Solar Adoption by Mandates*

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Abstract

Rooftop solar photovoltaic mandates are becoming a popular policy across Europe and the United States. In this paper, we leverage the frontrunner experience of California to examine their economics. First, we evaluate the private payoffs of solar adoption for residential new construction. To do so, we assemble a rich dataset of new construction building projects and parameterize an engineering model to provide estimates of private payoffs across our sample. Second, we evaluate the hypothesis of what we call a "solar gap" by comparing the cost-effectiveness estimates from the engineering model to observed builder decisions. We find substantial variation in the cost-effectiveness of solar across building locations and characteristics, though the estimated private payoffs are generally positive across a robust variety of model parameterizations and financial assumptions. We observe that the majority of buildings in our data do not adopt solar despite engineering estimates suggesting opportunities for positive payoffs. We also do not find evidence of a positive relationship between expected payoffs and adoption. Lastly, we estimate the effectiveness of both San Francisco's citywide solar mandate and California's statewide mandate. Across a variety of empirical approaches, we find that both the citywide and statewide mandates increased solar adoption.

JEL Codes: H70; Q42, Q48

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1 Introduction

In the absence of a first-best international or even national climate policy, many states and local jurisdictions are adopting their own second- and n^{th}-best policies to reduce greenhouse gas emissions. Some of these policies are various building codes and technology mandates. In recent years, proposed building policies have included bans on natural gas, requirements for electric appliances, and various energy efficiency standards. One increasingly common policy is introduced by municipalities mandating rooftop solar photovoltaic (PV) panels on new construction. Municipalities in California, including the prominent example of San Francisco, have been frontrunners in this respect. Importantly, in January 2020, the state of California began requiring that all newly constructed low-rise residential buildings in the state install rooftop solar PV, thus imposing a solar mandate statewide in the world's 4^{th} largest economy. Our paper examines the economics of solar mandates in California, leveraging their frontrunner role for informing policy there as well as in the many jurisdictions that recently adopted or are currently considering solar mandates, including the European Union and Switzerland.

In this paper, we address the following questions. First, we assess solar adoption at baseline in the absence of mandates. Many of the solar mandates were preceded by reports suggesting that rooftop solar photovoltaics were cost-effective for all new construction (Davis et al. 2014; Energy and Environmental Economics Inc. 2017). If that were the case, however, we would expect adoption to be ubiquitous, and mandates would be unnecessary and nonbinding. However, we find that many builders do not adopt solar on new construction in the absence of mandates.

Second, we examine the rationale for solar mandates. One justification for solar mandates has been the claim that many builders forego cost-effective solar investments, leaving money on the table. That is, the finding that most new construction projects have not adopted solar could be evidence of what we call a "solar gap" where builders fail to adopt solar even when it would be cost-effective to do so. Alternatively, the modest adoption rates could reflect some misspecification or missing costs known to builders but not accounted for in the engineering models that have found ubiquitous cost-effectiveness. In other contexts, the literature has explored the hypothesis of the "energy efficiency gap" where observed adoption of energy efficiency technologies have not aligned with engineering estimates of cost-effectiveness, in part because of principal-agent issues and behavioral failures (see Allcott and Greenstone 2012; Gillingham and Palmer 2014; Gerarden et al. 2017 for reviews of the literature), but also because of overly optimistic engineering estimates (Metcalf and Hassett 1999; Davis et al. 2014; Grimes et al. 2016; Levinson 2016; Fowlie et al. 2018).

We address this second question on the hypothesis of a solar gap as follows. First, we evaluate the private payoffs of solar adoption for residential new construction. Using detailed building-level data, we parameterize an engineering model to provide estimates of solar cost-effectiveness in our sample (i.e., profitability based on private costs and benefits). We compile our novel building project-level data from a variety of sources including municipal building permits records, fine-scale climate and solar irradiance data, rooftop-level shading estimates from Google Project Sunroof, and restricted-access electricity consumption data for a sample of new construction building projects that we obtained in 2018. This portion of our analysis focuses on the San Francisco Bay Area because several municipalities in the region adopted their own municipal mandates in advance of the statewide policy, making this region a good context for examining baseline adoption. Cost-effectiveness reports behind those municipal mandates as well as the eventual statewide mandate pointed to ubiquitous cost-effectiveness of solar PV. For our own analysis of solar system design, performance, and cost-effectiveness, we use the System Advisor Model (SAM) from the U.S. National Renewable Energy Laboratory (NREL). The estimates from the engineering model provide a distribution of project payoffs across project characteristics and allow us to investigate sensitivity to model parameterization. NREL's System Advisor Model is actually the same model used in many of the abovementioned cost-effectiveness reports, but we find much greater heterogeneity in project cost-effectiveness in parameterizing the model across our dataset of observed building projects and their detailed characteristics. Although estimated payoffs are generally positive, the payoffs are generally small especially compared to overall new construction costs.

However, even the absence of ubiquitous cost-effectiveness may not necessarily imply absence of a "solar gap." Along the distribution of payoffs, there may still be builders leaving money on the table, even in presence of non-monetary costs. Hence, after parameterizing and estimating the engineering model across our building projects data, we compare payoff estimates with actual solar adoption decisions, at the building level. We observe that solar adoption does not follow positive expected payoffs. In fact, we find little evidence of any strong relationship between solar adoption and the level of estimated payoffs, and builders forego solar across the entire support of payoff estimates. We conclude that these findings do suggest the existence of a "solar gap" where some builders forego solar even among the most cost-effective projects.

Lastly, we take an ex-post approach and test a variety of econometric specifications to estimate the policy impact on solar adoption relative to a no-policy counterfactual. In particular, we estimate the effectiveness of both San Francisco's citywide solar mandate and California's statewide policy using synthetic methods, among others. These exercises estimate the extent to which mandates may increase the adoption of solar with respect to the counterfactual, which also implies measuring the degree of compliance and uptake of exemptions as provided by the mandates. Even in the case of limited compliance and exemptions, solar mandates may still effectively increase adoption. Overall, we find evidence that both San Francisco's citywide mandate and California's statewide mandate did increase solar adoption, though in the case of San Francisco's mandate we determine that adoption ex post remains below 100 percent. We investigate exemptions and compliance accordingly.

To our knowledge, ours is the first study to investigate the economics of solar mandates, a policy that is currently being adopted with a growing number of jurisdictions, aside from the ex-ante cost-effectiveness reports. In our analysis of the economics of these mandates, we contribute to several strands of literature. One relevant stream of research is the literature on building codes at the municipal and state level in a variety of contexts, including building codes motivated to achieve environmental outcomes (e.g., Levinson 2016, Kotchen 2017, and Carattini et al. 2024). We also contribute to the literature on distributed solar policies (e.g., Borenstein 2012) and solar adoption decisions generally (e.g., Bollinger and Gillingham 2012 and Dong et al. 2023). Further, our exploration of a possible "solar gap" presents an additional context for studying the mechanisms identified in the extensive literature on the energy efficiency gap (e.g., Hausman 1979, Allcott and Greenstone 2012, and Gillingham and Palmer 2014). Ex-post comparisons of engineering estimates to observed outcomes include Davis et al. (2014) on household cooling appliances and Fowlie et al. (2018) on building weatherization.

Our paper proceeds as follows. Section 2 reviews related literature and provides institutional background and design details about the mandates that we examine in this paper; Section 3 describes our estimates of private payoffs, including our data sources and engineering model parameterization, and evaluates evidence of a solar gap; Section 4 presents our policy evaluation for both

San Francisco's citywide mandate and California's statewide mandate; and Section 5 concludes.

2 Background

2.1 The possible case for solar mandates

Canonical environmental economics suggests that standards and mandates are less efficient polices than market-based instruments. However, standards and mandates may for instance be rationalized under the circumstances of an "energy-efficiency gap" where individuals or firms fail to take seemingly cost-effective actions for a variety of behavioral or institutional reasons, which additional economic incentives from market-based instruments may not be able to address. Across a variety of technologies and institutional settings, the economics literature has explored the existence of an "energy-efficiency gap," and identified various potential mechanisms for its emergence (starting with Hausman 1979 and Jaffe and Stavins 1994; see also the reviews by Allcott and Greenstone 2012, Gillingham and Palmer 2014, and Gerarden et al. 2017). Similarly, the existence of a "solar gap" could provide support for solar mandates, and many of the explanations for the energy-efficiency gap in other settings may be applicable in the failure of homeowners and builders to undertake profitable rooftop solar investments.

Prominent energy-efficiency gap explanations for under-adoption include market failures, such as liquidity constraints, imperfect information, and principal-agent problems. Behavioral economics explanations include myopia and inattention. For example, Tsvetanov and Segerson (2013) present a behavioral model of consumer purchase decisions wherein consumers can be "tempted" by the low purchase price of less energy-efficient goods. Under this model of welfare outcomes, the authors demonstrate that energy-efficiency standards can dominate a tax in the presence of this behavioral distortion. In the rooftop solar context, payoffs (or electricity bill savings) are realized over long horizons, often 20 to 30 years. Also, in the context of new construction, builders may be inattentive to the value of the solar investment because it is small relative to the overall building project, which may cost several hundreds of thousands or even millions of dollars. Levinson and Niemann (2004) explore principal-agent problems and information asymmetries in energy-efficient investments in rental buildings, suggesting that landlords may pay tenants' utilities to internalize the value of their energy efficiency investments, which is an option that however also comes with downsides, including that it may not be salient to prospective tenants during their rental search. It is possible that builders face similar challenges in capitalizing the value of solar in the ultimate sale or rental of the building. Through rational expectations, builders that do not plan to keep the property over the long run may then decide against the installation of solar panels.

Some strands of the energy-efficiency gap literature explore settings where a purported gap may not exist at all. For example, Myers (2019) exploits the differences in home sales prices between oil-versus gas-heated homes in Massachusetts, finding that changes in the relative prices of these fuels are rationally capitalized. Further, a routine finding in the literature is that engineering estimates overstate the savings from energy efficiency investments (Metcalf and Hassett 1999, Davis et al. 2014, Grimes et al. 2016, Levinson 2016, and Fowlie et al. 2018). In the context of California building codes, Levinson (2016) finds that realized savings are substantially lower than was forecast by regulators. Based on a literature review of engineering estimates finding that the promised energy savings do not actually materialize, Fowlie et al. (2018) suggest that many ex-ante engineering analyses may have systematic misspecifications. They also provide evidence from a field experiment on the gap between engineering estimates and realized savings.

The economics literature has identified a variety of explanations for overestimation of technology performance and payoffs in engineering studies. Engineering studies may fail to account for behavioral factors or assume idealized conditions, including optimized operations and maintenance. For example, drivers may drive more as fuel economy increases. Davis et al. (2014) explore circumstances where engineering models are overly pessimistic about the inefficiency of the old technologies being replaced. Another source of engineering model misspecification could be the presence of hidden costs, which are not accounted for in the engineering model (Gillingham and Palmer 2014). Hidden costs could include search frictions and administrative costs, such as the costs of finding a suitable solar installer and the administrative burden of managing the contractor, interconnecting to the electricity grid, and applying for government subsidies. We are going to refer to these costs with the generic term of "hassle." Further, engineering estimates may fail to account for the "rebound effect," where improved energy efficiency reduces operating costs, which leads to increased utilization. In this case, however, households also benefit from higher welfare.

As a counterpoint to the critiques of the engineering literature, some studies have identified settings where the engineering estimates are validated. Jacobsen and Kotchen (2013) find that building codes implemented in Florida in 2002 reduce electricity consumption by 4 percent and natural gas by 6 percent, in line with the ex-ante predictions. In a refinement of this work over an extended time horizon, Kotchen (2017) finds that the energy savings from the building code are persistent for natural gas consumption. However, he finds that electricity consumption appears to revert to pre-policy levels after a few years, suggesting that the effectiveness of the measures degrades over time. Our analysis extends these strands of literature comparing ex-post outcomes to ex-ante engineering estimates with an emphasis on the importance of heterogeneity in ex-ante misspecification.

2.2 Rooftop solar mandates

Originating in California, rooftop solar mandates are an increasingly common variety of building code mandates for new construction projects around the world. In January 2017, San Francisco became the first major city to implement a rooftop solar mandate, and the example was quickly followed by other municipalities in the San Francisco Bay Area and ultimately the state of California.[1] Prior to California's statewide implementation of the rooftop solar mandate in January 2020, more than two dozen California municipalities adopted solar photovoltaic requirements between 2017 and 2020, including Brisbane, Culver City, Davis, Fremont, Lancaster, San Francisco, San Mateo, Santa Monica, and Sebastopol (California Energy Commission 2016; California Statewide Codes & Standards Program 2022). Outside of California, jurisdictions with rooftop solar mandates include South Miami, Tokyo, and several German municipalities and German states, such as Baden-Württemberg, Berlin, and Hamburg, which were then followed by larger jurisdictions such as the European Union and Switzerland. While these policies share in common the requirement of rooftop solar on new construction, there is substantial variation in the specific details across jurisdictions.

In support of solar mandates, officials in several jurisdictions have cited ex-ante cost-effectiveness reports that estimate builders and building occupants achieve positive payoffs from the mandates (e.g., Davis Energy Group, Inc. et al. 2016 and Energy and Environmental Economics, Inc. 2017). These cost-effectiveness reports apply engineering models to a small number of hypothetical new

[1] See `https://sfplanning.org/project/better-roofs` for the mandate in the city of San Francisco (last accessed, May 9, 2024) and `https://www.energy.ca.gov/programs-and-topics/programs/building-energy-efficiency-standards/online-resource-center/solar` for the statewide mandate (last accessed, May 9, 2024).

buildings with stylized characteristics. The suggestion that rooftop solar is cost-effective on all new construction must be reconciled with the evidence from the data that most new construction buildings do not adopt solar at baseline, as shown in Figure 1 for San Francisco and other Bay Area municipalities. In our review of building permits data and solar adoption behavior, we did not find any jurisdictions with ubiquitous solar adoption on new construction in the absence of mandates.

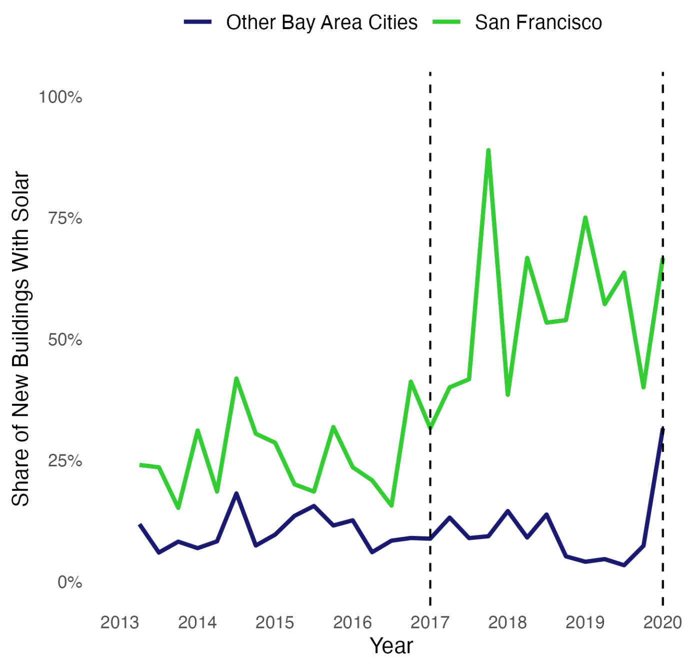
In official statements, the motivations for solar mandates have included reducing electricity production from fossil fuels and electricity system cost-savings and resiliency associated with distributed generation. In regions with cap-and-trade programs, such as California and much of Europe, the extent to which solar mandates may reduce greenhouse gas emissions depends on the exogeneity of the cap. If solar mandates increase the adoption of solar energy, which represents our research question, they then contribute to lower the price of allowances, potentially helping cap-and-trade programs withstand political pressure.

In any case, solar mandates are for some jurisdictions part of the pursuit of more specific outcomes, such as various "net-zero" emissions targets, including California's goal of zero net energy (ZNE) buildings. Also, informed by the finding of ubiquitous cost-effectiveness in the ex-ante engineering studies, some officials may have had interest in using the mandates to help more of their constituents fully capture the private benefits of solar adoption, including taking maximum advantage of national and regional incentive programs.

The exact requirements and exemptions of solar mandates vary by jurisdiction, so here, we summarize the main features of the of San Francisco citywide and California statewide policies with more detailed descriptions available in Appendices A.1 and A.2, respectively. In 2017, San Francisco implemented the Better Roofs Ordinance mandating rooftop solar installations on new construction residential, commercial, and municipal buildings. The policy went into effect for any new construction project that applied for building permits on or after January 1, 2017, with exemptions for buildings over ten stories, data centers, laboratory buildings, and non-residential buildings with gross floor area less than 2,000 square feet. Minimum size rules required that the solar installations cover at least 15 percent of the total roof area of multifamily and non-residential buildings, or 250 square feet for single-family homes. Aside from rooftop solar PV, the Better Roofs Ordinance allowed two alternative compliance pathways, which were either rooftop solar thermal or building a living roof (also known as green roof) engineered for stormwater management. San

Francisco enforced these and other building codes through the building permitting and inspection process, with fines up to $500 per day for a building code infraction. The Better Roofs Ordinance was superseded in January 2020 when the California Energy Commission introduced a statewide solar requirement in the 2019 Building Energy Efficiency Standards. The statewide standards required all newly constructed low-rise residential buildings (defined as residential buildings up to three stories) to install solar PV. The statewide standards did not apply to commercial and municipal buildings, nor include alternative compliance pathways.

Figure 1: Share of Newly Completed Residential Buildings Adopting Solar



Notes: Solar adoption shares are for completed residential new construction projects. (1) This sample of other Bay Area municipalities omits municipalities that adopted their own solar mandate prior to the 2020 California policy. The sample includes American Canyon, Daly City, Danville, Foster City, Oakland, unincorporated San Mateo County, and Santa Rosa. (2) Incomplete and ongoing building projects are omitted. (3) Dates are based on the year a project permit was first filed, which is also the applicability date for building codes and solar mandates. (4) We omit data after 2020 given the implementation of a statewide mandate in California. (5) See Sections 3.2 and 3.4 for data details and related data summaries.

3 Private payoffs and "solar gap"

3.1 Setup

We begin with a review of time series of new residential construction and solar adoption in municipalities of the San Francisco Bay Area. Sections 3.2 and 3.3 describe our data sources in detail. After reviewing the data, we pursue two distinct sets of analyses parameterizing an engineering model to estimate the private payoffs of a solar installation. First, we parameterize the engineering model to estimate the heterogeneity in the private payoffs of solar adoption, using our project-level data. Understanding the heterogeneity in estimated payoffs and the sensitivity of the model parameterization allows us to explore the importance of accounting for project-level characteristics, the possibility of model misspecification and bias, and the extent that unobserved costs might affect payoffs (including administrative and other "hassle" costs as introduced in Section 2). Second, we compare the engineering estimates to observed solar adoption decisions and test whether variation in project characteristics and payoffs rationalizes solar adoption decisions. Whether or not expected payoffs rationalize solar adoption speaks to the question of whether there is a "solar gap" where builders fail to adopt solar even when it would be cost-effective to do so. Engineering estimates of the private payoffs of a solar installation are not a welfare measure and do not account for social benefits and costs of each solar installation. Expected private payoffs are the measure of interest in the behavior of the private decision-maker, such as the home builder.

For the engineering estimates of private payoffs from a solar installation, we apply the System Advisor Model (SAM) from the U.S. National Renewable Energy Laboratory (NREL). SAM provides a rich representation of a rooftop solar project including geography-specific variation in climate and solar irradiance; installation materials, labor, and financing costs; taxes and subsidies; future electricity consumption and tariff structure; technological specifications of the solar module and inverter; and shading and other system losses. In fact, SAM accommodates dozens of possible user inputs and system configurations. To estimate the private payoff of the solar installation relative to a counterfactual without the solar panels, the SAM outputs include total costs over the system life, electricity production, electricity bill savings, compensation for excess electricity generation, taxes, and subsidies. Principally, SAM estimates the net present value (NPV) of the installation. In Sections 3.2 and 3.3, we detail the specific data sources we use to parameterize the model, and Appendix Section B.2 provides a more detailed model description. Having estimated the distribution of solar payoffs across all building projects, we are able to illustrate the heterogeneity in project payoffs. We also compare these distributions to payoffs estimated by previous cost-effectiveness reports, which generally only considered a few stylized sets of building characteristics. The comparison to prior engineering studies as well as our sensitivities with alternative SAM parameterizations allow us to assess the importance of using such granular project-level data and accounting for differences in project characteristics. We also compare our results to the finding of earlier cost-effectiveness studies that California solar projects have strictly positive payoffs across project types.

3.2 Building permits data

For our core data, we create a novel address-level dataset of new construction building projects in California municipalities, which we collect from individual permitting offices of individual municipalities and counties. In addition to new construction permits, we also collect solar and electrical permits.[2] In matching the solar electrical permits to building permits, we are able to identify the new construction projects that adopt rooftop solar.[3] Specifically, we match the new construction building permit addresses to solar permits in the corresponding jurisdiction's electrical permits. We are then able to validate these solar adoption statistics from individual jurisdictions' electrical and solar permitting databases against California's solar interconnection data.[4] The building permit data from individual municipalities and counties vary in the level of data availability and details of each project's characteristics. However, the general structure of the data tracks each project's status from initial filing date through various approvals and inspections to final completion. We restrict the data to only completed projects, for which we are able to observe the final status of a building's solar adoption decision. For this analysis, we focus on a dataset of $4,415$ residential building projects from ten Bay Area municipalities, including San Francisco. Among these municipalities, only San Francisco adopted a rooftop solar mandate prior to the statewide mandate

[2] In some cases, jurisdictions had permitting processes that tracked solar permits separately from other electrical permit types.

[3] In the permitting data, we find very few cases of solar thermal adoption. Therefore, we focus almost exclusively on rooftop solar PV adoption except in Section 4 where we evaluate the specific compliance pathways under San Francisco's citywide mandate.

[4] See `https://www.californiadgstats.ca.gov/` (last accessed, May 9, 2025).

Table 1: Residential New Construction and Solar Adoption, 2014-2016

San Francisco		
	Number of permits	331
	Number of permits with solar	90
	Share of permits with solar	27.19%
Other Bay Area Cities		
	Number of permits	3,444
	Number of permits with solar	378
	Share of permits with solar	10.98%

Notes: (1) This table is restricted to completed residential single-family and multifamily new construction buildings with permits first filed between 2014 and 2016, prior to the implementation of any solar mandates. (2) Dates are based on the year a project permit was first filed. (3) Building permits data were not available for all municipalities in all years.

beginning in 2020. Our building permits data is summarized in Table 1.

3.3 Engineering model data and parameterization

NREL's System Advisor Model (SAM) as well as other public and proprietary engineering models are widely available to assist homeowners and firms in their solar installation decisions, and solar salespeople and installers present clients with engineering estimates to inform their solar adoption decision and choose the design parameters. Versions of SAM have been available to the public since 2008 as a user-friendly desktop application and would have been available to the builders during our study period. In our analysis, builder's solve the problem of maximizing their expected private payoffs, including the solar adoption decision. Accordingly, the first step of our analysis is to parameterize SAM for our dataset of observed building projects using data that would have been available to these builders at the time of their solar adoption decision during their project planning and permitting process. That is, we use our data to parameterize SAM to estimate plausible expectations about the solar payoffs (net present values) for each project at the date the project was permitted. For each building project, we approximate the relevant decision time period as the year the builder first filed for their building permit. We provide additional details of SAM and our parameterization in Appendix B.1, including a formal statement of the builder's problem in Appendix Equation B.1.

To properly parameterize the engineering model and more fully explore the variation in project payoffs, our analysis supplements the dataset of actual building projects with a rich array of additional data to account for the observed heterogeneity in project characteristics. In particular, we account for variation in climate at a fine scale (i.e., 4km by 4km grid cells); differences in rooftop characteristics and shading; electricity consumption patterns; electricity tariffs; changing state and federal tax incentives; and installation and financing costs. Following from Equation B.1 as introduced in Section 3.1, expected private payoff is the relevant statistic in builder's solar adoption decision. While the engineering model (SAM) accommodates dozens of input parameters and generates a rich variety of outputs, Table 2 emphasizes the inputs that we are able to parameterize from our data as well as important default parameters to which our payoff estimates are particularly sensitive. In the remainder of this section, we summarize Table 2 and the data sources for the SAM parameterization with Appendix B.1 providing additional data details and citations.

Our installation cost data is from California's interconnected project sites data, which we use to construct a time series of median cost-per-watt-DC by California city and year. As shown in Appendix Figure B.1, solar costs have fallen substantially over our study period, so it is important to account for variation in builders' cost expectations over time. Using city-level cost variation accounts for differences in material and labor costs. Section 3.4 and Appendix Section C present estimated payoffs with a variety of alternative cost assumptions, including 95$^{\text{th}}$ instead of 50$^{\text{th}}$ percentile costs form the interconnection data; 50 percent higher costs; 10 percent lower costs; and various alternative incentive levels.

One consideration for the new construction mandates is that installation costs are less expensive on new construction than for retrofit projects on existing roofs, and therefore, targeting solar installations to new construction is more cost-effective. Indeed, Barbose et al. (2013) find evidence that solar installations are less expensive on new construction than retrofit buildings using California data from 2008 to 2012. Barbose et al. (2013) find a mean discount of \$0.75 per watt-DC, or approximately 10 percent. While not all solar mandates cost-effectiveness studies have adjusted their installation costs to reflect a new construction discount, one of the cost-effectiveness reports for San Francisco, Halberstadt (2014), did apply an adjustment based on Barbose et al. (2013). In our own data, we find mixed evidence for reduced installation costs associated with new construction,

Table 2: Engineering Model Summary and Data Sources

Parameter	Data source and description
Building permits	Sample of California building permits described in Section 3.2
Installation costs	Estimated from California interconnection data. Primary parameterizations use city-year medians. Sensitivities include 95th percentile costs and adjustments accounting for evidence that new construction installations are less expensive than retrofits
Financing costs	Annual time series of SAM defaults. Interest rates vary from 4 to 7.5%
Maintenance costs	SAM defaults
Electricity tariffs and net metering policies	NREL OpenEI database, public time series of PG&E tariffs, and CPUC information on net metering policies. Primary parameterization holds tariffs and policies constant over each project's analysis period. Sensitivities include alternative tariff and net metering policy expectations
Compensation for excess generation	Public time series of PG&E compensation rates. \$0.03/kWh in primary parameterization, higher in sensitivities
Electricity consumption	PG&E hourly interval data for a sample of new premises. Primary parameterizations use city-level median hourly consumption profiles. Sensitivity parameterizations use address-matched consumption
Federal Investment Tax Credit (ITC)	Federal legislation. 30%
California State and local incentives	Sensitivities account for some additional incentives, such as the New Solar Home Partnership Program (NSHP)
Global horizontal irradiance (GHI)	Typical meteorological year (TMY) files from NSRDB database include GHI (kWh/m^2/day) and other weather variables at 4km×4km grid cell resolution
Shading	Estimated for each building's roof using Google Sunroof satellite data and modeling
Analysis period	SAM default. 25 years
Solar owner discount rate	SAM default. 6.4%
Decision variables in optimization	
Solar adoption decision	Estimated. $solar_{ict} \in \{0, 1\}$
System size (capacity)	Estimated (kW)
Engineering outputs	
Electricity production	Estimated hourly
Electricity bills with and without solar	Estimated monthly
Net present value (NPV)	Discounted series of estimated costs and payoffs over analysis period

Notes: This table summarizes the data sources in our parameterization of NREL's System Advisor Model (SAM). (1) The items in this table are only a subset of SAM's numerous assumptions and available outputs. (2) Unless otherwise stated, we use SAM's default assumptions. (3) We parameterize the model for each project i in city c where year t is the beginning of the building project (i.e., the year the builder first filed for a building permit). (4) Appendix B.1 provides additional data details and citations.

with discount estimates ranging from 5 to as high as 22 percent. We present these results and corresponding methodology in Appendix Section B.3. Accordingly, Appendix Section C presents results with 10 percent lower installation costs, which modestly increases estimated payoffs.

Sunshine and other climate variables determine the availability of solar energy and panel performance. These data are available in Typical Meteorological Year (TMY) files from NREL's National Solar Radiation Database (NSRDB), which include an entire year of hourly temperature, global horizontal irradiance (GHI), and other relevant climate variables for a representative year based on weather observations from 1998 to 2022. NSRDB is gridded to 4km by 4km cells, which we match to our geocoded building permits. To determine rooftop shading conditions, we extract a measure of annual "usable sunlight" hours from Google Project Sunroof for each building project in our data. Google Project Sunroof uses satellite data to identify rooftop area and shading conditions, which we use to construct a shading measure for each roof using its "usable sunlight" hours relative to the other roofs in our sample.

California's net metering policy determines how solar owners are compensated for the electricity they produce and then use for their own consumption as well as any excess electricity they export to the grid. Since California introduced its first net metering policy, NEM 1.0, in 1996, there have been two major changes to the policy accompanied by substantial public debate and uncertainty. The most relevant policy change during our study period occurred in 2016 when California updated its net metering policy from NEM 1.0 to NEM 2.0, which required time-of-use electricity tariffs for solar customers. This policy became effective for customers of PG&E, the utility serving the Bay Area, on December 15, 2016. Under NEM 1.0, solar customers were effectively compensated for their electricity production at the same retail rate during all hours of the day. Under NEM 2.0, solar customers were compensated at a higher retail rate during "peak" hours and a much lower retail rate during the rest of the day. In our primary parameterizations, builders expect the prevailing NEM policy at the time of their permit application to prevail for the life of their solar installation. Indeed, through the evolution of NEM, California has grandfathered solar systems into their original NEM policies. However, to account for the policy uncertainty around net metering, we have included model parameterizations with alternative policy expectations, which we describe in Section 3.4.[5]

[5] Appendix B.1 provides additional history and details of California's evolving NEM policies.

Solar payoffs are largely determined by the interaction of a building's electricity consumption pattern with the tariff structure and net metering policy. The relatively lower compensation for excess generation under California's NEM policies described above generally disincentivizes builders from oversizing their solar systems. For the same reason, the largest electricity consumers can realize the greatest payoffs because they can offset their electricity consumption charges at a price closer to the retail electricity rate. Under NEM 2.0, where solar customers face tariffs that vary by time of day, the timing of electricity consumption is also an important determinant of the solar payoff. For historical Bay Area tariffs, available from the electric utility PG&E and archived in NREL's Utility Rate Database (URDB). For electricity demand, we rely on a sample of restricted-access PG&E residential metering and billing data for new premises in Bay Area municipalities. This sample includes almost $63,000$ addresses in 71 Bay Area municipalities with metering and billing data through 2018. The data were associated with premise IDs created in PG&E's billing system after January 1, 2009, because new premises in PG&E's billing data are typically associated with new construction. By using sample medians, we further increase our confidence that we are identifying electricity consumption associated with new and recently constructed buildings. For our primary parameterization, we use the PG&E sample city median hourly electricity demand. Hourly consumption data is especially important for estimating payoffs under time-of-use tariffs and period-specific net excess generation exported back to the grid. Appendix Section C compares our payoff estimates from our primary parameterization to an alternative approach where we use building-level hourly interval electricity consumption data from our sample of new PG&E premises. However, our model should reflect a builder's expectations about the building's future electricity consumption patterns. These expectations are not necessarily reflected in this alternative parameterization because a snapshot of observed building-level electricity consumption patterns are not necessarily predictive of *future* or even *expected* electricity consumption patterns.

In addition to California's net metering policy, there were several other incentive programs available to solar projects during our study period. The 30 percent Federal Investment Tax Credit (ITC) has been available since 2006, so we include this incentive in all of our parameterizations. The well-known California Solar Initiative (CSI) expired for most Bay Area residential customers in 2013, so the incentives were not available for most projects in our sample. Some projects in our sample were qualified for the New Solar Homes Partnership Program (NSHP), which accepted applications through April 1, 2018. NSHP incentives varied from \$0.25 to \$3.50 per watt-DC depending on application timing and project characteristics. Appendix Section C presents alternative parameterizations where we account for the effect of the NSHP program on payoffs to complement our primary parameterization results in Section 3.4. Appendix B.1 provides additional details on solar incentive programs and our parameterization assumptions.

For other parameter values, we use SAM defaults, which NREL updates as frequently as once or twice per year. Updates to SAM defaults are based on market data, user feedback, and NREL staff expert judgement. These default parameters include panel lifetime; operation and maintenance costs; financing costs; and the private discount rate of the decision-maker (i.e., the builder or homeowner). SAM also includes dozens of parameters related to solar panel and inverter technical characteristics and performance.

The default behavior of SAM is to estimate the net present value of a particular project of a particular size. For example, the default system capacity in SAM has ranged from 4 to 8 kW. However, in our SAM parameterizations, we seek to represent the behavior of a payoff-maximizing economic agent. Therefore, we apply an optimization to identify the system size that maximizes payoff conditional on each project's characteristics following Appendix Equation B.2 as discussed in Section 3.1 and Appendix B.2.

3.4 Evidence on private payoffs

We now present the results of parameterizing the engineering model to estimate the heterogeneity in the private payoffs of solar adoption on new construction buildings. As described in Section 3.3 above, we present distributions of payoffs for our primary parameterization as well as a variety of alternatives. These alternative parameterizations help us explore the robustness of our results, the sensitivity of the engineering model, and the most important determinants of solar payoffs. Lastly, we compare the estimated solar payoffs to the total overall costs of the new construction projects in our data as a possible measure of the relative importance of these solar payoffs in the context of an expensive and complex new construction building project. In this section, we present only payoffs of projects that filed for permits prior to 2017 before the applicability of any solar mandates. We start by focusing on absolute net present values. We then turn to relative benefits with respect to project costs.

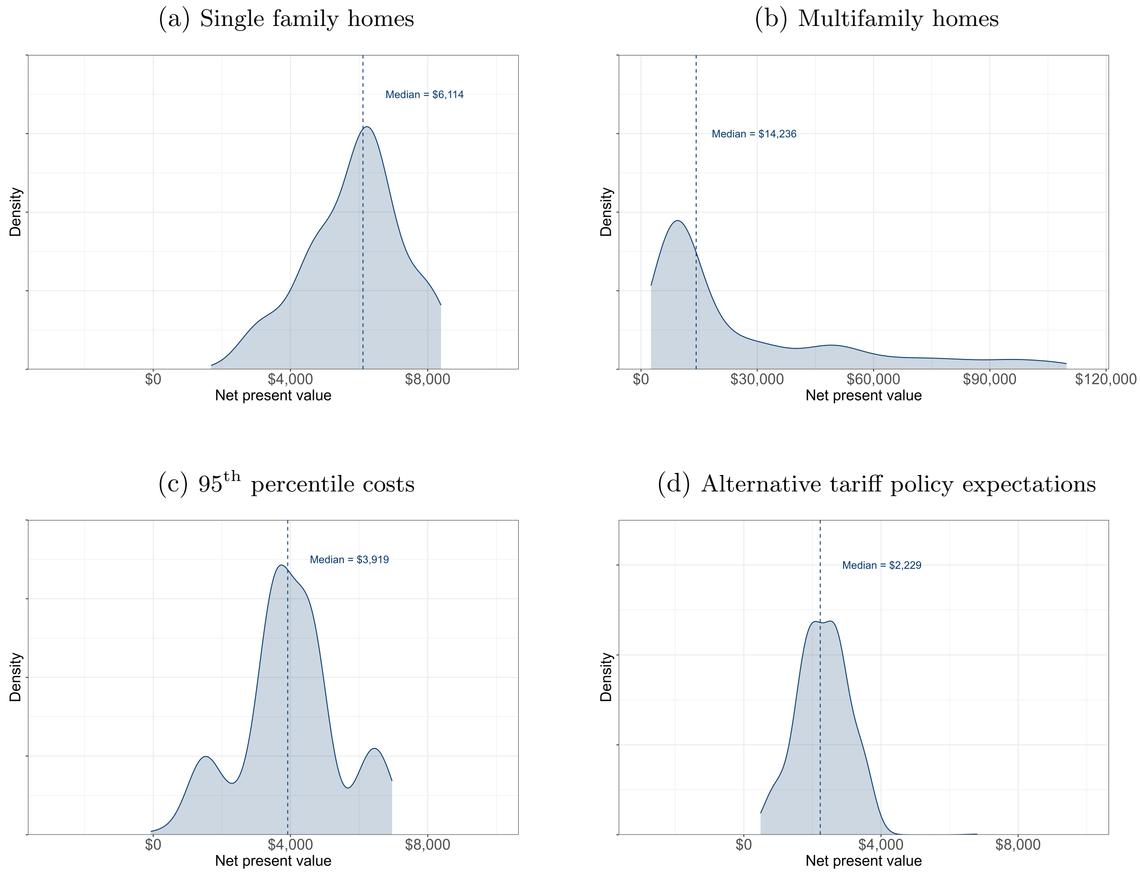
From our primary parameterization of the engineering model (SAM) described in Section 3.3 above, in Figures 2a and 2b we estimate that payoffs are positive for every building project in our data. These payoffs range from $\$1,700$ to $\$8,400$ for single family homes and exceed $\$100,000$ for very large multifamily buildings. However, we do identify negative payoffs for a minority of projects under alternative parameterizations, including higher installation costs, higher financing costs, larger solar systems, lower electricity consumption, and less favorable tariff structures. For example, the installation costs in the parameterization of Figure 2c are the 95^{th} percentile costs (by city and year) from California's interconnection data instead of the median used in the primary parameterization. Appendix Figure C.4c uses 50 percent higher installation costs than the primary parameterization. Even under these two higher installation cost parameterization, still less than 1 percent of the sample has negative expected payoffs. That said, under these higher cost parameterizations, almost 10 percent of the sample has expected payoffs less than $\$1,000$, without even accounting for any hassle or other unobserved costs.

Further, Appendix Figure C.5 compares our payoff estimates from our primary parameterization to an alternative approach where we use building-level hourly interval electricity consumption data from our sample of new PG&E premises. As discussed in Appendix C, the results under this alternative generally confirm this section's findings in that estimated payoffs are similar on average and continue to be positive for almost all projects. However, Appendix Figure C.5 does suggest that there may be even more heterogeneity in payoffs across buildings than suggested in Figure 2.

As discussed in Section 3.3, there were multiple changes to California's net metering policy and substantial policy uncertainty during our study period. Therefore, Figure 2d is parameterized assuming that net metering is replaced with a less favorable net billing policy. Under this counterfactual net billing policy, consumer's net excess generation is accounted for by month and time-of-day with an $0.03/kWh compensation rate based on an approximation of the wholesale market. Recall that California's NEM 1.0 policy already had this lower compensation rate for excess generation on an *annual* basis, discouraging investment in oversized systems. Therefore, while the alternative net billing policy in Figure 2d reduces payoffs and incentivizes even smaller systems as compared to net metering, expected payoffs remain positive. Similarly, Appendix Figure C.4b presents estimated payoffs for building projects filed after 2016. Despite falling solar installation costs in this period, the payoffs are generally lower after 2016 because of the less-valuable structure of NEM 2.0 (discussed above in Section 3.3). However, even under NEM 2.0, the support of our estimated payoffs remains positive.

Figure 3 illustrates the possibility that solar payoffs may have low relative importance for many builders. Specifically, Figure 3a presents estimated payoffs under our primary specification for a subset of building permits for which permit data included estimated *total* new construction costs. Figure 3b then presents those payoffs as *share* of the total project costs. The median single family building cost is $\$310,000$, so for the majority of projects, median payoffs are less than 2 percent of project costs. For almost all projects, solar payoffs are less than 5 percent of their project costs. Among the other demands of project management, builders may ignore the foregone solar payoffs, which are small even without accounting for administrative and hassle costs.

Figure 2: Estimated Distributions of Solar Payoffs

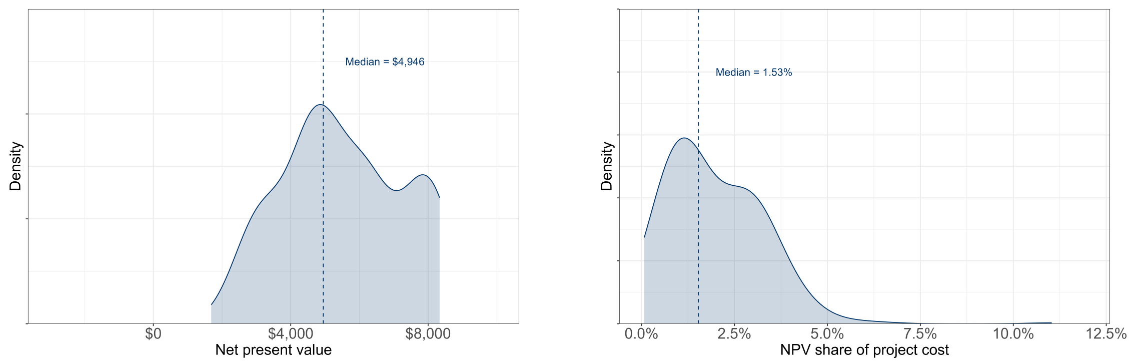


Notes: (1) Figures present medians and smoothed kernel density estimates of the distribution of estimated solar payoffs (net present values) from our parameterization of SAM across our sample of San Francisco Bay Area new construction building permits. (2) All distributions are for building permits issued between 2012 and 2016 (inclusive), prior to the implementation of solar mandates. (3) Panel 2a is restricted to single family buildings, as are all panels except Panel 2b. A small number of very large projects (fewer than 100) are omitted by the truncation of the x-axis. (4) Panel 2b is restricted to multifamily buildings. (5) Panel 2c is based on 95th percentile installation costs (by city and year) instead of 50th percentile costs in the primary parameterization. (6) Panel 2d assumes that net metering is replaced by a less valuable net billing policy. (7) Axes scales differ. All distributions are truncated to show the actual estimates of minima and maxima.

Figure 3: Payoff Importance: Estimated Distributions of Solar Payoffs and Overall Project Costs

(a) Estimated payoffs

(b) Share of total project cost



Notes: (1) In contrast to Figure 2, this figure is restricted to new single family homes for which project cost data is available. (2) Panel 3a presents the estimated solar payoffs (net present values). (3) Panel 3b presents the solar payoffs as a share of total cost for the entire building project. (4) Both panels present medians and smoothed kernel density estimates of the distribution of estimated solar payoffs from our parameterization of SAM across our sample of San Francisco Bay Area new construction building permits. (5) All distributions are for building permits issued between 2012 and 2016 (inclusive), prior to the implementation of solar mandates.

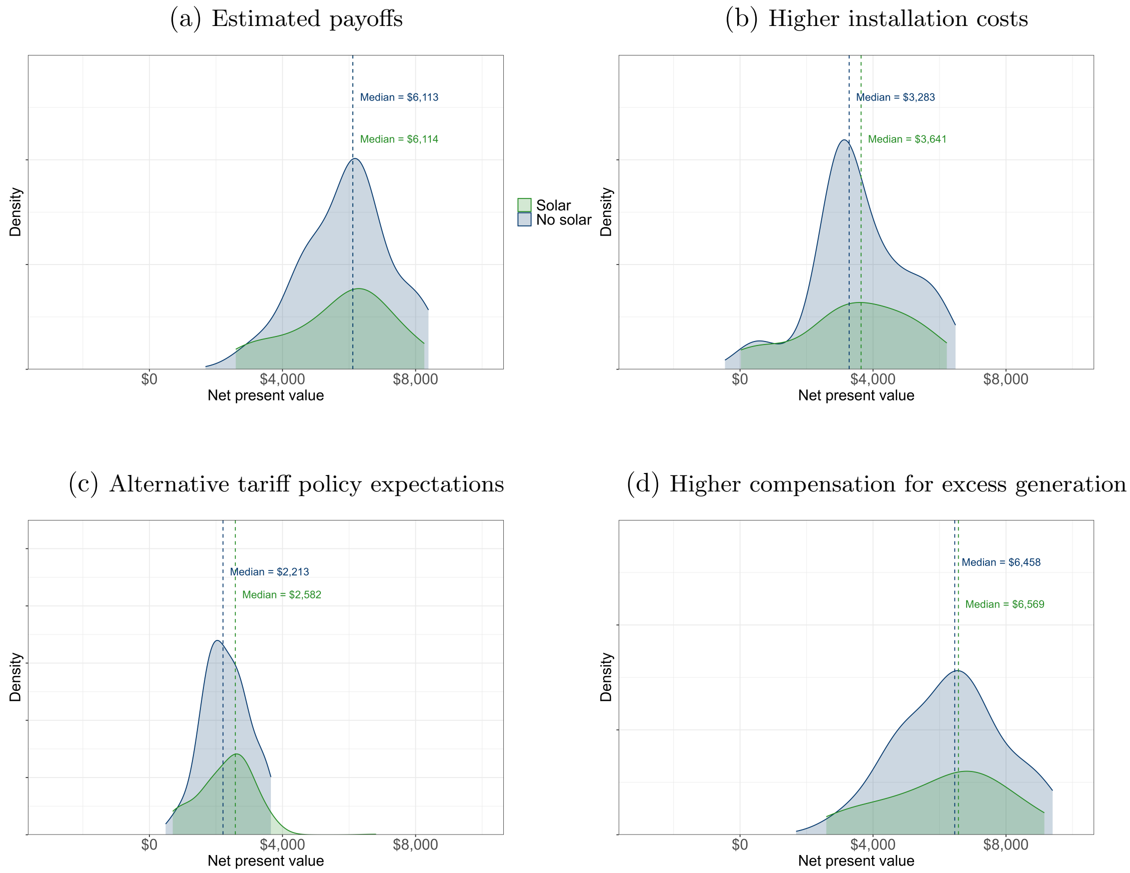
To summarize, we gather the following set of findings from Figures 2 and 3. First, we observe that there is substantial heterogeneity in payoffs across project characteristics, which underscores the value of project-specific data as opposed to the common practice in the engineering literature used for ex-ante policy simulations. Rather than detailed project-level data, these cost-effectiveness studies relied on a small number of representative projects with stylized characteristics. Second, we note that estimated payoffs are indeed positive for the great majority of the buildings in our study period, and this finding is robust to a battery of alternative parameterizations. Taken at face value, this finding supports the ex-ante conclusions of the cost-effectiveness reports. Third, we also observe that the payoffs are modest, especially relative to the overall costs of new construction buildings. Even a relatively small amount of unobserved costs could exceed the estimated payoffs. For example, an extra few thousand dollars of administrative or architectural costs associated with the solar installation would exceed the payoffs for many projects.

3.5 Evidence of a "solar gap"

Next, we apply our estimated payoffs to assess the question of whether a solar gap exists. Specifically, we test whether expected payoffs determine builder solar adoption decisions following Equations B.1 and B.2 and the discussion in Section 3.1. The failure to adopt solar in the presence of positive estimated payoffs may be rationalized by additional characteristics unobserved in our data but considered by the builder, such as some aesthetic rooftop features that preclude solar. However, even in the circumstance of unobserved project characteristics or additional costs, we still expect a relationship, everything else equal, between estimates of net present values and observed solar adoption decisions.

Figure 4 presents the distributions of expected solar payoffs among new building projects adopting solar as compared to buildings that do not. To avoid the effect of solar mandates, we only consider years 2012 to 2016, before San Francisco implemented its mandates (and before California implemented the statewide policy). In Figure 4, we observe no apparent relationship between estimated payoff and the solar adoption decision, and building projects fail to adopt solar across the entire distribution of expected payoffs. Figure 4 suggests no evidence that the level of payoffs are a determinant of adoption. One exception is in the tails of the distribution where we observe that the very lowest NPV projects forego solar. That is, for the very lowest value project with the lowest expected payoffs, builders are least likely to adopt solar, especially after accounting for non-monetary costs. However, the evidence that many builders are foregoing profitable solar suggests a true "solar gap." These findings are robust to a variety of alternative parameterizations, including higher installations costs (Panel 4b) and expectations of a less valuable net metering policy (Panel 4c) as described in Section 3.4.

Figure 4: Estimated Distributions of Solar Payoffs and Observed Solar Adoption



Notes: (1) Figures present medians and smoothed kernel density estimates of the distribution of estimated solar payoffs (net present values) from our parameterization of SAM across our sample of San Francisco Bay Area new construction building permits. (2) The green-shaded distributions are for projects we observed adopting solar in the building permits data. Blue-shaded distributions are estimated payoffs for non-adopters. (3) All distributions are for single family homes that began construction between 2012 and 2016 (inclusive), prior to the implementation of solar mandates. (4) Panel 4b is based on 50 percent higher costs of panels. (5) Panel 4c assumes that net metering is replaced by a less valuable net billing policy. (6) Panel 4d uses higher compensation for excess generation exported back to the grid (i.e., excess net annual generation). The compensation rate is $0.10/kWh instead of the $0.03/kWh rate in the primary parameterization. (7) All distributions are truncated to show the actual estimates of minima and maxima.

Table 3 presents the results of estimating the linear probability model of the relationship between observed solar adoption decisions and the engineering model estimates of solar payoffs. The estimating equations are described in more detail in Appendix C. Confirming the visual evidence of Figure 4, we fail to identify a positive relationship between expected payoffs and observed adoption. To avoid the effect of solar mandates, models (1) and (2) only include the pre-policy years, 2012 to 2016. Similarly, model (3) includes all years 2012 to 2019 but excludes San Francisco, which was subject to mandates after 2016. Across all models, the relationship between NPV and solar adoption is small — a $\$1,000$ change in NPV is only associated with a 1 percent change in probability of solar adoption. The inclusion of city and year fixed effects in models (2) and (3) substantially increases the standard errors, as these fixed effects also remove much of the variation in our engineering model parameterization. Principally, though, these estimations confirm the suggestion that many builders forego profitable solar investments and there is thus evidence of a "solar gap." In this respect, our results differ from the case of retrofits, where adoption tends to follow expected payoffs (e.g. Tibebu et al. 2021). Recall that the cost of projects vastly exceeds the cost of solar PV in our data, pointing to a different investment decision that builders need to make.

Table 3: Linear Probability Models of Solar Adoption

	(1)	(2)	(3)	(4)
Net present value (NPV) ($1,000s)	−0.021***	0.015	0.020	0.018
	(0.003)	(0.015)	(0.015)	(0.016)
Income ($1,000s)				0.001***
				(0.000)
Multifamily				−0.068
				(0.036)
Num.Obs.	1819	1819	2106	1527
R2	0.029	0.102	0.086	0.112
City fixed effects	No	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes
Restrict years: 2012 to 2016	Yes	Yes	No	Yes
Include San Francisco	Yes	Yes	No	Yes
R2 Adj.	0.029	0.096	0.080	0.105

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: (1) Model 1 estimates the linear probability model (Equation C.4) of solar adoption regressed on estimates solar payoff (net present value) from the engineering model (SAM). (2) Observations are residential new construction building permits from our sample of Bay Area municipalities during the pre-policy years (2012 to 2016). (3) Model 2 adds city and year fixed effects. (4) Model 3 includes all years 2012 to 2019 and excludes San Francisco, the treated city. (5) Model 4 is Model 2 with the addition of a multifamily building indicator.

In sum, as discussed in Section 3.4 above, we conclude that in most cases in our context, solar payoffs are expected to be positive, supporting the rationale for solar mandates. However, the payoffs are also relatively small, suggesting that this rationale for mandates is weaker once considering payoffs relative to the overall costs and complexity of a building project as well as the associated administrative and hassle costs. At the same time, we do find evidence supporting the idea of a solar gap, whereby builders leave money on the table as conjectured in the cost-effectiveness reports. In fact, we do not find that larger estimated payoffs are associated with higher likelihood of new construction solar adoption. We should note, however, that the extent of the solar gap is relatively limited, bounded above by the most optimistic calculations of net present values provided in this section and Appendix C.

4 Policy evaluation

In this section, we describe the application of synthetic control methods to evaluate the San Francisco Better Roofs policy and the California solar mandate. We apply synthetic control methods consistently to both policy evaluations, including using the same sets of predictor variables. Section D examines a sharp discontinuity in the design of the San Francisco Better Roofs policy, as described in Section 2.2.

4.1 Municipal mandate in San Francisco

We begin with the 2017 San Francisco solar mandate for newly constructed buildings. The outcome variable of interest is the share of new buildings with solar photovoltaics. The synthetic control method, introduced by Abadie and Gardeazabal (2003) and further developed in Abadie et al. (2010, 2015), provides a systematic way to construct a comparison unit using weighted combinations of control units. The synthetic control is constructed to approximate the characteristics of the treated unit before the intervention, providing a data-driven approach to counterfactual analysis.

The synthetic control is constructed by solving:

$$\min_{W} \sum_{k=1}^{K} v_k (X_{1k} - \sum_{j=2}^{J+1} w_j X_{jk})^2$$

$$\text{subject to } w_j \geq 0 \text{ and } \sum_{j=2}^{J+1} w_j = 1,$$

where X_{1k} represents the value of predictor k for San Francisco, X_{jk} is the value for control unit j, v_k is the weight assigned to predictor k, and w_j is the weight assigned to control unit j. In this setting, the control unit geographies are municipalities.

To select an initial donor pool, we sorted municipalities in the San Francisco Bay Area by an equally-weighted ranking of seven key criteria, including population size, population density, median household income, homeownership rate, solar irradiation, housing stock growth, and population growth. After processing data and removing municipalities with incomplete solar and building permit data, we generated a donor pool with 16 municipalities in the San Francisco Bay Area that most closely resembled San Francisco across these criteria. The donor pool municipalities are listed in Table 4. Prior to San Francisco's policy implementation in 2017, all municipalities have relatively low levels of solar adoption on residential new construction. The highest is Fremont (36%) followed by Santa Cruz (31%) and then San Francisco (27%).

To perform the synthetic control procedure with the San Francisco and donor pool building permit data, we select a number of predictors related to the residential demographics as well as the markets for new construction and rooftop solar. Our data spans January 2013 to December 2019, with the outcome measure aggregated at the quarterly level. Our predictors are primarily from the U.S. Census American Community Survey (ACS) 5-year estimates, including owner-occupied housing share, electric heating housing share, average household size, total population, growth rate in the stock of housing units, and educational attainment (share of adults with bachelors degree or higher). For a measure of each municipality's solar production potential, we use global horizontal irradiance (GHI) from NREL's National Solar Radiation Database (NSRDB). In particular, we construct a population-weighted mean GHI from the centroid of each municipality.

Table 4: San Francisco Mandate. Donor Pool Characteristics

Municipality	**Population**	**New construction solar share (%)**
San Francisco	840,039	26.9
Alameda	76,288	4.1
Berkeley	117,219	3.7
Cupertino	60,085	20.5
Daly City	97,126	3.6
Danville	43,353	13.1
Emeryville	10,813	13.2
Fairfield	109,468	20.1
Fremont	224,936	35.6
Oakland	407,484	14.2
Richmond	73,239	0.0
San Carlos	29,405	6.7
San Jose	998,848	10.3
Santa Clara	97,224	0.8
Santa Cruz	64,450	30.6
South San Francisco	66,699	14.2
Sunnyvale	116,814	0.2
Donor Pool Average	162,091	11.9

Notes: This table lists our donor pool cities, their populations, and their new construction solar adoption shares. The shares of solar adoption on new construction are for the pre-policy period (i.e., before 2017).

Drawing from the donor pool in Table 4 and the predictors described above, we now discuss our construction of synthetic San Francisco. Table 5 shows that the synthetic control successfully replicates San Francisco's pre-policy characteristics across important predictors. Specifically, the synthetic control closely matches San Francisco's occupied housing units share (37.0% for the synthetic control vs. 33.7% for San Francisco); electric heating housing share (33.7% vs. 30.0%); household size (2.42 vs. 2.32); and solar irradiance (4.90 vs. 4.72 GHI). As can be expected, when San Francisco tends to be an outlier, some imbalances remain, particularly for total population (293,264 vs. 840,039); housing unit growth rate (0.1% vs. 0.7%), and education (45% of adults with a bachelor degree vs. 54%).

Table 5: San Francisco Mandate. Balance Table for Predictors

Predictor	San Francisco	Donor Pool Avg.	Synthetic Control
Owner occupied housing units (share)	33.7	50.9	37.0
Electric heat housing units (share)	30.0	28.5	33.7
Average household size	2.32	2.68	2.42
Total population	840,039	162,091	293,264
Housing unit growth rate	0.7	0.4	0.1
Solar irradiance (GHI)	4.72	4.98	4.90
Bachelor degree (share)	53.8	51.3	45.2

Notes: For each of seven predictors used in our synthetic control, this table compares San Francisco characteristics to the donor pool averages as well as the synthetic control corresponding to the predictor and geographic weights in Table 6.

Table 6 presents the composition of synthetic San Francisco, including the predictor and geography weights. Three primary municipalities are used to construct the counterfactual. In decreasing order of importance, the synthetic control is composed of Oakland (69%), Santa Cruz (17%), and Emeryville (15%). The most important predictor is owner-occupied housing share (72% weight), followed by electric heating share (11%), household size (10%), population (4%), and housing growth rate (2%).

Complementing the comparison of actual and synthetic San Francisco characteristics in Table 5, Figures 5 and 6 further illustrate the pre-period fit of our synthetic control. In Figure 5, the observed solar adoption share in San Francisco (solid green line) closely tracks synthetic San Fran-

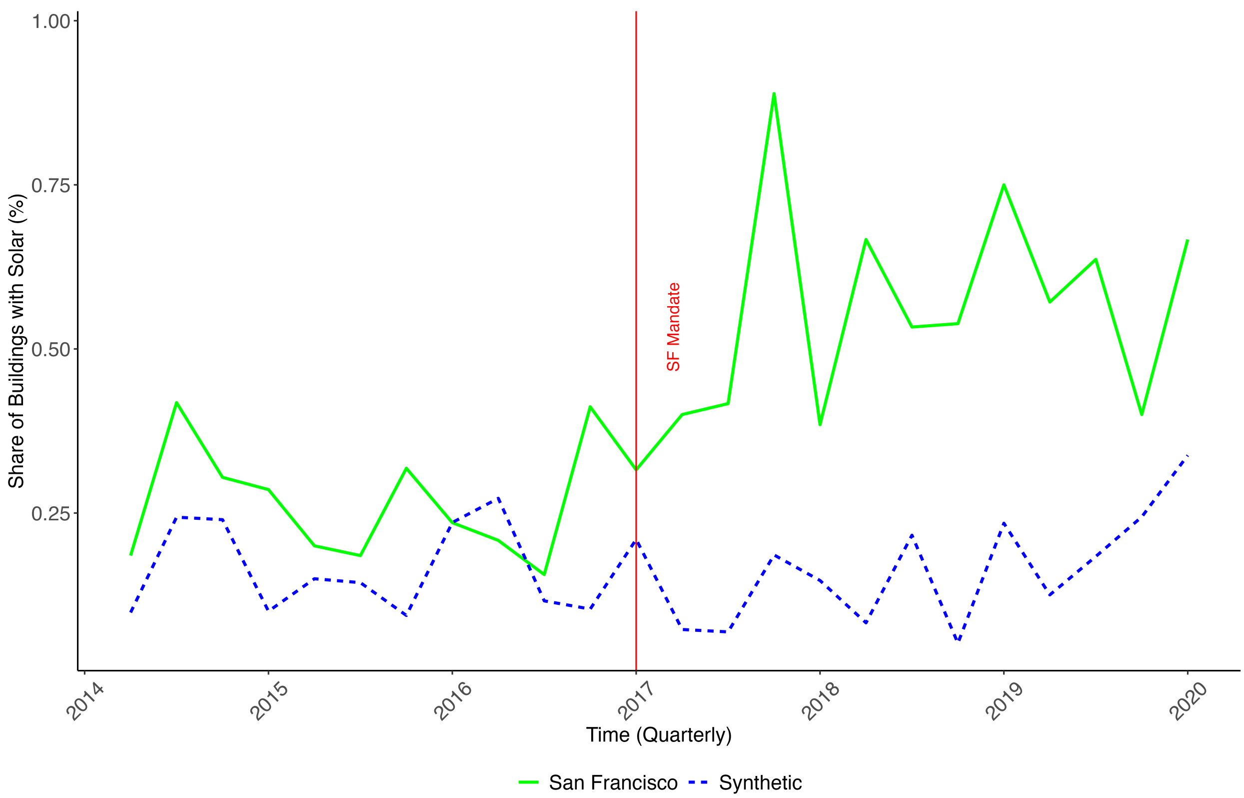
Table 6: San Francisco Mandate. Composition of the Synthetic Control and Estimated Effect

Estimate (Δ solar share on new construction)	0.28
Predictor weights:	
Owner occupied housing units (share)	0.722
Electric heat housing units (share)	0.108
Average household size	0.095
Total population	0.042
Housing unit growth rate	0.024
Solar irradiance (GHI)	0.008
Bachelor degree (share)	0.001
Municipality weights:	
Oakland	0.689
Santa Cruz	0.165
Emeryville	0.145
Temporal scale	Quarterly

Notes: (1) This table presents the predictor and geographic weights used to construct the synthetic control to evaluate the San Francisco mandate. (2) The table also presents the estimated effect of the San Francisco mandate. The estimated effect is the change in solar share on new construction after the mandate in the observed data compared to the synthetic control. This estimated effect is illustrated graphically in Figures 5 and 6. (3) The table omits municipalities with zero or close-to-zero weights.

cisco (dashed blue line) in the quarters proceeding implementation of San Francisco's Better Roofs Ordinance. Figure 6 then plots the differences between the two series, which are well-centered around zero in the pre-period. The relatively small and stable gap during the pre-treatment period supports our synthetic control construction, suggesting it effectively captures San Francisco's solar adoption patterns before the mandate.

Figure 5: San Francisco Mandate. Actual and Synthetic San Francisco Solar Shares on New Construction

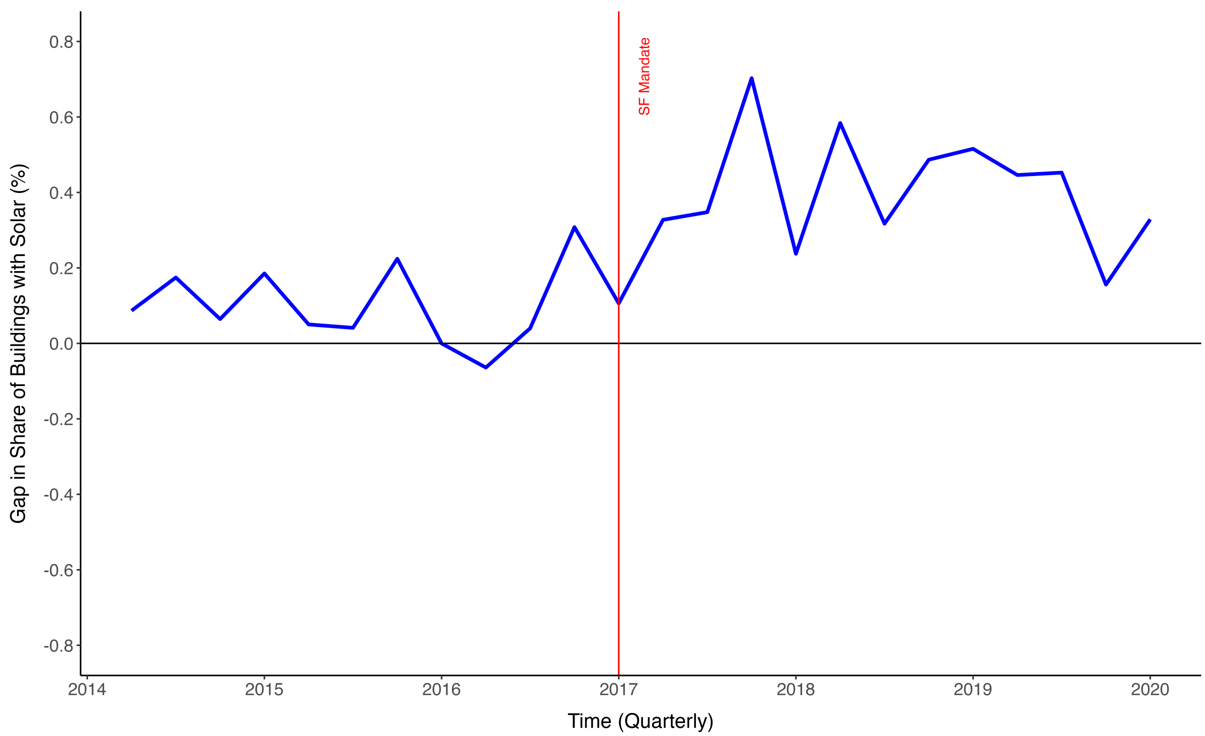


Notes: (1) This figure plots the observed time series of San Francisco solar shares on new construction as well as the synthetic control corresponding to the predictor and geographic weights in Table 6. (2) The time on the x-axes reflects building permit issuance, which is the relevant date for the policy.

Figures 5 and 6 show that San Francisco's actual solar adoption shares increase markedly after the 2020 mandate implementation as compared to the synthetic counterpart, implying a clear and sustained divergence and positive gap. Table 6 presents the value of this estimated policy effect—an increase in the share of residential new construction solar adoption by 28 percentage points.

While post-treatment adoption at 55% is still far short of 100%, this outcome is consistent with the flexible policy design of the Better Roofs Ordinance, which allowed alternative compliance and exemptions as described in Section 2.2 and Appendix A.1.

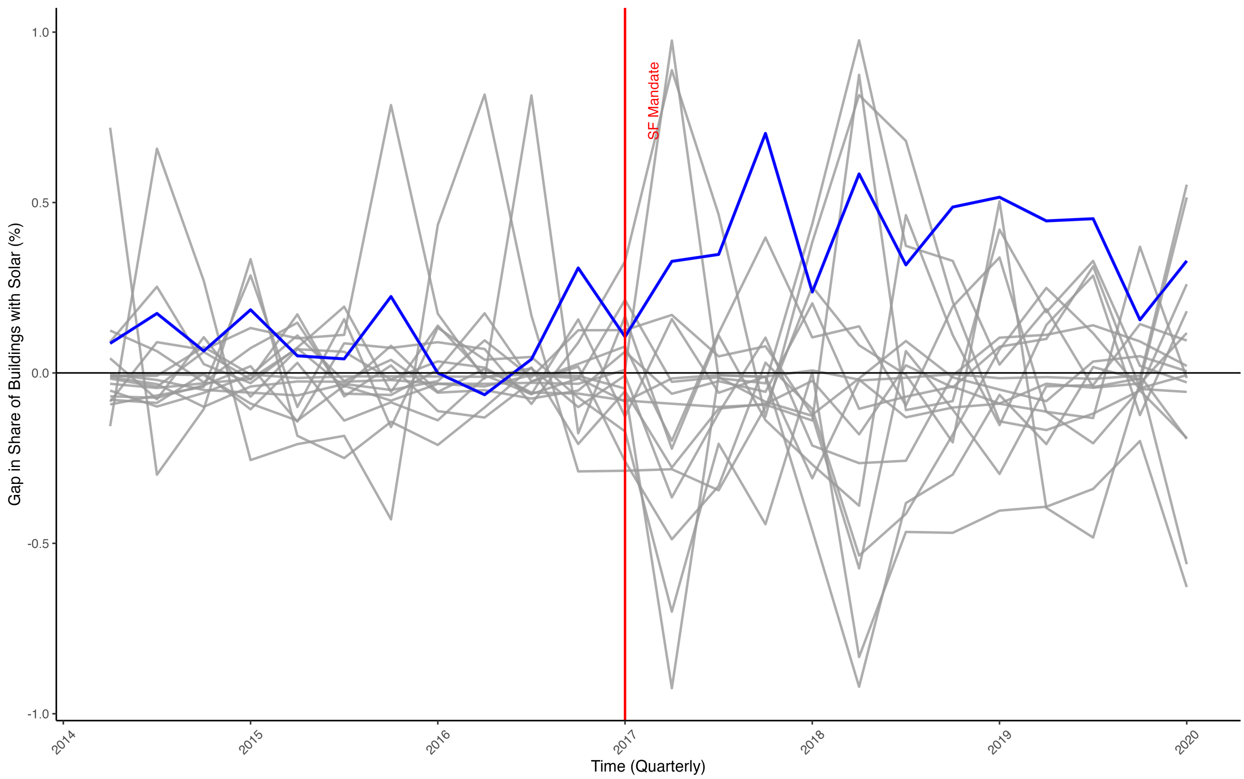
Figure 6: San Francisco Mandate. Gap Between Actual and Synthetic San Francisco Solar Shares on New Construction



Notes: This figure plots the difference (or "gap") between the observed time series of San Francisco solar shares on new construction and the synthetic control. These results correspond to the series in Figure 5 and the estimated effect in Table 6.

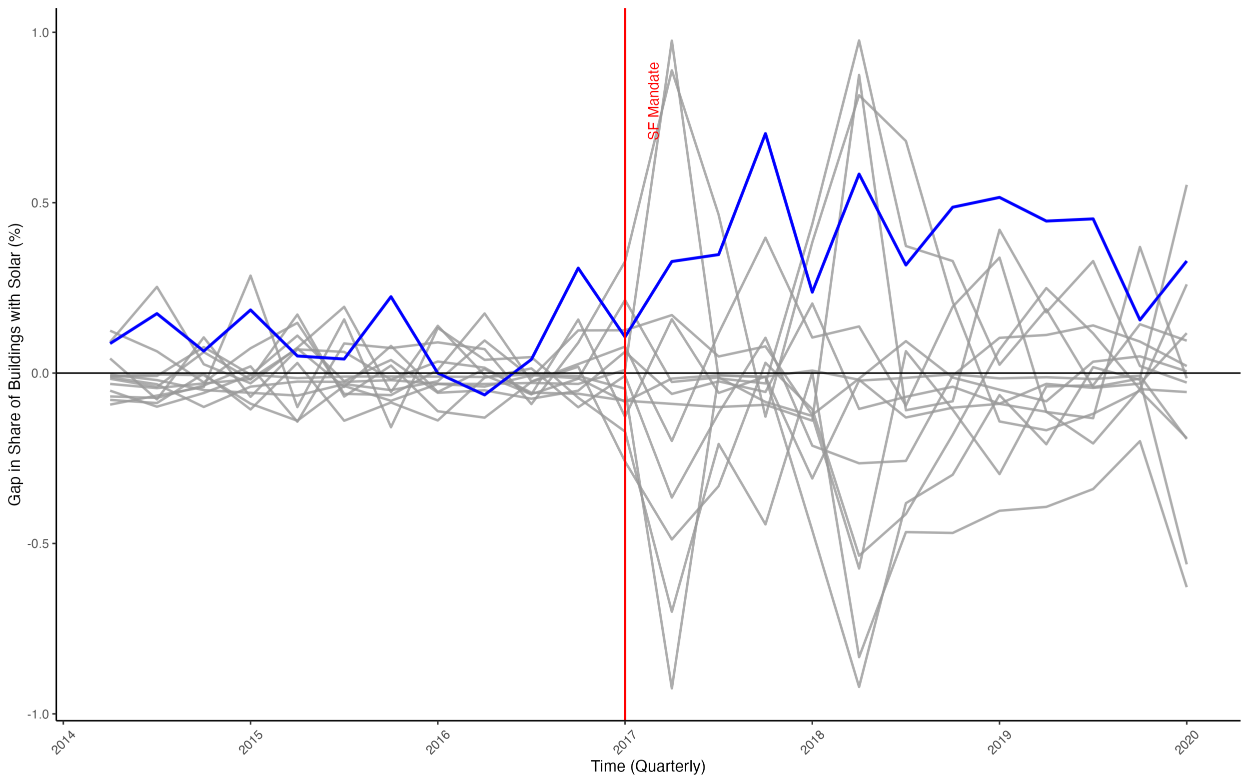
Abadie et al. (2010) recommend placebo tests to evaluate the robustness of synthetic control results. Figure 7 implements this placebo test by applying the synthetic control method to each control municipality in our donor pool. The blue line represents San Francisco's gap, while the gray lines show the placebo gaps for control municipalities. The magnitude and consistency of San Francisco's positive treatment effect stands out relative to the distribution of placebo effects, underlining the conclusion that the Better Roofs policy effectively increased the adoption of solar photovoltaics on new construction. Figure 8 shows the same placebo test for a subset of the donor pool, which has a pre-treatment mean squared prediction error no larger than San Francisco's.

Figure 7: San Francisco Mandate. New Construction Solar Share Gap and Placebo Gaps Using All Donor Pool Municipalities



Notes: This figure compares the gap produced from our synthetic control (also plotted in Figure 6) to a series of placebos where the synthetic control methodology is applied to each of the municipalities in the donor pool.

Figure 8: San Francisco Mandate. New Construction Solar Share Gap and Placebo Gaps Using Selected Donor Pool Municipalities



Notes: This figure compares the gap produced from our synthetic control (also plotted in Figure 6) to a series of placebos where the synthetic control methodology is applied to each of the municipalities. We discard control municipalities with a pre-treatment mean squared prediction error (MSPE) larger than San Francisco's.

Complementing our main result using synthetic control, we implement a synthetic difference-in-difference (SDID) estimator (Arkhangelsky et al. 2021) to evaluate the effect of San Francisco's solar mandate on the share of new buildings with solar permits. Table 7 presents this SDID estimate. The SDID estimator yields a treatment effect of 0.258 (25.8 percentage points), very similar to our synthetic control estimate, supporting the robustness of our findings. Notably, the geographic weights in the SDID approach are more evenly distributed across donor municipalities compared to synthetic control, with the largest weights assigned to Danville (9.1%), Santa Cruz (7.9%), and Berkeley (7.7%). The predictor weights also differ, with housing unit growth rate (8.6%) and solar irradiance (4.6%) receiving the highest weights, reflecting the SDID method's different optimization.

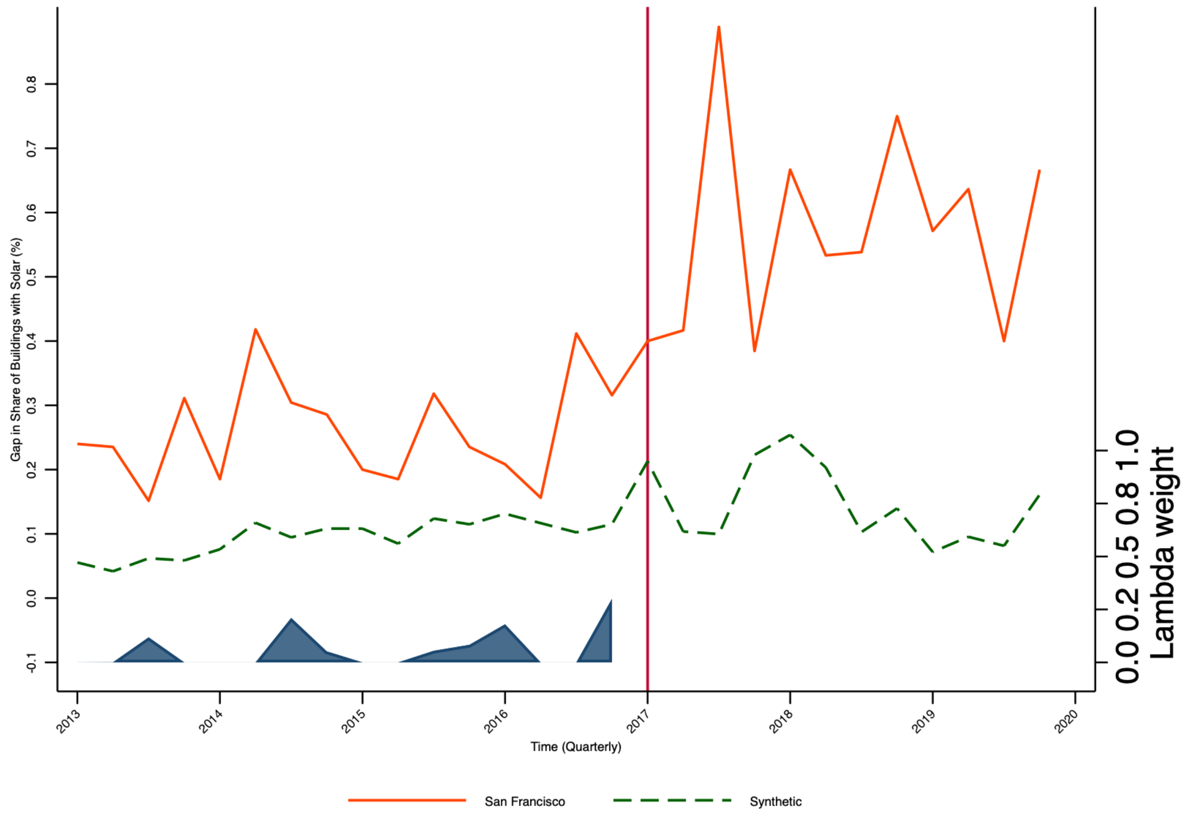
Figure 9 illustrates our SDID to complement the results in Table 7. In Figure 9, we observe a clear divergence post-treatment, with substantially higher adoption of solar among new construction in San Francisco compared to the counterfactual (the reweighted control group).

Table 7: San Francisco Mandate. Composition of the Synthetic Difference-in-Differences Control

Estimate (Δ solar share on new construction)	**0.280**
Standard Error	*0.095*
Predictor weights:	
Housing unit growth rate	0.086
Solar irradiance (GHI)	0.046
Owner occupied housing units (share)	0.036
Total population	0.010
Electric heat housing units (share)	0.009
Bachelor degree share	0.000
Geographic weights:	
Danville	0.091
Santa Clara	0.079
Berkeley	0.077
San Carlos	0.073
Oakland	0.072
Richmond	0.065
Alameda	0.065
Daly City	0.065
Fairfield	0.064
Cupertino	0.064
San Jose	0.060
Sunnyvale	0.057
Emeryville	0.054
Santa Cruz	0.047
Fremont	0.042
South San Francisco	0.023
Temporal scale	Quarterly

Notes: (1) This table presents the predictor and geographic weights used to construct the synthetic difference-in-differences estimator to evaluate the San Francisco mandate. (2) The table also presents the estimated effect of the San Francisco mandate. The estimated effect is the change in solar share on new construction after the mandate in the observed data compared to the synthetic control. This estimated effect is illustrated graphically in Figures 9.

Figure 9: San Francisco Mandate. Actual and Synthetic Difference-in-Differences Solar Shares on New Construction



4.2 Statewide mandate in California

We now turn to an evaluation of California's statewide rooftop solar mandate, using synthetic control methods as in our evaluation of the San Francisco mandate in Section 4.1. We begin with constructing a synthetic control for California from a donor pool of the other states, which have not adopted such mandates. At the state level, we do not directly observe the share of solar installations on new construction buildings. However, we can construct a proxy measure, which is residential solar PV capacity additions (kW) per residential new construction building permit issued. In the construction of this solar adoption measure, the numerator includes total residential solar capacity additions, not only those associated with new construction. Therefore, our outcome of interest in this section is any change in the relationship between new solar capacity additions and new construction, and our solar adoption measure is constructed accordingly.

We observe the monthly count of new residential buildings permits issued by state from the U.S. Census Building Permits Survey (BPS), and we observe monthly new residential solar capacity changes from the U.S. Energy Information Administration EIA-861M Monthly Electric Power Industry Report. Our solar adoption measure is then the amount of added residential solar capacity per newly issued residential building permit (i.e., kW per building permit). Of course, there are lags between the issuance of a new building permit, the construction of a new residence, and the interconnection of a solar system. Our review of San Francisco Bay Area building permits identified a lag of generally 1 to 2 years between permit issuance and solar adoption, with some projects taking much longer. Therefore, more precisely, our solar adoption measure d_q is the amount of added solar capacity kW_q in quarter q per newly issued building permit b_q, 2 to 6 quarters prior. That is, our outcome variable is $d_q = \frac{kW_q}{(\sum_{t=q-6}^{t=q-2} b_t)/4}$. Since there are many more building permits at the state level than in our analysis of the San Francisco citywide mandate, we also have the option of monthly specifications where our outcome variable d_m in month m is $d_m = \frac{kW_m}{(\sum_{t=m-18}^{t=m-6} b_t)/12}$.

Similar to our evaluation of the San Francisco mandate, for the construction of our synthetic control for California, we select a number of predictors related to residential demographics as well as the markets for new residential construction and rooftop solar, given the outcome variable. Our predictors are primarily from the U.S. Census American Community Survey (ACS) 5-year estimates, including owner-occupied housing share, electric heating housing share, average household size, total population, growth rate in the stock of housing units, and educational attainment (share of adults with bachelors degree or higher). For a measure of each state's solar production potential, we use global horizontal irradiance (GHI) from NREL's National Solar Radiation Database (NSRDB), as previously described. In particular, we construct a population-weighted mean GHI from the centroid of the state's three most populous counties to help ensure a relevant irradiance measure for each state as opposed to an alternative measure that might be biased by meteorological conditions in rural or undeveloped regions.

After processing data and removing states with incomplete solar and building permits data, we arrive at a donor pool with 41 jurisdictions (40 states and the District of Columbia), which we list in Table 8. Our data spans January 2014 to July 2022. Table 8 shows that our average pre-policy solar adoption measure for California is 16.0 kW per new residential building permit, substantially higher than most donor pool states. As discussed above, recall that the numerator in our solar adoption measure is total residential solar capacity additions, so this value is not to be interpreted as the average size of a residential new construction solar installation. Rather, the magnitude of the measure reflects California's leading position in residential solar adoption prior to the mandate. Other jurisdictions with favorable solar conditions and state policy support have comparable values, including the District of Columbia, Connecticut, Hawaii, Massachusetts, and New York.

Drawing from the donor pool in Table 8 and the predictors described above, we now discuss our construction of synthetic California. Table 9 shows that the synthetic control successfully replicates California's pre-policy characteristics across important predictors. Specifically, the synthetic control closely matches California's share of owner-occupied housing units (56.1% vs. 55.6%) and the share of bachelor degree holders (both 33%). However, some imbalances remain, particularly for total population (7,881,313 vs. 39,138,368) and, to a much lesser degree, solar irradiance (5.01 vs. 5.52 GHI).

Table 8: California Mandate. Donor Pool Characteristics

State	**Population**	**Avg. Solar PV kW Per New Building Permit**
California	38,602,411	16.0
Arizona	6,745,522	5.6
Colorado	5,361,874	1.5
Connecticut	3,586,923	17.9
Delaware	933,876	1.7
District of Columbia	658,453	23.5
Florida	19,973,056	1.0
Hawaii	1,407,822	17.5
Idaho	1,642,542	0.7
Illinois	12,841,343	2.7
Indiana	6,590,435	0.5
Iowa	3,104,413	0.8
Kansas	2,895,083	0.4
Kentucky	4,409,654	0.3
Louisiana	4,633,054	1.1
Maine	1,330,620	1.5
Maryland	5,947,268	7.5
Massachusetts	6,740,020	13.0
Michigan	9,919,087	0.6
Minnesota	5,454,700	0.6
Missouri	6,058,661	1.4
Montana	1,023,608	0.6
Nevada	2,844,631	5.4
New Hampshire	1,330,791	4.1
New Jersey	8,892,451	9.7
New Mexico	2,083,756	4.5
New York	19,634,431	10.0
North Carolina	9,951,573	0.5
North Dakota	729,557	0.0
Ohio	11,597,131	0.7
Oregon	3,989,634	1.3
Pennsylvania	12,775,266	2.0
South Carolina	4,841,319	1.0
South Dakota	849,218	0.0
Tennessee	6,551,315	0.1
Texas	26,970,303	1.0
Utah	2,951,390	2.3
Vermont	625,577	8.2
Virginia	8,298,129	0.7
Washington	7,092,246	1.0
West Virginia	1,841,173	0.4
Wisconsin	5,751,544	0.5
Donor Pool Average	6,118,523	3.7

Notes: This table lists our donor pool states, their populations, and the mean of our solar adoption measure. As detailed in Section 4.2, our state-level solar adoption measure is residential solar capacity additions (kW) per residential new construction building permit issued. The solar adoption estimates are for the pre-policy period between 2017 and 2019. Alabama, Alaska, Arkansas, Georgia, Mississippi, Nebraska, Oklahoma, Rhode Island, and Wyoming are excluded due to limited data, which leaves a total donor pool of 40 states and the District of Columbia.

Table 10 presents the composition of California's synthetic control including the predictor and geography weights for both a monthly and a quarterly specification. In the quarterly specification, Nevada receives the highest weight (40%) followed by New York (28%), Arizona (17%), and District of Columbia (15%). The most important predictor is owner-occupied housing share (61% weight), followed by adults with bachelor's degree (23%), solar irradiance (7%), housing growth rate (4%), electric heating share (4%), and population (less than 1%). The monthly specification composition is relatively similar with some exceptions. Arizona takes the highest weight (50%), while Nevada and New York take much lower weights (20% and 14%, respectively). There are more notable differences in the predictor weights between the models. In the quarterly specification, owner occupied housing share takes the highest weight (61%) followed by educational attainment (23%) and then solar irradiance (7%). In the monthly specification, solar irradiance takes the highest weight (40%) followed by owner occupied housing share (32%) and housing unit growth rate (15%). In both specifications, electric heating, population level, and household size take low weights (all less than 5%).

Complementing the comparison of actual and synthetic California characteristics in Table 9, Figures 10 and 11 further illustrate the pre-period fit of our synthetic control. In Figure 10, the observed solar adoption measure for California (solid green line) closely tracks synthetic California (dashed blue line) in the quarters proceeding the statewide solar mandate. Figure 11 then plots the differences between the two series, which are quite well-centered around zero in the pre-period. The relatively small gap during the pre-treatment period supports our synthetic control construction, suggesting it effectively captures California's solar adoption patterns before the mandate. As discussed above, recall that our solar adoption measure on the y-axis includes *total* residential solar adoption in the numerator, so this measure cannot be interpreted as the *size* of solar systems on residential new construction.

Figures 10 and 11 show that California's actual solar adoption measure increases markedly after the 2020 mandate implementation as compared to the synthetic trend with a clear and sustained positive divergence. Table 10 presents the values of this estimated policy effect, which are quite consistent between the monthly and quarterly specifications with the two specifications estimating a policy effect of 8.81 and 8.62 kW per new construction building permit, respectively. These values are somewhat high, since a typical system for a single family home in California is generally less

Table 9: California Mandate. Balance Table for Predictors

Predictor	California	Donor Pool	Synthetic California
Total population	39,138,368	6,204,694	7,881,313
Solar irradiance (GHI)	5.52	4.38	5.01
Housing unit growth rate	0.6	0.9	1.0
Electric heat housing units (share)	26.5	33.8	33.9
Owner occupied housing units (share)	55.6	68.0	56.1
Average household size	2.96	2.55	2.61
Bachelor degree holders (share)	33.3	32.0	33.2

Notes: For each of seven characteristics considered in constructing our synthetic control, this table compares California characteristics to the donor pool averages and our synthetic control, as well as the synthetic control corresponding to the predictor and geographic weights from model (2) of Table 10, estimated with quarterly data.

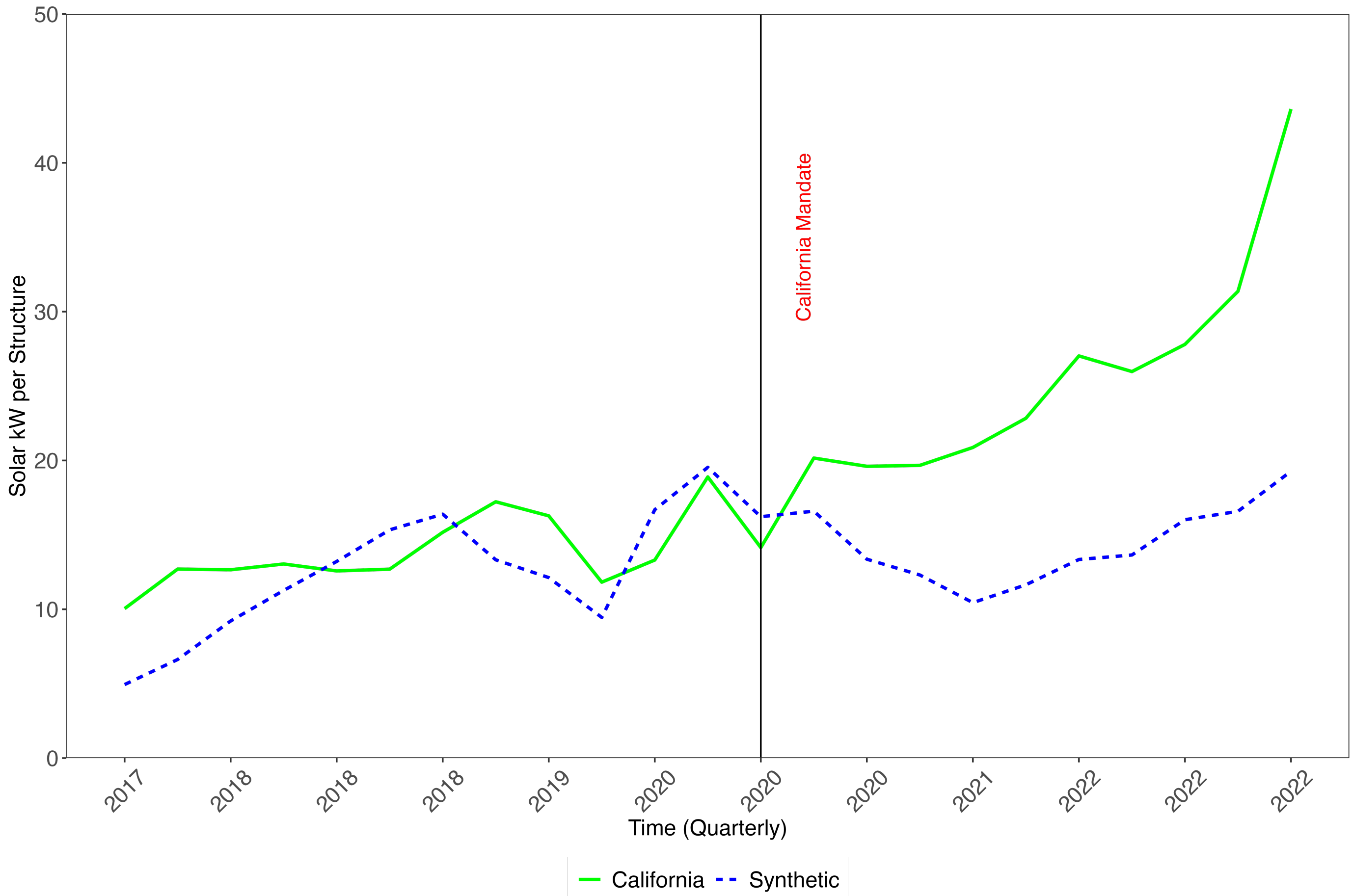
than 8 kW. However, systems are typically larger for multifamily homes, which are also covered by the policy.

Table 10: California Mandate. Composition of the Synthetic Control and Estimated Effect

	(1)	(2)
Estimate (Δ kW per building permit)	8.62	8.81
Predictor weights:		
Solar irradiance (GHI)	0.401	0.067
Owner occupied housing units (share)	0.316	0.612
Housing unit growth rate	0.146	0.044
Adults with bachelor's degree (share)	0.080	0.229
Electric heat housing units (share)	0.039	0.040
Total population	0.018	0.007
Household size (average)	0.000	0.000
State weights:		
Arizona	0.496	0.171
Nevada	0.198	0.403
District of Columbia	0.166	0.149
New York	0.140	0.275
Hawaii	0.000	0.002
Temporal scale	Monthly	Quarterly

Notes: (1) Section 4.2 describes the construction of our solar adoption measure, which is residential solar capacity additions (kW) per new construction building permit issued. (2) We estimate models (1) and (2) with monthly and quarterly data, respectively. (3) The table omits states with zero or close-to-zero weights.

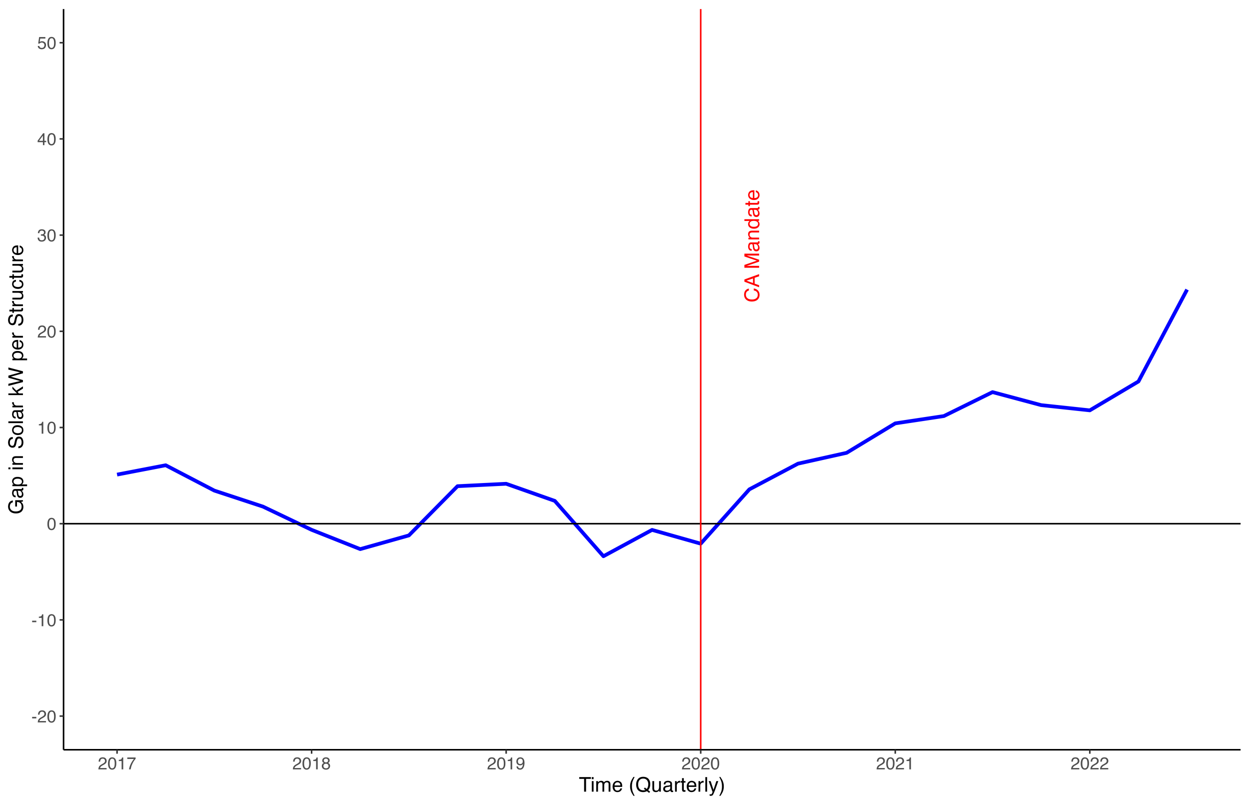
Figure 10: California Mandate. Actual and Synthetic California Solar Shares on New Construction



Notes: (1) Section 4.2 describes the construction of our solar adoption measure, which is total residential solar capacity additions (kW) per new construction building permit issued. (2) Table 10 presents the corresponding synthetic control predictor and geography weights. This figure corresponds to model (2) estimated with quarterly data. (3) The time on the x-axes reflects building permit issuance, not the date of solar adoption because date of building permit issuance is the relevant date for the policy.

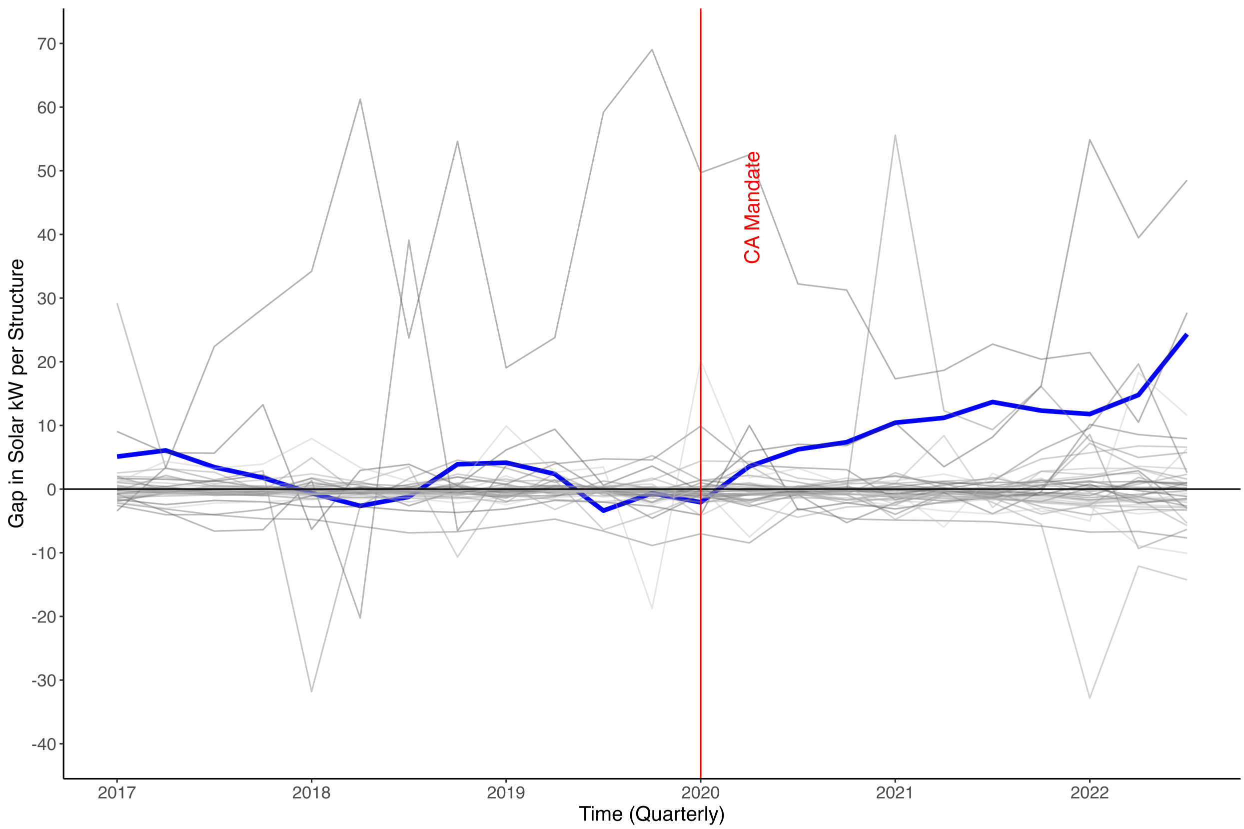
Figure 12 once again implements a placebo test by applying the synthetic control method to each control state in our donor pool. The blue line represents California's gap, while the gray lines show the placebo gaps for control states. The magnitude and consistency of California's positive treatment effect stands out relative to the distribution of placebo effects, underlining the conclusion that the state solar mandate effectively increased the adoption of solar photovoltaics on new construction. Figure 13 shows the same placebo test for a subset of the donor pool, which has a pre-treatment mean squared prediction error no larger than California's.

Figure 11: California Mandate. Gap Between Actual and Synthetic California Solar Shares on New Construction



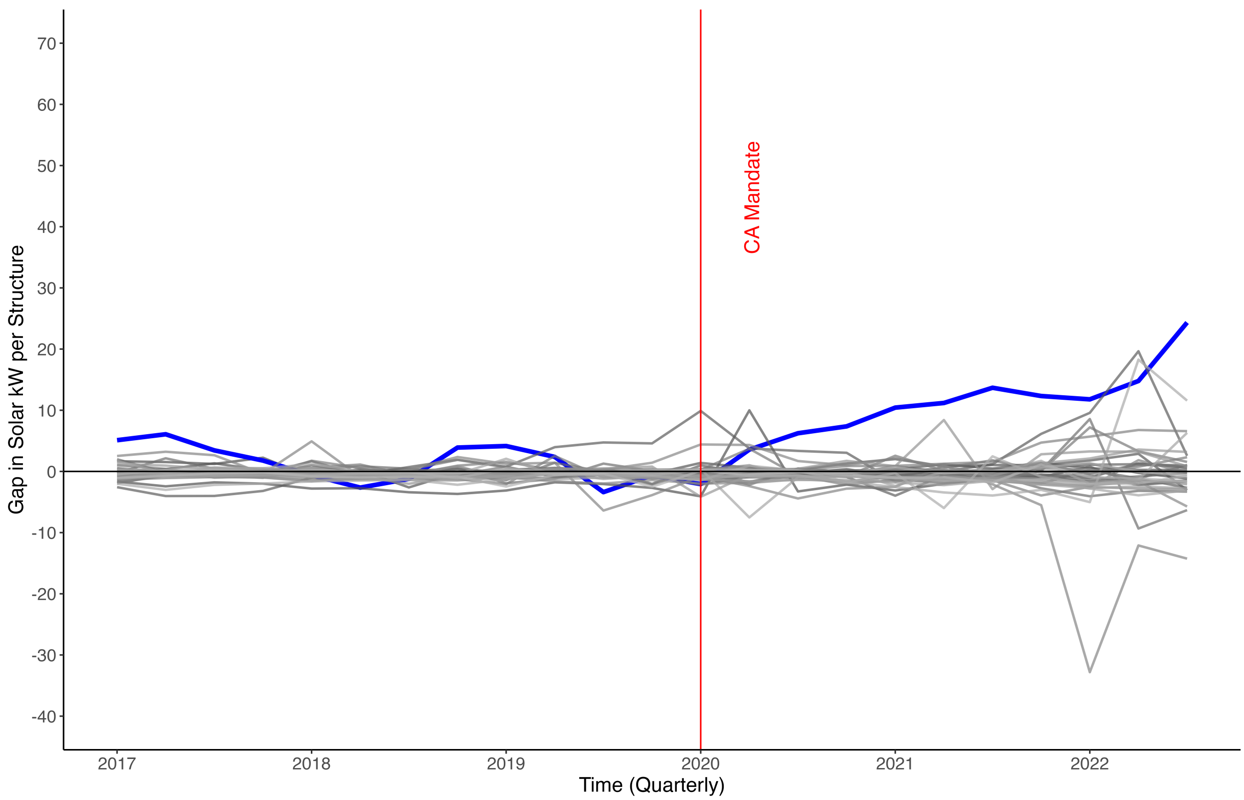
Notes: This figure plots the difference (or "gap") between the observed time series of our solar adoption measure for California and the synthetic control. These results correspond to the series in Figure 10 and model (2) (quarterly data) in Table 10.

Figure 12: California Mandate. New Construction Solar Share Gap and Placebo Gaps Using All Donor Pool Municipalities



Notes: This figure compares the gap produced from our synthetic control (also plotted in Figure 12) to a series of placebos where the synthetic control methodology is applied to each of the municipalities in the donor pool. This figure shows all 41 donor states.

Figure 13: California Mandate. New Construction Solar Share Gap and Placebo Gaps Using Selected Donor Pool Municipalities



Notes: This figure compares the gap produced from our synthetic control (also plotted in Figure 12) to a series of placebos where the synthetic control methodology is applied to each of the municipalities in the donor pool. This figure shows all 41 donor states. We discard control states with a pre-treatment mean squared prediction error (MSPE) larger than California's.

As in the Section 4.1 evaluation of the San Francisco mandate, we once again implement a synthetic difference-in-differences (SDID) estimator (Arkhangelsky et al. 2021) to complement our standard synthetic control estimates of the causal effect of California's solar mandate.

Figure 14 illustrates the SDID results, showing California's outcome trajectory (solid orange line) compared to the reweighted SDID synthetic control (dashed green line). The shaded triangular regions indicate the treatment and control units, with clear divergence evident in the post-treatment period. Table 11 presents the SDID method's estimate of the policy effect—an additional 6.29 kW of solar per new residential building permit. This estimate is lower than our standard synthetic control estimates above, but generally confirms the finding of a substantial positive policy effect.

Figure 14: California Mandate. Actual and Synthetic Difference-in-Differences Solar Shares on New Construction

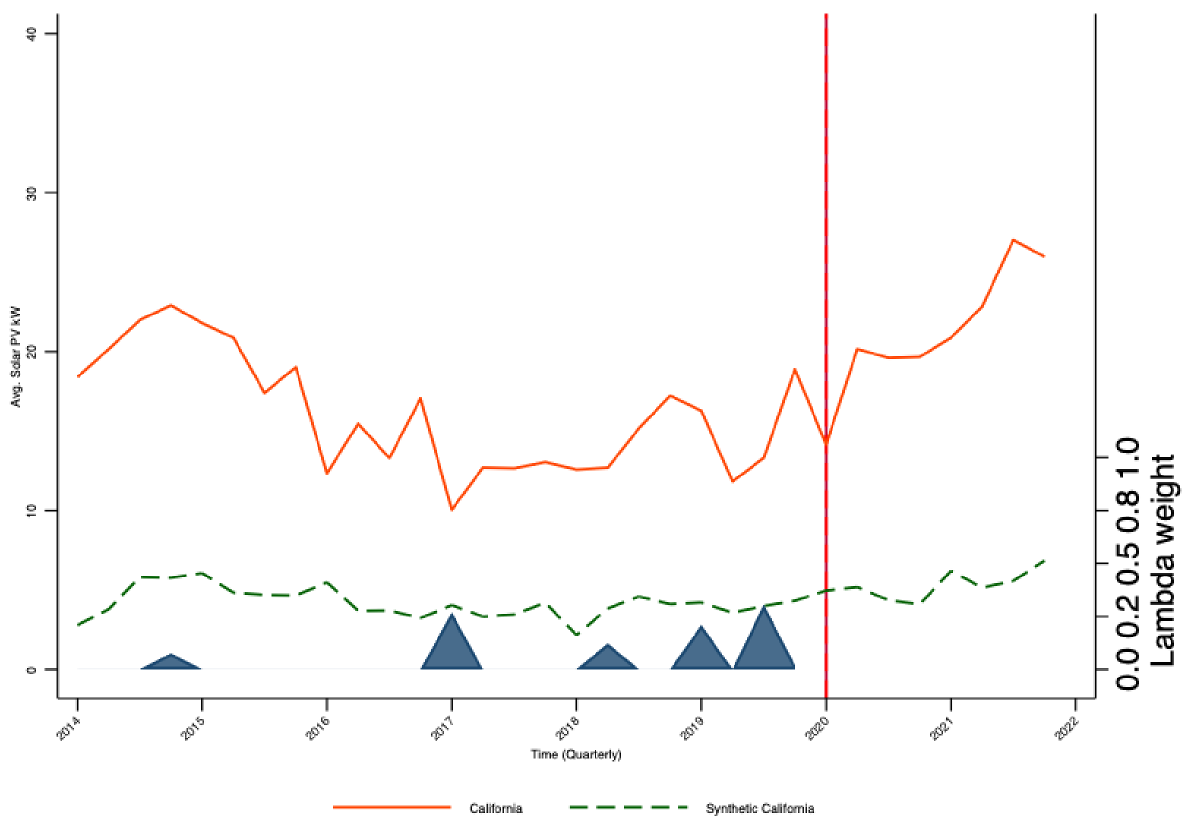


Table 11: California Mandate. Composition of the Synthetic Difference-in-Differences Control

	(1)
Estimate (kW per structure)	6.290
Standard Error	*1.496*
Predictor weights:	
Total population	1.108
Housing unit growth rate	0.503
Owner occupied housing units (share)	0.426
Electric heat housing units (share)	0.321
Bachelor degree share	0.016
Solar irradiance (GHI)	0.000
State weights:	
Maryland	0.064
New York	0.063
Nevada	0.058
Connecticut	0.052
New Hampshire	0.050
Massachusetts	0.038
Arizona	0.035
Louisiana	0.033
Delaware	0.033
Washington	0.029
Tennessee	0.029
Colorado	0.028
Oregon	0.027
South Dakota	0.026
North Carolina	0.026
Kentucky	0.026
Michigan	0.025
North Dakota	0.025
West Virginia	0.023
Utah	0.023
Idaho	0.022
Ohio	0.022
Maine	0.022
Indiana	0.021
Wisconsin	0.020
Texas	0.020
Minnesota	0.019
Iowa	0.017
Kansas	0.017
Florida	0.016
Virginia	0.016
South Carolina	0.015
Missouri	0.011
New Jersey	0.011
Pennsylvania	0.009
New Mexico	0.009
Montana	0.007
Vermont	0.007
Illinois	0.003
Temporal scale:	Quarterly

5 Conclusions

This paper examines the economics of solar mandates, which impose the use of solar on new constructions, and the case for their use. These mandates gained prominence in California, supported by engineering studies suggesting that solar panels are cost-effective and profitable on all new construction. These mandates have then expanded quite rapidly in Europe and elsewhere in the United States.

In this paper, we tackle three research questions. First, we examine whether solar is ubiquitous in the absence of a mandate, given its presumed cost-effectiveness. We find that it is not. Second, we leverage many data sources and use an engineering model to analyze the private payoffs of solar adoption for residential new construction and whether solar is consistently cost-effective when more fully accounting for building characteristics and the variety of building types in the setting where solar mandates were first introduced. We find much greater heterogeneity in project cost-effectiveness in parameterizing the model across our dataset of observed building projects and their detailed characteristics. Although estimated payoffs are generally positive, they tend to be small compared to overall new construction costs. We further compare payoff estimates with actual solar adoption and find little evidence of any strong relationship between solar adoption and the level of estimated payoffs, suggesting that factors other than solar payoffs dominate the adoption decision. This evidence does support the concept of a "solar gap," whereby many builders do not consider profitable opportunities to install solar, thus supporting one of the rationalizations for mandates.

Third, we engage in a policy evaluation exercise and provide evidence that the 2017 municipal solar mandate in the frontrunner city of San Francisco as well as the 2020 statewide mandate in California have increased the adoption of solar among new construction. However, adoption remains below 100 percent.

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A Supplemental solar mandate policy details

A.1 Supplemental details on the San Francisco's Better Roofs Ordinance

The 2017 Better Roofs Ordinance ("Better Roofs," Ordinance No. 221-16) was an amendment to San Francisco's Planning Code and the Green Building Code. Better Roofs was intended to contribute to the city's climate objectives (Ordinance No. 81-08), which include a greenhouse gas-free electric system by 2030 and emission reductions of 40% below 1990 levels by 2025 and 80% below 1990 levels by 2050 (Brockman and Hooper 2016).[6]

The ordinance made San Francisco the first major city in the United States to require solar installations on new buildings, though more than two dozen smaller California municipalities adopted solar photovoltaic requirements between 2017 and 2020 (California Energy Commission 2016; California Statewide Codes & Standards Program 2022). San Francisco also joined other major U.S. cities including Chicago, Portland, and Washington, D.C., that require living roofs on certain new buildings, though San Francisco's approach offers more flexibility in compliance pathways.[7]

The Better Roofs policy built on existing city regulations. Since 2010, the San Francisco Green Building Code had included "a modest renewable energy requirement for new commercial buildings larger than 25,000 square feet," but this could be met through purchasing Renewable Energy Certificates (RECs) or improving energy efficiency rather than on-site generation (Brockman and Hooper 2016). The Better Roofs mandate strengthened these requirements by mandating on-site renewable generation.

San Francisco's Better Roofs Ordinance also extended California's statewide Title 24 requirement to build "solar ready," to which we return in Section A.2. San Francisco, and other local jurisdictions, were authorized under Title 24 to enact more stringent standards when reasonably necessary because of local conditions related to climate, geology, or topography. In 2013, Cali-

[6] The San Francisco Environment Department quantified the potential emissions impact as follows: "The aggregate impact of installing photovoltaics to minimally comply with the proposed Better Roof ordinance on all 200 major new construction projects in San Francisco Planning Department's project pipeline as of third quarter 2014 would be to avoid over 26,000 metric tons of carbon dioxide emissions per year" (Brockman and Hooper 2016).

[7] According to the San Francisco Department of Environment, "considerable research by the Planning Department, Environment, SFPUC, and the 2013 Greener and Better Roofs Roadmap report from SPUR's Green Roof Task Force recognizes that – in addition to being a prime location for renewable energy resources – roofs can host 'green' or 'living roofs' with many additional benefits such as reducing stormwater entering the sewer, enhancing biodiversity and habitat, sequestering carbon, capturing pollution, and connecting citizens with nature" (Brockman and Hooper 2016).

fornia's Title 24 building efficiency standards established that 15% of the roof area in most new buildings must be reserved for future installation of solar energy systems. San Francisco's policy strengthened this state policy by mandating that the solar-ready area be activated with renewable energy systems during initial construction (City and County of San Francisco 2016a). Established through Planning Code Section 149, the minimum Better Roof area requirement mirrors the Solar Ready Area specifications in California Energy Standards. Specifically, the ordinance required that solar be applied to (1) 15% of total roof area for multifamily and non-residential buildings; or (2) 250 square feet of the roof area of single-family residential buildings (Brockman and Hooper 2016). The ordinance applied to site or building permit applications for new residential buildings, commercial or municipal buildings submitted on or after January 1, 2017 (City and County of San Francisco 2016b). Notable exceptions include (1) buildings over ten stories,[8] (2) non-residential buildings with gross floor area less than 2,000 square feet, and (3) data centers and laboratory buildings.

In addition to solar photovoltaic (PV) systems, San Francisco's Better Roofs ordinance also offered two alternative compliance pathways, providing developers flexibility in meeting the city's sustainability goals. These two alternative pathways were either (1) a solar thermal system; or (2) a living roof, which incorporates vegetation to improve insulation, reduce urban heat, manage stormwater runoff, and enhance biodiversity (City and County of San Francisco 2016b).[9] Project developers could also combine these pathways so far as they demonstrated productive use of rooftop space to deliver environmental and in principle also economic benefits (City and County of San Francisco 2016a).

[8] Specifically, the ordinance applied to buildings of ten or fewer occupied floors (City and County of San Francisco 2016b).

[9] For each compliance pathway, San Francisco provided rationale for the expected economic and environmental benefits as well as specific compliance criteria. With respect to solar photovoltaic (PV) systems, the city cited the value of on-site renewable electricity in reducing reliance on fossil fuels and supporting the city's clean energy transition (Brockman and Hooper 2016). For water-heating solar thermal systems, the city discussed energy consumption related to water heating (Brockman and Hooper 2016). Living roofs were required to meet criteria for stormwater management. Living roofs were also required to achieve a compliance ratio of 2:1, meaning two square feet of living roof for each required square foot of solar (City and County of San Francisco 2016b). Solar PV systems were required to achieve a minimum performance standard of 10 watts-DC rated nameplate capacity per square foot of dedicated area (Brockman and Hooper 2016). Solar thermal systems were required to achieve a minimum performance standard 100 kBtu annual generation per square foot.

A.2 Supplemental details on the California's Solar PV Mandate

In California, solar photovoltaics are regulated by the Title 24 Building Energy Efficiency Standards (Energy Code), which were first enacted in 1978.[10] The standards operate under a conceptual framework divided into three basic sets: mandatory requirements applicable to all buildings, performance standards that vary by climate zone and building type, and prescriptive packages that provide alternative compliance pathways (California Energy Commission 2019). California's building energy efficiency requirements are updated every three years. With the 2019 Energy Code, California implemented a solar mandate, which required all newly constructed low-rise residential buildings (defined as residential buildings up to three stories) to install solar PV systems (California Energy Commission 2019). The 2019 Energy Code became effective on January 1, 2020. Besides requiring PV, it set thermal envelope standards and specified non-residential lighting requirements. The PV systems installed under the mandate need to meet performance and electricity output requirements. The requirements are based on the floor area of the building, the climate zone, and the goal to provide the full annual energy usage of the home. For residential buildings, the annual electrical output of the PV system shall be no less than the smaller of a PV system size determined using an equation provided by the legislator, as Equation 150.1-C[11] or the maximum PV system size that can be installed on the building's "Solar Access Roof Area" (California Energy Commission 2019).[12] The 2019 standards incorporated flexibility mechanisms addressing diverse building conditions and exceptions to the solar PV installation requirement. In particular, the following exceptions apply. No PV system is required if the SARA is less than 80 contiguous square feet. No PV system is required when the minimum PV system size specified is less than 1.8 kW. Buildings are exempt when significant shading would impede solar energy production, specifically when roof areas have less than 70 percent annual solar access accounting for shading from obstructions. Solar PV systems are also not needed if a solar-water heating system meeting specified installation criteria and having a minimum solar savings fraction of 0.50 is permanently installed at the time of

[10] California's Title 24 Building Energy Efficiency Standards trace their origins to the Warren-Alquist State Energy Resources Conservation and Development Act (Public Resources Code §§ 25000-25968), enacted by the California Legislature in 1974. By 1988, Title 24 applied to all occupancies in the state of California.

[11] Equation 150.1-C is given by $kW_{PV} = (CFA \times A)/1000 + (NDwell \times B)$, where: kW_{PV} is the size of the PV system, CFA stands for conditioned floor area, NDwell is the number of dwelling units, A is the adjustment factor, and B is the dwelling adjustment factor.

[12] Solar Access Roof Area (SARA) is the area of the roof that can accommodate a solar PV system, taking into account factors like the roof's size, shape, and shading from nearby trees or structures.

construction. Additional exceptions include buildings with three habitable stories or more having a total floor area less than or equal to 2000 square feet and meeting reduced solar zone requirements, buildings located in Wildland-Urban Interface Fire Areas meeting specified conditions, and buildings meeting certain demand response and energy efficiency measures. PV system sizes determined using Equation 150.1-C may be reduced by 25 percent if installed in conjunction with a battery storage system meeting qualification requirements and having a minimum usable capacity of 7.5 kWh. Buildings may also comply through approved community shared solar generation systems as an alternative to on-site installation.

The 2019 Energy Code also established "solar ready" requirements for newly constructed buildings that do not have solar PV systems installed. "Solar ready" requirements prepare buildings for future solar installation by mandating designated solar zones on roofs, structural design considerations for future solar loads, electrical pathways and reserved panel space for future solar connections, and appropriate construction documentation. These requirements apply to single family residences in subdivisions with ten or more homes, low-rise multifamily buildings, high-rise multifamily buildings with ten habitable stories or fewer, hotel or motel occupancies with ten habitable stories or fewer, and nonresidential buildings with three habitable stories or fewer (except healthcare facilities).

The 2022 Energy Code, effective January 1, 2023, further extended California's solar mandate to all residential buildings and most nonresidential buildings (California Energy Commission 2022). The 2022 standards also include a solar PV storage mandate. That is, all new buildings that are required to have a photovoltaic system also need a battery storage system.

B Supplemental details about data and engineering model

B.1 Supplemental details about data

Table B.1 lists our data and links to online sources followed by more detailed descriptions of each dataset to supplement the descriptions of our data in Sections 3.2, 3.3, and 4. Section B.2 provides additional description of NREL's System Advisor Model and our parameterization methodology.

Table B.1: Data Sources

Organization	Dataset	Data source information
California municipalities and counties	Building, electrical, and solar permits data	Individual municipal and county building departments
California Public Utility Commission (CPUC)	Interconnected Project Sites Data Set	`https://www.californiadgstats.ca.gov/downloads/`
Google	Project Sunroof	`https://sunroof.withgoogle.com/`
National Renewable Energy Laboratory (NREL)	National Solar Radiation Database (NSRDB) Typical Meteorological Year (TMY) Data	`https://nsrdb.nrel.gov/data-sets/tmy`
NREL	Utility Rate Database (URDB)	`https://openei.org/wiki/Utility_Rate_Database`
PG&E	Energy Data Request Program (EDRP)	`https://pge-energydatarequest.com/`
PG&E	Net Surplus Compensation Rates for Energy	`https://www.pge.com/assets/pge/docs/clean-energy/solar/AB920-RateTable.pdf`
PG&E	Tariffs: Electric Rate Schedules	`https://www.pge.com/tariffs/en.html`

Notes: See Appendix Section B.1 text for detailed descriptions of each dataset. Links last accessed, May 9, 2025.

Building, electrical, and solar permits data: We construct a novel address-level dataset of new construction building projects in California municipalities, which we collect from the permitting offices of individual municipalities and counties. In addition to new construction permits, we also collect solar and electrical permits. In some cases, jurisdictions had permitting processes that tracked solar permits separately from other electrical permit types. In matching the solar electrical permits to building permits, we are able to identify the new construction projects that adopt rooftop solar. Specifically, we match the new construction building permit addresses to solar permits in the corresponding jurisdiction's electrical permits. We are then able to validate these solar adoption statistics from individual jurisdictions' electrical and solar permitting databases against California's solar interconnection data (detailed below). The building permit data from individual municipalities and counties vary in the level of data availability and details of each project's characteristics. However, the general structure of the data tracks each project's status from initial filing date through various approvals and inspections to final completion. We restrict the data to only completed projects, for which we are able to observe the final status of a building's solar adoption decision. Our list of 17 San Francisco Bay Area municipalities includes San Francisco, Alameda, Berkeley, Cupertino, Daly City, Danville, Emeryville, Fairfield, Fremont, Oakland, Richmond, San Carlos, San Jose, Santa Clara, Santa Cruz, South San Francisco, and Sunnyvale.

California Interconnected Project Sites Data Set: These data include all grid-interconnected rooftop solar systems within the PG&E service territory since 1982. Primarily, we use these data to obtain a time series of solar installation costs, including median and 95$^{\text{th}}$ percentile cost-per-watt-DC by California city and year. We also use these data to validate the quality of our city-level electrical and solar permits data by comparing each city's overall number of solar installations by year between the two datasets.

NREL National Solar Radiation Database: Sunshine and other climate variables are essential SAM inputs to determine the availability of solar energy and panel performance. These data are available in Typical Meteorological Year (TMY) files from NREL's National Solar Radiation Database (NSRDB), which include an entire year of hourly temperature, global horizontal irradiance (GHI), and other relevant climate variables for a representative year based on weather observations from 1998 to 2022. NSRDB TMY data is gridded to 4km by 4km cells, which we match to our geocoded building permits.

Google Project Sunroof: To determine rooftop shading conditions, we extract a measure of annual "usable sunlight" hours from Google Project Sunroof for each building project in our data. Google Project Sunroof uses satellite data to identify rooftop area and shading conditions. We estimate a shading measure for each roof using its "usable sunlight" hours relative to the other roofs in our sample.

NREL Utility Rate Database (URDB): The Utility Rate Database (URDB) provides PG&E electricity tariff data for the years of our sample period.

PG&E public tariffs and solar compensation rates: Under the various iterations of California's net metering policies, solar customers are compensated for any excess generation back to the grid (on an annual basis) at a wholesale rate of around \$0.03/kWh. PG&E tariffs and solar compensation rates are both publicly available on PG&E's website. Historic tariffs and compensation rates are available on archived versions of these webpages from the Internet Archive.[13]

PG&E restricted-access data: In 2018, the electricity utility PG&E provided a restricted-access sample of billing and electricity consumption interval metering data for addresses from 73 Bay Area municipalities that were associated with premise IDs created in PG&E's billing system after January 1, 2009. New premises in PG&E's billing data are typically associated with new construction. The final sample included almost 63,000 addresses in 71 Bay Area municipalities with metering and billing data through December 31, 2017. We use these data for our hourly consumption profiles in the parameterization of the engineering model and estimation of project-level solar payoffs. Since PG&E can create new premise IDs that are not associated with new construction, we create city-median hourly electricity consumption profiles to increase our confidence that we are identifying electricity consumption associated with new and recently constructed buildings.

[13] See `https://web.archive.org/` (last accessed, May 9, 2025).

Also, Appendix Section C compares our payoff estimates from our primary parameterization to an alternative approach where we use building-level hourly interval electricity consumption data from our sample of new PG&E premises. However, the preferred specification should reflect a builder's expectations about the building's future electricity consumption patterns, and a snapshot of observed building-level electricity consumption patterns are not necessarily indicative of *future* or even *expected* electricity consumption patterns. Therefore, the use of observed building-level consumption data is not necessarily strictly preferred in parameterization of the engineering model.

California net metering policies: California's net metering policy determines how solar owners are compensated for the electricity they produce and then use for their own consumption as well as any excess electricity they export to the grid. Since California introduced its first net metering policy, NEM 1.0, in 1996, there have been two major changes to the policy accompanied by substantial public debate and uncertainty. Especially notable in our study period, in 2016, California updated its net metering policy from NEM 1.0 to NEM 2.0, which required time-of-use electricity tariffs for solar customers. This policy became effective for customers of PG&E, the utility serving the Bay Area, on December 15, 2016. Under NEM 1.0, solar customers were effectively compensated for their electricity production at the same retail rate during all hours of the day. Under NEM 2.0, solar customers were compensated at a higher retail rate during "peak" hours and a much lower retail rate during the rest of the day. Under both policies, solar customers were compensated for any excess generation back to the grid (on an annual basis) at a wholesale rate of around $0.03/kWh as discussed above (PG&E compensation rates). A NEM 3.0 policy went into effect in April 2023 after the end of our study period.[14]

Federal and California incentive programs: In addition to the net metering policy, there were several other incentive programs available to solar projects during our study period. The 30 percent Federal Investment Tax Credit (ITC) has been available since 2006, so we include this incentive in all of our parameterizations. The ITC was reduced to 26 percent in 2020 and 2021 before returning

[14] See CPUC (2025a) and CPUC (2025b) for more history and details of California's NEM policies.

to the 30 percent level with the Inflation Reduction Act in 2022. See Congressional Research Service (2021) for a history of the ITC.[15] The well-known California Solar Initiative (CSI) expired for most Bay Area residential customers in 2013, so the incentives were not available for most projects in our sample. Initial CSI incentives were up to $2.50 per watt-AC but declined over time. Archived tracking of the CSI phase-out schedule for PG&E's service territory is available via the Internet Archive.[16] Some projects in our sample likely qualified for the New Solar Homes Partnership Program (NSHP), which accepted applications through April 1, 2018.[17] NSHP incentives varied from $0.25 to $3.50 per watt-DC depending on application timing and project characteristics. Appendix Section C presents alternative parameterizations where we account for the effect of the NSHP program on payoffs to complement our primary parameterization results in Section 3.4.

[15] See Congressional Research Service (2021).
[16] See California Solar Initiative (2015).
[17] See California Energy Commission (2021).

B.2 Supplemental details on engineering model parameterization

For the engineering estimates of private payoffs from a solar installation, we apply the System Advisor Model (SAM) from the U.S. National Renewable Energy Laboratory (NREL).[18] SAM provides a rich representation of a rooftop solar project including geography-specific variation in climate and solar irradiance; installation materials, labor, and financing costs; taxes and subsidies; future electricity consumption and tariff structure; technological specifications of the solar module and inverter; and shading and other system losses. In fact, SAM accommodates dozens of possible user inputs and system configurations. In Sections 3.2 and 3.3 as well as Appendix Section B.1 above, we detail the specific data sources we use to parameterize the model. To estimate the private payoff of the solar installation relative to a counterfactual without the solar panels, the SAM outputs include total costs over the system life, electricity production, electricity bill savings, compensation for excess electricity generation, taxes, and subsidies. Principally, SAM estimates the net present value (NPV) of the installation. For other parameter values, we use SAM defaults, which NREL updates as frequently as once or twice per year. Updates to SAM defaults are based on market data, user feedback, and NREL staff expert judgement. These default parameters include panel lifetime; operation and maintenance costs; financing costs; and the private discount rate of the decision-maker (i.e., the builder or homeowner). SAM also includes dozens of parameters related to solar panel and inverter technical characteristics and performance.

Abstracting away from the exact specificities of the SAM model, Equation B.1 summarizes SAM as a generalized engineering model M that estimates the value of solar V_τ installed at time τ

$$V_\tau(s, X_{i,\tau}) = \mathbb{E}_\tau\Big[\sum_{t=\tau}^{\tau+T} \beta^{(t-\tau)} M(s, X_i, \xi_\tau, \zeta_\tau)\Big] \tag{B.1}$$

where β is a discount factor and T is the useful life of the system. s is the size of the solar system (e.g., the capacity in kW), and $X_{i,\tau}$ is a matrix of characteristics of building project i initiated at time τ. $X_{i,\tau}$ might include the climate and solar irradiance at building's location, the building's expected electricity consumption, and roof characteristics including shading. $X_{i,\tau}$ may also include

[18] See `https://sam.nrel.gov/` (last accessed, May 9, 2025). Specifically, we use the Python implementation of the SAM model, NREL-PySAM version 5.1.0, which allows us to batch a large number of unique project characteristics and parameter assumptions. A description of the Python implementation is provided at `https://sam.nrel.gov/software-development-kit-sdk/pysam.html` (last accessed, May 9, 2025). NREL's well-known PVWatts model is nested within SAM, though SAM allows more flexible user inputs.

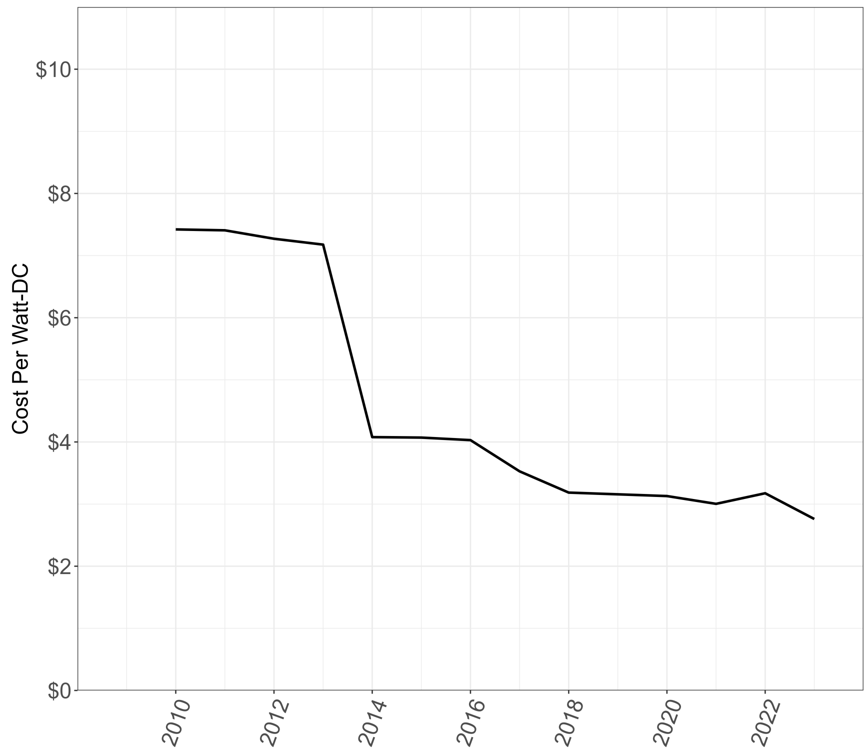
the specific electricity tariff and government incentives for a building project initiated at time τ. ξ_τ and ζ_τ are vectors of the default assumptions and parameters of model M, which may also vary with project initiation date τ. ξ_τ are the model's default financial parameters, such as installation tax treatment and loan rate. ζ_τ are the model's default engineering assumptions, such as the panel and inverter efficiency of converting solar energy into electricity. In more detailed models (or model parameterizations), more parameters may be determined from $X_{i,\tau}$, so fewer parameters appear in ξ_τ and ζ_τ. Equation (B.1) applies the expectation operator $\mathbb{E}_\tau$ at time τ because the homeowner or builder forms their expectations about the system's future performance and payoff in the same period as their initial investment decision.

Now suppose that builder or homeowner uses model M in time τ to choose the size of their solar system s to maximize their expected payoff according to

$$\max_{s\geq 0} V(s, X_{i,\tau}). \tag{B.2}$$

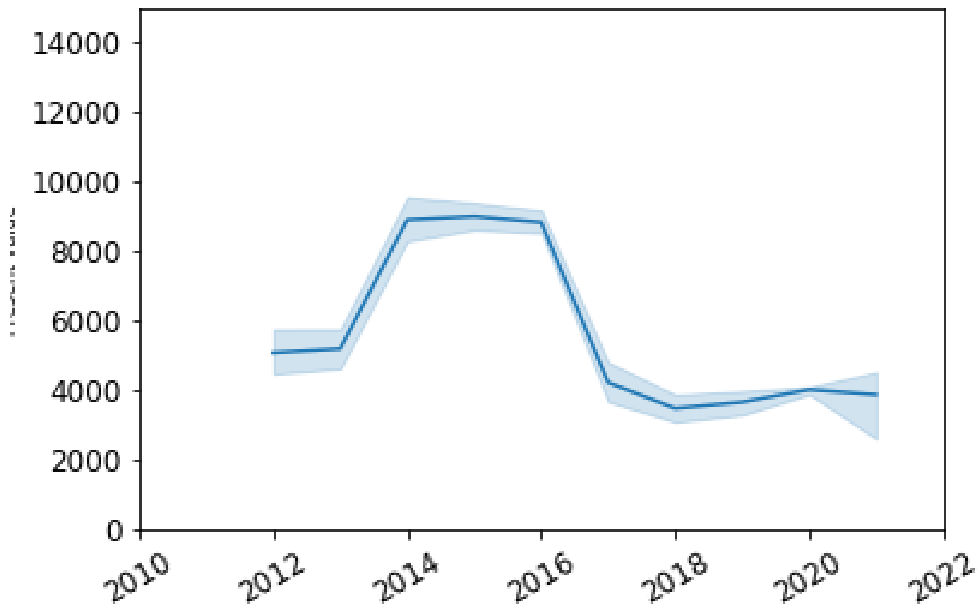
To solve Equation (B.2) with SAM, we initially test a variety of optimization routines, including a Bayesian optimization. However, we infer that there is a single global maximum for a given set of project characteristics $X_{i,\tau}$. Therefore, for computational efficiency, we ultimately maximize over a constrained integer grid search. As mentioned, we describe the specific details of our data and SAM parameterization in Sections 3.2 and 3.3. In particular, we use SAM to estimate expected private project payoffs (net present values) NPV_{ict} for each building project i initiated at time t in city c. We use the notation NPV_{ict} to differentiate our SAM estimates from the more general payoff notation $V(s^*, X_{i,\tau})$ in Equations (B.1) and (B.2). Having estimated the distribution of NPV_{ict} across all building projects i, we are able to illustrate the heterogeneity in project payoffs. We also compare these distributions to payoffs estimated by previous cost-effectiveness reports, which generally only considered a few stylized sets of building characteristics. The comparison to prior engineering studies as well as our sensitivities with alternative SAM parameterizations allow us to assess the importance of using such granular project-level data and accounting for differences in project characteristics $X_{i,\tau}$. We also compare our results to the finding of earlier cost-effectiveness studies that California solar projects have strictly positive payoffs across project types.

Figure B.1: Residential Solar Installation Costs (2023$)



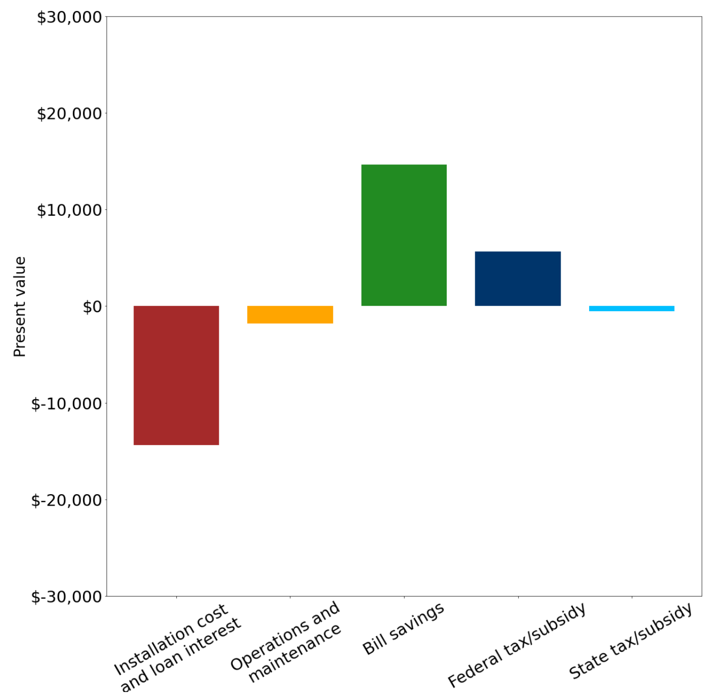
Notes: Residential solar panel costs are from historical versions of SAM. Since 2010, NREL has typically released new SAM versions once or twice per year. Installation costs include panels, inverter, other materials, labor, interconnection costs, and sales tax.

Figure B.2: Engineering Model Net Present Values Over Time



Notes: Shaded regions show 95 percent confidence intervals.

Figure B.3: Engineering Model Net Present Value Components for an Illustrative Example



Notes: Components of SAM's net present value (NPV) calculation correspond to the illustrative example in Table 2.

B.3 Supplemental details on solar installation costs on new construction compared to retrofits

Barbose et al. (2013) find evidence that solar installations are less expensive on new construction than retrofit buildings. Barbose et al. (2013) use California data from 2008 to 2012 and find a mean discount of \$0.75 per watt-DC, or approximately 10 percent. While not all solar mandates cost-effectiveness studies adjusted their installation costs to reflect a new construction discount, one of the cost-effectiveness reports for San Francisco, Halberstadt (2014), did apply an adjustment based on Barbose et al. (2013).

In our own data, we find mixed evidence for reduced installation costs associated with new construction. In particular, Table B.2 estimates various forms of Equation B.3, regressing the log of costs per watt-DC, $Cost_{ict}$, on an indicator for whether the project was new construction, New_{ict}

$$\ln(Cost_{ict}) = \beta New_{ict} + \gamma_c + \epsilon_{ict} \tag{B.3}$$

In this setup, the subscripts indicate project i in city c and year t, and γ_c accounts for city fixed effects.

Both specifications in Table B.2 use costs from California's public solar interconnection data. To create an indicator for new construction, we use our sample of PG&E new premises, which includes interconnection IDs that we merge with the public interconnection data. We then restrict the interconnection data to only include the 52 Bay Area municipalities and two years (2017 and 2018) for which we observe interconnections in the PG&E data.[19] In Column 1, we account for the limitation that some new premises in the PG&E data may not actually be new construction. That is, we restrict our new construction identifier to only addresses that we also observe in our new construction building permits data. However, this ends up being only 26 new construction projects as compared to 598 in Columns 2.

One limitation in Table B.2 is that we do not perfectly identify all new construction. However, since we know from the building permits data that the share of solar installations on new construction is small, we can still be confident that our new construction discount parameter is identified by the difference between *known* new construction projects and the much larger sample of primarily

[19] We also restrict the interconnection data to residential customers and systems less than 15 kW-DC.

retrofits. That said, our primary engineering model parameterizations in Section 3 do not apply any cost adjustment for new construction. Appendix Figure C.4d presents the distribution of estimated payoffs with 10 percent lower installation costs, which modestly increases the median payoff.

Table B.2: New Construction Installation Costs Compared to Retrofits

	(1)	(2)
New construction	−0.215*	−0.046***
	(0.086)	(0.013)
Sysem capacity (kW)	−0.039***	−0.039***
	(0.001)	(0.001)
City fixed effects	Yes	Yes
Use building permits	Yes	No
Num.Obs.	29 274	29 273
R2	0.053	0.053
R2 Adj.	0.052	0.052

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Following Equation B.3, we regress the log of costs per watt-DC on an indicator for whether the project was new construction. (1) The cost data is from years 2017 and 2018 in California's public solar interconnection data. (2) Column 1 further refine this new construction indicator by using only new construction projects that also appear in our municipal building permits data. (3) See the text of Appendix Section B.3 for further details and limitations.

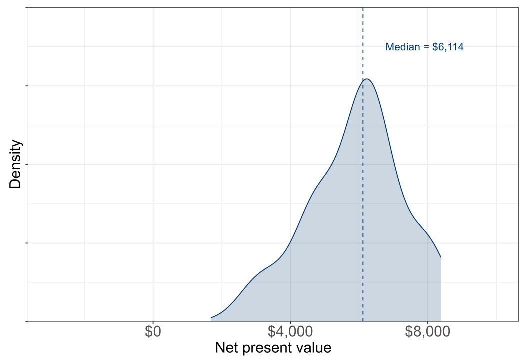
C Supplemental evidence on private payoffs and a "solar gap"

C.1 Estimated distributions of solar payoffs, alternative parameterizations

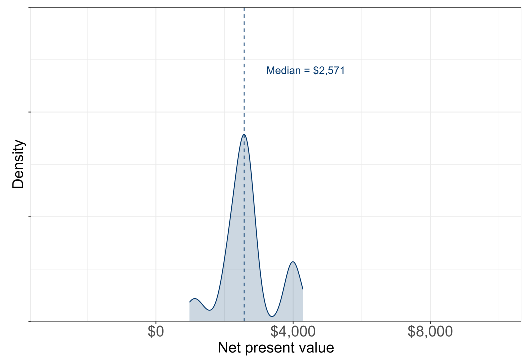
Figure C.4 presents estimated distributions of solar payoffs under alternative engineering model parameterizations to supplement Figure 2 in Section 3.4.

Figure C.4: Estimated Distributions of Solar Payoffs, Alternative Parameterizations

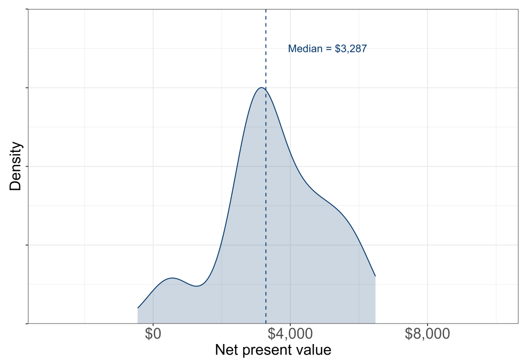
(a) Primary parameterization, pre-2017



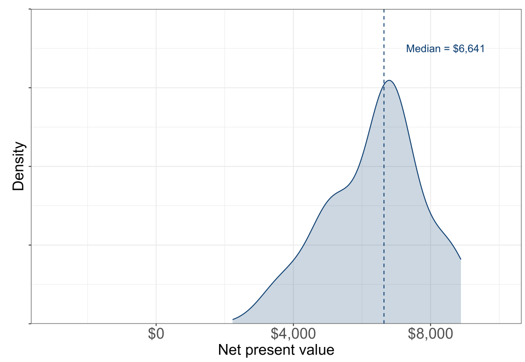
(b) Primary parameterization, 2017-2019



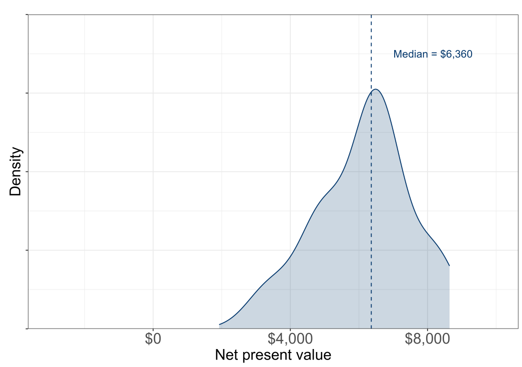
(c) 50 percent higher costs



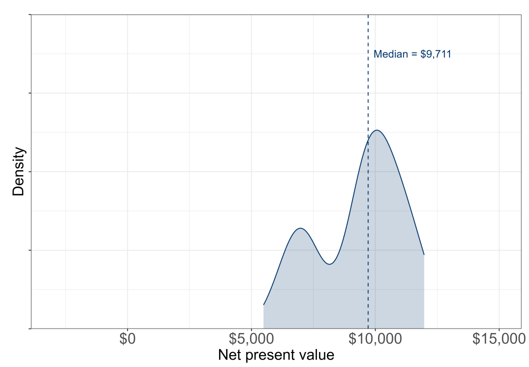
(d) 10 percent lower costs



(e) $0.25-per-watt-DC incentive



(f) $3.50-per-watt-DC incentive



Notes: Continued on next page.

Figure C.4 Notes: (1) Figures present medians and smoothed kernel density estimates of the distribution of estimated solar payoffs (net present values) from our parameterization of SAM across our sample of San Francisco Bay Area new construction building permits. These results supplement Figure 2 in Section 3.4. (2) Except for Panel C.4b, all distributions are for building permits for new single family homes issued between 2012 and 2016 (inclusive), prior to the implementation of solar mandates. Panel C.4b, presents payoffs for projects initiated between 2017 and 2019 after the implementation of some solar mandates and also California's revised net metering policy, NEM 2.0. (3) Panel C.4a presents the primary parameterization from Figure 2. (4) Panel C.4c presents 50 percent higher installation costs. (5) Panel C.4d presents 10 percent lower installation costs, consistent with the findings that new construction installations are less expensive than retrofits as discussed in Section 3.3 and Appendix B.3. (6) Panel C.4e represents an additional $0.25-per-watt-DC incentive, the lowest rate available in California's New Solar Home Partnership Program (NSHP). (7) Panel C.4f represents an additional $3.50-per-watt-DC incentive, the highest available NSHP rate.

C.2 Solar payoffs and adoption decisions

Table 3 in Section 3 presents estimates of the relationship between solar adoption decisions and our engineering estimates of solar payoffs. Specifically, in Table 3, we estimate the linear probability model of solar adoption on net present values npv_{ict}

$$solar_{ict} = \alpha_0 + \alpha_1 npv_{ict} + \boldsymbol{x'_{ict}}\boldsymbol{\beta} + \epsilon_{ict} \tag{C.4}$$

where $solar_{ict}$ is the observed solar adoption decision for project i in city c and year t. $\boldsymbol{x_{ict}}$ is a vector of covariates, and ϵ_{ict} is an error term. To avoid the effect of solar mandates, we only consider years 2012 to 2016, before San Francisco implemented its mandates (and before California implemented the statewide policy).

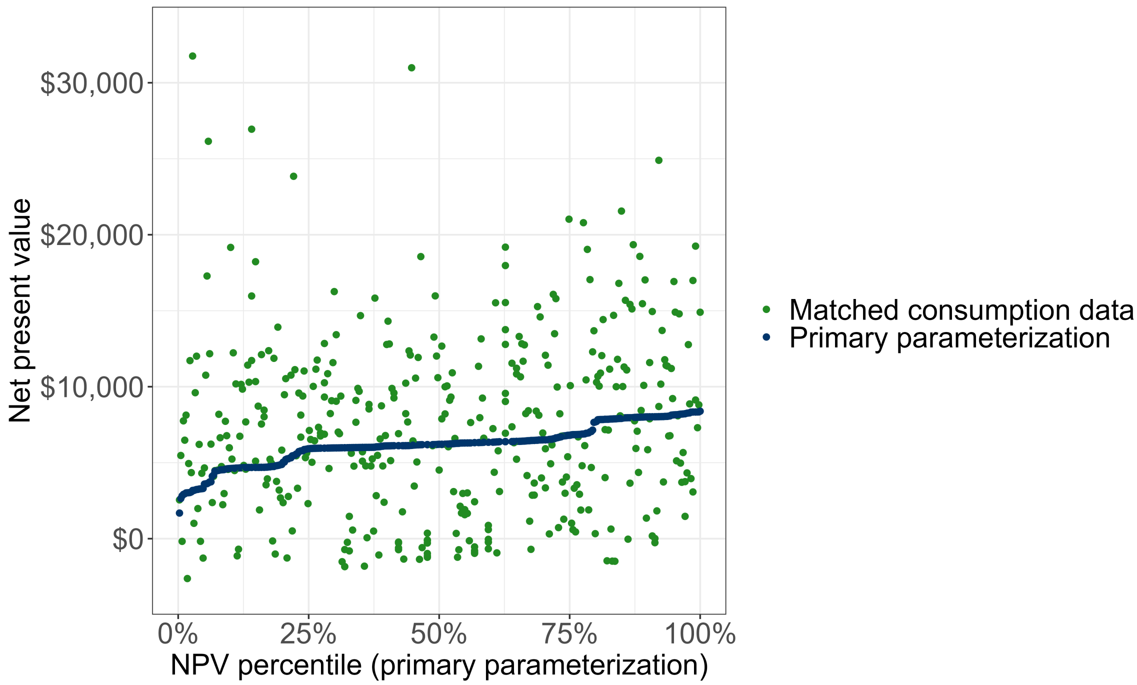
C.3 Engineering model estimates with alternative electricity consumption (load profiles)

Figure C.5 explores the importance of a building's electricity consumption pattern in determining the payoff of a solar investment. Payoffs are largely determined by the interaction of a building's electricity consumption pattern with the tariff structure and net metering policy. Under California's NEM 1.0 and NEM 2.0 policies, customers are compensated for any excess generation during an annual true-up at a much lower rate that approximates the wholesale market (historically around \$0.03 per kWh). Therefore, while customers are disincentivized from oversizing their systems, the largest electricity consumers can realize the greatest payoffs. Under NEM 2.0, where solar customers face tariffs that vary by time of day, the timing of electricity consumption is also an important determinant of the solar payoff.

Figure C.5 compares our payoff estimates from our primary parameterization to an alternative approach where we use building-level hourly interval electricity consumption data from our sample of new PG&E premises. In contrast, recall that in our primary parameterization, we use city-median hourly interval electricity consumption from the PG&E sample (described in Section 3.3). For our full sample of Bay Area new construction projects from municipal building permits, we only have corresponding electricity data available for a subset. Therefore, Figure C.5 only includes the single-family, non-solar new construction buildings for which we have electricity consumption data (398 buildings). We exclude solar buildings because we only observe *net* consumption in the PG&E data, and we do not directly observe solar production. Figure C.5 plots the payoffs estimated with our primary parameterization (the blue series) arranged from least to greatest estimated payoff. The green points are the corresponding payoff estimate for each respective project in the blue series using instead the observed electricity consumption interval data.

Our first observation from Figure C.5 is that the results generally confirm the findings of Sections 3.4 and 3.5. As found in the Section 3.4 primary parameterization results and numerous alternatives, Figure C.5 estimated payoffs continue to be positive for almost all projects. Confirming our findings of Section 3.5 and our discussion of the "solar gap," Figure C.5 shows builders foregoing solar across the entire support of estimated payoffs (since Figure C.5 shows payoffs estimates for non-solar buildings only). However, Figure C.5 does suggest that there may be even more heterogeneity in payoffs across buildings than indicated in Section 3. That said, estimated payoffs using the building-level consumption data are on-average similar to the more aggregate consumption data of the primary parameterization (i.e., the median payoffs are $6,831 and $6,211 using the building-level electricity consumption data and primary parameterizations, respectively). Also, note that the observed building-level electricity consumption patterns are not necessarily indicative of *future* or even *expected* electricity consumption patterns. Therefore, the use of observed building-level consumption data is not necessarily strictly preferred in parameterization of the engineering model. For example, 12% of projects in Figure C.5 have negative estimated payoffs, but even this relatively small share is likely overstated because many of these observations with the lowest payoffs are missing electricity consumption data in some intervals or have especially low usage from not-yet-occupied new buildings.

Figure C.5: Estimated Distributions of Solar Payoffs, Project-Matched Electricity Consumption



Notes: For the subset of new construction projects where we observe electricity consumption interval data, we compare our payoff estimates using the building-level consumption data as compared to our primary parameterization using city-level median consumption data from our sample of new premises. (1) The blue series presents the net present values estimated with our primary parameterization (i.e., Figure 2a) arranged from least to greatest estimated payoff. The green points are the corresponding payoff estimate for each respective project in the blue series using instead the observed electricity consumption interval data. (2) This figure is restricted to only single family homes without solar. We exclude solar buildings because we only observe net consumption in the PG&E data, and we do not directly observe solar production. (3) We exclude one project with exceptionally high electricity consumption and estimated payoffs.

D Supplemental evidence on the San Francisco mandate

D.1 Regression discontinuity

Finally, we investigate the causal effect of San Francisco's solar mandate on the number of solar permits using a regression discontinuity (RD) design. The nature of the solar mandate in San Francisco, which only applies to new construction of buildings with 10 stories or fewer, allows us to use the number of stories of a new building as the forcing variable. New buildings with more than 10 stories serve as the comparison group.

We first estimate a simple linear regression around the cutoff of 10 stories:

$$y^* = \beta_0 + \beta_1 x + \beta_2 (x - c)d + \theta d + \epsilon \tag{5}$$

where the outcome y is the share of solar permits, relative to new construction. x_i is the running variable, defined as the number of stories of new buildings, and c is the threshold of 10 stories.

We first consider the distribution of the running variable, as shown in Figure D.6. There is a substantial drop in the number of buildings of 10 stories or more. There are no new buildings with 10 stories in the sample, and substantially fewer new buildings with 11 or more stories compared to new construction of buildings with 9 or fewer stories. However, if building owners sought to circumvent the mandate, we would expect an excess of buildings with 11 stories and a corresponding lack of buildings of 10 stories. This pattern is not observed in the data. Nonetheless, the sparsity around the cutoff is not ideal for RD designs. However, we include the full analysis for transparency.

Figure D.6: San Francisco Building Height Distribution

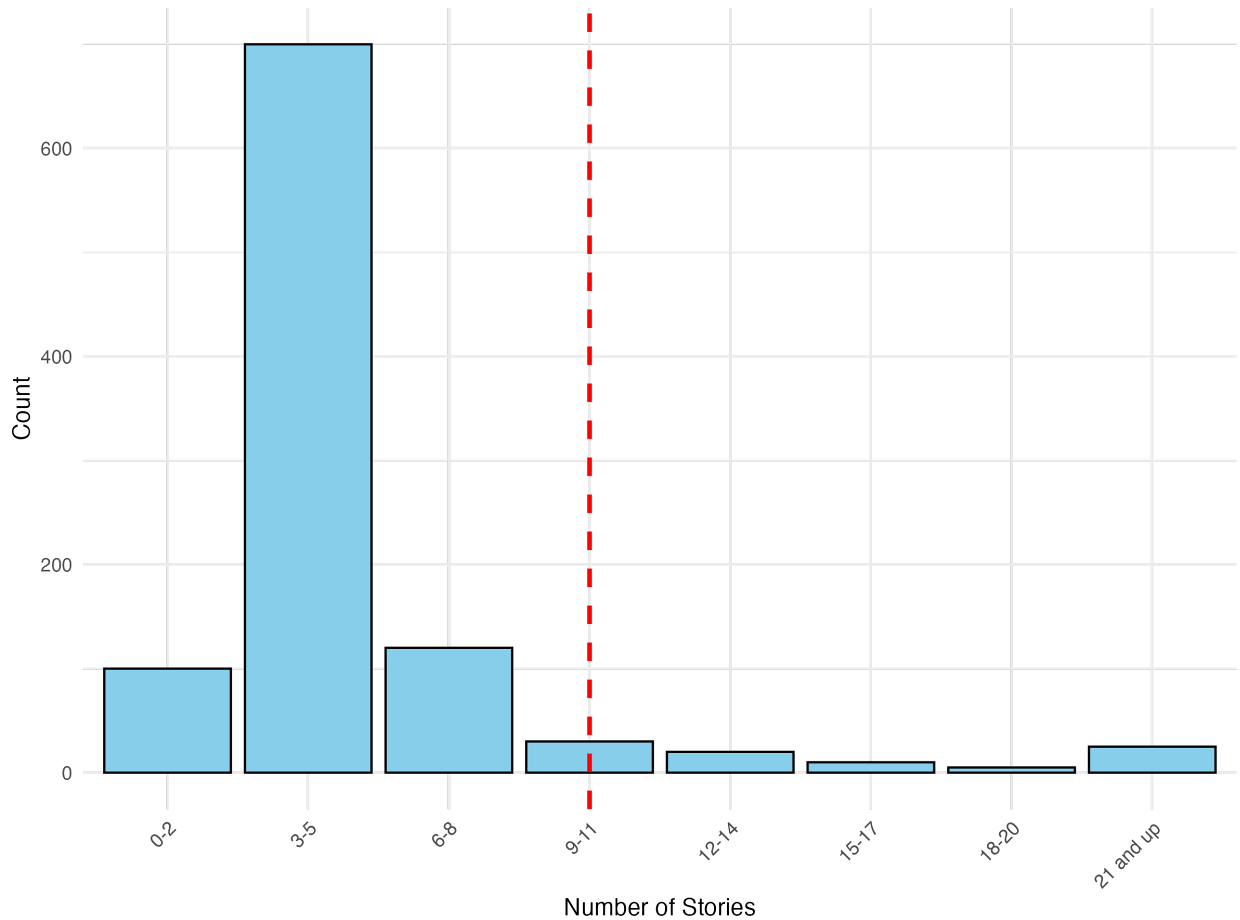


Figure D.7 visually illustrates our results using the RD design. Figure D.7 reveals a clear discontinuity at the 10-story threshold, with buildings subject to the mandate (those with 10 or fewer stories) showing markedly higher solar adoption rates than those exempt from the mandate (buildings with more than 10 stories). The treated observations (subject to the mandate) are to the right of the threshold, while control observations (exempt from the mandate) are to the left. The substantial jump in solar adoption rates at the cutoff suggests a strong treatment effect.

Figure D.7: Building Stories RDD. Outcome: Share of Solar PV Permits

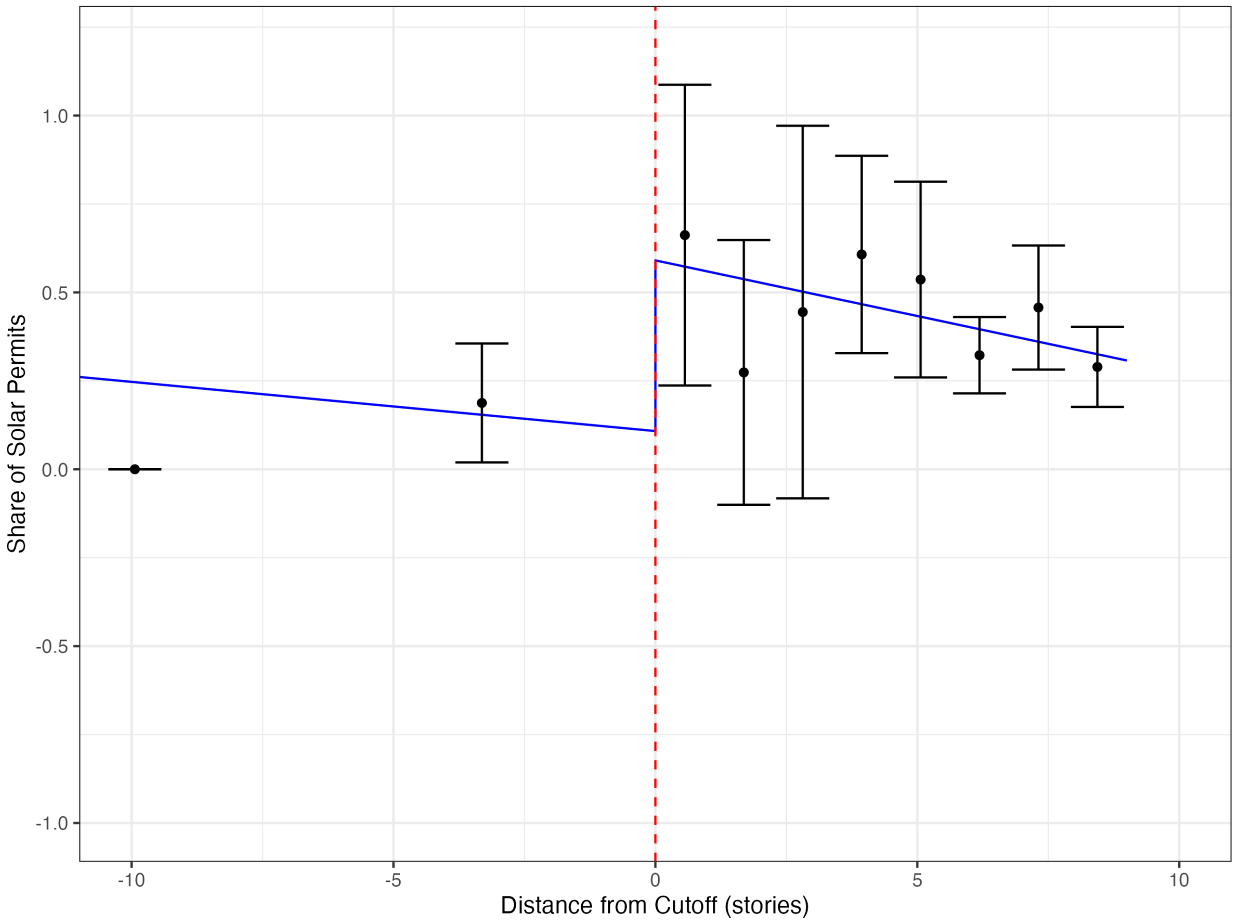


Table D.3: Regression Discontinuity Estimates for Solar Share with Linear Model

Method	Estimate Type	Estimate	Standard Error	Bandwidth
LL Kernel	Conventional	0.30	(0.226)	6.40
LL Kernel	Bias-corrected	0.19	(0.226)	6.40
LL Kernel	Robust	0.19	(0.43)	6.40

Table D.3 presents our RD estimates using different estimation approaches. The conventional local linear estimate suggests a treatment effect of 0.30 (30 percentage points), with a standard error of 0.226. While this estimate is not statistically significant at conventional levels, the magnitude is economically substantial and consistent with our other identification strategies. The bias-corrected and robust estimates yield slightly smaller treatment effects of 0.19 (19 percentage points), though with larger standard errors (0.43 for the robust estimate).