State Financial Incentives and Solar Energy Adoption in the United States

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Dedication

To Mama, Papa, and Ming, for their love and support.

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Abstract of Dissertation

State Financial Incentives and Solar Energy Adoption in the United States

Solar energy brings multiple environmental and social benefits, and state governments use public money in many ways to promote its adoption. This dissertation explores the effects of state financial incentives for solar energy adoption in the United States. The first chapter provides a review of the existing literature on this topic from various perspectives, including the effectiveness and efficiency of state financial incentives for solar energy, and social equity issues related to these incentives.

The second chapter uses county-level data across 16 states to test whether state financial incentives promoted residential solar PV adoption over the 2010-2020 period. I find that income tax credits increased residential PV adoption with statistical and substantive significance, while the effects of cash rebates were smaller and vaguer. I also find evidence suggesting the success of property tax exemptions. The results reflect a major change from the pre-2010 period when cash incentives were found most effective and tax incentives had insignificant effects.

The third chapter examines the distributional effects of the California Solar Incentive, an example of income-based financial incentive programs for renewable energy. I find that for single-family PV systems throughout 2011-2016, the incentives were significantly progressive as low-income households enjoyed much higher rebate rates than higher-income customers. However, because of the market power of top suppliers and over-subsidization in the low-income targeted program, customers rather than suppliers received only 35% of rebate benefits overall, and the lowest income only received 25%.

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Chapter 1: State Financial Incentives and Solar Photovoltaic Adoption: A Literature Review

Solar photovoltaic (PV) technology, being a decentralized and renewable energy source with minimal carbon emissions and air pollution in its operational phase, has gained favor from policymakers for its environmental and social benefits. Governments employ public funds in diverse ways to encourage the adoption of PV systems. Typical policy options include cash incentives, tax incentives, and subsidized loans. In the 2000s, the United States witnessed a surge in state-level financial incentives designed to promote PV adoption. Researchers have conducted extensive assessments of these incentives during this period, accumulating a wealth of insights that contemporary policymakers can draw upon when creating, adjusting, or discontinuing incentives.

This essay conducts a comprehensive review of the existing literature regarding the effectiveness, efficiency, and equity considerations of state-level financial incentives for PV adoption in the United States. In Section 1.1, I introduce the background of state financial incentives for solar adoption, explaining the rationale underpinning the allocation of public resources for advancing solar energy adoption, while also offering an overview of solar-related financial incentives within the United States. Subsequently, Sections 1.2 through 1.4 delve into the existing literature concerning state financial incentives and solar energy from three aspects:

1) To what extent do state financial incentives effectively stimulate PV adoption? In the residential sector, most researchers find a clear positive effect of cash incentives but not tax incentives. In the commercial sector, evidence is mixed. Additionally, renewable energy credits have emerged as an efficacious instrument in the commercial sector.

2) Are state financial incentives cost-effective at promoting PV adoption and reducing greenhouse gas emissions? While the cost varies across states, scholars generally concur on the notion that these incentives tend to be economically burdensome.

3) How are benefits from state financial incentives for PV adoption distributed among different income groups? The prevailing scholarship indicates that high-income households receive a disproportionately higher share of subsidies as they are more likely to adopt PV systems, but programs targeting low-income households have promoted equity in the distribution of subsidies in recent years.

1.1 Background

1.1.1 The rationale of publicly funded financial incentives for PV adoption

Using public money to promote PV adoption is supported by two major reasons: environmental externalities and energy stability. The first rationale is to correct the positive externalities associated with using solar energy. The per kilowatt-hour lifecycle CO2 emissions of a PV system is only 4-9% of that of a fossil fuel power plant (NREL 2021). By replacing or reducing the use of fossil fuel and other high-emission energy sources, using PV helps mitigate the environmental, health, economic, and social risks associated with carbon emissions, of which the social cost is estimated to range from $44 to $413 per ton, with a mean at $185 (in 2020 U.S. dollars) (Prest et al. 2022).

However, the upfront cost of a PV system is considerably higher than that of a conventional energy system with the same electric generating capacity, so consumers, especially in the residential sector, lack the motivation to adopt PV and can be myopic even if a PV system is economically beneficial in the long run. Besides, electricity generated from different sources is homogenous, making it difficult for consumers to know where

their electricity comes from. Therefore, government intervention is needed to correct this market failure until the PV market becomes self-sustaining.

The second rationale for subsidizing PV adoption is to diversify the national energy portfolio, which protects the stability of energy supply and the economy. The United States is highly dependent on fossil fuel power plants. Renewable energy sources excluding hydroelectric only account for around 15% of U.S. electricity generation, and the share of electricity generated from solar power is currently less than 5% in the country (EIA 2022). As a major importer and exporter of fossil fuels, the United States is exposed to the risks associated with the volatile international fossil fuel supply and price. Recent power crises in parts of the United States, Europe, and China have highlighted the vulnerability of economies dependent on just one or two energy sources. Many believe that to protect energy security, there is a pressing need to accelerate the growth of renewable and distributed energy sources like solar energy (e.g., Cox, Beshilas, and Hotchkiss 2019, Wetstone 2022).

1.1.2 Financial incentives for PV adoption in the United States

In this essay, financial incentives for PV systems are policies that use government revenue to subsidize the installation or operation of such systems. Common types include cash incentives, tax incentives, subsidized loans, and feed-in tariffs. Cash incentives involve rebates and grants for PV installations. The incentive amount can either be a lump sum or proportional to the output capacity or generated electricity of a PV system. Tax incentives encompass credits, deductions, exemptions, and preferential rates of taxes for PV system purchases or PV-generated electricity. The most common taxes involved are property, sales, and income taxes, and some governments also provide incentives through

other taxes like the excise tax. Feed-in tariffs (FIT) guarantee a long-term above-market price for electricity provided to the grid from PV systems. These incentives are usually financed by general government revenue or surcharges imposed on all utility customers. In addition, subsidized loans offer a below-market interest rate for loans used on solar system investments. Governments can issue these loans directly through public funds or grants, or indirectly through private financial institutions, and the low interest rates can be secured by direct public expenditures or loan guarantees.

Besides, governments can enact renewable portfolio standards (RPS) that mandate a certain share of the total electricity to come from renewable energy by a certain year, with the option to set a minimum share (carve-out) of electricity that must come from solar technology. Residents, corporations, and utilities who own grid-connected PV systems can receive solar renewable energy credits (SRECs), production credits per megawatt-hour, from the government and trade them in the market. Utilities can use SRECs to fulfill their solar carve-out requirements or, in case of a shortfall, make the solar alternative compliance payment (SACP), which effectively operates as a penalty per megawatt-hour. In essence, SACP can be considered a corrective tax, and SRECs, as forgone tax revenue, constitute a publicly funded financial incentive.

These financial incentives for PV adoption are provided at various governmental levels. At the federal level in the United States, solar energy subsidies are predominantly delivered through income tax incentives. The most prominent example is the Investment Tax Credit (ITC), a federal income tax credit equal to 30% of the cost of a solar system installed on a taxpayer's property. Created by the Energy Policy Act of 2005, ITC has been extended several times, most recently by the Inflation Reduction Act (IRA) in August 2022.

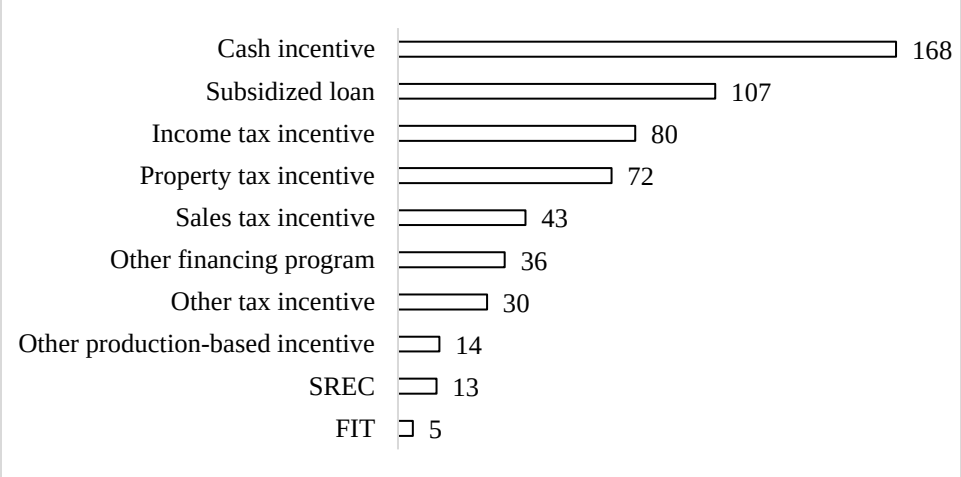
According to the current plan, ITC will start to phase out in 2033 and expire in 2035 for residential customers (2034 and 2036 for commercial customers).

Under IRA, businesses can choose between ITC and the Production Tax Credit (PTC), a ¢2.6 per kilowatt-hour federal income tax credit for electricity generated by their solar systems in the first ten years of the system's operation. PTC was previously available for solar energy from 1992 to 2005 and was reinstated by IRA in 2022. Besides, both personal and corporate taxpayers can exclude solar subsidies from their taxable income if these subsidies are provided by governments or utilities for residential energy conservation. In most circumstances, corporations can also depreciate their solar systems over five years under the Modified Accelerated Cost-Recovery System (MACRS).

Financial incentives adopted at the state level are more diverse. As shown in Figure 1.1, cash incentives are the most prevalent among historical and existing financial incentives for PV adoption, according to the records in the Database of State Incentives for Renewable Energy (DSIRE) as of 2022. Cash incentives outnumber financing programs and tax incentives by a large margin, primarily due to their ease of claim. Additionally, states often provide multiple cash incentives targeting various user groups, including general residents, low-income residents, and businesses, while other incentive categories exhibit less variability. A nationwide sample of state incentives for PV adoption in 2016 reveals that the average U.S. state offered 2.5 cash incentives, 1.2 property tax incentives, 0.8 income tax incentives, and 0.6 sales tax incentives (Ryan, Donou-Adonsou, and Calkins 2019).

By contrast, SRECs and FITs are much less prevalent. While most states have enacted their RPS, SRECs are only adopted in 11 states[1] and the District of Columbia. This limited scope is unsurprising, given the substantial administrative, compliance, and transaction costs associated with the trading scheme. FITs are available in just five states[2], particularly because utilities, even with government subsidies, are reluctant to commit to long-term contracts for highly-priced solar-generated electricity as solar system costs continue to decrease (Trabish 2016). In markets where FITs have been widely employed and found success, such as in Europe, Australia, and China, policymakers are also exploring measures to reduce or discontinue these incentives due to high policy maintenance costs (da Silva et al. 2019).

Figure 1.1 Number of state financial incentives for solar energy, up to 2022



Source: DSIRE (2022)

Moreover, numerous incentives for PV adoption are provided by local governments and utilities. In situations where a state-level incentive is absent, incentives offered by various local authorities can fill the void, often serving as a substantial substitute when a significant portion of the state's population benefits from local incentives. To illustrate,

[1] Among them, Massachusetts has replaced its SREC program with FIT.
[2] California, Hawaii, Massachusetts, Vermont, and Washington.

consider the approach taken by Texas, where a decentralized system is employed for providing rebates for PV installations. Texas lacks a state-level rebate program, but various local governments and utilities, including the four largest utilities, offer PV rebates. This extensive local coverage ensures that the majority of Texan residents have access to these incentives. In addition to complementing federal and state-level programs, local incentives bring additional advantages to customers by offering increased flexibility, customization, and competition. From a national sample of 186 U.S. cities, Li and Yi (2014) estimate that other things being equal, cities with local financial incentives exhibit nearly 70% more PV capacity deployment compared to cities without such incentives.

When incentives from different levels of government coexist, their cumulative value can be substantial. Consider Massachusetts as an example. While the state has discontinued its state-level cash incentives for residential PV installations, various rebate programs still operate at the local level. For instance, if a household living in the territory of Hudson Lights and Power chooses to install a PV system, it is eligible for a $1.2 rebate per installed watt from the utility. Additionally, the household is eligible for the federal ITC equal to 30% of the system's net price. Assuming the system is priced at $2.7 per watt, the average price of residential PV in the U.S. in 2020, the federal ITC is worth $0.45 per watt ($0.3 \times (\$2.7\text{-}1.2)$). Furthermore, Massachusetts provides a state income tax credit equivalent to 15% of the total price minus federal incentives, which amounts to $0.34 per watt. The household is also exempted from the 6.25% state sales tax, translating to savings of $0.17 per watt. Combining federal, state, and local incentives, the household benefits from total savings of $2.16 per watt, or 80% of the system price upfront. Moreover, the household continues to receive financial incentives over time. The system is exempted

from local property taxes for 20 years, and the household can sell electricity generated from the system at a rate of up to $0.17 per kilowatt-hour for ten years through Solar Massachusetts Renewable Target, a state-level FIT program. This example illustrates how the multitude of financial incentives provided by various authorities makes residential PV installations in Massachusetts not only affordable but potentially profitable.

1.2 Are state financial incentives effective in promoting PV adoption?

This section reviews the literature on the effectiveness of state-level financial incentives in promoting PV adoption. Most empirical studies on this topic focus on the period spanning from 2000 to 2015, as this period saw the creation of most financial incentives for PV adoption. Although the United States started to promote solar energy in the 1970s, most incentives enacted before the 21st century are regulatory. This phenomenon is explained by Doris (2012) in her policy staging theory, which posits that different policy incentives are needed at different stages of market development. During the early phases of market preparation and creation, policymakers should prioritize legislative and regulatory actions that enable and facilitate consumer adoption of new technologies. As the market becomes ready, financial incentives can then be employed to foster its expansion.

Among the various state financial incentives, cash and tax incentives have been the subject of most extensive research. Thus, in the rest of this section, I first discuss the effectiveness of cash and tax incentives, assessing their impact on both residential and commercial sectors. I then summarize studies on the effectiveness of SRECs and subsidized loans. In addition, Tables 1.1 and 1.2 compare empirical studies on the effectiveness of state-level PV financial incentives, respectively focusing on residential and commercial sectors.

1.2.1 Effectiveness of cash and tax incentives in the residential sector

While a household's decision to adopt solar is influenced by a range of factors, including sociodemographic characteristics, housing conditions, environmental concerns, and political inclinations, researchers consistently find that the most important driver is economic (e.g., Rai, Reeves, and Margolis 2016, Jacksohn et al. 2019). Hence, financial incentives should play a pivotal role in promoting PV adoption. A few studies (e.g., Kwan 2012) test financial incentives as a whole and find them effective in encouraging residential PV adoption. However, as detailed below, the effectiveness of these incentives is not uniform due to various factors.

Researchers generally find that cash incentives significantly stimulate residential PV installations. Using a nationwide sample from 1997 to 2009, Sarzynski, Larrieu, and Shrimali (2012) found that other things being equal, states offering cash incentives witnessed a 248% higher volume of PV installations than states without such incentives. This finding is echoed by two other nationwide studies (Stanford 2014, Matisoff and Johnson 2017). Specifically, Matisoff and Johnson (2017) showed that cash incentives are most effective when accompanied by subsidized financing programs.

Similarly, in a study focused on Northeastern states, Crago and Chernyakhovskiy (2017) observed that from 2005 to 2012, a $1 per watt increase in rebate was associated with a 47% increase in annual PV capacity growth. Cohen, Elbakidze, and Jackson (2022) studied 27 states east of the Mississippi River and found that from 2004 to 2015, cash incentives positively influenced the number of PV installations. Using data from 2007 to 2012, Hughes and Podolefsky (2015) estimated that a $0.1 per watt increase in state-level rebate corresponded to a 10% increase in new PV installations per capita in California, and

the number of installations would have been 53% lower in the absence of the rebates. The positive impact of cash rebates in California is also corroborated by Sun and Sankar (2022) with data from 2006 to 2017.

By contrast, most of these studies found no evidence for the effectiveness of tax incentives in promoting residential PV adoption (Hughes and Podolefsky (2015) and Sun and Sankar (2022) do not examine incentives other than rebates). Stanford (2014) discovered a positive effect of property tax exemptions but not income or sales tax incentives. In a simulation of Tennessee's solar industry, Sawhney et al. (2014) demonstrated that cash incentives were more effective in jumpstarting the state's solar industry than tax incentives.

In addition, two studies detected no clear effect of either cash or tax incentives, which could be attributed to limitations in their sample or methodology (Shrimali and Jenner 2013, Ryan, Donou-Adonsou, and Calkins 2019). Shrimali and Jenner (2013) studied 27 state-level incentives in 16 states from 1998 to 2009 and found that while cash and property tax incentives helped reduce residential PV system costs, they did not significantly boost system deployment, although this finding might result from a limited sample size. Ryan, Donou-Adonsou, and Calkins (2019) analyzed state-level incentives existing in 2016 for both residential and commercial PV systems, but their findings offer ambiguous evidence regarding the effectiveness of cash or tax incentives. They suggested that this could be related to a weak measure of incentive strength used in their study, which considered the number of incentives offered rather than their monetary value. In addition, their pooling of residential and commercial PV installations may have hindered their ability to detect clear effects, as customer behavior in the two sectors differs.

Regarding the disparity in effectiveness between cash and tax incentives found in most studies, researchers provide a threefold explanation: incentive size, timing of benefit receipt, and incentive salience. First, the size of an incentive significantly influences its effectiveness. Before the 2010s, cash incentives tended to be large enough to make PV investments financially viable, whereas state tax incentives are often limited in size. For instance, Matisoff and Johnson (2017) estimated that in 2005, when the average price of PV systems in the United States was $8.8 per watt, the average value of state and utility cash incentives was $2.3 per watt, covering 26% of the system price. In contrast, the average value of property, sales, and income tax incentives was $1.07, $0.51, and $0.47, respectively. The stark differences in incentive size imply that when only one incentive is available, cash incentives tend to be more effective in promoting solar installations than tax incentives. When cash and tax incentives coexist, and assuming that the effect of financial incentives follows the law of diminishing returns, it is likely that a large cash incentive combined with the 30% federal ITC is sufficient to push the total incentive amount beyond the point of maximum yield, so the marginal effect of adding a tax incentive would be moderate. In addition, the non-refundable nature of many tax incentives further decreases their value for taxpayers with insufficient tax liability (Sarzynski 2010). However, as the empirical analysis in Chapter 2 shows, in the 2010s, as the value of cash incentives continuously decreased and that of income tax incentives remained stable, the latter overperformed the former in terms of promoting residential PV adoption.

Second, the timing of incentive receipt impacts its effectiveness through its effect on the present value of the incentive. Under bounded rationality, imperfect information, and generally rising but uncertain energy prices, consumers tend to use high implied

discount rates when purchasing energy-efficient equipment (Greene 2011). Most cash incentives can be easily claimed shortly after system purchase or installation (Sarzynski 2010), while among the major tax incentives, only sales tax incentives are delivered automatically upon purchase. For income tax incentives, customers need to wait until the next tax filing season to receive their benefits. Property tax incentives can only be claimed in installments over a long period, often exceeding 20 years, which heavily discounts their value. In a study on financial incentives for hybrid vehicles, Gallagher and Muehlegger (2011) found that a $1077 upfront price reduction was associated with over three times more sales than a $2011 income tax credit.

The salience of an incentive, the third influencing factor, is related to an incentive's perceived benefits. The benefits of an incentive perceived by households with bounded rationality may differ from its actual value. Rai and Beck's (2015) survey results demonstrated that such perception is a major determinant in households' decision to adopt solar. Cash incentives are notable for their immediate and direct payments, making it easy for customers to perceive their actual value. By contrast, property and income tax incentives deliver benefits in a delayed manner through tax bills, separating incentive receipt from the purchase itself, and this temporal gap can reduce the prominence of these incentives to customers (Matisoff and Johnson 2017).

Moreover, various factors contribute to the reduced salience of property and income tax incentives. Compared with cash incentives, income tax incentives are more difficult to understand for individuals because of the uncertainty surrounding future tax liability, marginal tax rates, and whether tax credits can be carried forward. Such complexity increases the transaction and compliance costs of claiming income tax incentives and

diminishes their salience (Schenk 2011, Gallagher and Muehlegger 2011, Matisoff and Johnson 2017). Property tax incentives are typically provided in the form of an exemption, resulting in no apparent change in the property tax bill associated with the installation of a solar system. Consequently, tax exemptions are harder to notice than direct payments like cash incentives (Sarzynski, Larrieu, and Shrimali 2012). Besides, property tax payments are often bundled with insurance and mortgage costs, further decreasing the salience of property tax incentives (Matisoff and Johnson 2017).

Even in the case of sales tax incentives where benefits are delivered upon purchase, the visibility is reduced when prices are listed as tax-exclusive. Research has shown that when prices do not explicitly include taxes, sales taxes tend to be less noticeable (e.g., Chetty, Looney, and Kroft 2009, Li, Linn, and Muehlegger 2014), and this reduced visibility extends to sales tax incentives.

1.2.2 Effectiveness of cash and tax incentives in the commercial sector

Like residential users, commercial users adopt solar energy to lower their energy bills and receive associated subsidies. Additionally, businesses invest in solar systems to enhance their pro-environmental social responsibility image, which can contribute to increased profits (Cohen, Elbakidze, and Jackson 2020). It is worth noting that as commercial users tend to adopt PV earlier than residential users, the rise in PV adoption in the commercial sector could diffuse to the residential sector; when financial incentives are provided for both sectors, commercial PV adoption may thereby act as a mediator in using financial incentives to promote residential PV adoption (Shrimali and Jenner 2013, Best and Burke 2023).

In the commercial sector, systems are typically larger compared to residential installations. Moreover, compared with residents, commercial entities are generally more rational and have a greater capacity for understanding and maximizing the benefits of tax incentives. Therefore, unlike in the residential sector, cash incentives do not naturally possess an advantage over tax incentives in the commercial sector, and the effectiveness of the two incentive types can differ between the two sectors.

To date, six studies have empirically tested the effectiveness of state financial incentives in promoting commercial PV adoption in the United States, yet consensus remains elusive on this matter. Regarding cash incentives, half of the studies support their effectiveness (Shrimali and Jenner 2013, Crago and Koegler 2018, Frey and Mojtahedi 2018), while the other half do not (Borchers, Xiarchos, and Beckman 2014, Ryan, Donou-Adonsou, and Calkins 2019, Cohen, Elbakidze, and Jackson 2020). As for tax incentives, Shrimali and Jenner (2013) discovered that property tax incentives increased the deployment of commercial PV systems, but there was no clear effect from income and sales tax incentives. Crago and Koegler (2018) identified a positive effect of sales tax waivers, although they did not cover other tax incentives. Cohen, Elbakidze, and Jackson (2020) pooled tax incentives and found that their presence encouraged companies to install PV systems. Ryan, Donou-Adonsou, and Calkins (2019) found no explicit impact from sales, income, or property tax incentives on PV adoption. Besides, Borchers, Xiarchos, and Beckman (2014) pooled all financial incentives and showed that they did not significantly affect renewable energy adoption among U.S. farms.

Part of the divergence in findings can be attributed to sample differences. As geographical regions and time frames change, so do the size and duration of incentives, tax

liability and discount rates of companies, electricity prices, and other factors influencing PV adoption.

Another possible reason is the variation in the measures of PV adoption and incentives across studies. Shrimali and Jenner (2013) and Crago and Koegler (2018) used the annual added PV capacity in a state, but the former measured incentives by their presence (dummy variables) while the latter employed incentive rates. Borchers, Xiarchos, and Beckman (2014) tested whether the presence of financial incentives affected a farm's decision (dummy variable) to adopt renewable energy. Frey and Mojtahedi (2018) investigated how changes in rebate level affected the capacity of an average PV system. Ryan, Donou-Adonsou, and Calkins (2019) examined the relationship between total PV-generated electricity and the presence of an incentive type or the number of incentives in that type in a state. Cohen, Elbakidze, and Jackson (2020) evaluated the extent to which the presence of an incentive motivated national companies to install additional PV systems within a state.

Lastly, the differences in findings can be a result of different empirical models. When a substantial number of observations in the sample show zero PV installations, as observed by Crago and Koegler (2018) and Cohen, Elbakidze, and Jackson (2020), the ordinary least squares (OLS) method becomes inappropriate due to the presence of excessive zeroes and non-normally distributed data. Researchers, in such instances, select among multiple non-linear models like Poisson, negative binomial, or Tobit. While these models do not necessarily help reveal causal impacts, they can provide a better fit for the relationship between policy availability/strength and PV installations.

Overall, it is hard to predict the effectiveness of cash or tax incentives in fostering commercial PV adoption from a theoretical perspective, and existing empirical studies do not offer consistent conclusions, underscoring the necessity for further investigations on this topic.

1.2.3 Effectiveness of SREC

The effectiveness of Solar Renewable Energy Certificates (SRECs) varies notably between the residential and commercial sectors. Researchers generally find it successful in the commercial sector (Crago and Koegler 2018, Cohen, Elbakidze, and Jackson 2020) but ineffective in the residential sector (Crago and Chernyakhovskiy 2017, Matisoff and Johnson 2017).

Two primary factors help explain this difference. First, SREC prices can be highly volatile, because while the government-mandated solar carve-out changes relatively infrequently, annual solar system growth, and thus the SREC supply, changes much faster (Coulon, Khazaei, and Powell 2015). Compared with corporates, residents have limited capacity to absorb the risks, rendering SREC trading a less attractive income stream for residential customers (Burns and Kang 2012). Second, the unit of a SREC is one megawatt-hour. To ensure that income from SREC trading offsets transaction costs, a notable quantity of SRECs is necessary. Commercial users, who typically install larger PV systems, are more likely to reach this threshold compared to residential users, whose PV systems have an average capacity of around five kilowatts (Matisoff and Johnson 2017). Burns and Kang (2012) presented evidence for SRECs' limited value in the residential sector: when considering SRECs as the sole incentive, the net present value of

a residential PV system within the first 15 years would be negative in four of the seven states they investigated.

An exception to this pattern is a study by Cohen, Elbakidze, and Jackson (2022). The authors found that from 2004 to 2015, SREC promoted residential PV installations in the Eastern United States. They also observed that when states closed their SREC markets to out-of-state solar facilities, it drove up in-state SREC prices, leading to more solar installations. In addition, another research from these authors revealed that the effect of SREC on commercial PV adoption strengthened with the number of years an SREC market has been in operation, possibly because policy stability bolstered firms confidence in their ability to benefit from SREC sales over the lifetime of their solar installations (Cohen, Elbakidze, and Jackson 2020).

1.2.4 Effectiveness of subsidized loans

Surprisingly, despite subsidized loans being one of the most prevalent state financial incentives for promoting PV adoption, few studies have tested its effect. Matisoff and Johnson (2017) added interaction terms to their model and discovered that cash incentives were most effective at promoting residential PV adoption when coupled with government-sponsored financing programs like subsidized loans. Neither Matisoff and Johnson (2017) nor other researchers have tested the effect of subsidized loans in the residential sector separately. Crago and Koegler (2018) and Cohen, Elbakidze, and Jackson (2020) covered loan programs in the commercial sector, but neither found a significant effect.

Several factors may account for the limited exploration of state loan programs and their relationship with PV adoption. One possible explanation lies in the complicated

terms and conditions associated with loan programs, making it challenging to quantify their value when measuring incentive rates in empirical studies. Another possibility is that many studies use dummy variables to measure the presence of incentives, and cross-state analyses often include fixed effects at the state or a lower geographic level. Given the widespread availability of loan programs, this incentive type may persist across the entire sample period for all states under examination. Consequently, researchers encounter difficulties in assessing its effect since there is no within-state variation. Despite potential limitations, future research could focus on state loan programs to better understand the effects of this widely employed incentive.

Table 1.1 Empirical studies on state financial incentives and residential PV adoption

Article	Sample Period	Sample Area	Unit of Analysis	Models	Key findings on financial incentive effectiveness
Sarzynski, Larrieu, and Shrimali (2012)	1997-2009	50 states plus DC	State (51)	OLS and Panel Corrected Standard Errors (PCSE)	Cash incentives promote total capacity growth. No clear effect of tax incentives.
Shrimali and Jenner (2013)	1998-2009	16 states	Incentive program (27)	OLS and PCSE	Cash and property tax incentives reduce system costs but do not significantly promote annual capacity growth.
Stanford (2014)	2007-2012	50 states plus DC	State (51)	OLS	Cash and property tax incentives promote per-capita capacity and installations. No clear effect of sales or income tax incentives.
Hughes and Podolefsky (2015)	2007-2012	California	Zip code	Negative binomial	$0.1/watt increase in rebate is associated with 10% increase in per capita new installation count.
Crago and Chernyakhovskiy (2017)	2005-2012	12 Northeast states plus DC	County (300)	Tobit model	$1/watt increase in rebate is associated with 47% increase in annual capacity growth. No clear effect of sales or income tax incentives or SREC prices.
Matisoff and Johnson (2017)	2002-2012	49 states (no Hawaii) plus DC	State (50)	OLS	Cash incentives promote per capita capacity growth when coupled with government-sponsored financing programs. Tax incentives and SREC do not.
Cohen, Elbakidze, and Jackson (2022)	2004-2015	26 Eastern states plus DC	State (27)	OLS	Cash incentives and SREC increase the number of installations. Income and property taxes do not.
Sun and Sankar (2022)	2006-2017	California	County (56)	OLS	Rebates effectively promoted annual capacity growth.

Table 1.2 Empirical studies on state financial incentives and commercial PV adoption

Article	Sample Period	Sample Area	Unit of Analysis	Models	Key findings on financial incentive effectiveness
Shrimali and Jenner (2013)	1998-2009	16 states	Incentive program (27)	OLS and PCSE	Cash and property tax incentives increase annual capacity growth. No clear effect from income and sales tax incentives.
Borchers, Xiarchos, and Beckman (2014)	2007	48 states (no Alaska and Hawaii)	State (48) and farm	Multilevel logit	Financial incentives do not significantly affect farm's decision to adopt renewable energy.
Crago and Koegler (2018)	2005-2013	12 Northeast states plus DC	County (300)	Tobit model	Rebates, SREC prices, and sales tax exemptions increase annual capacity growth. No significant effect of loans.
Frey and Mojtahedi (2018)	2007-2014	California	PV system (4540)	OLS	10% increase in rebates leads to 1.4-2.6% increase in PV system capacity.
Ryan, Donou-Adonsou, and Calkins (2019)	2016	50 states	State (50)	OLS	No clear effects of cash or tax incentives on total solar-generated electricity.
Cohen, Elbakidze, and Jackson (2020)	2002-2015	50 states plus DC	State (51) and firm (32)	Zero-inflated Poisson models	Tax incentives and SREC are positively related to PV installation, but cash incentives and loan programs are not.

1.3 Are state financial incentives for PV adoption efficient?

This section delves into the body of literature concerning the cost-effectiveness of state financial incentives for PV adoption. While these incentives can prove successful in boosting PV adoption and subsequently curbing greenhouse gas emissions, there is a growing realization that they may not represent the most efficient approach, which stems from the recognition of two primary risks. One risk is that the market, either independently or under the influence of other financial incentives (such as federal subsidies), could

progress to the optimal level of PV adoption, rendering state-level incentives redundant. The other risk is that the cost associated with providing state financial incentives might surpass the cost of alternative carbon reduction methods or even the social cost of carbon, consequently diminishing overall social welfare. In light of these scenarios, researchers have undertaken examinations to assess the cost-effectiveness of state financial incentives.

1.3.1 Efficiency in promoting PV adoption

Technology advances have continuously driven down the costs of solar system installation and operation. Based on calculations by Feldman et al. (2021), from 2010 to 2020, the average cost of a residential PV system in the United States decreased from $7.53 to $2.71 per watt before subsidies. As a result, the incentive amount needed to maintain the cost competitiveness of solar energy also decreased over time. Frazier, Marcy, and Cole (2019) project that by 2030, solar PV will generally become economically viable regardless of whether the federal ITC remains at its current rate of 30%. Sun and Sankar (2022) posit that the relationship between the effectiveness of financial incentives and solar system price forms a bell-shaped curve. Per their estimations, when the installation cost of residential PV systems dropped below $8.8 per watt, the impact of Californian Solar Initiative (CSI), a cash rebate program, started to decline.

In response to these dynamics, many incentives have adopted a declining schedule of incentive rates. For example, from 2007 to 2015, the CSI rebate rate for general market residential and commercial customers gradually decreased from $2.5 to $0.2 per watt. However, as government-determined incentive rates usually change more slowly than market-driven system prices, the cost-effectiveness of state financial incentives may still erode over time, even with a declining rate schedule.

Apart from shifts in market conditions, the interaction of incentives can also make state financial incentives inefficient or ineffective. By simultaneously offering financial incentives at the federal, state, and local levels, governments risk over-subsidizing solar energy adoption. Sarzynski Sarzynski (2010) and Coffman et al. (2016) demonstrated that although the 35% state income tax credit in Hawaii effectively promoted the state's residential PV adoption, it might not be necessary as PV systems were economically favorable to Hawaiian households with or without the state tax credit thanks to high electricity prices and the federal ITC. Coffman et al. (2016) estimated that even without the state income tax credit, residential PV investment in Hawaii enjoyed a 16% internal rate of return and a 6-year payback period, while the lifespan of a PV system generally exceeds 20 years. Hence, the state tax credit becomes a "windfall" gain to Hawaiian consumers (Sarzynski 2010). Matisoff and Johnson (2017) also exhibited that from 2002 to 2012, about 67% of state and utility solar incentive amounts in the United States were likely spent on programs that did not increase residential PV installations.

1.3.2 Efficiency in reducing greenhouse gas emissions

The primary objective in promoting PV adoption is to mitigate greenhouse gas emissions, emphasizing the necessity for evaluating the cost-effectiveness of state financial incentives from a carbon reduction perspective. Economists widely contend that addressing the negative externality linked to greenhouse gas emissions is best achieved through the direct pricing of these activities, rather than subsidizing emissions-reducing activities (Borenstein 2012a). In this regard, carbon pricing mechanisms, such as carbon taxes and emissions trading systems, are generally favored over cash and tax incentives from an economic standpoint.

There are two major reasons why government subsidies may fall short. First, to maximize the cost-effectiveness of emissions abatement, all market participants should face the same price on emissions, which is the one that equates the marginal benefits and costs of abatement (Goulder and Parry 2008). However, government-funded financial incentives are usually limited in scope, targeting specific technologies or sectors, so they tend to unequalize abatement costs and distort incentives (Baranzini et al. 2017). Additionally, these incentives are often financed by an increase in distortionary taxes (Metcalf 2008), inducing additional welfare loss.

Second, while these incentives encourage the consumption of renewable energy relative to fossil fuels, they also lower the average energy price (Wigley 1997). This phenomenon, known as the "rebound effect", has been well documented in the context of PV adoption (e.g., Greening, Greene, and Difiglio 2000, Sorrell, Dimitropoulos, and Sommerville 2009, Borenstein 2015, Chan and Gillingham 2015). For instance, by studying homes in Phoenix, Arizona from 2013 to 2017, Qiu, Kahn, and Xing (2019) estimated that for homes with a PV system, each additional kilowatt-hour of solar electricity generation led to a 0.18-kilowatt-hour increase in total electricity consumption. While PV systems themselves will trigger a rebound effect as the electricity they generate has a negligible marginal cost (Oliver, Moreno-Cruz, and Beppler 2019), Boccard and Gautier (2021) also showed in a Belgian setting that financial incentives like rebates, tax credits, and renewable energy credits encouraged households to install PV systems that could produce more electricity than their past consumption, with about two-thirds of the surplus electricity being consumed.

As a result, the abatement cost of government-funded financial incentives can be remarkably high. To illustrate, based on data from 2005 and 2006, Metcalf (2008) computed that the federal tax revenue loss tied to reducing CO2 emissions through the ethanol tax credit exceeded $1,700 per ton of CO2. By contrast, per Rennert et al. (2022), the current mean estimate of the social cost of carbon is $185 per ton.

Ideally, both problems associated with government-funded financial incentives can be addressed through carbon pricing. A perfect carbon pricing scheme encompasses all market participants and discourages energy consumption by driving up energy prices. International empirical studies have validated the cost-effectiveness of carbon pricing. For example, Gugler, Haxhimusa, and Liebensteiner (2021) found that in Germany, the average marginal cost of abatement for solar FITs was €978 per ton of CO2, while that of carbon pricing, measured as additional expenditures incurred by increasing the carbon price by $1, was only €52 per ton under the average carbon price (€7.82 per ton) and decreased for higher carbon prices.

However, carbon pricing mechanisms face substantial challenges in practical implementation. As of now, the United States lacks a nationwide carbon pricing scheme, with state or regional emissions trading systems limited to select coastal states. Therefore, government-funded financial incentives serve as second-best options and at least do more good than harm (Borenstein 2012a). As shown in Table 1.3, recent studies indicate that the abatement costs of U.S. state financial incentives for PV adoption, though varying greatly, generally fall within the upper bound of the social cost of carbon ($413 per ton of CO2) estimated by Rennert et al. (2022).

Table 1.3 Carbon abatement cost of state PV financial incentives: select estimates

Article	Sample Period	Sample Area/Program	Estimated Carbon Abatement Cost ($/ton of CO2)
Sarzynski (2010)	1994-2008	10 states	57-300, 163 on average
Hughes and Podolefsky (2015)	2007-2012	California Solar Imitative	130-196
Crago and Chernyakhovskiy (2017)	2005-2012	13 Northeast states	134-269
Vaishnav, Horner, and Azevedo (2017)	1999-2015	10 states	70-350 (breakeven social cost of carbon under 2% discount rate)

1.4 Are state financial incentives for residential PV adoption equitable?

This section reviews the distributional impacts of state financial incentives for solar energy adoption. After an overview of the distributional inequity of PV adoption and associated financial incentives, I discuss the policy choices to improve PV adoption equity financially.

1.4.1 PV adoption inequity and associated financial incentives

Since the primary purpose of financial incentives for solar energy is to enhance efficiency by internalizing positive externalities, the focus on promoting equity becomes less pronounced in their design. Nevertheless, ensuring fair access to solar energy and associated subsidies across communities with different income levels holds significance for at least two reasons. First, about 42% of potential residential rooftop PV capacity in the United States is on the homes of households earning no more than 80% of the area median income (AMI) (Sigrin and Mooney 2018). Therefore, facilitating access for low-income households is crucial for achieving widespread adoption of solar energy, which is essential to the two rationales for solar-related financial incentive: sufficiently realize the benefits of solar energy and use distributed energy sources to enhance energy security. Second, because many financial incentives for PV adoption are financed by surcharges on all

electricity ratepayers, it is important that PV technology is accessible to all electricity ratepayers. This helps avoid the incentives being contested on fairness grounds, incentives primarily benefiting high-income ratepayers while burdening low-income households with increased electricity prices would face challenges in garnering political support (Johnson et al. 2017, Brown et al. 2020).

However, low-income households are less likely to invest in solar and benefit from the subsidies. In 2018, only 18% of U.S. residential solar adopters earned less than the national median household income, while 28% of them earned more than $150,000 (Barbose et al. 2020). In another estimate, households earning more than $200,000 per year were about four times more likely to adopt PV than those earning less than $50,000 (O'Shaughnessy, Barbose, Wiser, Forrester, et al. 2021). As a result, researchers generally find financial incentives for residential solar adoption regressive. For example, Borenstein and Davis (2016) evaluated a group of tax credits for clean energy investments, including PV installations, and found that the top 20% of income earners received about 60% of the credits, while the lowest 60% of income earners only received about 10% of the credits.

Research by Wolske (2020) suggests that high-income and low-income solar PV adopters show similar inclinations toward environmental preferences, novel technologies, and motivation to save money through solar energy, indicating that the socioeconomic disparities in PV adopters are a result of other factors. Low-income households tend to have limited cash resources and restricted access to financing, making it less feasible for them to afford the high upfront costs associated with PV systems, so they are less likely to own rather than rent a system; they also tend to have lower energy demands, face lower electricity prices under tiered tariff structures, and have limited tax liability (Mueller and

Ronen 2015, Coffman et al. 2016, Borenstein 2017). Thereby, low-income residents are less likely to profit from solar systems and associated subsidies, especially when subsidies are only available to system owners (Crago, Grazier, and Breger 2023). Coffman et al. (2016) found that even in Hawaii, a state with generous residential subsidies, there was still a three-year (or 40%) difference in PV investment payback periods between low- and high-income households in 2014.

In addition to financial barriers, low-income households face various nonfinancial barriers to solar adoption. First, low-income residents are more likely to rent their homes. In the second quarter of 2023, the homeownership rate among households earning at least the median family income was 79%, while this rate was only 53% for those earning less than this income (Census 2023). Consequently, they lack the interest in installing a non-portable solar system on the property they do not own. their landlords, who in most circumstances are not responsible for their tenants' energy costs, also lack the incentive to invest in a solar system. This split-incentive problem poses a significant barrier to solar energy adoption in communities with a high concentration of privately owned, low-income rental housing (Reames 2020). Second, low-income households are more likely to live in buildings that require other maintenance and upgrades to enable solar installations (Mueller and Ronen 2015). Third, lower-income households are more likely to lack internet access and have limited English proficiency, which reduces their awareness about the benefits of renewable energy and related policy incentives (Lukanov and Krieger 2019, Reames 2020).

The distributive inequity of PV adoption and associated financial incentives is compounded by two factors. First, the disparity in solar adoption rates between low- and high-income households is reinforced through peer effects, differences in customer referral

opportunities, and community-based or income-targeted marketing (O'Shaughnessy, Barbose, Wiser, Forrester, et al. 2021). Second, low-income households are more likely to be energy-burdened, meaning they spend more than 6% of their income on energy costs[3]. In 2017, an average U.S. household earning no more than 60% of the state median income or 150% of the poverty line (whichever is greater) spent 17.2% of its income on energy, which is over five times the share spent by other households (HHS 2018). While low-income households are more likely to be energy-burdened, they lack access to technologies like PV that help save energy costs (Brown et al. 2020).

1.4.2 Improving PV systems' affordability for low-income households

In response to the barriers that low-income households face in adopting PV systems, governments have implemented a combination of solar justice policies. While nonfinancial barriers can be addressed through initiatives such as solar energy advocacy and workshops, financial challenges are mitigated through direct subsidies or other programs aimed at enhancing the affordability of PV systems (Reames 2020, Brown et al. 2020, O'Shaughnessy, Barbose, Wiser, Forrester, et al. 2021).

Some states directly subsidize PV adoption in low-income communities through rebates or energy bill reduction. Many of these incentives remain available even after incentives for the general market have expired, so that low-income households, who tend to be late in PV adoption, are not excluded from the subsidies (O'Shaughnessy, Barbose, Wiser, and Forrester 2021). For example, in Washington, DC, the Solal for All program provides a 50% reduction on electricity bills to residents earning no more than 80% of AMI who subscribe to community solar facilities. In California, while the rebate rate of CSI's

[3] The rationale behind this threshold is that a household should spend no more than 30% of its income on housing expenses, of which no more than 20% should be energy expenses (Colton 2011).

general market program was from $0.2 to $2.5 per watt, its program targeting single-family households with incomes no greater than 80% of AMI ranged from $3 to $7 per watt. Additionally, to improve PV access for low-income residents living in rental apartments, CSI provided special rebates ranging from $1.1 to $4 per watt for PV installations on multifamily housing where at least 20% of the onsite tenants were low-income. While the general market program ended in 2016, the two affordable solar programs continued to operate until 2022 and 2021. Research by O'Shaughnessy, Barbose, Wiser, Forrester, et al. (2021) shows that these means-tested incentives have successfully improved PV adoption equity. The authors found that financial incentives for low-income households in three states shifted PV deployment from high-income ZIP codes to underserved ZIP codes with lower income levels.

Apart from directly subsidizing low-income households with public money, governments can add other incentives to make PV systems more affordable and accessible. Two common options are third-party ownership (TPO) and Property Assessed Clean Energy (PACE) programs. TPO enables customers to rent rather than own a PV system on their roof or located elsewhere. They can either pay a fixed monthly fee over time (lease mode) or pay for the system's electric output at a pre-negotiated rate under a power purchase agreement (PPA). This allows customers to avoid the high upfront costs of PV systems, though they forfeit the right to claim associated subsidies (Davidson, Steinberg, and Margolis 2015). Under PACE, the government cooperates with private institutions to provide loans for solar system purchases and allows the owner to repay the loan over time through an additional fee on their property tax bill. Because of the enforcement of property tax and the transferability of PACE upon property sales, lenders view PACE as low-risk

and can offer low-cost, long-term loans (Mueller and Ronen 2015). Therefore, PACE is more accessible to low-income households than regular loans. Both TPO and PACE are available to all customers, and researchers have shown that they are effective in promoting PV adoption in the general market (e.g., Drury et al. 2012, Rai and Sigrin 2013, Crago and Chernyakhovskiy 2017, Ryan, Donou-Adonsou, and Calkins 2019 for TPO, and Kirkpatrick and Bennear 2014, Ameli, Pisu, and Kammen 2017, Deason and Murphy 2018, Winecoff and Graff 2020 for PACE). O'Shaughnessy, Barbose, Wiser, Forrester, et al. (2021) demonstrate that these approaches have also narrowed the gap in PV adoption among high- and low-income communities.

Under the joint influence of solar justice policies and declining PV system costs, low-income households, while still underrepresented among PV adopters, have seen their share gradually increase (Borenstein 2017, Vaishnav, Horner, and Azevedo 2017, Lukanov and Krieger 2019, Barbose et al. 2020). This trend toward greater equity becomes self-reinforcing as increased PV adoption fosters learning and peer effects within neighborhoods and drives further reductions in PV system prices (O'Shaughnessy, Kim, and Darghouth 2023). Barbose et al. (2020) estimated that from 2010 to 2018, the share of U.S. PV adopters earning no more than 80% of the AMI rose from 10% to 15%. Per O'Shaughnessy, Kim, and Darghouth's (2023) prediction, the percentage of PV adopters earning less than the U.S. median income will increase from 18% in 2020 to 25-29% by 2030.

It is noteworthy that in addition to income disparity, researchers also find racial and ethnic disparities in residential PV adoption in the United States. Using nationwide data from 2012 to 2016, Sunter, Castellanos, and Kammen (2019) discovered that even after

controlling for median household income, compared with no-majority tracts[4], census tracts with black, Hispanic, and Asian majorities experienced 69%, 30%, and 2% fewer rooftop PV installations on average, while white-majority tracts had 21% more. Possible causes for the lower adoption rates in black and Hispanic communities include a lack of initial PV deployment and limited participation in the renewable energy workforce among black and Hispanic workers, both of which hinder PV diffusion in these neighborhoods. Their findings have been echoed by Reames (2021), Gao and Zhou (2022) (who also controlled for education, homeownership, and housing units), Crago, Grazier, and Breger (2023), and Jackson (2023). However, race or ethnicity is seldom used as a criterion in solar justice policies. Gao and Zhou (2022) demonstrated that although racial and ethnic disparities in residential PV adoption decreased from 2012 to 2019, it was not an outcome of solar justice policies. To improve energy and environmental justice, policymakers should begin considering racial and ethnic factors when designing incentives.

1.5 Summary

Solar photovoltaic (PV) technology offers a means to address the environmental externalities associated with greenhouse gas emissions and enhance energy stability. To this end, U.S. state governments employ public funds to provide a range of financial incentives for PV adoption, including cash incentives, tax incentives, subsidized loans, and renewable energy credits. This essay conducts a comprehensive review of the existing literature to assess the effectiveness, efficiency, and equity implications of state-level financial incentives for solar PV adoption within the United States.

[4] Census tracts where no single racial or ethnic group comprises over 50% of the population.

In the residential sector, prevailing evidence suggests that cash incentives exhibit a positive impact, while tax incentives demonstrate limited effectiveness. This discrepancy primarily arises from the fact that tax incentives tend to feature lower incentive rates, delayed disbursement, and a lack of perceptibility and comprehensibility for residential consumers. In contrast, studies focusing on the commercial sector present mixed findings, with no consensus on the impacts of cash or tax incentives. Renewable energy credits, on the other hand, are generally deemed effective in the commercial sector, but less so for residential customers due to heightened price volatility and trading costs. Notably, subsidized loans, while widely available, remain an underexplored area in academic research.

While publicly funded subsidies have demonstrated potential in promoting PV adoption and reducing carbon emissions, researchers generally recognize that they are not the most efficient approach. This recognition arises from several concerns. First, the market could progress to the optimal level of PV adoption without the aid of state-level incentives. Second, financial subsidies can introduce distortions in the market as they favor certain technologies or sectors and are often funded by distortionary taxes. Third, renewable energy subsidies often lead to an increase in total energy consumption. These factors may drive the abatement cost of state financial incentives to a level surpassing the cost of alternative approaches or even the social cost of carbon, consequently diminishing total social welfare. Nonetheless, in the absence of fully developed carbon pricing mechanisms, subsidies represent a second-best option, typically incurring acceptable abatement costs.

Moreover, low-income households encounter a range of financial and nonfinancial barriers to PV adoption, stemming from limitations in financial capacity, homeownership

rates, housing conditions, access to information, energy demand, and tax liability. Consequently, they receive a disproportionately lower share of financial incentives for PV adoption. Direct subsidies targeting these households and financing programs that help avoid high upfront system costs are proven to be effective in mitigating the income disparities of PV financial incentives. However, while current policies aim to address income inequity, they often overlook the racial and ethnic disparities that are significant in the context of PV financial incentives.

To bridge the knowledge gap in the effects of PV financial incentives, future research efforts may focus on evaluating the impacts of loan programs and exploring policy designs aimed at promoting racial and ethnic equity.

Chapter 2: Impact of State Financial Incentives on Residential Solar Energy Adoption in the United States

Twenty-three percent of solar power capacity in the United States comes from small-scale residential solar photovoltaic (PV) systems, which increased from 3.3 gigawatts in 2014 to 27 gigawatts in 2022 and is forecasted to reach 47 gigawatts in 2024 (EIA 2023). The rapid development in residential solar deployment closely relates to the declining cost of installing and using a solar system, in which financial incentives play an important role.

This essay uses county-level data from 15 states and the District of Columbia to evaluate the effectiveness of different types of state financial incentives for residential PV adoption during the 2010-2020 period. While earlier studies that focused on the pre-2010 era generally indicated that cash incentives were effective in boosting residential PV adoption, with tax incentives showing less promise, this analysis reveals a shift in the effectiveness of these incentives. Income tax credits emerged as a significant driver during the past decade. Other things equal, a one-percentage-point increase in the income tax credit rate raised PV capacity growth by 8-12%. By contrast, the effects of cash incentives were smaller and vaguer. These changes in effectiveness were probably driven by the relative size changes of cash and tax incentives: from 2010 to 2020, while the average state income tax credit rate remained between 20-25%, the average general-market cash rebate rate declined from nearly 30% to 8%. With less confidence, I also find evidence for the positive effects of property tax exemptions on residential PV adoption. In contrast, no significant evidence is found to support the effectiveness of sales tax

exemptions, subsidized loans, or Solar Renewable Energy Certificates (SRECs) based on this analysis.

This essay proceeds as follows. Section 2.1 introduces financial incentives and other factors influencing residential PV adoption and summarizes existing literature. Section 2.2 proposes the research question. Sections 2.3 and 2.4 explain the empirical approach and data. Section 2.5 presents and discusses the results. Section 2.6 concludes with policy implications.

2.1 Background

2.1.1 Financial incentives for residential PV adoption

A household decides to invest in a PV system when the expected benefit from using the system exceeds its upfront cost. Hence, financial incentives aimed at promoting PV adoption help reduce a system's upfront cost or increase its benefits during its lifespan. In the United States, common state-level financial incentives for residential PV adoption include cash rebates, income tax credits, sales tax exemptions, property tax exemptions, subsidized loans, and solar renewable energy credits (SRECs). As discussed in Section 1.1.2, these incentives are usually financed by general government revenue or utility surcharges, either through direct spending or as tax expenditures. The first three incentives represent one-time benefits that reduce PV system costs upfront. Cash rebates directly subsidize PV system installations with an amount usually proportional to system capacity, i.e., the maximum amount of electricity the system can generate. Income tax credits usually equal a percentage of the system cost. In some states, solar system purchase is exempted from the sales tax.

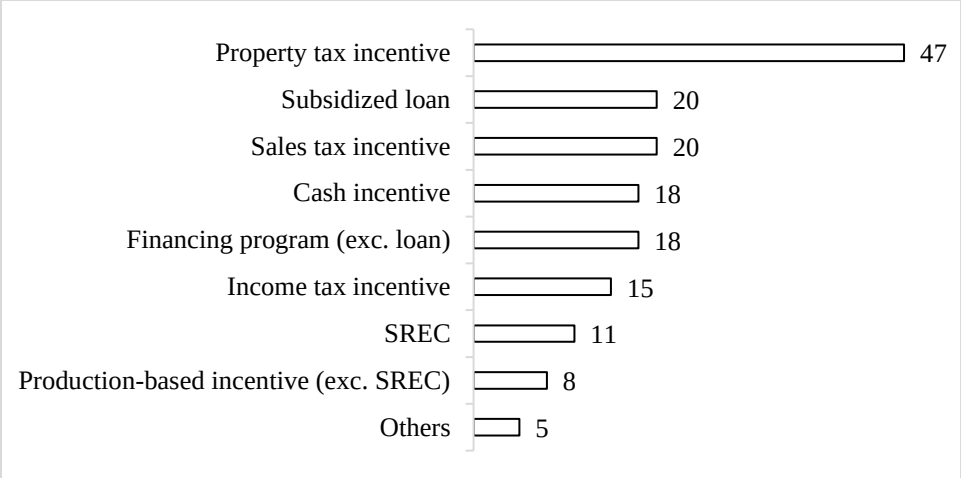
Other financial incentives serve to reduce the cost or increase the benefit of owning or using PV systems over time. Property tax exemptions exclude the added value of a PV system from property tax assessment, resulting in lower annual property tax payments. Many states offer financing programs that lower installment payments for PV systems. The most used one is the subsidized loan, which provides below-market interest rates for loans used on solar system investments. In addition, states can offer incentives based on the amount of electricity a PV system produces in a period, and the most popular production-based incentive in the United States is the solar renewable energy credit (SREC). Residents, corporates, and utilities who own grid-connected solar systems can receive SRECs, production credits awarded per megawatt-hour of generated electricity, and sell them in the market.

As shown in Figure 2.1, property tax incentives are currently the most common financial incentives for residential PV adoption at the state level. Subsidized loans, sales and income tax incentives, and cash incentives are also widely used. SRECs are available in ten states and the District of Columbia.

In addition to state-level incentives, several financial incentives for residential PV installation exist at the federal level. The most notable one is the Investment Tax Credit (ITC), a 30% federal income tax credit for residential PV installations. Moreover, many incentives are provided by local governments and utilities. When a state-level incentive is not in place, incentives from different local authorities can fill the gap and may largely substitute the state incentive if most of the state population is covered by local incentives. As incentives from different levels of authority complement or substitute each other, the

effectiveness of state incentives can be influenced by their interaction with federal and local ones.

Figure 2.1 Number of state financial incentives for residential PV, 2022



Source: DSIRE (2022)

2.1.2 Other factors influencing residential PV adoption

Apart from financial incentives, states use regulatory policies to promote residential solar adoption. Major regulatory policies include renewable portfolio standards (RPS), third-party ownership, net metering, and solar rights regulations. RPS generally mandates a certain share of the total electricity sold in a state to come from renewable energy sources by a certain year. Third-party ownership allows homeowners to rent a solar system from a developer, allowing them to enjoy the benefits of solar power without bearing substantial upfront costs. Customers can either pay a fixed monthly fee or pay for the system's electric output at a rate usually lower than the local utility under a power purchase agreement. Net metering allows customers who generate their own electricity through solar systems to send excess electricity to the grid using bi-directional meters. In return, customers receive energy credits that can be used to offset part or all of the electricity they purchase from the

utilities within a certain period. Solar rights regulations bar local jurisdictions from prohibiting the installation of solar systems.

Besides, solar energy adoption in a region is related to various non-policy factors. Solar resources (sunshine) and electricity costs are key determinants of the financial benefits of a PV system and greatly affect solar deployment. For example, Kwan (2012) showed that between 2005 and 2010, each additional kilowatt-hour in solar insolation[5] received in a ZIP code increases the expected count of housing units with PV installations by 89%, and each standard deviation increase in the cost of electricity raises residential PV share by 85%. Demographic characteristics affecting solar energy adoption in an area include income, urbanization, education, age, and political affiliation. Researchers generally find a positive relationship between solar energy adoption and median income, median home value, share of the population with a bachelor's degree or higher, and share of Democrats, while the evidence on the impacts of age, population density, and housing density is mixed (e.g., Zahran et al. 2008, Sarzynski 2010, Kwan 2012, Crago and Chernyakhovskiy 2017).

2.1.3 Existing literature

A handful of studies have examined the effect of state financial incentives on U.S. residential PV adoption with a focus on the 2000s. As summarized in Table 1.1, most researchers found that cash incentives significantly promoted residential PV installation, but tax incentives did not (e.g., Sarzynski, Larrieu, and Shrimali 2012, Sawhney et al. 2014, Crago and Chernyakhovskiy 2017, Matisoff and Johnson 2017). This divergence in effectiveness can be partly attributed to the variations in the magnitude and claim

[5] Solar insolation is the amount of solar radiation incident upon a unit horizontal surface over a specified time for a given locality.

procedures associated with these two incentive types. Cash incentives often exceeded 30% of the total system cost, rendering PV investments financially attractive. By contrast, state tax incentives were typically more modest, with state income tax credits hovering around 20%, and sales tax exemptions usually around 7%. Plus, most cash incentives can be easily claimed shortly after system purchase, whereas the claim process for income tax incentives tends to be long and complicated, and the non-refundability of many tax credits decreases their actual value for taxpayers with insufficient tax liability (Sarzynski 2010).

Empirical evidence on the effectiveness of subsidized loans for residential PV is scant. Few studies have isolated the impact of subsidized loans from other financial incentives. Nevertheless, by adding interaction terms to their model, Matisoff and Johnson (2017) exhibited that cash incentives were most effective when coupled with government-sponsored financing programs like subsidized loans.

The findings among researchers remain inconclusive on the effect of SRECS. Crago and Chernyakhovskiy (2017) found little evidence that SREC price affected residential PV installations. They explain that the high price volatility and transaction costs associated with SRECs discouraged residents from participating in SREC trading. However, Cohen, Elbakidze, and Jackson (2022) discovered a positive impact of SREC price on residential PV installations in the Eastern United States.

Over the past decade, with the ongoing reduction in solar system costs and the cumulative impact of existing incentives, many states made notable adjustments to their solar-related financial incentives. Numerous new incentives were introduced while others were paused or ended. Some incentives, especially cash rebates, saw a shrink in incentive rate and/or scope. For example, New Mexico discontinued its 10% Solar Market

Development income tax credit in 2017 but renewed it in 2020. The typical general-market incentive rate of the California Solar Initiative, a rebate program, declined from $1.9 per watt in 2009 to $0.2 per watt in 2016, after which the general-market program was concluded, and only programs targeting low-income households were kept. However, no existing study has conducted a cross-state analysis to examine the persistence of previous research findings. This paper aims to provide an updated analysis while also exploring the impact of subsidized loans, a widely available incentive type not explicitly addressed in previous studies focused on the residential sector.

2.2 Research Question

From 2010 to 2020, which types of state financial incentives were effective in promoting residential solar photovoltaic adoption in the United States?

2.3 Empirical Approach

I use the following model to estimate the impact of policy incentives on annual residential PV installation across states between 2010 and 2020. The unit of analysis is county-year.

$$Y_{it} = \beta_0 + \beta_1 F_{st} + \beta_2 R_{st} + \beta_3 C_{it} + \gamma_i + \delta_t + \varepsilon_{it}$$

where Y_{it} is the natural logarithm[6] of added residential PV capacity for county *i* in year *t*. As a robustness check, I also test the effects on new PV installation counts. Since the dependent variables are log-transformed, the coefficient before a dependent variable represents the proportional change in added PV capacity or new PV installation counts associated with a unit increase in the dependent variable.

[6] The log transformation brings the highly skewed distribution of PV capacity additions or installations closer to normal. To deal with the zero values, all PV capacity additions or installations values are increased by 1 before the log transformation.

F_{st} is a vector of dummy variables for the availability of financial incentives (cash rebates, income tax credits, property tax exemptions, SRECs, and subsidized loans) in state *s* and year *t*. R_{st} is a vector of state regulatory policy dummy variables, including RPS, net metering, and solar rights regulations. I do not include third-party ownership as it was available across all sample states throughout the sample period, so no variation in the availability of this policy can be exploited. Sales tax exemptions and net-metering are also excluded in the dummy specifications model as there is no within-state variation of their availability during the sample period (Table A2.4), so its effect is inestimable when state fixed effects are added (explained later).

In another specification, I use continuous variables for cash rebates (rebate amount as a percentage of system cost), income tax credits (credit amount as a percentage of system cost), sales tax exemptions (exempted sales tax rate), and property tax exemptions (exempted property tax rate). In a third specification, I test how the effects of a policy changed over time by replacing each policy variable with the number of years since its adoption when the policy was in place.

C_{it} is a vector of county-level control variables, including annual average solar insolation, annual state average residential electricity price, logarithm of median household income, logarithm of median housing value, logarithm of housing density, median age, share of people with bachelor's degree or higher in the population aged 25 years and over, and share of Democratic votes in the nearest Presidential election.

γ_i represents state fixed effects and captures state-specific time-invariant factors that affect solar energy adoption. δ_t represents year fixed effects and captures location-

invariant factors, such as federal policy. As a robustness check, I also present results with county and year fixed effects in Appendix Table A2.2.

It should be noted that when state fixed effects are added to the model, the policy effect estimates rely on within-state policy variations. In other words, the effect estimates of policy dummies (or incentive rates) rely on the states that experienced policy availability (or incentive rate) change during the sample period. For policies that did not experience availability changes in any of the sample states, i.e., sales tax exemptions and net metering, their availability status become state-specific and time-invariant factors and are absorbed by state fixed effects, so the model with policy dummies and state fixed effects will fail to identify their impacts. Consequently, both policy dummies are excluded from the independent variables. However, since there were within-state changes in sales tax rates (as detailed in Appendix Table A2.5), sales tax exemptions can be included in the model with incentive rate specifications.

ε_{it} is the error term. Since policy variables are consistent across counties of the same state, standard errors are clustered by state in the baseline model. One concern is that the small number of state clusters may lead to a bias in the clustered standard errors (Angrist and Pischke 2009). For comparison, I include estimation results with standard errors clustered at the county level in Appendix Table A2.4. County-clustering will not change the magnitude of the effect estimate but will reduce their standard errors since the variation among observations within each cluster is reduced when the level of clustering changes from state to county.

Another challenge to this empirical analysis is that 47% of the observations have zero PV installations, resulting in an excess of zeros and over-dispersion in the dependent

variable. In addition, since there is no available data on solar systems uninstalled in the sample county-years, the value of added PV capacity/installations is truncated with a lower limit at zero. Under these circumstances, estimates from an OLS regression can be inconsistent and biased.

To address these issues, I employ the Tobit and Poisson models. The Tobit model handles truncated data, while the Poisson model is suitable for addressing overdispersion. It is important to acknowledge that both models have their limitations in this analysis. The Tobit model does not effectively handle overdispersion, and the Poisson model, although suitable for count variables (in this case, the number of installations), may not be ideal for continuous data (system capacity). Theoretically, zero-inflated models are more capable of handling excessive zeroes. However, the sample size of this study is not large enough to enable these models.

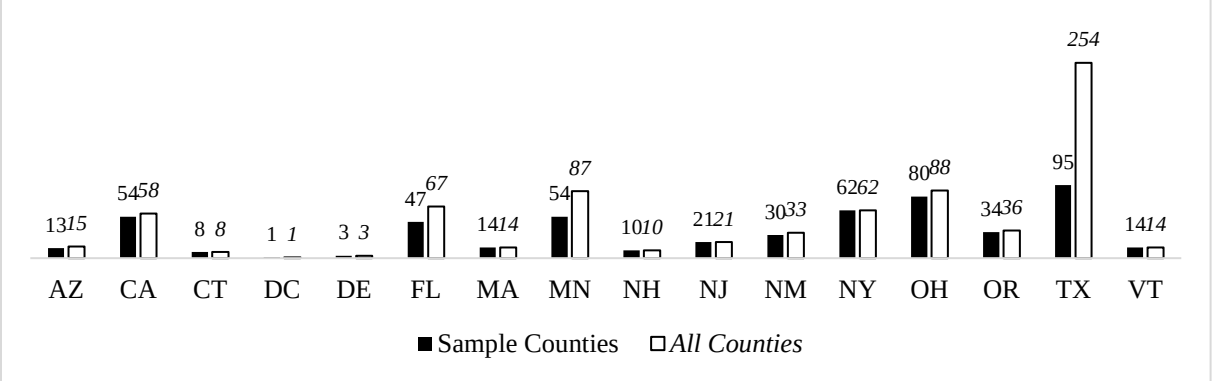
Some factors may influence both PV adoption and solar-related policies at the same time. For example, large solar technology companies might promote PV installation at the same time they lobbying for policy incentives (Sarzynski, Larrieu, and Shrimali 2012), or there might be simultaneously increasing confidence in solar technology among homeowners and policymakers (Crago and Chernyakhovskiy 2017). In addition, there might be a lag between policy adoption and the emergence of policy impacts. I use the one-year lag of policy dummies and incentive rates to address these concerns. However, as the omitted variables that positively affect PV installations are likely to be positively correlated with policy incentives, they will lead to an upward bias in the estimates of policy impacts.

2.4 Data

Data on residential solar PV installation come from Lawrence Berkeley National Laboratory's Tracking the Sun project (Barbose et al. 2022). The project collects data from various entities, including state agencies and utilities, for PV systems participating in incentive programs, renewable energy credit registration systems, and interconnection processes. Some states may not participate in data collection in certain years. My sample comes from the 16 states[7] that have system location information available and have data coverage for at least seven years during the 2010-2020 period. While these states are concentrated in the Northeast, the Southwest, and the West Coast, they include both developed and emerging solar PV markets.

To select systems for residential use, I keep observations where the host customer is in the residential sector. Further, to understand how policy incentives affect household decisions, I exclude systems with an output larger than 10 kilowatts, as they are mostly installed on collective housing properties owned by corporates.

Figure 2.2 Number of counties by state



[7] AZ, CA, CT, DC, DE, FL, MA, MN, NH, NJ, NM, NY, OH, OR, TX, VT. Coverage is missing for MN in 2012-13 and 2019-20, OR in 2018-20, and VT in 2016-20.

The sample covers 540 counties in the 16 states. As shown in Figure 2.2, the sample has (nearly) full coverage for counties in most states, 70% coverage for counties in Florida, 62% coverage for counties in Minnesota, and 37% coverage for counties in Texas. While the coverage rates for Florida, Minnesota, and Texas are relatively low on a county count basis, the sample counties respectively account for 94%, 89%, and 66% of the population in these states in the most recent sample year.

Counties not covered in the sample have no installation records in the dataset over 2010-2020. This is because either they had no installation, or they were not covered by the data providers. Because it is hard to determine which is the case, these counties are removed from the sample, consequently limiting the external validity of the findings. As shown in Appendix Table A2.1, compared with sample counties, on average, excluded counties have lower median income, median housing value, housing density, resident education attainment, and Democratic vote share. Findings from this research suggest that while the effect of other demographic characteristics on solar adoption is unclear, lower housing density and higher Democratic vote share are associated with higher solar adoption rates. Therefore, in the case of missing data coverage, it is hard to speculate whether the excluded counties tend to be higher or lower than average in terms of solar adoption.

For counties with installation records in some but not all years over the sample period, I assign zero installations to years with no records, a practice common in studies using sub-state jurisdictions as the unit of analysis (e.g., Hughes and Podolefsky 2015, Crago and Chernyakhovskiy 2017). However, it is important to note that this practice is based on a strong assumption, which is to assume that the data provider had consistent

service territories over the sample period and reported all installations in their service territories.

Policy data come from the Database of State Incentives for Renewables and Efficiency (DSIRE 2022). DSIRE has high coverage of current and expired state incentives for PV adoption. In addition, I conducted Google searches and consulted news, reports, and government documents to cover as many incentives effective in the sample period as possible. State incentives still omitted after this information-gathering process should not be large in number or incentive size and are unlikely to have a meaningful impact on the estimation results. Table 2.1 summarizes the number of states offering each policy incentive by year during the sample period. Detailed information on policy availability and incentive rates by state and year is presented in Appendix Tables A2.4 and A2.5.

For the three upfront financial incentives, I measure their incentive rates as their value relative to the total system cost. Most cash rebates are offered as a dollar-per-watt incentive based on the installed system capacity. When multiple rates exist in a rebate program, I use the rate applicable to most households. I then divide this rebate rate by the annual national average residential PV system cost per watt, as sourced from Feldman et al. (2021), to convert it into a percentage of the system cost. The measure of income tax credit rates is straightforward as they are originally provided as a share of system cost. Since sales taxes are ad-valorem, the incentive rate of a sales tax exemption is simply the sales tax rate.

I measure the strength of a property tax exemption by the property tax rate, calculated as the ratio of median property tax to median housing value in a county using the American Community Survey (ACS) five-year estimates (Census 2022). The value of

a property tax exemption equals the net present value of total exempted property taxes in the PV system's lifespan. Property taxes on a PV system are typically based on the assessment of the system's value added to the property. While assessment rules vary across jurisdictions, in most circumstances, it is determined by system capacity and per-watt market value at the time of assessment. Hence, assuming a homogeneous expectation of PV system lifespan among households and controlling for system capacity and installation time, the value of a property tax exemption is highly and positively correlated with the property tax rate.

Solar radiation data come from the National Solar Radiation Database (NREL 2022). State-level annual average residential sector electricity retail price data are obtained from the Energy Information Administration (EIA 2022). Demographic data come from the ACS five-year estimates (Census 2022). Presidential election results are sourced from the MIT Election Data and Science Lab (MIT 2022). Table 2.2 provides summary statistics of continuous and count variables over the sample period. Sample means of the tax rate and control variables are close to national averages, indicating that the sample exhibits good representativeness.

Table 2.1 Number of states offering incentive by policy and year, 2010-2020

Policy	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Cash rebate	13	10	9	9	8	7	7	7	7	7	7
Income tax credit	6	6	6	6	6	6	6	5	4	4	5
Sales tax exemption	9	9	9	9	9	9	9	9	9	9	9
Property tax exempt.	13	13	14	14	14	14	14	14	14	14	14
SREC	6	7	7	7	7	7	7	7	7	7	6
Subsidized loan	5	5	5	5	5	5	5	6	6	6	6
RPS	14	14	14	14	14	14	14	15	15	15	15
Net metering	15	15	15	15	15	15	15	15	15	15	15
Solar rights regulations	14	14	14	14	14	14	14	14	15	15	15

Table 2.2 Summary statistics, 2010-2020

Variable	Mean	Median	Min	25% Percentile	75% Percentile	Max
Annual PV capacity additions (kW)	669.4	4.9	0	0	4.9	94,115.1
Annual PV installation count	109.7	1.0	0	0	1.0	18,430.0
Cash rebate rate (% of system cost)	7.8	0	0	0	0	62.4
Income tax credit rate (% of system cost)	6.2	0	0	0	0	31.0
Exempted sales tax rate (% of system cost)	3.2	0	0	0	0	8.5
Exempted property tax rate (% of value-added)	1.1	1.0	0	0.7	1.0	3.5
Average electricity price (¢/kWh)	12.6	11.2	8.9	10.6	11.2	19.3
Average solar radiance (GHI, kWh/m^2/yr)	189.4	179.6	125.5	163.7	179.6	261.9
Median annual household income ($)	49,339.6	46,550.8	19,092.9	40,629.5	46,550.8	110,013.5
Median housing value ($)	176,742.2	140,577.2	31,400.0	100,930.2	140,577.2	1,000,000.0
Owner-occupied housing units	51,585.1	15,057.0	140.0	5,382.5	15,057.0	1,738,476.0
Housing units per km^2	132.4	17.5	0.1	6.9	17.5	14,965.1
Median age	40.3	40.1	25.9	36.9	40.1	68.0
Bachelor's degree+ in age 25+ (%)	24.4	22.0	5.1	16.4	22.0	67.6
Democrat votes in Presidential Elections (%)	42.4	40.9	9.2	29.8	40.9	92.1

N=5552. All monetary values are adjusted to 2010 USD. Median housing value is capped at $1M in ACS.

2.5 Results and Discussion

2.5.1 Main results

Table 2.3 presents Tobit and Poisson estimation results with state and year fixed effects and state-clustered standard errors for the impacts of state financial and regulatory incentives on the natural logarithm of residential PV capacity growth and new PV installation counts across two specifications. The first specification uses dummy variables for all policies, and the second specification incorporates incentive rates for cash and tax incentives and uses dummies for other policies. All dummy and incentive rate variables are one-year lags.

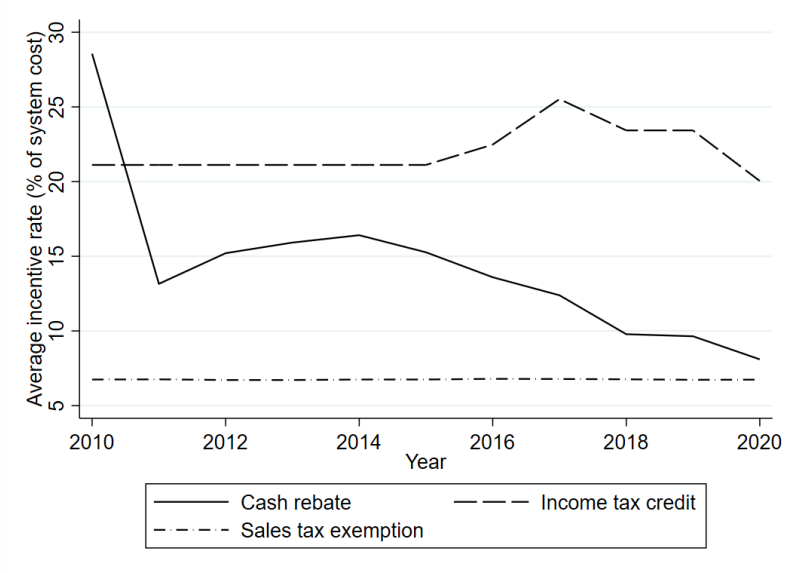
As robustness checks, I present estimation results with county and year fixed effects and state-clustered standard errors in Appendix Table A2.2 and results with state and year fixed effects and county-clustered standard errors in Appendix Table A2.3. Most estimates are consistent under different fixed effects or standard error clustering methods.

Across specifications, income tax credits have substantively and statistically significant positive effects on both PV capacity growth and new installations. Cash rebates have positive effect estimates across specifications, though they are smaller than those of income tax credits and only statistically significant in a few specifications (mostly when standard errors are clustered at the county level). Sales tax exemption rates do not show statistically significant effects on PV adoption across specifications.

For the three upfront financial incentives, namely cash rebates, income tax credits, and sales tax exemptions, a key factor driving the differences in their effect estimates is the incentive rate. Figure 2.3 shows the change in average rates of the upfront incentives (as a percentage of system cost) between 2010 and 2020. While the average state income tax

credit rate remained between 20-25%, the average general-market cash rebate rate declined from nearly 30% to 8%. The average sales tax rate, by contrast, remained below 8%.

Figure 2.3 Average rate comparison of upfront financial incentives, 2010-2020



This change in the relative sizes of cash and income tax incentives also helps explain why previous studies focusing on the 2000s found cash incentives effective while income tax credits were not, but the opposite was observed during 2010-2020. The results, however, do not suggest that the cash rebate itself is not an effective tool, but rather reflect a trend in cash rebates across states. In the past decade, with the residential PV market maturing and states running out of their budget, some state rebate programs available to the general market were discontinued and others greatly reduced their incentive rate. Particularly, the sharp decline in cash rebate rates in the early 2010s, as observed from Figure 2.3, likely stemmed from the deteriorated financial condition of state governments caused by the 2008 financial crisis. Many states continued to offer generous rebates to targeted populations, such as low-income households, for small system installations. The cash rebate rate variable, while accounting for variations in the incentive rate, does not capture changes in the market segment eligible for such incentives. It is possible that the

special rebate programs, limited in scope, do not have salient effects on promoting total residential PV growth.

Another reason for the discrepancies in estimated effects of the three incentives may lie in the source of policy variation. During the sample period, cash rebates witnessed changes in availability in seven out of the 16 sample states, and more states experienced fluctuations in cash incentive rates. By contrast, only two states, New Mexico and Oregon, experienced changes in income tax credit availability or incentive rate. For sales tax exemption, none of the sample states experienced policy availability changes, and only three states experienced incentive rate changes. These differences indicate that findings regarding cash rebates may have broader applicability compared with those concerning income or sales tax incentives.

Estimates on the availability of property tax exemptions are positive and statistically significant, consistent with the findings of Stanford (2014). However, these estimates rely on a single jurisdiction, the District of Columbia, the only "state" and "county" underwent a change in the availability of property tax exemptions. That said, the results indicate that the property tax exemption in D.C., which started in 2012, successfully promoted residential solar adoption. On the other hand, since the exempted property tax rate varied by county-year, estimates on its effect are much more generalizable. Increases in the exempted property tax rate show a positive impact on solar adoption, though the estimates are only statistically significant in certain specifications under state fixed effect models.

As most PV systems have a lifespan of 25 to 30 years and property tax rates change minimally, property tax exemptions provide continuous, stable, and easy-to-claim savings

to property owners. For example, assuming a linear depreciation of a solar system over 25 years in property tax assessments, a constant property tax rate of 1.1% (sample mean), and a household employing a 3% discount rate, the net present value of a property tax exemption on the solar system equals 11% of the system cost. One possible explanation for the success of property tax exemptions is that with cash incentives fading out, the cumulative value of a property tax on PV systems became more salient to residents and deterred PV adoption in states without a property tax exemption. However, this explanation makes a strong assumption on the rationality of homeowners, as perceiving the cumulative value of a property tax often requires complicated calculations.

Estimates of SRECs are positive, but their significance levels are sensitive to the model specification. Moreover, like in the case of property tax exemption, only one sample state (Connecticut) experienced availability changes in SRECs. Therefore, it is hard to draw a conclusion on the effectiveness of SRECs from this analysis.

I find no significant impact of subsidized loans on residential PV adoption. This is different from Matisoff and Johnson (2017), who found government-sponsored financing programs like loans effective when combined with cash incentives. One potential explanation for this discrepancy is the evolving landscape of the solar market. The sample of Matisoff and Johnson (2017) came from the period before 2012 when TPO was not widely available. TPO allows customers to pay for the usage of the PV system by month so that they can avoid the high upfront system cost without incurring debt. As TPO has become ubiquitous (available in all sample state-years), it is not surprising that loans have lost their appeal to consumers. Another possibility is that the market interest rate during the sample period was relatively low, with the federal funds effective rate not exceeding

2.5% and close to zero half of the time, so a lower interest rate sponsored by government appeared less necessary and attractive.

Regarding regulatory policies, estimates on RPS are not statistically significant across specifications. This is possibly because RPS directly regulates utilities but not households, so its influence on households' decisions to install solar systems is weak when incentives targeting the residential sector are considered. Again, the estimates rely on only two states that experienced RPS availability changes, namely Ohio and Vermont. Likewise, there is no conclusive evidence on the effectiveness of solar rights regulations as the estimates rely solely on the District of Columbia and their substantive and statistical significance is sensitive to model specifications.

In terms of other covariates, the estimates suggest that across different counties within the same state, higher solar radiance, higher housing value, lower housing density, and higher shares of Democratic votes were associated with higher residential solar adoption rates. Although lacking statistical significance, state average electricity price demonstrated positive and large effects on solar adoption rates, suggesting that increases in electricity prices may still play an important role in incentivizing households to install solar systems.

Table 2.3 Policy effect on residential PV adoption

	Tobit				Poisson			
	(1) Capacity Dummy	(2) Capacity Rate	(3) Count Dummy	(4) Count Rate	(5) Capacity Dummy	(6) Capacity Rate	(7) Count Dummy	(8) Count Rate
Cash	1.272	0.031	0.987	0.025*	0.285	0.010	0.302	0.011
	(0.808)	(0.017)	(0.614)	(0.012)	(0.223)	(0.007)	(0.233)	(0.007)
Income tax	1.627**	0.154*	1.167*	0.111*	0.477**	0.047**	0.481**	0.048*
	(0.623)	(0.068)	(0.482)	(0.053)	(0.153)	(0.018)	(0.161)	(0.019)
Sales tax	-	0.166	-	0.046	-	0.075	-	0.106
	-	(2.419)	-	(1.938)	-	(0.438)	-	(0.439)
Property tax	1.638**	0.793*	1.107*	0.480*	0.523**	0.175	0.509**	0.204
	(0.599)	(0.345)	(0.443)	(0.223)	(0.187)	(0.110)	(0.190)	(0.123)
1=SREC	1.265*	0.973	1.032*	0.842	0.147	0.108	0.131	0.091
	(0.591)	(0.585)	(0.491)	(0.526)	(0.163)	(0.176)	(0.185)	(0.202)
1=Loan	-0.047	-0.181	0.088	0.005	-0.098	-0.127	-0.095	-0.125
	(0.549)	(0.588)	(0.437)	(0.484)	(0.182)	(0.213)	(0.207)	(0.251)
1=RPS	-0.118	-0.396	0.071	-0.124	-0.044	-0.139	0.024	-0.088
	(0.447)	(0.446)	(0.329)	(0.320)	(0.077)	(0.094)	(0.082)	(0.100)
1=Solar rights	0.275	0.587	0.151	0.333	0.445**	0.561**	0.346*	0.436*
	(0.663)	(0.746)	(0.478)	(0.548)	(0.144)	(0.201)	(0.147)	(0.199)
Solar radiance	0.050***	0.049***	0.036***	0.035***	0.004	0.003	0.005	0.004
	(0.012)	(0.013)	(0.008)	(0.009)	(0.004)	(0.005)	(0.004)	(0.004)
Electricity price	0.648	0.629	0.473	0.448	0.136	0.131	0.131	0.126
	(0.407)	(0.412)	(0.321)	(0.325)	(0.098)	(0.102)	(0.105)	(0.111)
Ln(Med. income)	0.517	-0.177	0.319	-0.113	-0.023	-0.226	-0.019	-0.261
	(0.934)	(0.893)	(0.656)	(0.623)	(0.325)	(0.323)	(0.316)	(0.323)
Ln(Med. hous. val.)	0.150	0.886*	0.380	0.831***	0.374*	0.577**	0.376*	0.616***
	(0.394)	(0.357)	(0.251)	(0.175)	(0.184)	(0.184)	(0.185)	(0.179)
Ln(Hous. density)	-0.308*	-0.354**	-0.385***	-0.412***	-0.645***	-0.656***	-0.610***	-0.622***
	(0.131)	(0.119)	(0.101)	(0.091)	(0.042)	(0.037)	(0.045)	(0.040)
Median age	0.006	0.008	0.016	0.018	0.023	0.022	0.024	0.024
	(0.039)	(0.039)	(0.030)	(0.030)	(0.013)	(0.013)	(0.013)	(0.013)
Bachelor's+ %	0.038*	0.033	0.020	0.017	-0.004	-0.005	-0.004	-0.005
	(0.018)	(0.019)	(0.013)	(0.014)	(0.007)	(0.007)	(0.008)	(0.008)
Democrat vote %	0.018***	0.016***	0.015***	0.013***	0.009*	0.008*	0.012**	0.011**
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

N=5552. Columns 1-4 show Tobit estimation results. Columns 4-6 show Poisson estimation results. Dependent variable is ln(added PV capacity) in columns 1, 2, 5, 6 and ln(PV installations) in columns 3, 4, 7, 8. Cash and tax incentives are dummies in columns 1, 3, 5, 7 and incentive rates in columns 2, 4, 6, 8. Other policies are dummies in all specifications. All models are estimated with an offset for ln(owner-occupied housing units) and state and year fixed effects. Standard errors clustered by state are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.5.2 Combined upfront incentive rates

Section 2.5.1 suggests that the size of an incentive matters in deciding its effectiveness, which leads to the question of whether the total amount of incentives affects residential PV adoption. Here, I add up the rates of the three upfront financial incentives (cash rebates, income tax credit, and sales tax exemptions) and test the effect of the combined rate along with other incentives. As shown in Table 2.4, most of the effect estimates are not statistically significant. This is consistent with Matisoff and Johnson (2017), who similarly did not identify a statistically significant effect of the total state and local incentive amount on PV installations. The results indicate that the individual rates of specific incentives are more influential in shaping adoption decisions than the combined incentive rate.

Table 2.4 Effect of combined upfront incentive rate on residential PV adoption

	Tobit		Poisson	
	(1)	(2)	(3)	(4)
	Capacity	Count	Capacity	Count
Rate_Upfront incentives	0.032	0.025*	0.010	0.011
	(0.018)	(0.012)	(0.007)	(0.007)
Rate_Property tax	0.781*	0.470*	0.172	0.201
	(0.343)	(0.218)	(0.108)	(0.121)
1=SREC	1.000	0.854	0.119	0.105
	(0.554)	(0.499)	(0.152)	(0.175)
1=Loan	-0.133	0.037	-0.108	-0.104
	(0.559)	(0.459)	(0.196)	(0.229)
1=RPS	-0.374	-0.109	-0.134	-0.084
	(0.431)	(0.309)	(0.091)	(0.097)
1=Solar rights	0.657	0.382	0.578**	0.453*
	(0.717)	(0.524)	(0.194)	(0.190)

N=5552. Columns 1-2 show Tobit estimation results. Columns 3-4 show Poisson estimation results. Dependent variable is ln(added PV capacity) in columns 1 and 3 and ln(PV installations) in columns 2 and 4. All models are estimated with county-level controls for solar insolation, state average residential electricity price, demographics (median household income, median housing value, housing density, median age, share of people with bachelor's degree or higher in the population aged 25 years and over, share of Democratic votes in the nearest Presidential election), an offset for ln(owner-occupied housing units), and state and year fixed effects. Standard errors clustered by state are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.5.3 Marginal effects

Tables 2.5-2.8 present the marginal effects of cash rebates and tax incentives. I provide the effects of increasing the incentive rate by one percentage point from different initial rates on 1) the expected percentage change in PV capacity growth, 2) the expected percentage change in PV capacity growth given there is added PV capacity, and 3) the probability of having PV capacity additions.

To summarize, during 2010-2020, other things equal, a one-percentage-point increase in the income tax credit rate raised PV capacity growth by 8-12%, and a one-percentage-point rise in the exempted property tax rate led to a roughly 5% increase in PV capacity growth. On the other hand, estimates on cash rebates and sales tax exemption are not statistically significant.

Note that the marginal effects increase with the initial incentive rates. Crago and Chernyakhovskiy (2017) find similar results for cash incentives. This finding suggests that an incentive appears more attractive to residents when its base rate is higher, which adds to the evidence of the close relationship between incentive effectiveness and incentive size.

Table 2.5 Marginal effects: Cash rebates

	(1)	(2)	(3)
Initial rate (%)	E(Y)	E(Y|Y>0)	P(Y>0)
Mean=7.815	0.023	0.020	0.004
	(0.013)	(0.011)	(0.002)
0	0.022	0.019	0.004
	(0.012)	(0.010)	(0.002)
5	0.023	0.020	0.004
	(0.013)	(0.011)	(0.002)
10	0.024	0.020	0.004
	(0.014)	(0.011)	(0.002)
15	0.024	0.021	0.004
	(0.014)	(0.012)	(0.002)
20	0.025	0.021	0.004
	(0.015)	(0.013)	(0.002)

N=5552. Y=ln(added PV capacity). Marginal effects are estimated under model 2 of Table 2.3. Standard errors clustered by state are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.6 Marginal effects: Income tax credits

Initial rate (%)	(1) E(Y)	(2) E(Y|Y>0)	(3) P(Y>0)
Mean=6.176	0.094*	0.077*	0.017*
	(0.040)	(0.031)	(0.007)
0	0.078**	0.065**	0.017*
	(0.026)	(0.022)	(0.007)
5	0.091*	0.075*	0.017*
	(0.037)	(0.029)	(0.007)
10	0.104*	0.084*	0.016*
	(0.048)	(0.038)	(0.006)
15	0.116*	0.095*	0.015**
	(0.057)	(0.046)	(0.005)
20	0.126	0.105	0.012***
	(0.065)	(0.055)	(0.002)

N=5552. Y=ln(added PV capacity). Marginal effects are estimated under model 2 of Table 2.3. Standard errors clustered by state are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.7 Marginal effects: Sales tax exemptions

Initial rate (%)	(1) E(Y)	(2) E(Y|Y>0)	(3) P(Y>0)
Mean=3.168	0.094	0.078	0.015
	(1.014)	(0.832)	(0.165)
0	0.086	0.073	0.015
	(0.852)	(0.710)	(0.167)
2	0.091	0.076	0.015
	(0.955)	(0.786)	(0.167)
4	0.096	0.080	0.015
	(1.056)	(0.865)	(0.163)
6	0.100	0.084	0.015
	(1.156)	(0.945)	(0.157)
8	0.105	0.087	0.015
	(1.253)	(1.026)	(0.146)

N=5552. Y=ln(added PV capacity). Marginal effects are estimated under model 2 of Table 2.3. Standard errors clustered by state are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 2.8 Marginal effects: Property tax exemptions

Initial rate (%)	(1) E(Y)	(2) E(Y|Y>0)	(3) P(Y>0)
Mean=1.128	0.479*	0.405*	0.079*
	(0.204)	(0.167)	(0.032)
0	0.408**	0.352**	0.078*
	(0.144)	(0.123)	(0.032)
0.5	0.440**	0.375**	0.079*
	(0.170)	(0.142)	(0.033)
1	0.471*	0.399*	0.079*
	(0.197)	(0.162)	(0.033)
1.5	0.502*	0.424*	0.078*
	(0.223)	(0.183)	(0.031)
2	0.533*	0.448*	0.077**
	(0.248)	(0.204)	(0.029)

N=5552. Y=ln(added PV capacity). Marginal effects are estimated under model 2 of Table 2. Standard errors clustered by state are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.5.4 Policy age

I then test how the age of a policy, i.e., the number of years since its adoption when the policy was in place, affected residential PV adoption. Net metering, with various starting years across states, can be included this time. As shown in Table 2.9, estimates on property tax exemptions and cash rebates are statistically and substantively significant across specifications. Estimates on net metering, though not statistically significant in some specifications, are substantive in magnitude.

The results indicate that residential PV adoption increased with each additional year these incentives were in place, underscoring the strong relationship between these policies and the formation of the residential PV market. This trend aligns with previous studies that highlighted the efficacy of cash incentives in driving residential solar adoption during the 2000s (e.g., Sarzynski, Larrieu, and Shrimali 2012, Crago and Chernyakhovskiy 2017).

It is worth noting that property tax exemptions and net metering are two of the oldest incentives for solar energy in the United States. On average, property tax exemptions

became available in 1990, and net metering in 1997 among the sample states. The results suggest that they demonstrated enduring impacts on residential PV adoption.

Table 2.9 Effect of policy age on residential PV adoption

	Tobit		Poisson	
	(1)	(2)	(3)	(4)
	Capacity	Count	Capacity	Count
Yr_Cash	0.125**	0.107***	0.052**	0.055**
	(0.041)	(0.029)	(0.017)	(0.020)
Yr_Income tax	0.030*	0.017	0.011*	0.009
	(0.014)	(0.011)	(0.005)	(0.005)
Yr_Sales tax	-0.375*	-0.280	-0.104	-0.110
	(0.163)	(0.153)	(0.094)	(0.106)
Yr_Property tax	0.802***	0.611**	0.243*	0.264*
	(0.231)	(0.210)	(0.109)	(0.123)
Yr_SREC	0.133	0.113	-0.001	-0.001
	(0.127)	(0.113)	(0.036)	(0.039)
Yr_Loan	0.051*	0.038*	0.016	0.016
	(0.020)	(0.016)	(0.009)	(0.010)
Yr_RPS	0.031	0.042	0.020	0.041
	(0.166)	(0.115)	(0.081)	(0.086)
Yr_Net metering	0.557***	0.405**	0.189*	0.188
	(0.164)	(0.151)	(0.087)	(0.099)
Yr_Solar rights	-0.064	-0.083	0.039	0.038
	(0.077)	(0.070)	(0.024)	(0.027)

N=5552. Columns 1-2 show Tobit estimation results. Columns 3-4 show Poisson estimation results. Dependent variable is ln(added PV capacity) in columns 1 and 3 and ln(PV installations) in columns 2 and 4. All models are estimated with county-level controls for solar insolation, state average residential electricity price, demographics (median household income, median housing value, housing density, median age, share of people with bachelor's degree or higher in the population aged 25 years and over, share of Democratic votes in the nearest Presidential election), an offset for ln(owner-occupied housing units), and state and year fixed effects. Standard errors clustered by state are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

2.6 Conclusion

In this essay, I find that over the period of 2010-2020, income tax credits significantly promoted residential PV adoption, and a one-percentage-point increase in the income tax credit rate raises PV capacity growth by 8-12%. By contrast, the stimulating effects of cash rebates were smaller and vaguer. I have less confidence in concluding that property tax exemptions had positive effects on residential PV adoption, and there is no substantial evidence to support significant effects from sales tax exemptions or subsidized

loans. I cannot draw meaningful conclusions on the effectiveness of SRECs from this analysis.

Combined with findings in previous studies, the results indicate that neither the cash rebate nor the income tax credit is inherently more effective than the other, but the size of the incentive matters. In addition, I find that the combined incentive amount does not determine the effectiveness of the financial incentives, and an incentive appears more attractive to residents when its base rate is higher. This implies that to promote residential solar adoption, rather than distributing the budget among multiple incentives with the same purpose, state governments should concentrate the investment on one financial incentive and set the rate of the chosen incentive at a level high enough to attract residential customers.

The findings also suggest that states may keep offering or start to offer property tax exemptions for residential PV systems. This incentive is relatively affordable for governments, as the expenditure is spread over time, and the administrative burden is minimal, making it a feasible option for encouraging residential solar adoption.

Chapter 3: Distributional Effects of Income-based Financial Incentives for Solar Energy: Evidence from California

Financial incentives for solar energy adoption often favor higher-income households, as they are more capable of investing in solar installations and tend to opt for larger systems (Coffman et al. 2016, Borenstein 2017). However, as discussed in Section 1.4.1, ensuring fair access to solar energy is essential for realizing the efficiency and energy security objectives of solar subsidies and securing the political feasibility of these incentive programs. To promote PV adoption equity, some governments have introduced supplemental programs with high incentive rates targeting low-income households. The California Solar Initiative (CSI), one of the largest state-level financial incentive programs for solar energy in the United States, is an example of this practice. The initiative consisted of rebate programs for both the general market and low-income families, with rebate rates declining with income. This study takes advantage of CSI data to examine how an income-based incentive structure impacts the distribution of financial incentives.

I find that for single-family PV systems installed between 2011 and 2016, although most CSI rebate receivers were middle- or high-income households, most rebate amounts were directed towards low-income households as they benefited from substantially higher rebate rates compared to their higher-income counterparts. However, customers who purchased systems only received around 35% of rebate benefits, and low-income households earning less than $50,000 per year only received around 25%. The rest of the benefits were captured by solar system sellers and installers. These low pass-through rates to customers resulted from the dominance of major suppliers in the market and excessive subsidization within the low-income program.

This essay proceeds as follows. Section 3.1 introduces the relevant components of CSI and summarizes existing literature. Section 3.2 proposes the research question. Section 3.3 explains the empirical approach. Section 3.4 describes the data. Section 3.5 presents and discusses the results. Finally, Section 3.6 concludes with policy implications.

3.1 Background

3.1.1 California Solar Initiative

In January 2007, California launched the Go Solar California campaign, a $3.3-billion effort to install 3,000 megawatts of new distributed solar capacity within the following decade and transform the market for solar energy by reducing the cost of solar equipment. The portion of the effort overseen by the California Public Utilities Commission (CPUC) is known as the California Solar Initiative (CSI). Funded by electricity ratepayers, CSI provided cash rebates for solar system installations under several programs. To analyze the distributional effects of CSI rebates, this study focuses on two programs: the General Market program and the Single-family Affordable Solar Homes program (SASH). Both programs subsidized PV systems installed on single-family homes, enabling an estimation of the system user's household income that would be difficult for installations on multi-family properties. Table 3.1 summarizes the CSI incentive structure for single-family systems under the General Market program and SASH.

The General Market program, the largest CSI component that ended in 2016, offered rebates to all eligible customer-sited solar electric generating (typically PV) systems with the service territories of three large utilities[8]. The incentive amount was based on system capacity, which is a system's expected generation output. The rebate rate

[8] Pacific Gas and Electric Company (PG&E), Southern California Edison Company (SCE), and San Diego Gas & Electric Company (SDG&E).

decreased with the cumulated installed capacity of the program and gradually declined from $2.5 to $0.2 per watt over time for residential systems.

Table 3.1 CSI incentive structure: Single-family systems

Program	Income	Federal tax liability	Rebate ($/watt)	
			Before 2015	2015 and after
General Market	N/A	N/A	0.2-2.5 depending on application time	
SASH	≤80% AMI	$1,001+	4.75 or 6	
		$1-1,000	5.25 or 6.5	3
		$0	5.75 or 7	
SASH	≤50% AMI	N/A	Free 1kw system	Cancelled

Note: For each level of federal tax liability, SASH rebate rates varied depending on household size and income before 2015.

SASH provides rebates for solar installations to eligible low-income owners of existing single-family homes. It was reauthorized in 2015 and ended in 2022. The original SASH program, known as SASH 1.0, fully subsidized a one-kilowatt system (capped at $10,000 per system, i.e., $10 per watt) for households with income not exceeding 50% of the area median income (AMI). However, these one-kilowatt systems were relatively small compared with an average U.S. residential PV system, typically possessing a capacity of around five kilowatts. Regardless of system size, households with income not exceeding 80% of AMI were eligible for incentives ranging from $4.75 to $7 per watt. The specific rate within this range was determined based on household size, income level, and federal tax liability. Rebate rates were classified into two categories and decreased with tax liability under each category. The eligibility for the higher category mainly included an income cap increasing with household size. SASH 2.0, the program reauthorized in 2015, offered a universal incentive of $3 per watt to households with income not exceeding 80% of AMI.

SASH 1.0 and 2.0 incentive rates did not decline over time like those in the market-transforming General Market program. Systems installed under the General Market

program were not eligible for SASH even if the customer may have qualified for SASH. Unlike the General Market Program, which was administered by the three large utilities in their respective service territories, SASH was solely administered by GRID Alternatives, a Californian nonprofit solar installer. All SASH customers purchased systems from GRID Alternatives and most of them also chose the organization as the installer.

3.1.2 Existing Literature

Researchers generally find renewable energy subsidies highly regressive as the high costs associated with installing renewable energy systems create barriers for lower-income groups to take advantage of the subsidies. For example, Reames (2020) found that higher rooftop PV penetration was associated with higher-income census tracts. Borenstein (2017) discovered that compared with all customers of the Pacific Gas and Electric Company, CSI General Market customers were highly concentrated in high-income groups, though such concentration declined over time. Borenstein and Davis (2016) showed that for two federal residential energy credits[9], average credit amounts increased steadily with annual gross income and there was a near zero take-up among tax filers earning less than $20,000 a year.

Moreover, a rebate does not necessarily translate into equal amounts of reduction in final prices, as suppliers selling and installing the systems may increase prices in response to customers' higher willingness to pay after rebates. Rebate benefits are often distributed unequally between customers and suppliers, and the pass-through rate of rebates reflects the share of benefits received by customers, i.e., the reduction in customers' out-of-pocket expenses incurred by a unit increase in rebates. Driven by the wealth disparity between consumers and suppliers, including their shareholders, this rate influences

[9] The nonbusiness energy property credit and the residential energy efficient property credit. Only the latter is relevant to residential solar panels.

distributional equity among different income groups. Additionally, it reflects the cost-effectiveness of rebates in fulfilling their primary objective of lowering the expenses associated with PV systems for customers.

Several recent studies have estimated the pass-through rate of CSI General Market rebates. Using data from CSI and its predecessor program from 2001 to 2012, Dong, Wiser, and Rai (2018) identified nearly full pass-through for host-owned (HO) systems (bought upfront by customers), while Li (2018) found a 62% pass-through for third-party-owned (TPO) systems (rented by customers) between 2010 and 2014. By taking into account other solar incentives including the federal Investment Tax Credit (ITC) and using pretax system prices, Pless and van Benthem (2019) estimated that a $1 increase in rebates translated into a $0.78 reduction in solar system prices for HO systems and a $1.53 reduction for TPO systems during 2010-2013. They attributed the over-shifting in the TPO market to imperfect competition and sufficiently convex demand. Part of the differences in the pass-through rate estimates among studies may be explained by the different market competition landscape in the sample markets and periods. Using CSI General Market data from 2006 to 2015, Chen (2018) discovered that for HO systems, large suppliers captured nearly all rebate benefits while small suppliers conceded most benefits to customers.

Existing research in the U.S. setting has focused on assessing the income distribution of PV adopters, but there is limited attention on how the benefits of state financial incentives for PV adoption, especially those with an income-based incentive structure, are distributed across income groups. O'Shaughnessy, Barbose, Wiser, Forrester, et al. (2021) demonstrated that from 2010 to 2018, CSI SASH and two other means-tested PV incentives in Connecticut and New York promoted PV adoption among low-income

residents and shifted PV deployment from high-income ZIP codes to low-income ones. However, they did not analyze to what extent these programs affected the distribution of PV incentive amounts across income groups. In addition, no existing study has explored whether the pass-through rate of financial incentives for renewable energy varies across income groups. This study aims to fill these gaps with evidence from CSI.

3.2 Research Questions

1) How was the CSI rebate for single-family PV systems distributed across income groups? How did this distribution differ between the General Market program and SASH? How did it differ between host-owned and third-party-owned systems?
2) What was the pass-through rate of the CSI rebate for single-family PV systems? How did it differ across income groups and between the General Market program and SASH?

3.3 Empirical Approach

3.3.1 Matching households to income brackets

CPUC does not provide income data of CSI applicants, but the American Community Survey (ACS) provides income distribution for each ZIP Code Tabulation Area (ZCTA)[10]. To match households to income brackets, I utilize the design factor of a PV system, a variable included in the CSI datasets. The design factor is a ratio comparing the system's simulated capacity with that of a baseline system[11]. The simulated capacity takes multiple product design features into account, so the design factor indicates the quality of system design, and a higher ratio indicates better quality. Since it is reasonable to assume that higher-income households tend to choose systems with better quality, I rank

[10] Developed by the U.S. Census Bureau, ZCTAs are generalized areal representations of USPS ZIP Code service areas.
[11] A baseline system is an optimal system with the same module count, module capacity, and inverter efficiency as the customer's system.

households based on their PV systems' design factors and assign them to income brackets according to the income distribution in their ZIP codes. This is the usage-rank method developed by Borenstein (2012b), who used electricity usage to rank and assign households to income brackets in a census block group.

However, solar system quality and household income may be uncorrelated (a negative correlation is implausible). In this case, households could be randomly allocated to income brackets based on the income distribution within a ZIP code. This random-rank method is similar to assigning AMI to all households as it gives every household the same expected income, but it utilizes the full income distribution in the ZIP code and is more informative than assigning every household the median income (Borenstein 2012b). As the true correlation between household income and solar system quality is likely positive but imperfect, I choose the usage-rank method for baseline analysis with the random-rank and AMI methods used for robustness checks.

The usage-rank method is flawed if the rebate amount is highly correlated with the design factor. In such a case, high-income groups will automatically earn high rebates as a result of this income ranking mechanism. Nevertheless, the correlation between rebate amount and design factor is only 0.02, qualifying the design factor as a ranking variable.

Another candidate for the ranking variable is the system capacity. It is reasonable to assume that higher-income households have higher electricity demand and would install systems with larger capacities. However, the correlation between system capacity and rebate amount is 0.9, which is too high for a ranking variable.

I improve the precision of this matching mechanism by utilizing the eligibility criteria of different CSI programs. Households with income no more than 80% of AMI

were eligible for SASH. Since SASH provided much more generous rebates than the General Market program, I assume that all applicants with income no more than 80% of AMI would opt for SASH and not the General Market program. This means that for the General Market program, no household is assigned to an income bracket with an upper limit lower than 80% of its ZIP code's AMI. I thereby calculate the share of households in income bracket g and ZIP code z for the General Market program as follows:

$$Share\ of\ Household_{gz} = \begin{cases} 0, brackets\ with\ upper\ limit < 80\% \times AMI_z \\ \dfrac{w_{gz}}{sum\ of\ w\ of\ all\ remaining\ brackets}, remaining\ brackets \end{cases}$$

where w is the share of households in an income bracket from the ACS income distribution data.

For SASH, households eligible for a free one-kilowatt system must earn no more than 50% of AMI, and the income of those eligible for other SASH incentives could not exceed 80% of AMI. I separate applicants of free one-kilowatt systems from other SASH applicants and respectively conduct income bracket matching for the two groups: in each ZIP code, no SASH applicant is assigned to an income bracket whose lower limit exceeds 80% (or 50% for the free program) of its ZIP code's AMI. The share of households in income bracket g and ZIP code z for SASH is calculated as follows:

$$Share\ of\ Household_{gz} = \begin{cases} 0, brackets\ with\ lower\ limit > 80\% \times AMI_z\ (50\%\ \text{for free 1kw program}) \\ \dfrac{w_{gz}}{sum\ of\ w\ of\ all\ remaining\ brackets}, remaining\ brackets \end{cases}$$

The income-based incentive structure of SASH 1.0 provides additional information to refine household income ranks within SASH. However, the sample includes both SASH

1.0 and 2.0 applicants, and a SASH 2.0 applicant receiving $3 per watt did not necessarily had less income than a SASH 1.0 applicant receiving at least $4.75 per watt. In addition, the SASH 1.0 incentive structure accounted for household size, so it is less useful in ranking total instead of per-capita income. Therefore, I do not further adjust income ranking using the incentive structure of SASH 1.0.

It is unlikely that the same household would install solar systems more than once within the sample period. Hence, I assume that each rebate application corresponds to a unique household and pool applicants in the same ZIP code as if they applied in the same year, despite they might have actually applied in different years during the sample period. I use the income distribution and AMI in 2011 for calculations in the income bracket matching process.

3.3.2 Analyzing distributional effects

After matching households to income brackets, I evaluate the distributional impacts of CSI rebates by analyzing total and per-watt rebates by income bracket for each program and single-family systems combined. I also compare the concentration curves and concentration indices, graphs and indices similar to the Lorenz curve and Gini coefficient for income equality analysis, between programs and ownership types.

In addition, I calculate the pass-through rate of CSI rebates for different income groups and programs. The CSI datasets include the total reported cost of a solar system before rebates. This variable reflects the true cost of a HO system as it is the price a customer pays to purchase the system. For TPO systems, this variable is an installer-reported value of a system. In the TPO model, third-party firms install the system on a customer's site, receive subsidies for the system upfront, and collect payments from the

customer over time. Since third-party firms have the incentive to overreport the value of the system to receive higher subsidies (Trabish 2013), the reported cost variable does not reflect the true price of a TPO system. The true price of TPO systems can be calculated with the negotiated payment terms in contracts between customers and third-party firms. Because TPO contract data is not publicly available, I exclude TPO systems from the pass-through rate analysis, limiting the sub-sample to HO systems.

The net price for an HO system is the total reported cost minus incentives, including the CSI rebate and the 30% federal ITC. While the actual ITC amount for each customer is not available, I assume it is fully monetized. Thus, for system *i*,

$$ITC_i = 0.3 \times (Purchase\ Price_i - Rebate_i)$$

And the net price of the system is the purchase price minus the CSI rebate and ITC.

Following Pless and van Benthem (2019), I use the reduced-form regression below to estimate the pass-through rate of CSI rebates for the General Market program, SASH, and single-family systems combined, and under each program, separately for different income brackets:

$$P_i = \beta_0 + \beta_1 Rebate_i + \beta_2 X_i + \beta_3 W_z + \delta_k + \varphi_u + \kappa_c + \tau_t + \varepsilon_i$$

where P_i is the net price ($/watt) of HO system i; $Rebate_i$ is the CSI rebate amount ($/watt); X_i is a set of control variables for system characteristics, including system capacity and system capacity squared; W_z is a set of ZIP-code level demographic control variables, including the share of people with a bachelor's degree or higher in the population over 25 years old and the logarithms of median income, median housing value, housing density, and median age; δ_k are county fixed effects; φ_u are utility fixed effects; κ_c are contractor fixed effects; τ_t are weekly dummy variables and their squares, which control

for the non-linear weekly pricing trend; and ε_i is the error term. Standard errors are clustered at the ZIP code level. In this specification, β_1 is the estimate for the pass-through rate, reflecting the change in the net price following a $1 increase in the rebate amount.

3.4 Data

CPUC provides application data for all CSI programs. Variables include application ID, incentive amount, total system cost, rebate date[12], host customer ZIP code, program category, ownership type, completion status, system characteristics, design factor, program administrator, utility, and contractor. ZIP-code level median income, income distribution, and demographic data come from the American Community Survey five-year estimates.

CPUC publishes two CSI datasets: a working dataset encompassing applications for both the General Market and low-income programs, and a low-income dataset that includes more detailed information for low-income programs. To construct the dataset used for this analysis, I use the working dataset as the foundation and complement it with information only available in the low-income dataset, such as the utility serving each low-income system.

The sample includes completed General Market and SASH applications in the residential sector reserved between 2011 and 2016. I begin my sample in 2011 as the ZIP-code level income profile was not publicly available before this year.[13] I end my sample in 2016, the year when the General Market program ended. Consistent with my practice in

[12] Following previous studies, I use "first reservation request review date" as the rebate date because it determines when rebates are reserved and has the least missing values among all date variables (Chen 2018).

[13] Census tracts are smaller statistical areas than ZIP codes and census-tract level income profile data before 2011 are available. However, while the census tract number of each application is available for SASH, CSI does not publish this information for the General Market program.

Chapter 2, I drop General Market systems with a capacity higher than 10 kilowatts as they are likely installations for multi-family housing properties. In addition, 45 observations are dropped from the sample for one of the following reasons: 1) missing data on income distribution or any of the covariates, 2) observations located in ZIP codes with zero population or housing units, or 3) abnormally high rebate rates exceeding $20 per watt. The final sample contains 91,651 applications, with 85,740 (94%) from the General Market program and 5,911 (6%) from SASH. The sample applications come from 1,220 ZIP codes, covering about 70% of all ZIP codes in California. The distribution of sample systems and the number of covered ZIP codes by program and year are presented in Appendix Tables A3.1 and A3.2.

Table 3.2 provides summary statistics for key variables by program over the sample period. Although lower in capacity and per-watt system price, SASH installations on average received higher rebate rates, highlighting the program's objective to provide substantial subsidies for low-income households. The TPO rate for SASH installations appears low in the sample period because TPO was not allowed for SASH until 2015. In 2015, 39% of SASH systems were installed under a TPO contract, and this share almost doubled in 2016, reaching 76%.

In terms of income and demographic profiles, compared to ZIP codes with General Market program installations, those with SASH installations tend to have higher housing density, higher shares of households in lower income brackets, and lower median household income, homeownership rate, median housing value, median age, and education level.[14] Overall, the sample means correspond to the nature of the two different programs.

[14] Note that the two groups of ZIP codes have overlaps.

Table 3.2 Summary statistics: Installed single-family systems, 2011-2016

		General Market (N=85,740)			SASH (N=5,911)			Combined (N=91,651)		
	Variable	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
System character-istics (System level)	Rebate ($/watt)	0.3	0.0	1.9	4.9	0.9	10.3	0.6	0.0	10.3
	System price ($/watt)	6.4	0.6	31.6	5.7	1.0	12.4	6.3	0.6	31.6
	System capacity (kW)	4.6	0.6	10.0	3.0	0.9	7.1	4.5	0.6	10.0
	Design factor	0.94	0.34	1.35	0.96	0.85	1.00	0.95	0.34	1.35
	Third-party ownership	0.7	0.0	1.0	0.2	0.0	1.0	0.6	0.0	1.0
Income, 2011 (ZIP code level)	Med. HH income ($)	63,381	37,672	89,605	57,798	38,753	89,605	63,021	37,672	89,605
	% HH, $0-10k	4.0	0.0	36.4	6.7	0.0	36.4	4.2	0.0	36.4
	% HH, $10-15k	3.7	0.0	35.0	6.9	0.0	24.7	3.9	0.0	35.0
	% HH, $15-25k	7.3	0.0	60.4	12.5	0.0	33.5	7.6	0.0	60.4
	% HH, $25-35k	7.6	0.0	50.0	11.8	0.0	26.6	7.8	0.0	50.0
	% HH, $35-50k	11.0	0.0	62.2	14.7	2.2	36.4	11.2	0.0	62.2
	% HH, $50-75k	16.5	0.0	54.8	18.2	3.3	31.4	16.6	0.0	54.8
	% HH, $75-100k	13.7	0.0	47.9	11.3	0.0	26.1	13.5	0.0	47.9
	% HH, $100-150k	18.3	0.0	65.9	11.3	0.0	32.7	17.8	0.0	65.9
	% HH, $150-200k	8.7	0.0	48.0	3.8	0.0	27.9	8.4	0.0	48.0
	% HH, $200k+	9.2	0.0	54.3	2.8	0.0	28.2	8.8	0.0	54.3
Demograph-ics and Housing (ZIP code level)	Housing units per km^2	413.0	0.0	11,989.1	441.3	0.4	6,652.5	414.8	0.0	11,989.1
	% Owner-occ. housing	67.5	4.8	100.0	54.4	6.0	90.9	66.6	4.8	100.0
	Med. housing val. ($)	427,550	14,251	1,836,629	259,451	53,322	1,365,553	416,708	14,251	1,836,629
	Median age	37.8	19.6	76.9	33.6	19.9	64.3	37.5	19.6	76.9
	% Bachelor's degree +	34.5	0.0	100.0	16.8	1.0	80.1	33.3	0.0	100.0

Note: All dollar values are adjusted to 2010 USD.

3.5 Results and Discussion

3.5.1 Distributional equity of CSI rebates

Table 3.3 presents the income distribution for the General Market program, SASH, and single-family applicants combined after matching households to income brackets using methods described in Section 3.3.1. This distribution is the same for the usage and random rank methods since they utilize the same income distribution data. Given that all General Market applicants are assigned to income brackets higher than 80% of AMI, and SASH applicants are assigned to income brackets not exceeding 50% or 80% of AMI depending on the incentive form, no General Market applicant falls into income brackets lower than $25,000, and no SASH applicant has an estimated income over $75,000 per year. The combined income distribution for all single-family applicants leans towards higher income brackets, with around 63% of households concentrated in brackets above $75,000 due to the dominance of General Market applicants in the sample. When assigning AMI to all households, only three income brackets ($35,000-50,000, $50,000-75,000, and $75,000-100,000) remain, with the highest bracket still having more households than the lowest. Overall, the income distribution of single-family applicants suggests that more middle- and high-income households benefited from CSI rebates than low-income ones.

Table 3.4 shows the average total and per-watt rebate by income bracket under the usage rank method. Results under the random rank and AMI methods are available in Appendix Tables A3.3 and A3.4. SASH applicants enjoyed much more generous per-watt rebates than General Market applicants. As a result, SASH applicants also received higher total rebates, even though SASH systems had a smaller average capacity. When considering single-family applicants as a whole, low-income households obtained higher

total and per-watt rebates than higher-income ones. Specifically, households with income lower than $25,000 received $5 per watt on average, while those earning more than $75,000 received less than $0.35 per watt. Results under the random rank and AMI methods also exhibit such progressivity, although with less stark contrast in rebate amounts under the AMI method due to its lower granularity and less variance in income distribution. Within each program, there is no salient difference in rebate amounts across income brackets.

These findings are visualized by the concentration curves and summarized by the concentration indices shown in Figure 3.1 (usage rank) and Appendix Figures A3.1 (random rank) and A3.2 (AMI method). In each graph, similar to the Lorenz curve, the solid line is the concentration curve of rebates, depicting the cumulative fraction of total rebates claimed by each percentile of applicants ranked by income. For comparison, the diagonal line, shown as the dashed line, indicates a rebate distribution proportional to income. Analogous to the Gini coefficient, the concentration index[15] is calculated as the ratio of the area between the concentration curve and the diagonal line to the total area under the diagonal line. A concentration index of zero indicates perfect equality, whereas a value of one denotes perfect inequality. The concentration index is negative when the concentration curve lies above the diagonal line and indicates that lower-income applicants receive a share of rebates larger than their share in the applicant population.

As shown in Figure 3.1, rebate amounts were almost proportional to income under each program, with the General Market rebates being slightly regressive and SASH rebates being slightly progressive. However, rebates for single-family systems had an overall

[15] Shown as “Gini” in the graph.

concentration index of -0.31, indicating that the generous SASH incentives significantly contributed to the progressivity of total rebates.

I then compare the rebate distribution for host-owned (HO) and third-party-owned (TPO) systems. TPO was available throughout the sample period for the General Market program, but only after 2015 for SASH under the SASH 2.0 scheme. To compare the two ownership types in the same period, I use a sub-sample covering the years 2015 and 2016. Figures 3.2 and 3.3 demonstrate that, for both ownership types, rebate distributions were almost proportional to income under the General Market program or SASH, while the concentration index for single-family systems combined was -0.29 for HO systems and -0.19 for TPOs. SASH rebates appeared to be less effective in promoting the overall progressivity of rebates under TPO than under HO. However, this difference in concentration indices mainly reflects the switch between the two SASH schemes and does not necessarily indicate that TPO rebates were less progressive than HO rebates by design. SASH TPO systems were only eligible for the $3-per-watt rebate universal for all SASH 2.0 applications, but some SASH HO systems reserved in 2015 and 2016 still received SASH 1.0 incentives ranging from $4.75 to $7 per watt. This discrepancy translates into lower average rebates for SASH TPO systems compared with their HO counterparts, diminishing their influence on the overall progressivity of rebates.

Notably, concentration indices for total rebates during 2015-2016 were higher than the index of the whole sample (-0.31), reflecting a decrease in the progressivity of the rebate program during the sample period. This shift can be partially attributed to the more substantial reduction in SASH rebate rates (from $4.75-7 to $3 per watt) compared to General Market rates (from $2.5 to $0.2) within the sample period.

To summarize, I find that within the General Market program or SASH, rebates were almost proportional to income during the sample period. However, the high levels of SASH rebates introduced a significant level of progressivity in total rebates for single-family systems.

Table 3.3 Income distribution: single-family applicants with installed systems, 2011-2016

	Usage/Random Rank Method						Area Median Income Method					
	General Market		SASH		Combined		General Market		SASH		Combined	
Income bracket	Count	Share (%)	Count	Share (%)	Count	Share (%)	Count	Share (%)	Count	Share (%)	Count	Share (%)
$0-10k	0	0.0	912	15.4	912	1.0	0	0.0	0	0.0	0	0.0
$10-15k	0	0.0	689	11.7	689	0.8	0	0.0	0	0.0	0	0.0
$15-25k	0	0.0	1,340	22.7	1,340	1.5	0	0.0	0	0.0	0	0.0
$25-35k	410	0.5	1,272	21.5	1,682	1.8	0	0.0	0	0.0	0	0.0
$35-50k	7,660	8.9	1,208	20.4	8,868	9.7	9,674	11.3	1,864	31.5	11,538	12.6
$50-75k	20,034	23.4	490	8.3	20,524	22.4	55,956	65.3	3,375	57.1	59,331	64.7
$75-100k	16,203	18.9	0	0.0	16,203	17.7	20,110	23.5	672	11.4	20,782	22.7
$100-150k	21,144	24.7	0	0.0	21,144	23.1	0	0.0	0	0.0	0	0.0
$150-200k	9,873	11.5	0	0.0	9,873	10.8	0	0.0	0	0.0	0	0.0
$200k+	10,416	12.2	0	0.0	10,416	11.4	0	0.0	0	0.0	0	0.0
Total	85,740	100.0	5,911	100.0	91,651	100.0	85,740	100.0	5,911	100.0	91,651	100.0

Table 3.4 Average rebate amount by income bracket: All systems, 2011-2016, usage rank

Income bracket	General Market		SASH		Combined	
	Total	Per watt	Total	Per watt	Total	Per watt
$0-10k	-	-	14,434.79	5.04	14,434.79	5.04
$10-15k	-	-	14,589.27	4.91	14,589.27	4.91
$15-25k	-	-	14,990.87	4.95	14,990.87	4.95
$25-35k	1,456.10	0.30	14,493.76	4.83	11,315.73	3.73
$35-50k	1,363.81	0.30	14,217.62	4.92	3,114.76	0.93
$50-75k	1,357.39	0.30	13,630.81	5.07	1,650.19	0.41
$75-100k	1,432.54	0.31	-	-	1,432.42	0.31
$100-150k	1,474.48	0.33	-	-	1,474.49	0.33
$150-200k	1,536.71	0.34	-	-	1,541.29	0.34
$200k+	1,552.01	0.34	-	-	1,548.27	0.34
Overall	1,445.80	0.32	14,480.52	4.94	2,286.47	0.62

Note: All values are in 2010 USD.

Figure 3.1 Concentration curves and indices: All systems,2011-2016, usage rank

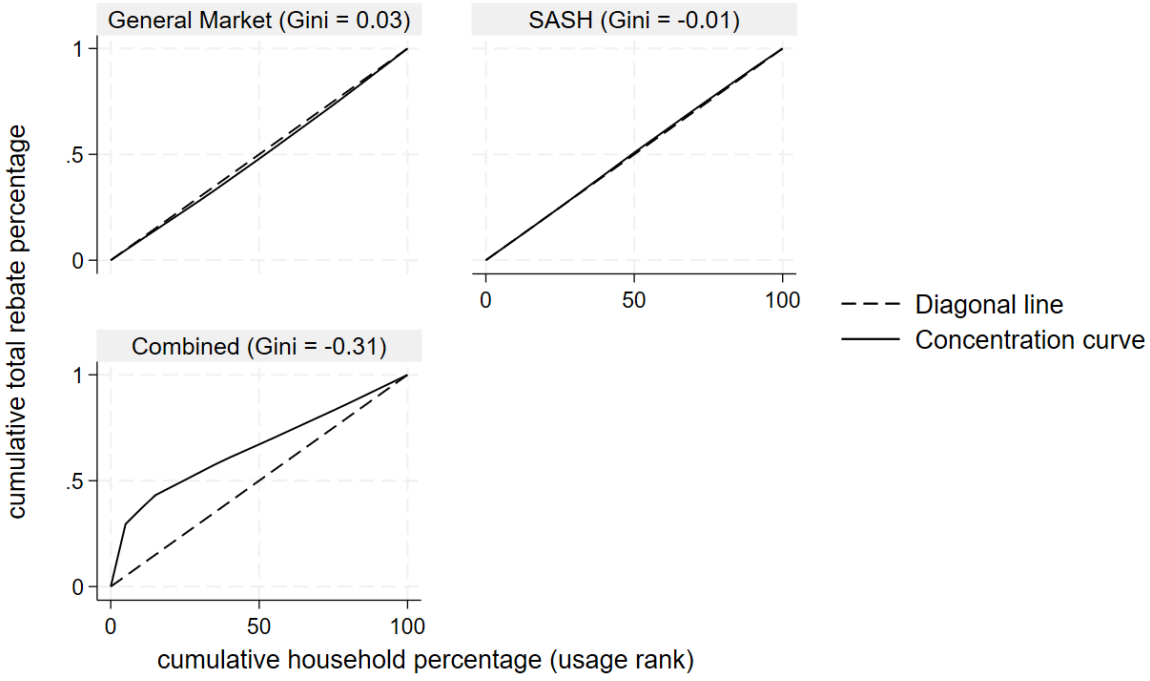


Figure 3.2 Concentration curves and indices: Host-owned systems, 2015-2016, usage rank

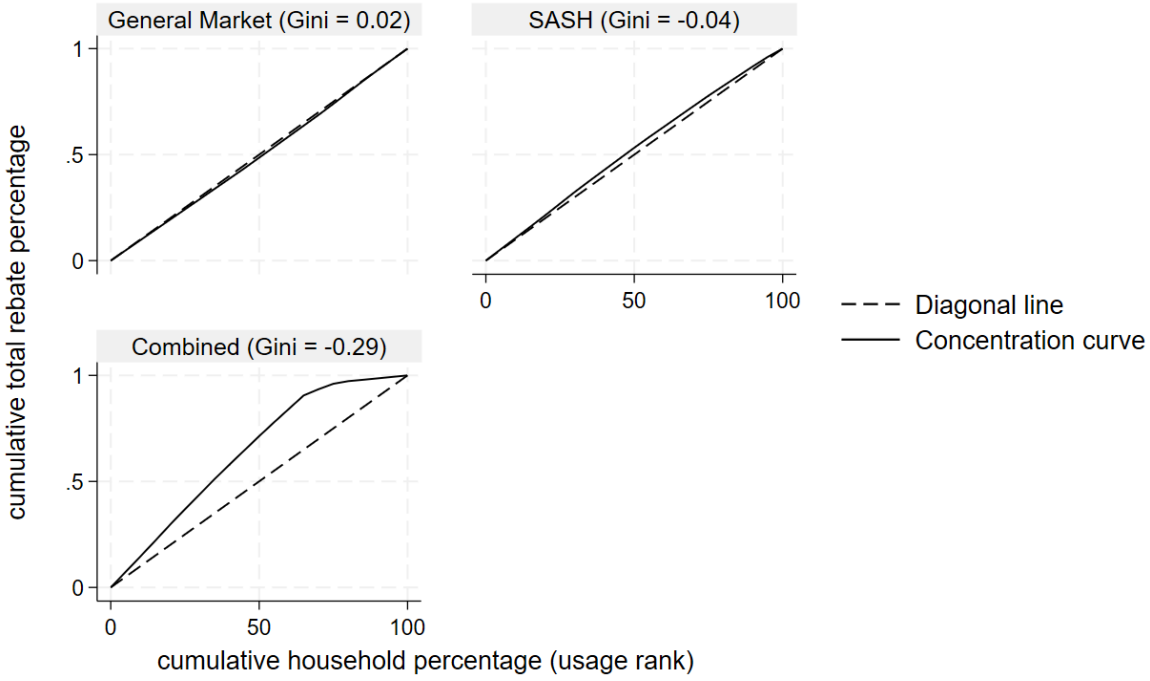
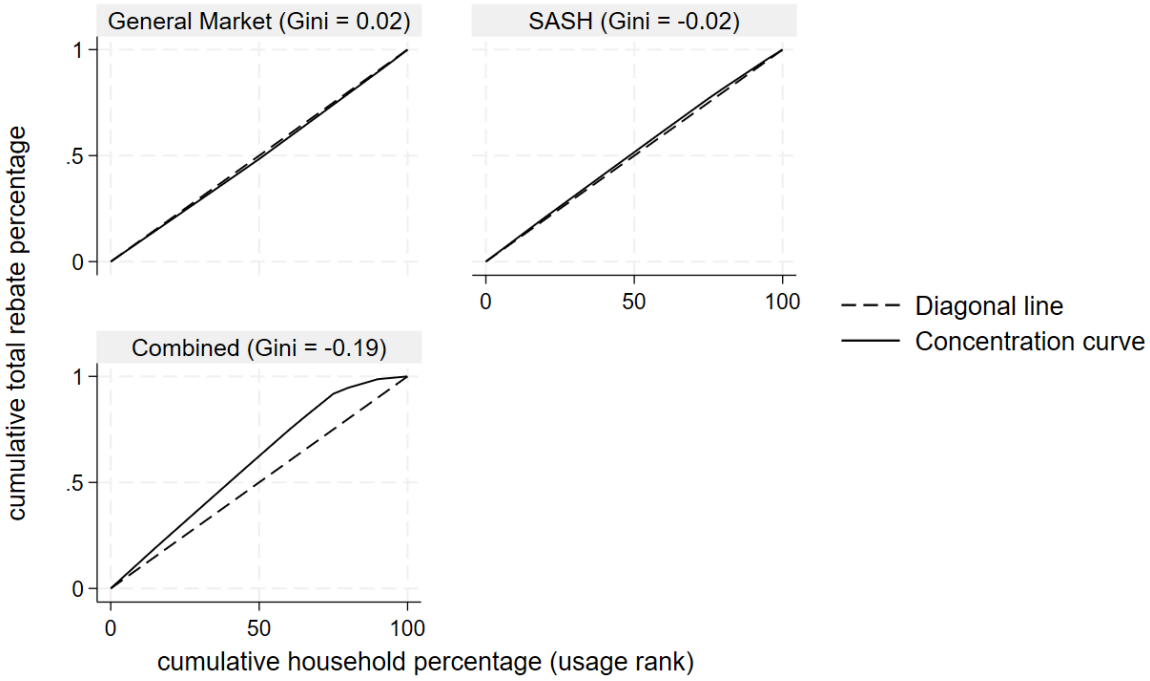


Figure 3.3 Concentration curves and indices: Third-party-owned systems, 2015-2016, usage rank



3.5.2 Pass-through rate for different programs and income groups

In this section, I estimate the pass-through rate of CSI rebates for single-family systems using the reduced form regression elaborated in Section 3.3.2 and study how it varied across programs and income groups. As previously explained, this pass-through analysis only applies to HO systems because the reported cost of a TPO system does not reflect its true price to households. The sample subset considered comprises 34,607 systems, consisting of 29,723 General Market program systems and 4,884 SASH systems.

As shown in Tables 3.5 and 3.6, over 2011-2016, a $1 increase in rebate per watt reduced the net system price by $0.35 per watt for single-family systems combined and by $0.41 per watt for General Market systems. These estimates are lower than those of Dong, Wiser, and Rai (2018) and Pless and van Benthem (2019), who found 78% to 100% pass-through among General Market systems in the 2000s and early 2010s. One possible explanation for this difference in the passthrough rate of General Market rebates is that in the 2010s, the residential PV market in California became more consolidated and less competitive, giving suppliers more pricing power. For General Market HO systems, compared with 2007-2010, during 2011-2016, the number of contractors decreased by 10%, and the number of contractors with at least 1% market share decreased by 15%. Only 65 out of the 1,404 solar contractors installed at least 100 systems in this period. They accounted for 5% of all contractors but installed 55% of the systems. Chen (2018) revealed that large suppliers could capture high shares of rebate benefits. Consistently, as shown in Appendix Table A3.7, I find that customers served by these top contractors only received 26% of rebate benefits, while those served by other contractors received 62%. These results

suggest that market consolidation could be a major contributor to the relatively low pass-through rate in the sample period.

Among all income groups, middle-income households earning between $75,000 and $100,000 per year experienced the highest pass-through rate, which slightly exceeded 50%, while low- and high-income households faced lower rates. Consistent patterns are observed under the random rank and AMI methods shown in Appendix Tables A3.5 and A3.6.

High-income households received a smaller portion of rebate benefits, probably because they were less sensitive to price, allowing suppliers to set higher prices and reap more benefits. Nevertheless, under the usage rank method, the richest households earning more than 150,000 per year received the second highest share of benefits (about 46%) among all income groups. They are also the only income group where more households chose smaller contractors installing fewer than 100 systems during the sample period rather than the top contractors. While 51% of households in this income group opted for smaller contractors, fewer than 45% of households in other income groups made this choice. This again suggests that market competition, which was more intense among smaller contractors, positively affected the pass-through rate of rebate benefits.

By contrast, low-income households earning no more than $50,000 received the lowest share (27%) of rebate benefits. Among these households, 26% applied for the General Market program. Table 3.6 shows that the estimate of their pass-through rate is not statistically significant, possibly because the number of observations in this group is not large enough compared with the number of fixed effects and clusters in the model, resulting in a weak statistical power to detect the effect of rebates on net prices. The rest

74% were SASH applicants. As presented in Table 3.7, their pass-through rate was around 25% and lower than that of their higher-income ($50,000-75,000) SASH counterparts.

The low pass-through rate among the lowest-income SASH applicants can be attributed to two main factors. First, GRID Alternatives was the sole seller of SASH systems and installed 93% of SASH HO systems in the sample. Consequently, the monopoly status of GRID Alternatives reduced the bargaining power of SASH applicants compared to higher-income households in the more competitive General Market. Second, 66% of sample SASH HO systems are fully subsidized, meaning their price equals the rebate amount, so their net price is always zero and would not be affected by variations in the rebate amount. These fully subsidized systems thereby drive down the magnitude of the correlation between rebates and net prices. As shown in Appendix Table A3.8, excluding fully subsidized systems increases the pass-through rate for SASH to 41%, a level close to that of General Market systems.

The prevalence of fully subsidized systems within SASH stems from the rebate rates under SASH 1.0. Out of the 3,223 fully subsidized HO systems, only 22 were intentionally designed as free one-kilowatt systems for households with incomes no higher than 50% of AMI. The remaining systems were fully subsidized because their reported per-watt system price matched their rebate rate. Per CPUC regulations, SASH rebates should not exceed the applicant's out-of-pocket expenses. Therefore, when the rebate rate was sufficient to cover the unit system price, customers found themselves indifferent to any unit price not exceeding the rebate rate, as lower prices would not increase the actual benefits they received. Under such circumstances, suppliers were incentivized to set the system price at a level equal to the total eligible rebate to maximize the rebate benefits they

obtained. From 2011 to 2015, PV system cost in the United States declined from $6.62 to $3.36 per watt (Feldman et al. 2021), while SASH 1.0 rebate rates remained unadjusted at $4.75 to $7 per watt. The high levels of SASH 1.0 incentives were likely more than enough to cover PV system prices in California. This explains why most sample SASH HO systems were installed out of the free one-kilowatt program but still fully subsidized.

The two factors explaining the relatively low pass-through rate for SASH customers suggest that this low rate does not reflect an unequal distribution of rebate benefits between high- and low-income households, but rather reflects the inefficiency of SASH rebates attributable to its incentive design. Nevertheless, the high incentive levels of SASH 1.0 had at least three distributional effects, particularly within the low-income community. First, while households who earned no more than 50% of AMI and participated in the free program were eligible for a one-kilowatt system at most, households with comparable or even higher incomes who applied for other SASH 1.0 incentives could receive free but larger systems. This impaired the distributional equity among low-income households and put the necessity of the free program into question. Second, considering the per-watt cost of PV systems, the range of SASH 1.0 rebate rates ($2.25) is relatively wide, which might have encouraged suppliers to approach and pick the lowest-income households, thereby sharing benefits from the highest rebate rate. The generous $7-per-watt level, only available to applicants with zero tax liability, applies to 60% of fully subsidized systems in the sample. This might have increased the welfare of the most financially disadvantaged but could be considered inequitable for other low-income households. Third, PV system suppliers rather than consumers received the part of rebates exceeding the fair market price of a system. As shown in Table 3.7, around 75% of SASH rebates were reaped by suppliers.

Although GRID Alternatives is a non-profit promoting solar adoption among low-income communities, the low pass-through rate raises the question of to what extent these rebates should be used to subsidize suppliers.

SASH 1.0 was replaced by SASH 2.0 in 2015. The free one-kilowatt program was discontinued, and the rebate rate decreased to $3 per watt for all applicants. While the depleting budget largely drove the reform, the problems and consequences discussed above might have also played a role.

To summarize, from 2011 to 2016, households purchasing PV systems received around 35% of CSI rebate benefits, a relatively low level partly due to the market power of a few large suppliers. Specifically, customers of the General Market program received 41%, while SASH customers received only 25%. Across income groups, middle-income households received the highest share, about 50%, of rebate benefits, while the lowest income group received the lowest share, which is less than 30%. This disparity resulted from the over-subsidization under the SASH 1.0 scheme and the monopoly in the SASH market.

Table 3.5 Passthrough rate by income bracket: Combined host-owned systems, 2011-2016, usage rank

	(1) All	(2) $0-50k	(3) $50-75k	(4) $75-100k	(5) $100-150k	(6) $150k+
Rebate per watt	-0.345***	-0.273***	-0.418***	-0.512***	-0.324**	-0.459***
	(0.021)	(0.024)	(0.075)	(0.123)	(0.102)	(0.087)
System capacity	-0.425***	-0.490***	-0.470***	-0.317***	-0.383***	-0.380***
	(0.018)	(0.055)	(0.040)	(0.038)	(0.032)	(0.029)
System capacity^2	0.030***	0.039***	0.033***	0.022***	0.027***	0.026***
	(0.002)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)
Ln (Median income)	-0.078*	-0.133*	0.066	0.073	0.023	0.024
	(0.037)	(0.067)	(0.083)	(0.079)	(0.064)	(0.062)
Ln (Med. hous. val.)	0.100**	0.159*	0.164	0.098	0.100	0.072
	(0.037)	(0.066)	(0.091)	(0.073)	(0.069)	(0.065)
Ln (Hous. density)	0.011*	0.015	-0.010	-0.009	0.010	0.013
	(0.006)	(0.009)	(0.013)	(0.012)	(0.010)	(0.010)
Ln (Median age)	0.106*	-0.036	0.071	-0.154	0.205*	0.322***
	(0.051)	(0.093)	(0.115)	(0.117)	(0.086)	(0.086)
% Bachelor's +	0.000	-0.002	0.004	0.003	0.000	-0.001
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
R^2	0.85	0.93	0.85	0.81	0.77	0.73
Observations	34,607	5,974	5,677	5,153	7,728	10,075
Clusters	1,160	665	926	879	906	916

Note: Dependent variable is net system price per watt. All models are estimated with weekly quadratic time trends and county, utility, and contractor fixed effects. Standard errors clustered by ZIP code are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.6 Passthrough rate by income bracket: Host-owned General Market systems, 2011-2016, usage rank

	(1) All	(2) $0-50k	(3) $50-75k	(4) $75-100k	(5) $100-150k	(6) $150k+
Rebate per watt	-0.403***	-0.166	-0.272*	-0.512***	-0.324**	-0.459***
	(0.055)	(0.309)	(0.137)	(0.123)	(0.102)	(0.087)
System capacity	-0.405***	-0.630***	-0.463***	-0.317***	-0.383***	-0.380***
	(0.018)	(0.136)	(0.040)	(0.038)	(0.032)	(0.029)
System capacity^2	0.028***	0.047***	0.032***	0.022***	0.027***	0.026***
	(0.002)	(0.011)	(0.004)	(0.003)	(0.003)	(0.003)
Ln (Median income)	-0.063	-0.034	0.066	0.073	0.023	0.024
	(0.038)	(0.170)	(0.087)	(0.079)	(0.064)	(0.062)
Ln (Med. hous. val.)	0.114**	0.112	0.205*	0.098	0.100	0.072
	(0.040)	(0.148)	(0.093)	(0.073)	(0.069)	(0.065)
Ln (Hous. density)	0.006	0.017	-0.016	-0.009	0.010	0.013
	(0.006)	(0.025)	(0.014)	(0.012)	(0.010)	(0.010)
Ln (Median age)	0.139**	0.124	0.053	-0.154	0.205*	0.322***
	(0.053)	(0.189)	(0.119)	(0.117)	(0.086)	(0.086)
% Bachelor's +	0.001	0.005	0.004*	0.003	0.000	-0.001
	(0.001)	(0.005)	(0.002)	(0.002)	(0.002)	(0.001)
R^2	0.73	0.80	0.78	0.81	0.77	0.73
Observations	29,723	1,524	5,243	5,153	7,728	10,075
Clusters	1,122	431	911	879	906	916

Note: Dependent variable is net system price per watt. All models are estimated with weekly quadratic time trends and county, utility, and contractor fixed effects. Standard errors clustered by ZIP code are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.7 Passthrough rate by income bracket: Host-owned SASH systems, 2011-2016, usage rank

	(1) All	(2) $0-35k	(3) $35-50k	(4) $50-75k
Rebate per watt	-0.253***	-0.250***	-0.253***	-0.296***
	(0.018)	(0.019)	(0.040)	(0.068)
System capacity	-0.786***	-0.778***	-0.761***	-1.020***
	(0.079)	(0.081)	(0.108)	(0.177)
System capacity^2	0.090***	0.091***	0.081***	0.117***
	(0.010)	(0.010)	(0.013)	(0.026)
Ln (Median income)	-0.217***	-0.228***	-0.205	0.063
	(0.059)	(0.068)	(0.127)	(0.203)
Ln (Med. hous. val.)	0.176**	0.224**	0.044	-0.177
	(0.057)	(0.074)	(0.107)	(0.257)
Ln (Hous. density)	0.009	0.007	0.014	0.031
	(0.008)	(0.009)	(0.016)	(0.030)
Ln (Median age)	0.009	0.006	-0.009	0.335
	(0.075)	(0.087)	(0.128)	(0.507)
% Bachelor's +	-0.004*	-0.004	-0.000	-0.008
	(0.002)	(0.002)	(0.003)	(0.006)
R^2	0.61	0.63	0.70	0.75
Observations	4,884	3,427	1,023	434
Clusters	437	421	251	108

Note: Dependent variable is net system price per watt. All models are estimated with weekly quadratic time trends and county, utility, and contractor fixed effects. Standard errors clustered by ZIP code are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

3.6 Conclusion

In this essay, I study the distributional impacts of the California Solar Initiative (CSI) rebates, an example of income-based financial incentive programs for residential PV adoption. I match rebate recipients to income brackets by using the design factor, an indicator of solar system quality, as a proxy of the system user's income level. I find that from 2011 to 2016, rebates for single-family systems were significantly progressive. Most rebates were directed to low-income households thanks to the high rebate rates of the means-tested SASH program.

This analysis also reveals that in the market for host-owned systems, only around 35% of CSI rebate benefits were received by customers instead of suppliers. This relatively low pass-through rate is possibly due to the high pricing power of the largest suppliers. Moreover, low-income households earning less than $50,000 per year only received around 25% of the rebate benefits, for two reasons. First, the monopoly in the SASH market weakened the customers' bargaining power. Second, the excessive subsidies under the SASH 1.0 scheme allowed suppliers to reap the difference between the system cost and the total rebate, incentivizing them to set system prices higher than the fair market price. Additionally, this over-subsidization, in conjunction with the different subsidy forms under SASH, led to a scenario where a larger system could be gifted to a household with the same or even higher income than others, thereby impacting the horizontal and vertical equity of SASH rebates.

As California is an established solar market, the findings from this study are particularly relevant to mature markets but also offer insights for policymakers in emerging markets, providing considerations for later stages of market development. The findings add

evidence to the effectiveness of income-based incentive structures in promoting the distributional equity of financial incentives for PV adoption. They also underscore the importance of timely aligning incentive rates with system costs, particularly in a market where PV system prices change rapidly. In addition, to increase the share of incentive benefits received by customers, policymakers should avoid inhibiting market competition. They should also improve the access to information on available contractors, especially among low-income communities that are discriminated against by community-based or income-targeted marketing (O'Shaughnessy, Barbose, Wiser, Forrester, et al. 2021). Finally, the findings suggest that policymakers should be careful when creating different forms of incentives, as the interplay between incentive forms and their associated rates influences the distributional equity of the incentives.

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Appendix

Table A2.1 Mean of demographic covariates: Sample vs excluded counties, 2010-2020

Variable	Sample	Excluded
Median annual household income ($)	49,339.6	43,441.2
Median housing value ($)	176,742.2	101,833.0
Owner-occupied housing units	51,585.1	9,568.9
Housing units per km^2	132.4	9.8
Median age	40.3	40.7
Bachelor's degree+ in age 25+ (%)	24.4	18.0
Democrat votes in Presidential Elections (%)	42.4	28.6

Sample N=5,552. Excluded N=2,929. All monetary values are adjusted to 2010 USD. Median housing value is capped at $1M in ACS.

Table A2.2 Policy effect on residential PV adoption (County and year FEs)

	Tobit				Poisson			
	(1) Capacity Dummy	(2) Capacity Rate	(3) Count Dummy	(4) Count Rate	(5) Capacity Dummy	(6) Capacity Rate	(7) Count Dummy	(8) Count Rate
Cash	1.174	0.031*	0.888	0.023*	0.230	0.007	0.234	0.007
	(0.624)	(0.014)	(0.471)	(0.010)	(0.168)	(0.005)	(0.180)	(0.006)
Income tax	1.653**	0.153**	1.135**	0.105*	0.429**	0.039**	0.375*	0.035*
	(0.556)	(0.056)	(0.421)	(0.042)	(0.140)	(0.014)	(0.149)	(0.015)
Sales tax	-	0.243	-	0.112	-	0.003	-	-0.003
	-	(2.290)	-	(1.652)	-	(0.364)	-	(0.327)
Property tax	1.964***	0.536	1.395***	0.387	0.542**	0.201	0.471*	0.218
	(0.576)	(0.572)	(0.395)	(0.455)	(0.173)	(0.172)	(0.191)	(0.205)
1=SREC	1.198*	0.930*	0.975*	0.794	0.131	0.116	0.131	0.126
	(0.510)	(0.473)	(0.430)	(0.434)	(0.126)	(0.120)	(0.146)	(0.146)
1=Loan	0.019	-0.088	0.121	0.041	-0.101	-0.137	-0.101	-0.134
	(0.479)	(0.527)	(0.378)	(0.432)	(0.148)	(0.182)	(0.163)	(0.207)
1=RPS	0.063	-0.187	0.198	0.014	0.008	-0.078	0.074	-0.019
	(0.380)	(0.365)	(0.278)	(0.276)	(0.057)	(0.076)	(0.057)	(0.084)
1=Solar rights	-0.031	0.448	-0.194	0.144	0.149	0.276	-0.020	0.065
	(0.776)	(0.803)	(0.567)	(0.586)	(0.197)	(0.247)	(0.175)	(0.219)
Solar radiance	0.075***	0.069***	0.054***	0.049***	0.018*	0.016*	0.016*	0.014*
	(0.018)	(0.019)	(0.013)	(0.014)	(0.007)	(0.007)	(0.007)	(0.007)
Electricity price	0.565	0.543	0.395	0.375	0.114	0.115	0.109	0.109
	(0.347)	(0.356)	(0.263)	(0.271)	(0.078)	(0.086)	(0.080)	(0.089)
Ln(Med. income)	3.079*	2.601	2.711*	2.358*	2.271***	2.124**	3.028***	2.897***
	(1.492)	(1.367)	(1.253)	(1.174)	(0.684)	(0.738)	(0.761)	(0.825)
Ln(Med. hous. val.)	0.806	1.096	0.637	0.858	0.509	0.699	0.820	1.012
	(2.398)	(2.286)	(1.781)	(1.749)	(0.791)	(0.841)	(0.768)	(0.841)
Ln(Hous. density)	-10.706	-10.429*	-8.836*	-8.617*	-5.102*	-4.645*	-5.923*	-5.332*
	(5.504)	(4.889)	(4.165)	(3.713)	(2.070)	(2.069)	(2.419)	(2.514)
Median age	-0.014	-0.002	-0.049	-0.040	-0.109**	-0.107**	-0.136***	-0.134**
	(0.078)	(0.075)	(0.066)	(0.063)	(0.039)	(0.040)	(0.041)	(0.042)
Bachelor's+ %	0.037	0.021	0.030	0.018	-0.003	-0.010	-0.017	-0.024
	(0.042)	(0.038)	(0.033)	(0.030)	(0.023)	(0.025)	(0.030)	(0.032)
Democrat vote %	0.025	0.024	0.029	0.029	0.015	0.014	0.013	0.012
	(0.038)	(0.037)	(0.027)	(0.026)	(0.012)	(0.012)	(0.013)	(0.013)

N=5552. Columns 1-4 show Tobit estimation results. Columns 4-6 show Poisson estimation results. Dependent variable is ln(added PV capacity) in columns 1, 2, 5, 6 and ln(PV installations) in columns 3, 4, 7, 8. Cash and tax incentives are dummies in columns 1, 3, 5, 7 and incentive rates in columns 2, 4, 6, 8. Other policies are dummies in all specifications. All models are estimated with an offset for ln(owner-occupied housing units) and county and year fixed effects. Standard errors clustered by state are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A2.3 Policy effect on residential PV adoption (SE clustered by county)

	Tobit				Poisson			
	(1) Capacity Dummy	(2) Capacity Rate	(3) Count Dummy	(4) Count Rate	(5) Capacity Dummy	(6) Capacity Rate	(7) Count Dummy	(8) Count Rate
Cash	1.272***	0.031***	0.987***	0.025***	0.285***	0.010***	0.302***	0.011***
	(0.206)	(0.006)	(0.156)	(0.005)	(0.062)	(0.002)	(0.070)	(0.002)
Income tax	1.627**	0.154**	1.167**	0.111**	0.477**	0.047**	0.481**	0.048**
	(0.568)	(0.057)	(0.398)	(0.040)	(0.168)	(0.017)	(0.168)	(0.017)
Sales tax	-	0.166	-	0.046	-	0.075	-	0.106
	-	(0.683)	-	(0.566)	-	(0.198)	-	(0.213)
Property tax	1.638***	0.793***	1.107***	0.480**	0.523***	0.175*	0.509***	0.204*
	(0.326)	(0.202)	(0.240)	(0.157)	(0.136)	(0.087)	(0.131)	(0.096)
1=SREC	1.265***	0.973***	1.032***	0.842***	0.147**	0.108	0.131*	0.091
	(0.184)	(0.190)	(0.160)	(0.172)	(0.049)	(0.058)	(0.055)	(0.066)
1=Loan	-0.047	-0.181	0.088	0.005	-0.098	-0.127*	-0.095	-0.125
	(0.181)	(0.197)	(0.133)	(0.148)	(0.053)	(0.059)	(0.058)	(0.065)
1=RPS	-0.118	-0.396	0.071	-0.124	-0.044	-0.139	0.024	-0.088
	(0.259)	(0.263)	(0.169)	(0.172)	(0.096)	(0.099)	(0.096)	(0.100)
1=Solar rights	0.275	0.587***	0.151	0.333**	0.445***	0.561***	0.346***	0.436***
	(0.179)	(0.160)	(0.133)	(0.120)	(0.069)	(0.065)	(0.070)	(0.073)
Solar radiance	0.050***	0.049***	0.036***	0.035***	0.004	0.003	0.005	0.004
	(0.009)	(0.009)	(0.006)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)
Electricity price	0.648***	0.629***	0.473***	0.448***	0.136***	0.131***	0.131***	0.126***
	(0.089)	(0.085)	(0.069)	(0.066)	(0.024)	(0.025)	(0.026)	(0.028)
Ln(Med. income)	0.517	-0.177	0.319	-0.113	-0.023	-0.226	-0.019	-0.261
	(0.848)	(0.815)	(0.618)	(0.599)	(0.316)	(0.321)	(0.332)	(0.337)
Ln(Med. hous. val.)	0.150	0.886*	0.380	0.831**	0.374*	0.577**	0.376*	0.616**
	(0.389)	(0.385)	(0.285)	(0.278)	(0.161)	(0.190)	(0.163)	(0.193)
Ln(Hous. density)	-0.308**	-0.354***	-0.385***	-0.412***	-0.645***	-0.656***	-0.610***	-0.622***
	(0.096)	(0.097)	(0.073)	(0.074)	(0.037)	(0.039)	(0.040)	(0.041)
Median age	0.006	0.008	0.016	0.018	0.023*	0.022*	0.024**	0.024*
	(0.021)	(0.021)	(0.016)	(0.016)	(0.009)	(0.009)	(0.009)	(0.009)
Bachelor's+ %	0.038*	0.033	0.020	0.017	-0.004	-0.005	-0.004	-0.005
	(0.018)	(0.018)	(0.013)	(0.013)	(0.007)	(0.007)	(0.008)	(0.008)
Democrat vote %	0.018*	0.016	0.015*	0.013*	0.009**	0.008*	0.012**	0.011**
	(0.008)	(0.008)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)

N=5552. Columns 1-4 show Tobit estimation results. Columns 4-6 show Poisson estimation results. Dependent variable is ln(added PV capacity) in columns 1, 2, 5, 6 and ln(PV installations) in columns 3, 4, 7, 8. Cash and tax incentives are dummies in columns 1, 3, 5, 7 and incentive rates in columns 2, 4, 6, 8. Other policies are dummies in all specifications. All models are estimated with an offset for ln(owner-occupied housing units) and state and year fixed effects. Standard errors clustered by county are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A2.4 Policy availability by state and year

		Year										
Incentive	State	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Cash	AZ	N	N	N	N	N	N	N	N	N	N	N
rebate	CA	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	CT	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	DC	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y
	DE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	FL	Y	N	N	N	N	N	N	N	N	N	N
	MA	Y	Y	Y	Y	Y	N	N	N	N	N	N
	MN	Y	N	N	N	N	N	N	N	N	N	N
	NH	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NJ	Y	Y	N	N	N	N	N	N	N	N	N
	NM	N	N	N	N	N	N	N	N	N	N	N
	NY	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	OH	Y	N	N	N	N	N	N	N	N	N	N
	OR	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	TX	N	N	N	N	N	N	N	N	N	N	N
	VT	Y	Y	Y	Y	Y	N	N	N	N	N	N
Income tax	AZ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
credit	CA	N	N	N	N	N	N	N	N	N	N	N
	CT	N	N	N	N	N	N	N	N	N	N	N
	DC	N	N	N	N	N	N	N	N	N	N	N
	DE	N	N	N	N	N	N	N	N	N	N	N
	FL	N	N	N	N	N	N	N	N	N	N	N
	MA	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	MN	N	N	N	N	N	N	N	N	N	N	N
	NH	N	N	N	N	N	N	N	N	N	N	N
	NJ	N	N	N	N	N	N	N	N	N	N	N
	NM	Y	Y	Y	Y	Y	Y	Y	N	N	N	Y
	NY	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	OH	N	N	N	N	N	N	N	N	N	N	N
	OR	Y	Y	Y	Y	Y	Y	Y	Y	N	N	N
	TX	N	N	N	N	N	N	N	N	N	N	N
	VT	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

		Year										
Incentive	State	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Sales tax	AZ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
exemption	CA	N	N	N	N	N	N	N	N	N	N	N
	CT	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	DC	N	N	N	N	N	N	N	N	N	N	N
	DE	N	N	N	N	N	N	N	N	N	N	N
	FL	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	MA	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	MN	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NH	N	N	N	N	N	N	N	N	N	N	N
	NJ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NM	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NY	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	OH	N	N	N	N	N	N	N	N	N	N	N
	OR	N	N	N	N	N	N	N	N	N	N	N
	TX	N	N	N	N	N	N	N	N	N	N	N
	VT	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Property	AZ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
tax	CA	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
exemption	CT	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	DC	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y
	DE	N	N	N	N	N	N	N	N	N	N	N
	FL	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	MA	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	MN	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NH	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NJ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NM	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NY	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	OH	N	N	N	N	N	N	N	N	N	N	N
	OR	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	TX	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	VT	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

		Year										
Incentive	State	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
SREC	AZ	N	N	N	N	N	N	N	N	N	N	N
	CA	N	N	N	N	N	N	N	N	N	N	N
	CT	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	N
	DC	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	DE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	FL	N	N	N	N	N	N	N	N	N	N	N
	MA	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	MN	N	N	N	N	N	N	N	N	N	N	N
	NH	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NJ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NM	N	N	N	N	N	N	N	N	N	N	N
	NY	N	N	N	N	N	N	N	N	N	N	N
	OH	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	OR	N	N	N	N	N	N	N	N	N	N	N
	TX	N	N	N	N	N	N	N	N	N	N	N
	VT	N	N	N	N	N	N	N	N	N	N	N
Subsidized loan	AZ	N	N	N	N	N	N	N	N	N	N	N
	CA	N	N	N	N	N	N	N	N	N	N	N
	CT	N	N	N	Y	Y	Y	Y	Y	Y	Y	Y
	DC	N	N	N	N	N	N	N	N	N	N	N
	DE	Y	Y	Y	N	N	N	N	Y	Y	Y	Y
	FL	N	N	N	N	N	N	N	N	N	N	N
	MA	N	N	N	N	N	Y	Y	Y	Y	Y	Y
	MN	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NH	N	N	N	N	N	N	N	N	N	N	N
	NJ	N	N	N	N	N	N	N	N	N	N	N
	NM	N	N	N	N	N	N	N	N	N	N	N
	NY	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	OH	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	OR	Y	Y	Y	Y	Y	N	N	N	N	N	N
	TX	N	N	N	N	N	N	N	N	N	N	N
	VT	N	N	N	N	N	N	N	N	N	N	N

		Year										
Incentive	State	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
RPS	AZ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	CA	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	CT	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	DC	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	DE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	FL	N	N	N	N	N	N	N	N	N	N	N
	MA	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	MN	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NH	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NJ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NM	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NY	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	OH	Y	Y	Y	Y	Y	N	N	Y	Y	Y	Y
	OR	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	TX	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	VT	N	N	N	N	N	Y	Y	Y	Y	Y	Y
Net metering	AZ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	CA	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	CT	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	DC	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	DE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	FL	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	MA	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	MN	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NH	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NJ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NM	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NY	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	OH	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	OR	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	TX	N	N	N	N	N	N	N	N	N	N	N
	VT	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

		Year										
Incentive	State	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Solar rights	AZ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
regulations	CA	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	CT	N	N	N	N	N	N	N	N	N	N	N
	DC	N	N	N	N	N	N	N	N	Y	Y	Y
	DE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	FL	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	MA	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	MN	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NH	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NJ	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NM	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	NY	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	OH	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	OR	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	TX	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
	VT	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table A2.5 Incentive rate by state and year

		Year										
Incentive	State	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Cash	AZ	0	0	0	0	0	0	0	0	0	0	0
rebate	CA	17.2	11.2	8.4	6.7	6.0	6.4	6.7	7.1	7.3	7.2	7.3
	CT	27.3	30.1	8.6	9.6	10.7	11.5	12.1	12.7	13.1	12.9	13.0
	DC	7.8	8.6	11.9	13.4	0	16.1	16.9	17.7	18.3	18.1	18.2
	DE	40.4	37.2	41.1	40.0	39.0	22.5	23.6	24.8	25.6	25.3	25.5
	FL	62.4	0	0	0	0	0	0	0	0	0	0
	MA	10.9	12.0	16.7	18.8	21.0	0	0	0	0	0	0
	MN	23.4	0	0	0	0	0	0	0	0	0	0
	NH	3.1	3.4	4.8	5.4	6.0	6.4	6.7	7.1	7.3	7.2	7.3
	NJ	27.3	9.5	0	0	0	0	0	0	0	0	0
	NM	0	0	0	0	0	0	0	0	0	0	0
	NY	15.6	17.2	23.9	26.9	28.5	24.1	18.5	14.2	11.0	10.8	7.3
	OH	46.8	0	0	0	0	0	0	0	0	0	0
	OR	7.8	8.6	11.9	13.4	15.0	16.1	16.9	17.7	18.3	18.1	18.2
	TX	0	0	0	0	0	0	0	0	0	0	0
	VT	19.5	12.9	15.5	12.1	7.5	0	0	0	0	0	0
Income tax	AZ	25	25	25	25	25	25	25	25	25	25	25
credit	CA	0	0	0	0	0	0	0	0	0	0	0
	CT	0	0	0	0	0	0	0	0	0	0	0
	DC	0	0	0	0	0	0	0	0	0	0	0
	DE	0	0	0	0	0	0	0	0	0	0	0
	FL	0	0	0	0	0	0	0	0	0	0	0
	MA	15	15	15	15	15	15	15	15	15	15	15
	MN	0	0	0	0	0	0	0	0	0	0	0
	NH	0	0	0	0	0	0	0	0	0	0	0
	NJ	0	0	0	0	0	0	0	0	0	0	0
	NM	10	10	10	10	10	10	10	0	0	0	10
	NY	25	25	25	25	25	25	25	25	25	25	25
	OH	0	0	0	0	0	0	0	0	0	0	0
	OR	31	31	31	31	31	31	31	31	0	0	0
	TX	0	0	0	0	0	0	0	0	0	0	0
	VT	6.24	6.24	6.24	6.24	6.24	6.24	6.24	6.24	6.24	6.24	6.24

		Year										
Incentive	State	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Sales tax exemption	AZ	5.60	5.60	5.60	5.60	5.60	5.60	5.60	5.60	5.60	5.60	5.60
	CA	0	0	0	0	0	0	0	0	0	0	0
	CT	6.00	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35	6.35
	DC	0	0	0	0	0	0	0	0	0	0	0
	DE	0	0	0	0	0	0	0	0	0	0	0
	FL	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00
	MA	6.25	6.25	6.25	6.25	6.25	6.25	6.25	6.25	6.25	6.25	6.25
	MN	6.88	6.88	6.88	6.88	6.88	6.88	6.88	6.88	6.88	6.88	6.88
	NH	0	0	0	0	0	0	0	0	0	0	0
	NJ	7.00	7.00	7.00	7.00	7.00	7.00	7.00	6.88	6.63	6.63	6.63
	NM	5.13	5.13	5.13	5.13	5.13	5.13	5.13	5.13	5.13	5.13	5.13
	NY	8.52	8.52	8.48	8.48	8.48	8.48	8.49	8.49	8.49	8.49	8.52
	OH	0	0	0	0	0	0	0	0	0	0	0
	OR	0	0	0	0	0	0	0	0	0	0	0
	TX	0	0	0	0	0	0	0	0	0	0	0
	VT	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00	6.00
Property tax exemption (state mean)	AZ	0.65	0.69	0.76	0.81	0.82	0.81	0.81	0.78	0.75	0.74	0.71
	CA	0.61	0.69	0.77	0.82	0.83	0.82	0.80	0.78	0.77	0.76	0.76
	CT	1.48	1.56	1.65	1.75	1.82	1.88	1.93	1.98	2.01	2.04	2.04
	DC	0	0	0.54	0.57	0.57	0.56	0.56	0.55	0.55	0.56	0.57
	DE	0	0	0	0	0	0	0	0	0	0	0
	FL	0.85	0.91	0.96	1.00	1.01	0.99	0.96	0.92	0.89	0.86	0.83
	MA	0.95	0.99	1.04	1.08	1.12	1.14	1.15	1.17	1.18	1.19	1.18
	MN	0.93	0.97	1.02	1.04	1.06	1.05	1.05	1.04	1.04	1.02	1.02
	NH	1.79	1.87	1.96	2.05	2.10	2.14	2.17	2.20	2.21	2.22	2.19
	NJ	1.87	2.00	2.12	2.25	2.35	2.41	2.47	2.51	2.54	2.56	2.53
	NM	0.52	0.52	0.54	0.57	0.60	0.60	0.61	0.63	0.64	0.64	0.64
	NY	2.08	2.12	2.17	2.22	2.27	2.29	2.31	2.33	2.33	2.32	2.29
	OH	0	0	0	0	0	0	0	0	0	0	0
	OR	0.83	0.85	0.89	0.95	0.98	1.00	0.99	0.98	0.97	0.95	0.91
	TX	1.49	1.48	1.49	1.52	1.52	1.50	1.49	1.49	1.49	1.48	1.44
	VT	1.59	1.62	1.65	1.70	1.72	1.75	1.79	1.84	1.89	1.91	1.92

Figure A3.1 Concentration curves and indices: All systems, 2011-2016, random rank

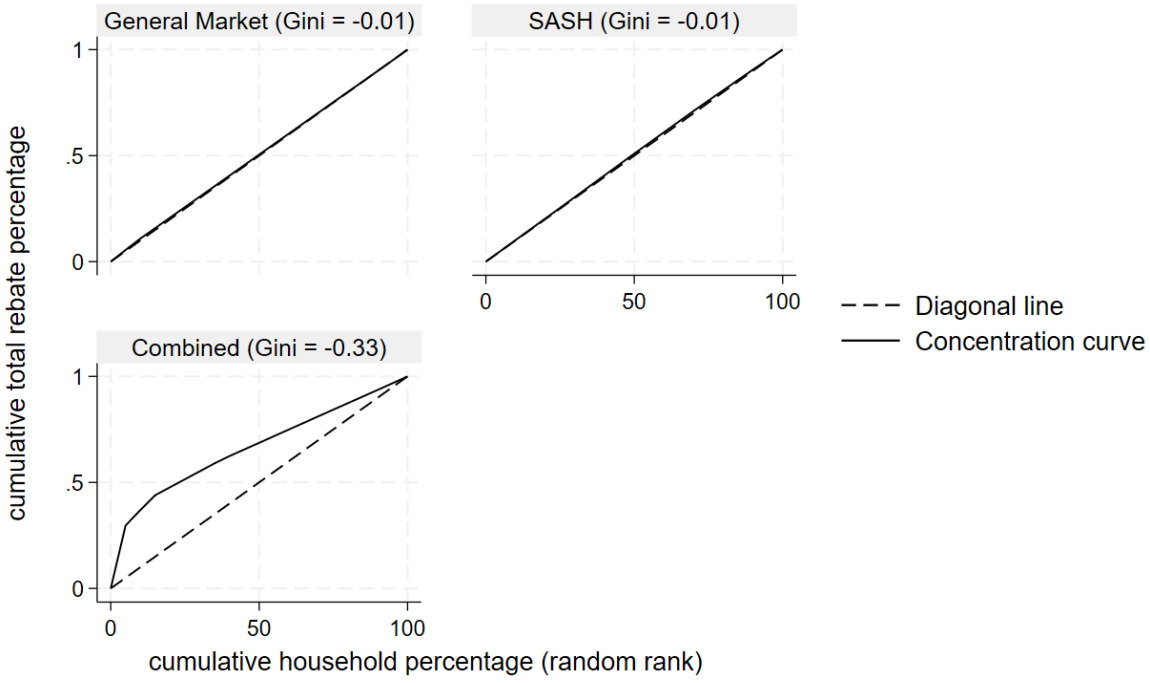

Figure A3.2 Concentration curves and indices: All systems, 2011-2016, AMI method

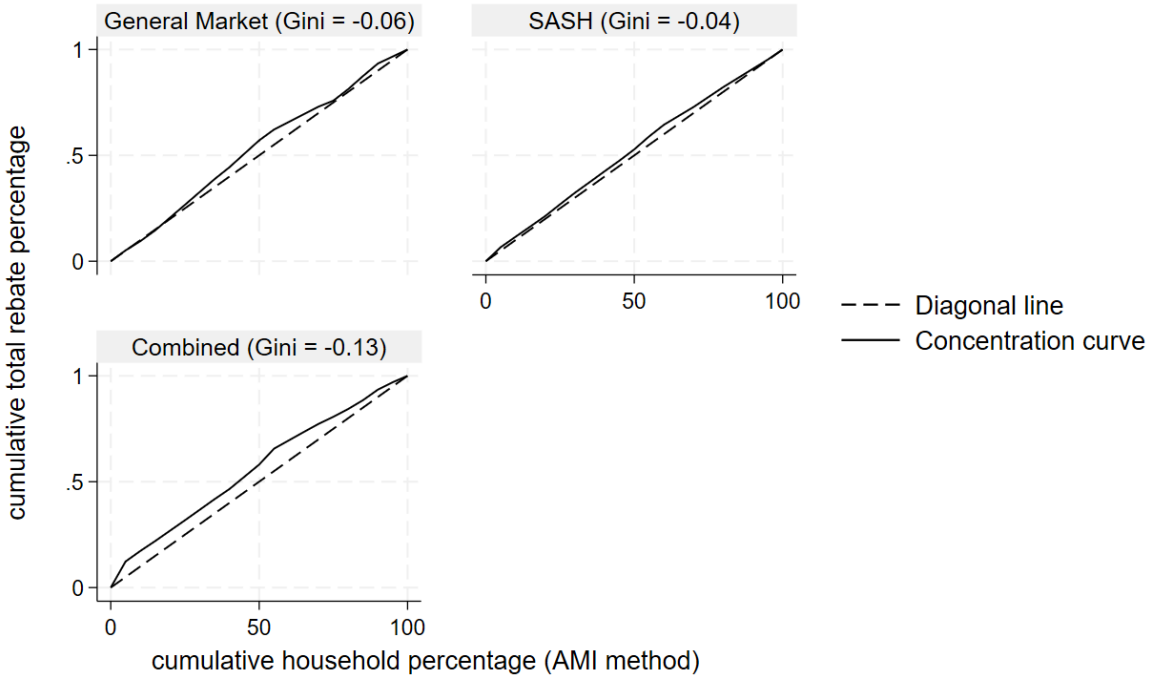

Table A3.1 Distribution of installed single-family systems by program and year

	Year						
Program	2011	2012	2013	2,014	2015	2016	Total
General	20,825	30,182	28,872	5,285	446	130	85,740
SASH	1,092	1,252	854	935	971	807	5,911
Combined	21,917	31,434	29,726	6,220	1,417	937	91,651

Table A3.2 ZIP code coverage by program and year

	Year						
Program	2011	2012	2013	2,014	2015	2016	Overall
General	1,092	1,106	1,040	473	82	60	1,204
SASH	220	241	217	181	203	203	474
Combined	1,111	1,124	1,057	581	268	250	1,220

Note: California has 1,769 ZCTAs.

Table A3.3 Rebate amount by income bracket: All systems, 2011-2016, random rank

	General Market		SASH		Combined	
Income bracket	Mean (Total Rebate) ($)	Mean (Rebate per watt) ($)	Mean (Total rebate) ($)	Mean (Rebate per watt) ($)	Mean (Total Rebate) ($)	Mean (Rebate per watt) ($)
$0-10k	-	-	14,691.70	5.08	14,691.70	5.08
$10-15k	-	-	14,700.42	4.87	14,700.42	4.87
$15-25k	-	-	14,822.03	4.92	14,822.03	4.92
$25-35k	1,707.42	0.34	14,572.29	4.90	11,436.38	3.79
$35-50k	1,579.05	0.34	14,091.95	4.91	3,283.56	0.96
$50-75k	1,427.03	0.32	13,564.03	4.97	1,716.79	0.43
$75-100k	1,434.31	0.32	-	-	1,434.31	0.32
$100-150k	1,431.10	0.32	-	-	1,431.10	0.32
$150-200k	1,415.40	0.31	-	-	1,415.40	0.31
$200k+	1,450.18	0.32	-	-	1,450.18	0.32
Overall	1,445.80	0.32	14,480.52	4.94	2,286.47	0.62

Note: All dollar values are adjusted to 2010 USD.

Table A3.4 Rebate amount by income bracket: All systems, 2011-2016, AMI method

Income bracket	General Market		SASH		Combined	
	Mean (Total Rebate) ($)	Mean (Rebate per watt) ($)	Mean (Total rebate) ($)	Mean (Rebate per watt) ($)	Mean (Total Rebate) ($)	Mean (Rebate per watt) ($)
$35-50k	1,383.23	0.28	15,513.32	4.66	3,665.99	0.98
$50-75k	1,465.91	0.32	14,146.57	5.03	2,187.24	0.59
$75-100k	1,419.97	0.33	13,292.93	5.26	1,803.89	0.49
Overall	1,445.80	0.32	14,480.52	4.94	2,286.47	0.62

Note: All dollar values are adjusted to 2010 USD.

Table A3.5 Passthrough rate by income bracket: Combined host-owned systems, 2011-2016, random rank

	(1) All	(2) $0-50k	(3) $50-75k	(4) $75-100k	(5) $100-150k	(6) $150k+
Rebate per watt	-0.345***	-0.256***	-0.450***	-0.381**	-0.458***	-0.254*
	(0.021)	(0.020)	(0.069)	(0.118)	(0.102)	(0.109)
System capacity	-0.425***	-0.398***	-0.443***	-0.395***	-0.388***	-0.440***
	(0.018)	(0.043)	(0.038)	(0.038)	(0.033)	(0.038)
System capacity^2	0.030***	0.029***	0.031***	0.028***	0.028***	0.031***
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
Ln (Median income)	-0.078*	-0.097	-0.010	-0.135	-0.150*	-0.063
	(0.037)	(0.058)	(0.069)	(0.077)	(0.069)	(0.073)
Ln (Med. hous. val.)	0.100**	0.098	0.147*	0.170*	0.151	-0.003
	(0.037)	(0.059)	(0.069)	(0.076)	(0.086)	(0.075)
Ln (Hous. density)	0.011*	0.018*	0.020	0.014	-0.010	-0.006
	(0.006)	(0.009)	(0.010)	(0.012)	(0.011)	(0.011)
Ln (Median age)	0.106*	-0.194**	0.111	0.256*	0.141	0.245*
	(0.051)	(0.074)	(0.098)	(0.113)	(0.110)	(0.102)
% Bachelor's +	0.000	-0.001	-0.000	-0.001	0.002	0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
R^2	0.85	0.94	0.82	0.78	0.76	0.73
Observations	34,607	6,897	7,333	5,554	7,349	7,474
Clusters	1,160	710	947	880	858	848

Note: Dependent variable is net system price per watt. All models are estimated with weekly quadratic time trends and county, utility, and contractor fixed effects. Standard errors clustered by ZIP code are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3.6 Passthrough rate by income bracket: Combined host-owned systems, 2011-2016, AMI method

	(1) All	(2) $35-50k	(3) $50-75k	(4) $75-100k
Rebate per watt	-0.345***	-0.258***	-0.361***	-0.254***
	(0.021)	(0.032)	(0.030)	(0.034)
System capacity	-0.425***	-0.241***	-0.432***	-0.461***
	(0.018)	(0.039)	(0.024)	(0.040)
System capacity^2	0.030***	0.015***	0.030***	0.035***
	(0.002)	(0.003)	(0.002)	(0.004)
Ln (Median income)	-0.078*	-0.294***	-0.069	-0.092
	(0.037)	(0.087)	(0.044)	(0.103)
Ln (Med. hous. val.)	0.100**	-0.052	0.188***	-0.062
	(0.037)	(0.114)	(0.042)	(0.104)
Ln (Hous. density)	0.011*	0.018	0.008	-0.003
	(0.006)	(0.012)	(0.007)	(0.011)
Ln (Median age)	0.106*	0.214	0.027	0.199
	(0.051)	(0.146)	(0.054)	(0.174)
% Bachelor's +	0.000	0.009**	-0.002	0.004*
	(0.001)	(0.003)	(0.001)	(0.002)
R^2	0.85	0.93	0.85	0.80
Observations	34,607	4,263	23,293	7,051
Clusters	1,160	248	697	238

Note: Dependent variable is net system price per watt. All models are estimated with weekly quadratic time trends and county, utility, and contractor fixed effects. Standard errors clustered by ZIP code are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3.7 Passthrough rate by contractor type: Host-owned General Market systems, 2011-2016, usage rank

	(1) All	(2) Installations > 100	(3) Others
Rebate per watt	-0.403***	-0.255***	-0.616***
	(0.055)	(0.067)	(0.076)
System capacity	-0.405***	-0.428***	-0.366***
	(0.018)	(0.023)	(0.029)
System capacity^2	0.028***	0.031***	0.025***
	(0.002)	(0.002)	(0.002)
Ln (Median income)	-0.063	-0.041	-0.099
	(0.038)	(0.048)	(0.051)
Ln (Med. hous. val.)	0.114**	0.114*	0.117*
	(0.040)	(0.053)	(0.054)
Ln (Hous. density)	0.006	0.007	0.004
	(0.006)	(0.008)	(0.008)
Ln (Median age)	0.139**	0.058	0.262***
	(0.053)	(0.066)	(0.076)
% Bachelor's +	0.001	0.000	0.001
	(0.001)	(0.001)	(0.001)
R^2	0.73	0.77	0.63
Observations	29,723	16,407	13,316
Clusters	1,122	949	1,058

Note: Dependent variable is net system price per watt. All models are estimated with weekly quadratic time trends and county, utility, and contractor fixed effects. Standard errors clustered by ZIP code are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A3.8 Passthrough rate by income bracket: Host-owned SASH systems (excl. fully subsidized), 2011-2016, usage rank

	(1) All	(2) $0-35k	(3) $35-50k	(4) $50-75k
Rebate per watt	-0.406***	-0.382***	-0.429***	-0.511***
	(0.024)	(0.031)	(0.088)	(0.100)
System capacity	-1.549***	-1.476***	-1.670***	-1.783*
	(0.180)	(0.197)	(0.453)	(0.692)
System capacity^2	0.204***	0.192***	0.218*	0.224
	(0.030)	(0.033)	(0.092)	(0.122)
Ln (Median income)	-0.301**	-0.363*	-0.352	0.712
	(0.116)	(0.177)	(0.441)	(0.521)
Ln (Med. hous. val.)	0.159	0.189	0.246	-0.601
	(0.114)	(0.182)	(0.385)	(0.614)
Ln (Hous. density)	0.006	-0.018	0.045	0.128*
	(0.015)	(0.026)	(0.038)	(0.059)
Ln (Median age)	0.267	0.156	-0.013	1.828
	(0.207)	(0.277)	(0.507)	(1.005)
% Bachelor's +	-0.006	-0.004	0.002	-0.017
	(0.004)	(0.006)	(0.011)	(0.019)
R^2	0.65	0.68	0.83	0.89
Observations	1662	1102	345	215
Clusters	265	233	124	67

Note: Dependent variable is net system price per watt. All models are estimated with weekly quadratic time trends and county, utility, and contractor fixed effects. Standard errors clustered by ZIP code are shown in parentheses. Significance is indicated by * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.