Google Project Sunroof's Web Interface

Because I use the Project Sunroof data to approximate how the distribution of rooftop solar adopters differs from the broader distribution of potential adopters, it is necessary to distinguish in some way between adopters and non-adopters within the Project Sunroof data itself. Fortunately, Project Sunroof's aerial imagery does identify properties with solar systems currently installed, enabling me to compare the distributions of adopters and non-adopters directly.[63] Figure 20 overlays the distribu-

[63]Because it is not known at what time each property in Project Sunroof with solar had its system installed, it is possible that adopters during the time of the California Solar Initiative program (2008-2014) have a different site quality distribution than that of the full set of adopters identified in Project Sunroof. However, my interest for this data is with the (presumably) much larger distinction between adopters and non-adopters, not the relatively minor distinction between adopters during and after CSI.

tions of maximum solar potential for (residential and commercial)[64] adopters of solar (red) on the distribution of the same for the whole (residential and commercial) populations of potential adopters (blue), with the height of each distribution reflecting total count.

Figure 20: Site Quality Measure from Google Project Sunroof



Notes: The left panel repeats Figure 20, showing the distribution of maximum solar production potential (g_i) for residential properties in blue, and the same restricted to adopters in red. The right panel shows the distribution of maximum solar production potential (g_i) for commercial properties in blue, and the same restricted to adopters in red.

It is visible in Figure 20 that in both cases (residential and commercial), adopters tend toward the right of the total distribution, reflecting that properties with better site quality are more likely to adopt. But because adopters are a relatively small subset of the total in either case, there are nonetheless many non-adopters with comparable site quality across the whole distribution of adopters.

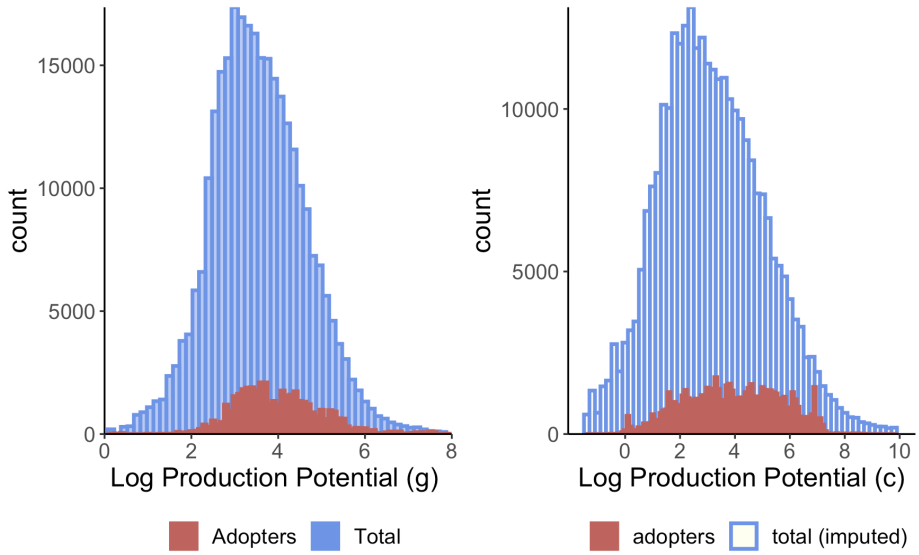
[64] Although the Project Sunroof data identifies which properties have adopted solar, it does not identify which properties are residential as opposed to commercial. This is important because the distribution of commercial properties has a heavy right tail, that is of very large commercial properties with vast roof space. I isolate residential and commercial properties in the Project Sunroof data via a computationally intensive spatial matching with California Assessor data, described in the upcoming Section 2.3.3.

Although the maximum solar potential variable (g_i) present in the Project Sunroof data enables me to compare the distributions of adopters and non-adopters as displayed Figure 20, in order to make use of this comparison in my model estimation, I will need to make a mathematical mapping between g_i and comparable site quality measures present in the CSI data, particularly the CSI Rating (c_i). Because there are no observations of g_i and c_i in common, this mapping cannot be rigorous, but is meant merely to adjust for the large average difference in site quality between adopters and non-adopters. Although different especially in their scale, g_i and c_i are both measures of site quality, and as such do share their most important elements in common.[65]

In order to impute the c_i distribution of non-adopters that I will use in my model estimation, I assume that adopters form a similarly shaped subset of the total distribution in c_i as they do in g_i. Three of the four distributions displayed in Figure 21 are observed data: the fourth is the imputed total c_i distribution.

[65] An important difference between g_i and c_i is that the former is a measure of *maximum* solar production potential, whereas c_i is the expected production of systems being actually installed. g_i is the property's full ability to produce solar energy; c_i is a function of property's needs as well as its ability. Properties with lower energy usage needs will choose smaller system sizes than the maximum their roof can support, resulting in lower c_i relative to g_i. However, larger properties will tend to have both more roof space and higher energy usage needs, and g_i and c_i share most other factors in common - roof angles, shading and local weather.

Figure 21: Non-Adopters' Site Quality Imputation



Notes: The left panel repeats Figure 20, showing the distribution of maximum solar production potential (g_i) for commercial properties in blue, and the same restricted to adopters in red. The right panel shows the observed distribution of production potential (c_i) for adopters in the CSI database in red, and the imputed overall c_i distribution in hollow blue.

The left panel of Figure 21 is only a repeat of Figure 20, with the distribution of maximum solar potential (g_i) for commercial adopters in red, and the distribution for all potential commercial adopters (adopters and non-adopters together) in blue. The right panel displays the c_i distribution for adopters in red, and the imputed total c_i distribution in hollow blue. To arrive at the imputed distribution, I split each of the adopters' distributions into 50 bins h, where each bin coincides with 2 percentile points, and fit a log-linear function of the bin cutoffs c_h of the adopters' c_i distribution on the bin cutoffs g_h of the adopters' g_i distribution. I then pass the g_i value for each non-adopter i through this fitted function, yielding the imputed distribution as shown. Each of these imputed values should not be viewed as the value of c_i per individual non-adopter i; but I take the distribution of these values to represent non-adopters' c_i distribution.

2.3.3 Additional Data Sources

While the CSI database and Google Project Sunroof together form the main bulk of my data, I use a few auxiliary data sources as well to fill in some additional needed variables. These auxiliary data are land use codes from California state assessor data, socioeconomic data from the US American Community Survey (ACS), political vote shares data from the MIT Election Data and Science Lab, and energy prices data from the US Energy Information Agency (EIA). I use the assessor data to identify residential and commercial properties, and the ACS and vote shares data to constitute proxies for personal taste for solar. Electricity prices are essential for calculating expected electricity cost savings, a key factor in the choice of whether to adopt solar.

I take land use codes from California state assessor data to identify residential and commercial properties in the Google Project Sunroof data. The Project Sunroof data critically enables me to compare the site quality distributions of adopters and non-adopters, but it does not identify which properties are commercial as opposed to residential. I spatially match properties in Project Sunroof to properties in the assessor data using latitude and longitude by nearest neighbor matching with a distance error tolerance of 5 meters. Although there may be some degree of error in the latitude and longitude coordinates, the matches do not need to be exactly correct, because I am only interested in the land use codes from the assessor data - i.e. residential or commercial.

To proxy for subjective taste for solar, I take socioeconomic variables from the ACS, and political vote shares data from the MIT Election Data and Science Lab. Commercial properties may have a negative taste if they believe potential customers and employees will dislike the appearance of solar panels, or also a positive taste if they wish to cultivate an appearance of being friendly to the environment. Unfortunately, both of these are unobservable, but I assume that the latter - the value of appearing to be friendly to the environment - is correlated with observable local demographics. I suppose that higher earning, higher educated, and more politically left-leaning populations are more likely to yield positive taste for solar. From the ACS I take county level median income, and propensity to be college educated, to capture earnings and education, respectively. To capture political orientation, I calculate (from the MIT Election Data and Science Lab data) county level average vote shares for major left-leaning (Democrat and Green) party Presidential candidates, averaged over all elections from 2000 to 2016.

The choice of whether to adopt solar hinges in part on expected electricity cost savings, which depend on current and expected future electricity prices. Expected electricity cost savings are another component of the net financial benefit of adopting solar, that is, in addition to the chosen subsidy. As such, electricity prices data, which I take from the US Energy Information Agency (EIA), are essential for quantifying the value of each choice option faced by potential adopters in each time period. I follow De Groote and Verboven (2019) in assuming that each potential adopter conjectures future electricity prices in each time period from a linear trend on past prices in their respective region of residence.

2.4 Empirical Evidence

Descriptive evidence from the CSI program shows that households and firms responded very differently to the choice of subsidies. When faced with the same choice options,[66] 17% of commercial adopters opted for the output subsidy, compared to fewer than 1% of residential adopters.

Table 2.1: Choice of Subsidy by Consumer Type

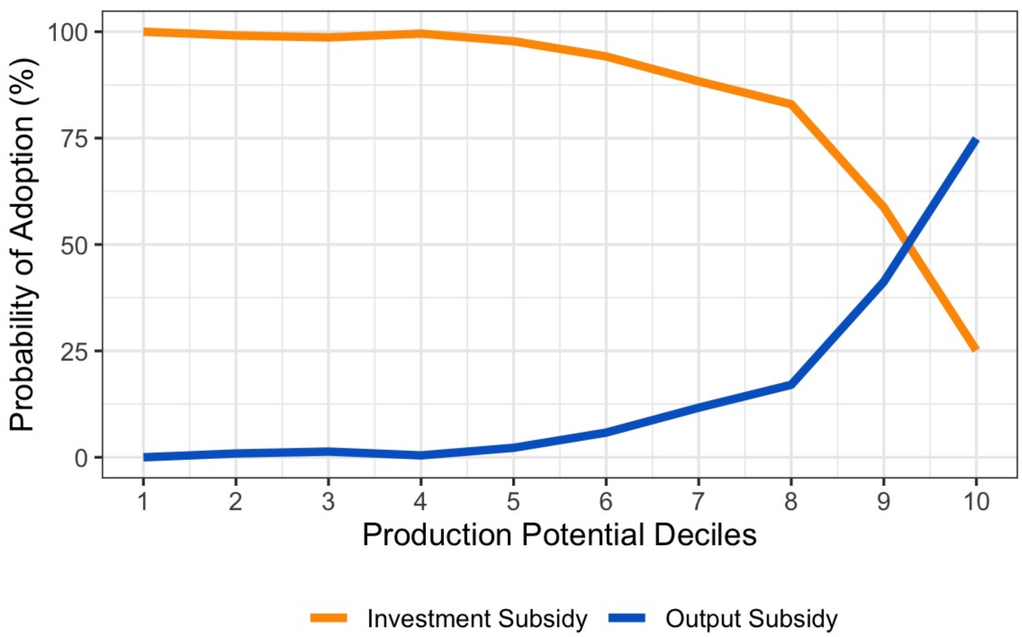
	Subsidy Type	
	Investment Subsidy	Output Subsidy
Residential	118,309	648
Commercial	1,919	395

[66]Some commercial adopters were only given the option of the output subsidy, so I exclude them from the data.

Because the choice between the two subsidy options hinges on how consumers trade off present and future financial benefits, the values in Table 2.1 provide evidence of a substantial difference in time preferences between firms and households. This implies that the optimal balance of investment and output subsidy rates for firms is likely to be different than that for households.

For any given value of the discount factor, each property's adoption choice behavior should also be a function of its production potential or site quality. Because properties with higher solar production potential stand to incur greater electricity cost savings in the event of adopting, the propensity to adopt should be increasing in site quality regardless of the choice of subsidy. But between the two subsidies - because the output subsidy is better targeted to site quality, and hence effectively offers something extra to the highest quality sites - the propensity to adopt with the output subsidy should be increasing in site quality at an especially steep rate. The upcoming Figures 22-24 confirm that both of these patterns indeed occur in the data, and also can help to clarify the essential roles played by each of my two major data sources. While the CSI database identifies which adopters selected each type of subsidy, Google Project Sunroof identifies non-adopters in contrast to adopters. Figure 22 plots the propensity to select either subsidy type in the CSI data, for each decile of the site quality distribution.

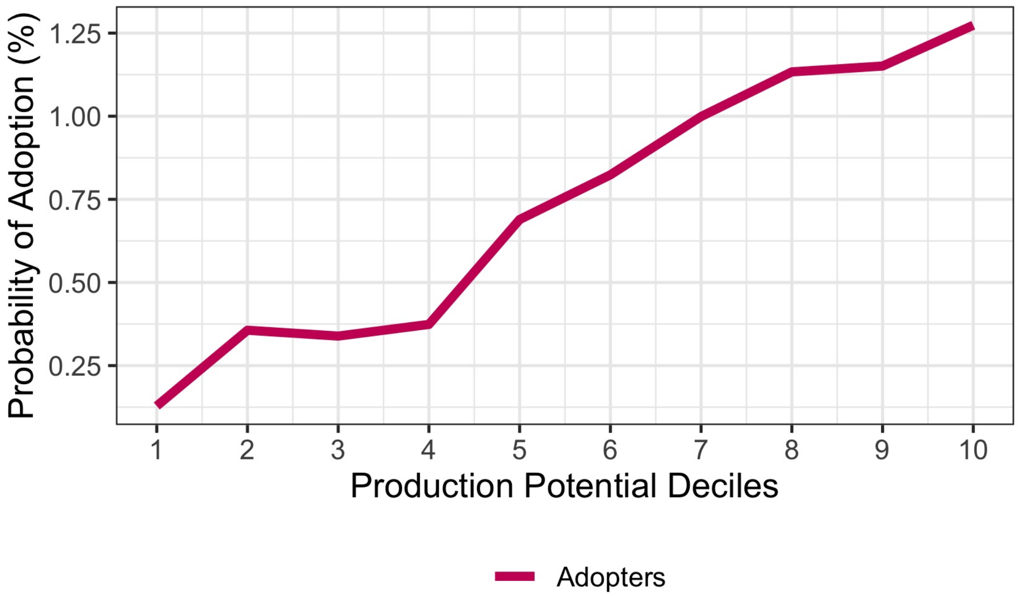
Figure 22: Conditional Propensity to Adopt With Either Subsidy Type



Notes: Commercial properties' conditional propensity to adopt with either subsidy type by c_i decile, conditional on adopting. c_i is the CSI Rating, CA's ex-ante estimate of each adopted system's lifetime expected production. The propensities are conditional on adoption, so sum to 100%. For comparability with Figures 23 and 24, however, the decile cutoffs are designated with respect to the whole distribution of potential adopters, as imputed from the Google data. Non-adopters c_i values are imputed following the procedure given in Section 2.3.2.

Notice that because the CSI data does not contain non-adopters, the plotted probabilities cannot be unconditional, but instead are conditional on adoption. As the displayed (conditional) propensity to adopt with the output subsidy increases in site quality, the propensity to adopt with the investment subsidy must decrease as a mirror image of the former. This does not imply same for the unconditional propensity to adopt with the investment subsidy - that is, including the choice to not adopt at all. Figure 23 plots the unconditional probability of adoption for each site quality decile in the Google Project Sunroof data.

Figure 23: Propensity to Adopt by g_i Decile

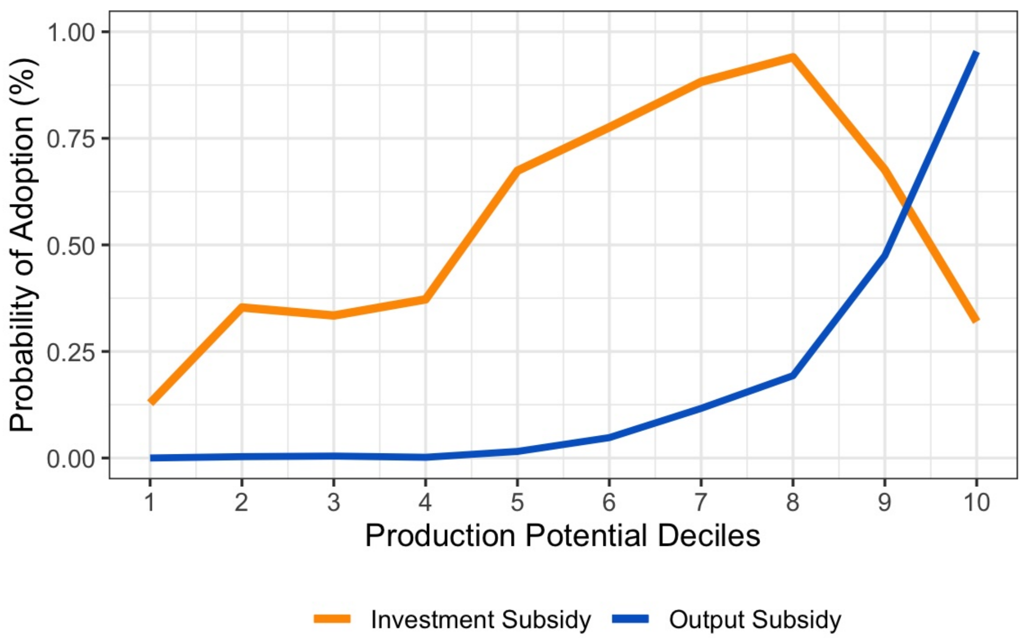


Notes: Commercial properties' propensity to adopt by g_i decile. g_i is Google Project Sunroof's estimate of the property's maximum solar energy production potential.

It is visible in Figure 23 that the propensity to adopt solar is increasing steadily in site quality: but lacking any information on subsidy types, the Project Sunroof data cannot dissect these adopters further.

It is only in harnessing both the CSI data and the Project Sunroof data together that we can see the unconditional propensities to adopt with either subsidy. One can roughly think of multiplying each of the conditional probabilities in Figure 22 by the corresponding decile probability in Figure 23 to yield the unconditional probabilities in Figure 24 below.

Figure 24: Unconditional Propensity to Adopt with Either Subsidy Type (Commercial)

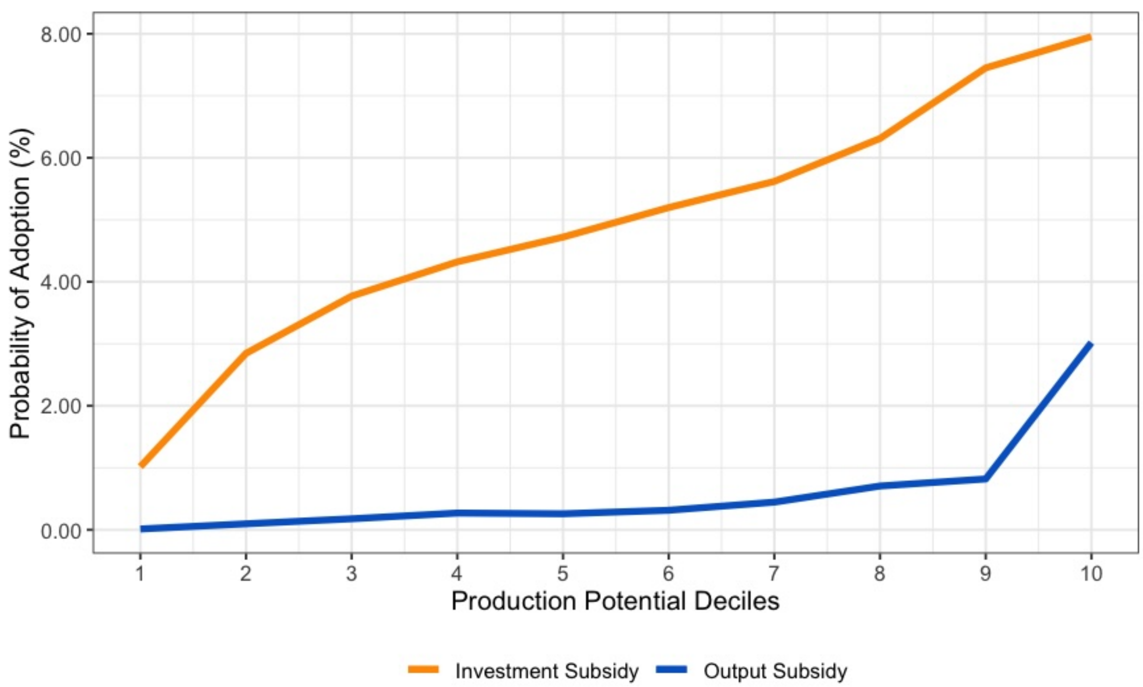


Notes: Commercial properties' unconditional propensity to adopt with either subsidy type by c_i decile. Non-adopters c_i values are imputed following the procedure given in Section 2.3.2.

Although the probability of choosing the investment subsidy conditional on adopting is decreasing in site quality as shown in Figure 22, the overall probability of adopting as shown in Figure 23 is increasing. Therefore, the unconditional probability of adopting with the investment subsidy, shown as the orange series in Figure 24, may be either increasing or decreasing. The probability of adopting with the output subsidy, on the other hand, is increasing through both channels - both conditionally as given in Figure 22, and in the absolute as given in Figure 23 - so is subject to an especially steep rise. Each of these patterns will form an essential part of the identifying variation for the model: While total (regardless of subsidy type) adoption increases in site quality due to electricity cost savings, adoption with the output subsidy in particular increases at an especially steep rate, due to the extra boost that it offers to the highest quality potential adopters.

Between commercial and residential properties, the patterns in adoption choice behavior with respect to site quality are similar in kind, but not in degree. In both cases, the overall propensity to adopt increases in site quality, while the conditional propensity to adopt with the investment subsidy decreases relative to that of the output subsidy: However, in the case of residential properties, the balance of these two components is such that the unconditional propensity to adopt with the investment subsidy is monotonically increasing in site quality alongside that of the output subsidy. Figure 25 below is the analogue of Figure 24 for residential properties:

Figure 25: Unconditional Propensity to Adopt with Either Subsidy Type (Residential)



Notes: Residential properties' unconditional propensity to adopt with either subsidy type by c_i decile. Non-adopters c_i values are imputed following the procedure given in Section 2.3.2. The output adoption probabilities are scaled 25x.

That is, although residential properties' propensity to adopt with the output subsidy increases sharply in the top decile, it is not enough to overwhelm the general increase for adoption with the investment subsidy as well. For commercial properties, on the other hand (as shown in Figure 24), the increase in adoption with the output subsidy is so strong in the top two deciles that adoption with the investment subsidy decreases, despite the sum of the two increasing. This may partly reflect just that the highest deciles for commercial properties are higher than those for residential properties, but also likely reflects that commercial properties are more responsive to the output subsidy due to having a higher discount factor (less impatience). The model estimation is needed to distinguish the roles played by each of these two factors in driving commercial properties' greater uptake of the output subsidy, and in so doing to pin down the value of the discount factor.

2.5 Model of Rooftop Solar Adoption

Under the California Solar Initiative (CSI), commercial properties faced a choice of whether to adopt rooftop solar, either with an investment subsidy or with an output subsidy, or to not adopt. I develop a dynamic discrete choice model to encapsulate the most critical factors in this choice. These factors split into two main groups: each property's (1) net financial benefit in the event of adopting solar, and (2) subjective taste for solar, including the desire to be seen as environmentally conscious. The net financial benefit is composed of three sub-components: (1a) subsidies, (1b) electricity cost savings, and (negatively) (1c) the cost of the solar system. The balance of the net financial benefit and subjective taste determines the adoption decision for each property.

On the financial benefits side, the intertemporal discounting factor β adjusts the utility value of financial benefits that will accrue in the future. β is linked particularly to the relative values of the investment and output subsidies, because investment subsidies are paid in the present, while output subsidies are paid in the future. If β is lower (individuals are more impatient), then the output subsidy becomes less attractive to potential adopters in utility terms, and therefore relatively less cost-effective as a subsidy.

Many studies on rooftop solar adoption, including De Groote and Verboven

(2019), Snashall-Woodhams (2019) and Malhotra (2023), have found that *residential* adopters tend to have a very low value of β (relative to financial market rates), indicating that they discount the future heavily in their choices of whether to adopt solar. This paper is the first, to my knowledge, to estimate the analogous β for commercial adopters. However, there are multiple reasons to expect that β should be not quite as low for firms as it is for households. Relative to households, firms have greater resources to assess long-term investments and risks, lower personal stakes in the outcomes, and more collateral with which to secure loans. Therefore, myopia, uncertainty, risk aversion, and unobserved liquidity constraints, all sub-factors of the estimated discount factor, all should be less likely to sway the decisions of firms than they are of households.

In addition to direct financial implications, subjective taste is also an important factor in the decision of whether to adopt rooftop solar. Studying residential adopters, Malhotra (2023) shows that there is a negative geographical correlation between taste and site quality in California, and that this increases the relative incentivizing effect of the output subsidy. Subjective taste for solar has a different meaning for firms than it does for households, but may nonetheless factor in similarly. Household decision makers are intimately affected by the choice of whether to install solar for the reason that if installed, solar panels are to become visible on the roofs of their own homes. Commercial decision makers are not thus personally affected, but nonetheless may choose to internalize the tastes of their local customer pools in the interest of developing brand value. For instance, a firm located in San Francisco might benefit from having a green-conscious reputation to target the large population of environmentally conscious individuals in the area who could potentially become customers. On the other hand, a firm in San Bernardino may not need such a reputation to attract customers.

Individuals i in the model are potential adopters of rooftop solar - that is, owners of commercial properties with rooftops.[67] In each time period t, the main choice d faced by each potential adopter i (who has not already adopted) can be written as:

$$d = \begin{cases} 0: & \text{do not adopt} \\ 1: & \text{adopt with investment subsidy} \\ 2: & \text{adopt with output subsidy} \end{cases}$$

The decision to adopt with either type of subsidy ($d > 0$) is a terminating action:[68] but not adopting ($d = 0$) preserves the option of adopting in a later time period. Conditional on the choice to adopt, i also chooses one of the available solar system product contracts, j. i's indirect utility is:

$$u^d_{i,j,t} = \nu^d_{i,j,t} + \xi^d_{z,j,t} + \epsilon^d_{i,j,t} \tag{35}$$

$$\nu^d_{i,j,t} = \begin{cases} \alpha \cdot R^{d>0}_{i,j,t} + \theta_i & \text{if } d > 0 \\ u^{d=0} + \beta \cdot E_t[\bar{V}_{i,t+1}] & \text{if } d = 0 \end{cases}$$

Commonly as in many demand models, the structural error term $\epsilon_{i,j,t}$ follows a type I extreme value distribution with respect to the choice options d, j, implying logit choice probabilities. The empirical error term $\xi^d_{z,j,t}$ will be absorbed via fixed effects, with z denoting i's county or region of residence. The conditional value of adoption $\nu^{d>0}_{i,j,t}$ is a balance (mediated by a willingness to pay parameter, α) between the net financial benefit $R^{d>0}_{i,j,t}$ (subsidy + electricity cost savings − system price) and i's subjective taste θ_i for whether or not to have solar (including the desire to be seen as environmentally conscious). The conditional value of not adopting is the baseline flow utility $u^{d=0}$ (this can be imagined as zero, with the value of not adopting possibly

[67] I assume owning firms internalize the expenses and tastes of tenant firms.

[68] The lifetime of a solar PV panel is about 20 years.

negative in comparison) plus the option value of waiting in order to potentially adopt solar in a future time period. The option value of waiting $\beta \cdot E_t[\bar{V}_{i,t+1}]$ is the expected value of i's best choice option in the next time period, discounted by β because that value is to realize one period hence.

2.5.1 Value of Adopting Solar

The conditional value of adopting solar, $\nu_{i,j,t}^{d>0} = \alpha \cdot R_{i,j,t}^{d>0} + \theta_i$, is relatively straightforward: because adoption is a terminating action, this value is equal to the expected discounted utility of the adopted solar system in the present time period (that in which the system is adopted). The intertemporal discount factor β critically weighs the sub-components of the net financial benefit $R_{i,j,t}^{d>0}$ against one another. Because the system installation price $p_{z,j,t}^{\mathrm{I}}$ is due in the present,[69] it is *not* weighted by β in utility terms. The the same goes for the investment subsidy. But the output subsidy as well as electricity cost savings accrue in the future, so must be weighted by β in utility terms. For $d = 1$ (adoption with investment subsidy) and $d = 2$ (adoption with output subsidy) respectively, the net financial benefits are,

$$R_{i,j,t}^{d=1} = \underbrace{r_{z,t}^{\mathrm{u}} \cdot c_{i,j}}_{\substack{\text{Investment}\\ \text{Subsidy}}} + \underbrace{\sum_{\tau=0}^{20 \text{ years}} (\delta \cdot \beta)^{\tau} \cdot E_t[q_{i,j,t+\tau}] \cdot E_t[p_{z,t+\tau}^{\mathrm{E}}]}_{\text{Electricity Cost Savings}} - \underbrace{p_{z,j,t}^{\mathrm{I}}}_{\substack{\text{Installation}\\ \text{Price}}} \tag{36}$$

$$R_{i,j,t}^{d=2} = \underbrace{r_{z,t}^{\mathrm{q}} \cdot \sum_{\tau=0}^{5 \text{ years}} (\delta \cdot \beta)^{\tau} \cdot E_t[q_{i,j,t+\tau}]}_{\substack{\text{Output}\\ \text{Subsidy}}} + \underbrace{\sum_{\tau=0}^{20 \text{ years}} (\delta \cdot \beta)^{\tau} \cdot E_t[q_{i,j,t+\tau}] \cdot E_t[p_{z,t+\tau}^{\mathrm{E}}]}_{\text{Electricity Cost Savings}} - \underbrace{p_{z,j,t}^{\mathrm{I}}}_{\substack{\text{Installation}\\ \text{Price}}}$$

where $r^{\mathrm{u}}, r^{\mathrm{q}}, p^{\mathrm{E}}$, and p^{I} denote the upfront subsidy rate, output subsidy rate, electricity price, and system installation price, respectively. The calibrated parameter δ

[69]The system price is adjusted for the federal Investment Tax Credit (ITC).

adjusts for solar panels depreciation as well as expected inflation of the US dollar.[70] The output subsidy is paid out over 5 years, whereas electricity cost savings accrue for an expectation of 20 years, reflecting the typical lifespan of solar panels. $c_{i,j}$ is the CSI Rating, which serves as the state's official estimate of the adopted system's expected lifetime total solar energy production, while $E_t[q_{i,j,t+\tau}]$ is the potential adopter's own expectation of their own solar energy production per period $t+\tau$. Because the choice of subsidy has no bearing on expected electricity cost savings, nor on system installation price, the net financial benefits $R^{d=1}_{i,j,t}$ and $R^{d=2}_{i,j,t}$ are identical except for the subsidy.

The net financial benefit $R^{d>0}_{i,j,t}$ of adopting solar may be either positive or negative, depending on whether the subsidy plus electricity cost savings outweigh the system price. The subjective taste term θ_i may be either positive or negative, also, depending on whether the desire to be seen as environmentally conscious outweighs the firm's visual distaste for the appearance of solar panels. However, unlike the net financial benefit which consists of mostly observed components, taste θ_i is primarily unobservable. Empirically, I proxy for θ_i with county (z) level socioeconomic indicators likely to correlated with local consumers' average taste for solar:[71] political leaning, education, and median household income. That is,

$$\theta_i = \theta^{\text{pol}} \cdot P^{\text{pol}}_{z,t} + \theta^{\text{edu}} \cdot P^{\text{edu}}_{z,t} + \theta^{\text{inc}} \cdot X^{\text{inc}}_{z,t} + \tilde{\theta}_i \tag{37}$$

where $P^{\text{pol}}_{z,t}$ is the fraction of the local population in i's county z who are politically left-leaning, $P^{\text{edu}}_{z,t}$ is the fraction with at least four years of higher education, and $X^{\text{inc}}_{z,t}$ is median household income. I leave the remaining unobserved portion of taste $\tilde{\theta}_i$ to merge with the model's empirical error term $\xi_{z,j,t}$ (absorbed in fixed effects), and structural error term $\epsilon_{i,j,t}$.

[70]The time intervals $t+\tau$ may be either months or years, only δ and β need to be adjusted accordingly.

[71]I assume that firms internalize local consumers' tastes in the interest of attracting potential customers.

2.5.2 System Characteristics and Site Quality

Multiple elements of the net financial benefit of adopting solar, $R^{d>0}_{i,j,t}$, depend on system size and other system j characteristics. A larger system will come with both higher expected production and higher installation price. The CSI rating $c_{i,j}$, which serves as the state's approximation of expected production, is equal exactly to the system size s_j multiplied by a Design Factor, $\tilde{c}_i$.

$$c_{i,j} = \tilde{c}_i \cdot s_j \tag{38}$$

The Design Factor $\tilde{c}_i$ is a unitless scalar that adjusts for local sunlight intensity, azimuth (compass orientation of the roof on which the system is to be installed), tilt (vertical angle of the roof), and shading. (The state's estimate of expected production is

$$c_{i,j} \cdot \sum_{\tau} \bar{h}$$

where $\bar{h}$ is a **constant** grand average number of hours of sun exposure per system per time period.) The potential adopter's own expectation of its own production $E_t[q_{i,j,t+\tau}]$, though not directly observed, should be closely related to $c_{i,j}$ and similarly constituted, as both are essentially estimates of the same expected production.

The system installation price $p^{\mathrm{I}}_{z,j,t}$ should also be a function of system characteristics j, particularly system size s_j. I model system price as a linear function of size, with both the slope and intercept varying by region z as well as time period t:

$$p^{\mathrm{I}}_{z,j,t} = p^{\mathrm{oI}}_{z,t} + p^{\mathrm{sI}}_{z,t} \cdot s_j \tag{39}$$

The intercept terms $p^{\mathrm{oI}}_{z,t}$ coincide with fixed costs. A $2kW$ system will be more than half as expensive as a $4kW$. Such decreasing average costs per kW size, implied by the presence of positive fixed costs, imply that optimal system sizes will be larger for properties i with higher site quality.

To reduce the complexity of the model, I assume that all factors driving the choice of system j characteristics are exogenous. This implies that all j subscripts in the model are superfluous: j characteristics are implications of the characteristics of properties i or their associated regions z. (Similarly, a z subscript would be superfluous wherever there is an i.) As a simplest example, the Design Factor $\tilde{c}_i$ should arguably be written as $\tilde{c}_{i,j}$ in theory, although it needn't be in empirical execution. The Design Factor includes system characteristics such as azimuth and tilt. My assumption is that a system's azimuth is not a free choice, but is instead implied by the property i's roof space and orientation. Each property has a predetermined set of roof spaces, one of which is best oriented for solar regardless of other factors in the model.

I assume that each chosen system size s_j, and all other system j characteristics, all are implied by their associated property i's exogenous characteristics, similarly as is each system's chosen azimuth. These exogenous i characteristics include the property's energy usage needs, roof space and orientation, sunlight intensity and shading. Although theoretically unappealing, this assumption of exogenous system characteristics helpfully simplifies the model, while preserving the vast bulk of what is likely to be important in practice for the question at hand. For example, although it is conceivable that optimal system sizes s_j may respond to subsidy rates on a very small margin, it is fair to assume that each property i's chosen system size - conditional on yes or no adoption - is (in the vast bulk) a function of its (exogenous) energy usage needs and roof space. I assume the parameters of the system pricing function, $p^{\mathrm{oI}}_{z,t}$ and $p^{\mathrm{sI}}_{z,t}$, likewise to be exogenous. This precludes any price setting behavior amongst solar supplier firms, but coincides with the vast bulk of what is likely to drive solar installation prices - namely, equipment and labor costs.

The assumption of exogenous system characteristics has, amongst other upsides, the benefit of simplifying the concept of site quality. Because expected production follows from site i characteristics (which are exogenous) and system j characteristics

- and the j characteristics themselves follow from the i characteristics - expected production is to be viewed as following entirely from site i characteristics. Therefore expected production - conditional on yes or no adoption - is exogenous, and synonymous with site quality. As such the CSI rating $c_{i,j} = c_i$ which is the state's estimate of i's expected production, and the commercial property i's own estimate of its own expected production $E_t[q_{i,j,t+\tau}] = E_t[q_{i,t+\tau}]$, both measures of expected production, serve as alternative measures of site quality. The extent to which these two measures disagree with one another is critical in the model, as the investment subsidy amount follows from the former, while the expected output subsidy amount follows from the latter.

2.5.3 Hidden Site Quality

In the model as it is written, the output subsidy can have no possible advantage over the investment subsidy unless the adopting firm i's estimate $E_t[q_{i,t+\tau}]$ of its own site quality is more accurate than the state's estimate c_i of the same. To proxy for $E_t[q_{i,t+\tau}]$, I fit ex-post actual production $q_{i,t}$ in hindsight as a function of ex-ante observable site and system characteristics, seeking maximal fit. I find in this empirical case that c_i does predict actual production $q_{i,t}$ (or q_i - averaged over t) very well,[72] but that the highest values of c_i underestimate the highest values of q_i. This is to say that q_i is an increasing function of c_i rather than a linear function. I therefore fit a nonlinear function of q_i on c_i, with intercepts c^{o} and slopes c^{q} varying by region z:

$$\begin{aligned} \log(q_i) &= c_z^{\mathrm{o}} + c_z^{\mathrm{q}} \cdot \log(c_i) + c^{\ell} \cdot \log(\ell_i) \\ y_i &= \exp(\widehat{\log(q_i)}) \end{aligned} \tag{40}$$

where ℓ_i is sunlight intensity data from Google Project Sunroof. The fitted values - which I call y_i - serve as an additional measure of site quality. Particularly y_i is

[72] I find a correlation of c_i with q_i of 0.79 amongst commercial adopters in the CSI data.

the most accurate available estimate, such as adopting firms i might have given full knowledge of their own properties. I therefore use y_i (iterated over time periods $t+\tau$) to proxy for the adopters' i estimate $E_t[q_{i,t+\tau}]$ of their own expected production, that which is more accurate than the state's estimate c_i of the same.

$$R_{i,t}^{d=1} = \underbrace{r_{z,t}^{\mathrm{u}} \cdot c_i}_{\substack{\text{Investment}\\ \text{Subsidy}}} + \underbrace{\sum_{\tau=0}^{\text{20 years}} (\delta \cdot \beta)^{\tau} \cdot y_i \cdot E_t[p_{z,t+\tau}^{\mathrm{E}}]}_{\text{Electricity Cost Savings}} - \underbrace{\left(p_{z,t}^{\mathrm{oI}} + p_{z,t}^{\mathrm{sI}} \cdot s_i\right)}_{\substack{\text{Installation}\\ \text{Price}}}$$

$$R_{i,t}^{d=2} = \underbrace{r_{z,t}^{\mathrm{q}} \cdot \sum_{\tau=0}^{\text{5 years}} (\delta \cdot \beta)^{\tau} \cdot y_i}_{\substack{\text{Output}\\ \text{Subsidy}}} + \underbrace{\sum_{\tau=0}^{\text{20 years}} (\delta \cdot \beta)^{\tau} \cdot y_i \cdot E_t[p_{z,t+\tau}^{\mathrm{E}}]}_{\text{Electricity Cost Savings}} - \underbrace{\left(p_{z,t}^{\mathrm{oI}} + p_{z,t}^{\mathrm{sI}} \cdot s_i\right)}_{\substack{\text{Installation}\\ \text{Price}}} \tag{41}$$

The use of the nonlinear function underlying y_i as hidden site quality - known to adopting firms but not to the state - begs the question as to why the state should not simply update its c_i measure to be equal to y_i. However, y_i should be thought of as an over-fitted function, harnessing information on actual production in hindsight such as should not be available to policy makers ex-ante in any practical setting. Thematically, the idea is that even with an investment subsidy program that is adjusted for site quality by the state ex-ante, the investment subsidy falls at least slightly short of the output subsidy in targeting to site quality for the reason that no ex-ante evaluation can be perfect. Granted, the adopter's evaluation of their own site quality is also ex-ante, but presumed to harness intimate knowledge that cannot be available to the state. This is to say that the output subsidy retains at least some small upside relative to the investment subsidy, though not necessarily that this upside is enough to overcome the output subsidy's relative downside of intertemporal discounting. The more accurate an investment subsidy program is in adjusting to site quality, the less scope there can be for the output subsidy to yield gains in cost-effectiveness.

2.5.4 Model Solution

Potential adopters i may choose to refrain from adopting solar, either in order to retain the option to adopt in a future time period, or to never adopt. The conditional value of not adopting $\nu_{i,t}^{d=0}$ is equal to the baseline flow utility $u^{d=0}$ plus the option value of waiting,

$$\nu_{i,t}^{d=0} = u^{d=0} + \beta \cdot E_t[\bar{V}_{i,t+1}] \tag{42}$$

where $\bar{V}_{i,t+1}$ is the value of behaving optimally from period $t+1$ onward, an aggregation of the values $\nu_{i,t+\tau}^{d>0}$ of all future options.

I follow De Groote and Verboven (2019), Scott et al. (2013) and Hotz and Miller (1993) in substituting out for $E_t[\bar{V}_{i,t+1}]$ in the Conditional Choice Probability (CCP) formulas. This will simplify the estimation of the dynamic discrete choice model. I will not need to specify whether the adoption decision is a finite or infinite time horizon problem, nor to specify how agents believe the future states to evolve. I only need to assume rational expectations on state transitions. By the assumption that the structural error terms $\epsilon_{i,t}^{d}$ are EV1 distributed, the conditional choice probabilities $P_{i,t}^{d}$ for each choice option d take the logit forms,

$$\begin{aligned} P_{i,t}^{d} &= \exp(\nu_{i,t}^{d}) \Big/ \sum_{d'} \exp(\nu_{i,t}^{d'}) \\ P_{i,t}^{d} \Big/ P_{i,t}^{d'} &= \exp(\nu_{i,t}^{d}) \Big/ \exp(\nu_{i,t}^{d'}) \end{aligned} \tag{43}$$

and the continuation value $\bar{V}_{i,t+1}$ takes the form,

$$\bar{V}_{i,t+1} = \gamma + \log \sum_{d'} \exp(\nu_{i,t+1}^{d'}) \tag{44}$$

where γ is Euler's Constant. Following Scott et al. (2013), I assume that potential adopters i predict $\bar{V}_{i,t+1}$ accurately up to a mean-zero error $\eta_{i,t}$,

$$E_t[\bar{V}_{i,t+1}] = \bar{V}_{i,t+1} - \eta_{i,t} \tag{45}$$

Equations (42) - (45) can be combined to yield a non-recursive solution to the choice probabilities (43). To do this, first replace the $E_t[\bar{V}_{i,t+1}]$ in (42) with that in (45),

$$\nu_{i,t}^{d=0} = u^{d=0} + \beta \cdot (\bar{V}_{i,t+1} - \eta_{i,t})$$

then apply the $\bar{V}_{i,t+1}$ formula (44),

$$\nu_{i,t}^{d=0} = u^{d=0} + \beta \cdot (\gamma + \log \sum_{d'} \exp(\nu_{i,t+1}^{d'}) - \eta_{i,t})$$

normalize $u^{d=0} + \beta \cdot \gamma = 0$, and let $-\beta \cdot \eta_{i,t}$ merge into $\xi_{z,t}^{d=0}$ and $\epsilon_{i,t}^{d=0}$ in (35). This results in,

$$\nu_{i,t}^{d=0} = \beta \cdot \log \sum_{d'} \exp(\nu_{i,t+1}^{d'}) \tag{46}$$

Now notice that,

$$\sum_{d'} \exp(\nu_{i,t+1}^{d'})$$

is the denominator of the logit conditional choice probability formula (43) evaluated for $P_{i,t+1}^{d}$,

$$P_{i,t+1}^{d} = \exp(\nu_{i,t+1}^{d}) \Big/ \sum_{d'} \exp(\nu_{i,t+1}^{d'})$$

Inverted, this is,

$$\log \sum_{d'} \exp(\nu_{i,t+1}^{d'}) = \nu_{i,t+1}^{d} - \log P_{i,t+1}^{d}$$

which can applied in (46) to yield,

$$\nu_{i,t}^{d=0} = \beta \cdot (\nu_{i,t+1}^{d} - \log P_{i,t+1}^{d}) \tag{47}$$

This equation is valid when evaluated for any given d choice,

$$\begin{aligned}
\nu_{i,t}^{d=0} &= \beta \cdot (\nu_{i,t+1}^{d=0} - \log P_{i,t+1}^{d=0}) \\
&= \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}) \\
&= \beta \cdot (\nu_{i,t+1}^{d=2} - \log P_{i,t+1}^{d=2})
\end{aligned}$$

Evaluating at $d = 0$ is not helpful though, as this yields only a solution for $\nu_{i,t}^{d=0}$ in terms of $\nu_{i,t+1}^{d=0}$, which in turn is solved only in terms of $\nu_{i,t+2}^{d=0}$, and so on. However, $\nu_{i,t+1}^{d=1}$ and $\nu_{i,t+1}^{d=2}$, as $\nu_{i,t}^{d=1}$ and $\nu_{i,t}^{d=2}$, have their own definitions as developed in 2.5.1 and 2.5.3,

$$\begin{aligned}
\nu_{i,t}^{d=1} \quad = \quad \alpha \cdot \Bigg(& \underbrace{r_{z,t}^{\mathrm{u}} \cdot c_i}_{\substack{\text{Investment}\\ \text{Subsidy}}} + \underbrace{\sum_{\tau=0}^{20 \text{ years}} (\delta \cdot \beta)^{\tau} \cdot y_i \cdot E_t[p_{z,t+\tau}^{\mathrm{E}}]}_{\text{Electricity Cost Savings}} - \underbrace{\left(p_{z,t}^{\mathrm{oI}} + p_{z,t}^{\mathrm{sI}} \cdot s_i\right)}_{\substack{\text{Installation}\\ \text{Price}}} \Bigg) \\
& + \underbrace{\theta^{\mathrm{pol}} \cdot P_{z,t}^{\mathrm{pol}} + \theta^{\mathrm{edu}} \cdot P_{z,t}^{\mathrm{edu}} + \theta^{\mathrm{inc}} \cdot X_{z,t}^{\mathrm{inc}}}_{\text{Taste for Solar}} \\
\nu_{i,t}^{d=2} \quad = \quad \alpha \cdot \Bigg(& \underbrace{r_{z,t}^{\mathrm{q}} \cdot \sum_{\tau=0}^{5 \text{ years}} (\delta \cdot \beta)^{\tau} \cdot y_i}_{\substack{\text{Output}\\ \text{Subsidy}}} + \underbrace{\sum_{\tau=0}^{20 \text{ years}} (\delta \cdot \beta)^{\tau} \cdot y_i \cdot E_t[p_{z,t+\tau}^{\mathrm{E}}]}_{\text{Electricity Cost Savings}} - \underbrace{\left(p_{z,t}^{\mathrm{oI}} + p_{z,t}^{\mathrm{sI}} \cdot s_i\right)}_{\substack{\text{Installation}\\ \text{Price}}} \Bigg) \\
& + \underbrace{\theta^{\mathrm{pol}} \cdot P_{z,t}^{\mathrm{pol}} + \theta^{\mathrm{edu}} \cdot P_{z,t}^{\mathrm{edu}} + \theta^{\mathrm{inc}} \cdot X_{z,t}^{\mathrm{inc}}}_{\text{Taste for Solar}}
\end{aligned} \tag{48}$$

Therefore (47) evaluated at either $d = 1$ or $d = 2$ yields a non-recursive solution for $\nu_{i,t}^{d=0}$. Choosing $d = 1$, the solution

$$\nu_{i,t}^{d=0} = \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}) \tag{49}$$

joins the $\nu_{i,t}^{d>0}$ expressions (48) to complete the model. The conditional choice probabilities (43) resolve as,

$$\begin{aligned}
P_{i,t}^{d=0} &= \frac{\exp(\beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}))}{\exp(\beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1})) + \exp(\nu_{i,t}^{d=1}) + \exp(\nu_{i,t}^{d=2})} \\
P_{i,t}^{d=1} &= \frac{\exp(\nu_{i,t}^{d=1})}{\exp(\beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1})) + \exp(\nu_{i,t}^{d=1}) + \exp(\nu_{i,t}^{d=2})} \\
P_{i,t}^{d=2} &= \frac{\exp(\nu_{i,t}^{d=2})}{\exp(\beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1})) + \exp(\nu_{i,t}^{d=1}) + \exp(\nu_{i,t}^{d=2})}
\end{aligned} \tag{50}$$

which alternatively can be written as,

$$\begin{aligned}
P_{i,t}^{d=0} &= \frac{1}{1 + \exp(\nu_{i,t}^{d=1} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1})) + \exp(\nu_{i,t}^{d=2} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}))} \\
P_{i,t}^{d=1} &= \frac{\exp(\nu_{i,t}^{d=1} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}))}{1 + \exp(\nu_{i,t}^{d=1} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1})) + \exp(\nu_{i,t}^{d=2} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}))} \\
P_{i,t}^{d=2} &= \frac{\exp(\nu_{i,t}^{d=2} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}))}{1 + \exp(\nu_{i,t}^{d=1} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1})) + \exp(\nu_{i,t}^{d=2} - \beta \cdot (\nu_{i,t+1}^{d=1} - \log P_{i,t+1}^{d=1}))}
\end{aligned} \tag{51}$$

where each ν term is function of data and the parameters to be estimated $\{\alpha, \beta, \tilde{\theta}, \theta^{\text{pol}}, \theta^{\text{edu}}, \theta^{\text{inc}}\}$, as given by (48).[73] The choice probabilities P for each choice option d are essentially data, with the caveat that each individual potential adopter i may only realize one choice (per time period), so that probabilities at the level of individuals i are observed only indirectly.

I follow the approach of Arcidiacono and Miller (2011), that is of estimating (51)

[73]It should be noted that the choice probabilities (51) are conditional on having not already adopted, so in unconditional terms apply strictly as written only for the initial period. All subsequent t periods' probabilities are to be multiplied by the unconditional $d = 0$ probability from the previous period, iterated from the initial period.

in two steps.[74] In the first step, I approximate the right hand side probabilities $P^{d=1}_{i,t+1}$ via a flexible logit predictive model. This is analogous to the familiar use of observed market shares to approximate probabilities - but adjusted per individual property i based on individual characteristics (c_i, y_i) as well as location z.[75] Taking the conditional choice probabilities as given in the second stage, the estimation then reduces to an essentially static multinomial logit criterion function with a precalculated offset term, as given by (51). That is, I take the approximated $P^{d=1}_{i,t+1}$ from the first step as data in the second (main) step of estimating (51) via simplex grid search Maximum Likelihood estimation.[76] The resulting parameter estimates for $\{\alpha, \beta, \theta^{\text{pol}}, \theta^{\text{edu}}, \theta^{\text{inc}}\}$ encapsulate commercial adopters' demand behavior for rooftop solar.

2.6 Empirical Results

I estimate the dynamic discrete choice model of rooftop solar adoption described in Section 2.5 in order to quantify the balance of motives underlying potential adopters' choices. The estimation results explain the factual pattern of adoption choices observed in the data, and shed light on potential adopters' tastes and preferences (demand parameters). By estimating the model separately for commercial and residential properties, critically, I am able to compare distinct values of each of the demand parameters across these two important types of consumers.

As discussed throughout Section 2.5, a few key parameters of the demand model are critical in driving the distribution of adoption decisions. Most of all, the intertemporal discount factor β measures how potential adopters weigh financial benefits in the present against those that will accrue in the future, influencing households' and firms' propensities to adopt and to select the output subsidy rather than the invest-

[74]De Groote and Verboven (2019) conduct an analogous two step estimation in their Online Appendix.

[75]The predictive model is a static analogue of (51) with added fixed effects and interaction terms, meant to maximize fit rather than identify parameters.

[76]As discussed earlier in this section, a few other components (y_i, $p^{\text{oI}}_{z,t}$, $p^{\text{sI}}_{z,t}$) of (51) are approximated as well in first steps of their own in parallel to $P^{d=1}_{i,t+1}$.

ment subsidy. As shown in Table 2.2, I estimate a much higher yearly discount factor for firms ($\beta = 0.94$) than for households ($\beta = 0.82$). This indicates that firms are a great deal less impatient than households are in their valuation of the future financial benefits of adopting solar, implying that policy makers should treat firms and households very differently in seeking for cost-effective subsidy schedules.

Table 2.2: Solar Adoption Model MLE Parameter Estimates

	Parameter	Residential Estimate	Commercial Estimate
price sensitivity (per \$$10^5$)	α	6.642	4.661
		(0.026)	(0.007)
monthly discount factor	β^{monthly}	0.984	0.995
		(0.004)	(0.012)
yearly discount factor	β^{yearly}	0.821	0.940
intercept taste for solar	$\bar{\theta}$	-4.998	-4.733
		(0.007)	(0.009)
d(taste)/d(Democrat)	θ^{pol}	0.836	1.125
		(0.234)	(0.112)
d(taste)/d(Income) (per \$$10^5$)	θ^{inc}	1.833	3.650
		(0.028)	(0.061)
d(taste)/d(Educated)	θ^{edu}	0.199	0.246
		(0.216)	(0.010)
corr(taste, site quality)	$\rho_{\theta,y}$	-0.289	-0.261

Notes: Parameter estimates from the dynamic discrete choice rooftop solar adoption demand model for residential and commercial properties in CA, respectively. Standard errors in parentheses.

In addition to the discount factor β, the correlation between taste and site quality ($\rho_{\theta,y}$) also plays a crucial role in shaping solar adopters' choice behavior and responsiveness to the subsidy options.[77] In contrast to the discount factor, where my estimates indicate a large difference in patience between firms and households, my estimates for $\rho_{\theta,y}$ indicate a similarity between firms and households in tastes. The

[77]Malhotra (2023) shows that in particular a negative value of $\rho_{\theta,y}$ will strengthen the cost-effectiveness of the output subsidy relative to that of the investment subsidy.

value of $\rho_{\theta,y} = -0.29$ in Table 2.2 encapsulates the fact that in California, the most environmentally conscious or left-leaning households in California tend to live in the least sunny areas (e.g. San Francisco), and vice versa (e.g. San Bernardino). The not far off value of $\rho_{\theta,y} = -0.26$ in Table 2.2 suggests that firms mirror or internalize the tastes of local households. That is, firms in (for example) San Francisco and San Bernardino exhibit about the same difference in subjective taste for solar as households do across the same locations. This may reflect local firms' incentive to cultivate brand images in accord with their local customer bases.

Although the correlation between taste and site quality is similar for firms and households, it should be noted that correlation does not indicate anything about the magnitude of the taste. Potential adopters' demand function[78] weighs this subjective taste (θ) against their expected net financial gain in the event of adopting solar, mediated by the willingness to pay parameter α. To get a sense of magnitudes, Table 2.3 below scales each of the estimated taste parameter values by the corresponding value of α: This effectively translates the taste parameters into values in dollar terms, against which potential adopters weigh their expected net financial gain in their decision of whether to adopt solar.

Table 2.3: Taste Parameter Estimates in Dollar Terms

	Parameter	Residential Estimate	Commercial Estimate
intercept taste for solar	$\bar{\theta}$	-\$75,200	-\$107,000
d(taste)/d(Democrat) (per % Dem)	θ^{pol}	\$126	\$268
d(taste)/d(Income) (per \$1000 Inc)	θ^{inc}	\$276	\$783
d(taste)/d(Educated) (per % Edu)	θ^{edu}	\$30	\$53

Notes: Dollar term estimates are obtained by dividing the taste parameter estimates in Table 2.2 by α. % Democrat, Income, and % (College) Educated refer to the average or median amongst households in the county in which the household or firm is located.

It is evident in Table 2.3 that the magnitude of every taste parameter value is slightly

[78] See Section 2.5.

higher for firms than the corresponding value for households. However, it must be remembered that the role of this subjective taste is to weigh against the expected net financial gain in the event of adopting solar, and that the magnitudes of financial gains are typically much larger for firms than for households. As such, subjective taste plays a much smaller overall role in firms' decision making than in households'.

Table 2.4: Comparison of Main Parameter Estimates

	β	$\rho_{\theta,y}$	med(R)	med(θ)
Residential	0.82	-0.29	\$28,600	-\$50,100
Commercial	0.94	-0.26	\$41,000	-\$44,900

Notes: Dollar term estimates are obtained by dividing the taste parameter estimates in Table 2.2 by α. Med(R) refers to median financial benefits and med(θ) refers to median taste for solar.

The comparisons in Table 2.4 reveal important differences in the underlying demand parameters between residential and commercial adopters of photovoltaic (PV) systems. First, the annual discount factor β (discount rate $= 1/\beta - 1$) indicates that firms are only about one third as impatient as households in their investment decisions, suggesting that commercial entities are not as myopic when evaluating the financial benefits of PV adoption. Second, the negative correlation between subjective taste and site quality ($\rho_{\theta,y}$) is similar in magnitude across the two adopter groups, suggesting that firms internalize the preferences of local residential households. Comparison of the magnitudes of the subjective taste and net financial gain as components of utility, however, shows that the taste plays a smaller role for firms than it does for households. The median financial gain (R) is higher for commercial adopters, as they typically have more roof space on which they can install larger PV systems. That their subjective taste is not also larger in magnitude, but in fact smaller, may reflect that commercial adopters are not as personally affected by the presence of solar panels on business premises as residential adopters are on their own homes, or simply that commercial adopters' decision making is more focused on the financial bottom line. Overall, these findings highlight that firms exhibit greater patience and prioritize financial considerations to a larger degree than residential consumers, who tend to be more influenced by personal taste factors.

These findings have significant policy implications for subsidies related to the adoption of solar photovoltaic (PV) technology. Malhotra (2023) analyzes the counterfactual scenario for residential users and shows that the most cost-effective subsidy design to achieve the same production level [79] involves a higher investment subsidy rate paired with a lower output subsidy rate. However, the cost-effective balance of investment and output subsidies will differ for firms compared to residential adopters. The cost-effectiveness of investment subsidies for residential adopters is driven mainly by their low discount factor (high impatience) with regard to future financial benefits, including any output subsidy payments. Because output subsidies are more efficient in targeting to site quality in both cases, the lack of impatience as a countervailing force in the case of firms particularly makes them the more cost-effective choice. In both cases, the estimated negative correlation between personal taste and site quality provides an additional boost the cost-effectiveness of output-based subsidies, making them the better subsidy design for firms in this setting even though they are not for households.

2.7 Policy Implications

The California Solar Initiative paid out a total of roughly $2.2 billion to subsidize commercial and residential rooftop solar systems, about one third of which went to residential adopters. The subsidized systems amounted to about 50.9 billion and 21.4 billion kWh in electricity production amongst commercial and residential properties, respectively. A hypothetical subsidy policy that would result in the same production with lower expenditure, or higher production with the same expenditure, would undoubtedly be preferable to the government than the policy that was run.

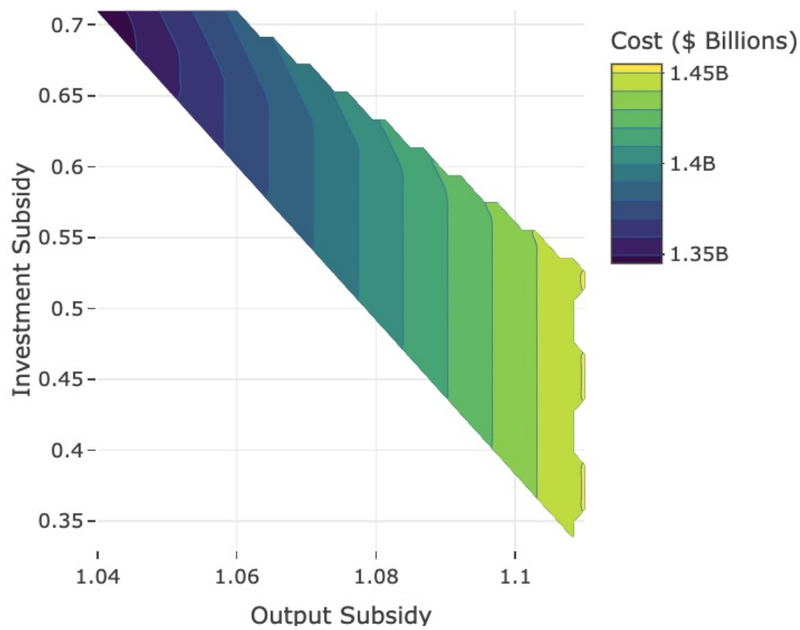
[79] The total solar production targeted in California Solar Initative.

The model estimation results obtained in Section 2.6 enable counterfactual simulations to predict how adoption choice behavior would respond under such alternative hypothetical subsidy policies.

I search for a cost-minimizing combination of subsidy rates amongst those that meet a given, fixed production target. I take as the production target that which was achieved under the CSI program, roughly 50.9 billion kWh for commercial properties and 21.4 billion for residential properties. In the CSI program, each of the (investment and output) subsidy rates declined in ten steps over time:[80] To hold this feature constant in my counterfactuals, I multiply each of the original CSI rate schedules by a scalar ranging from 0 to 2. However, where the CSI program offered the same set of rates to commercial as to residential properties, I allow for a separate rate schedule scalar for commercial and residential properties, for each of the two subsidy types. Figures 26 and 27, for commercial and residential properties, respectively, display the total program cost that I calculate would result from each combination of counterfactual subsidy rate schedules that meet the respective production targets of 50.9 billion and 21.4 billion kWh.

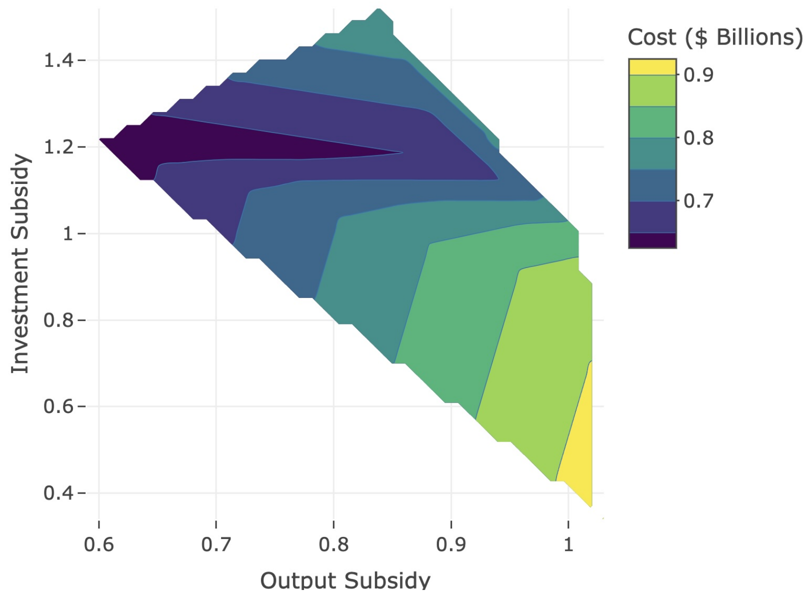
[80] See Table 2.5.

Figure 26: Total Subsidy Cost With Fixed Production Target: Commercial Properties



Notes: The investment and output subsidy rate axes plot the scalar by which the original CSI subsidy rate schedule is multiplied to yield each counterfactual rate schedule. The counterfactual subsidy program cost resulting from each rate schedule combination is plotted in color. All combinations included in the graph result in total solar electricity production roughly equal to 50.9 billion kWh, with a tolerance of 1% (50.4 - 51.4 billion kWh).

Figure 27: Total Subsidy Cost With Fixed Production Target: Residential Properties



Notes: The investment and output subsidy rate axes plot the scalar by which the original CSI subsidy rate schedule is multiplied to yield each counterfactual rate schedule. The counterfactual subsidy program cost resulting from each rate schedule combination is plotted in color. All combinations included in the graph result in total solar electricity production roughly equal to 21.4 billion kWh, with a tolerance of 1% (21.2 - 21.6 billion kWh).

While the counterfactual cost plots (above) are of roughly similar shape for commercial as for residential properties, it is the values on the axes that are most important. The axis values give the scalar by which the original CSI investment or output rate subsidy schedule was multiplied to arrive at each given counterfactual subsidy schedule. The darkest blue color, representing the lowest program cost, identifies the most cost-effective combination of subsidy schedules.

Most important to note are the axis values at which the cost-effective rate combination falls in each of the two plots (Figures 26 and 27). For residential properties, the cost-minimizing combination falls at roughly (0.60, 1.21), indicating output subsidy rates 40% lower than in the original CSI schedule, and investment subsidy rates 21% higher. For commercial properties, on the other hand, the cost-minimizing combination indicates a roughly 4% higher output subsidy paired with a 29% lower investment subsidy. That is, due to residential adopters' low discount factor at $\beta = 0.82$, money given to adopters in the future in the form of output subsidies is to a large extent wasted in utility terms, implying that it is cost-effective to shift funds into the input subsidy instead. However, because commercial adopters are not nearly as impatient, at $\beta = 0.94$, the output subsidy's relative advantage of better targeting to site quality becomes more important than the input subsidy's relative advantage of being paid up front. These cost-minimizing subsidy schedules deliver savings to the government of about \$160 and \$140 million in commercial and residential subsidies, respectively.

2.8 Conclusion

This paper exploits an unusual opportunity, offered by the California Solar Initiative, to estimate values of the intertemporal discount factor for commercial as well as residential adopters of rooftop solar. Correct values of the discount factor are crucial for the design of cost-effective subsidy policies to encourage the adoption of new green technology. This paper's results suggest that subsidy policies aimed at firms should assume higher discount factors (less impatience) than those aimed at households. In the context of green technology adoption, this implies that commercial properties should be offered relatively higher output subsidy rates, and residential properties relatively higher investment subsidy rates. The finding that firms are only about one third as impatient as households in the setting of rooftop solar adoption may serve as a best guess in other related settings as well.

This research can be extended in several ways. First, while this paper assumes a single discount factor for each of households and firms, the discount factor may be modeled as heterogeneous amongst firm, perhaps as a function firm size. Whether smaller firms behave more similarly to households than larger firms do, for example, may help shed light on deeper underlying reasons for households' exhibited impatience. Second, the model could be expanded to include unobserved heterogeneity in subjective taste for solar, beyond that which can be accounted for in demographic observables. Third, it may be worth exploring the role of peer effects in the adoption of green technologies amongst firms: Adoption choices amongst major firms like Amazon, Apple and Google may influence the choices of other firms. Incorporating these additional dimensions of firm characteristics and behavior may further help policy makers to distinguish optimal incentive policies for different segments of the market.

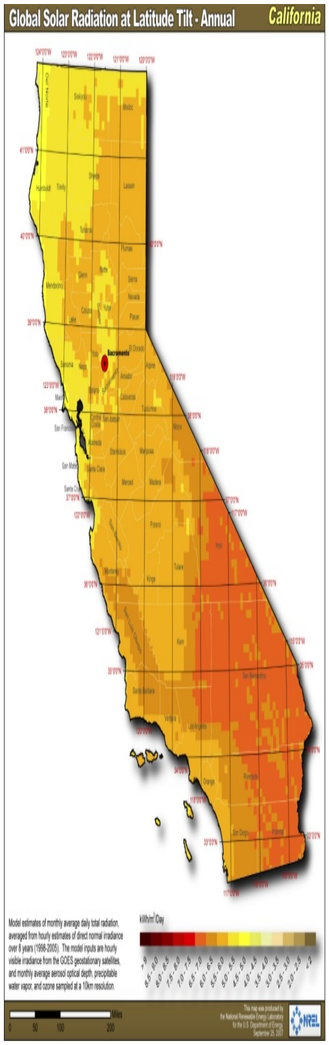
Appendix

Table 2.5: CSI Subsidy Rates

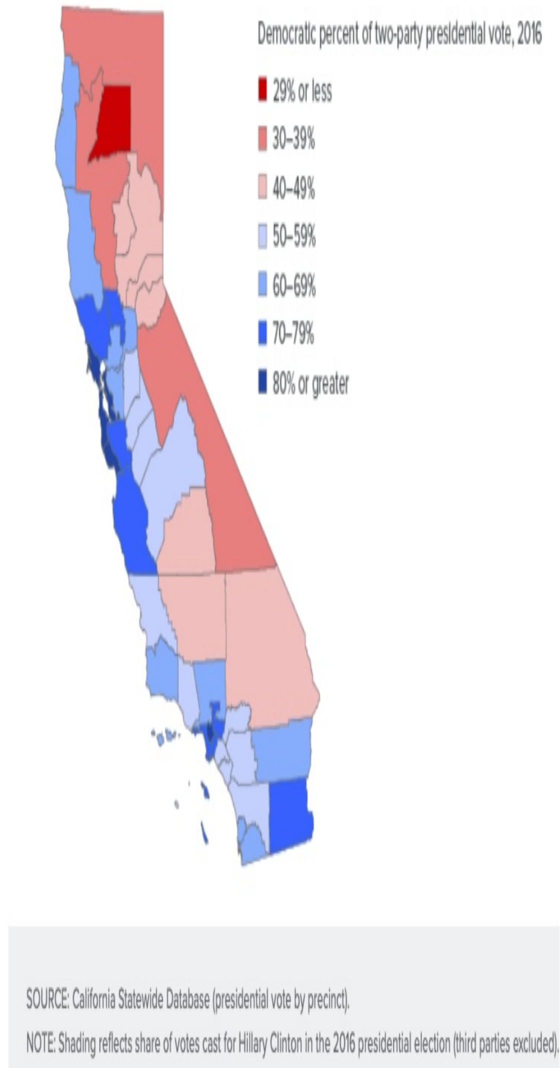
Step	Statewide MW in Step	EPBB Payments (per Watt)	PBI Payments (per kWh)
1	50	n/a	n/a
2	70	$2.50	$0.39
3	100	$2.20	$0.34
4	130	$1.90	$0.26
5	160	$1.55	$0.22
6	190	$1.10	$0.15
7	215	$0.65	$0.09
8	250	$0.35	$0.05
9	285	$0.25	$0.03
10	350	$0.20	$0.02

Notes: This schedule gives the pre-determined CSI subsidy rates. Both the EPBB (investment subsidy) and PBI (output subsidy) decline in 10 steps over time, based on the cumulative capacity installed in the state.

Figure 28: Sunlight Intensity and Political Leanings



Sunlight Intensity



Political Leaning

Notes: The map on the left shows variation in sunlight intensity across different regions of California. The map on the right shows variation in the political leaning; regions in red are more Republican leaning, while those in blue are more Democratic leaning. Together, the maps show that in regions with higher sunlight intensity, and therefore with higher site quality, property owners are more likely to be more Republican, and therefore to have lower personal taste for solar.

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