Shadows in the Sunlight: Do Solar Power's Benefits Shine Equally on Everyone?

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Abstract

This study critically assesses the structural inequities embedded within the allocation of non-refundable energy tax credits in the U.S. residential solar market. By analyzing tax credit data from the Internal Revenue Service (IRS) and individual-level data from the Annual Social and Economic Supplements (ASEC), this study reveals a stark 74% discrepancy in tax credit utilization between low and higher-income households. Furthermore, it identifies that 28% of homeowner households are ineligible for solar tax credits due to tax liability constraints. Employing a structural model, this research quantifies the adverse impacts of current tax policies and uses counterfactual scenarios to argue that policy reforms—specifically, making tax credits refundable could boost adoption rates by 23.8% overall, doubling the number of solar panel systems among the most economically vulnerable populations. Furthermore, we provide evidence showing that refundability has been instrumental in achieving a significant 8% reduction in emissions, encompassing CO2, SO2, NOx, and PM2.5. These findings serve as a pivotal call for policymakers to restructure energy tax credits to bridge the socioeconomic divide, thereby accelerating the transition towards a more sustainable and equitable energy system.

Keywords— Solar Panels, Tax Policy, Energy Justice, Distributional Effect, Renewable Energy

1 Introduction

Solar photovoltaic (PV) technology is increasingly recognized as a crucial element in the global push towards sustainable development, offering unparalleled opportunities for environmental conservation, public health improvement, job creation, and the fulfillment of sustainability goals worldwide. Attempting to harness the power from the sun, several countries have taken the lead in capturing the energy and using it as a viable source of electricity. The United States has made strides in positioning itself as one of five leaders in solar energy production, along with China, Japan, Germany, and India as ranked by the International Renewable Energy Agency (IRENA).[1]

Under President Biden's leadership, the United States has intensified efforts to exploit its solar resources, significantly enhancing its renewable energy capacity. According to the Solar Energy Industries Association (SEIA), there was a remarkable 35% increase in solar capacity installations, totaling 6.5 gigawatts-direct current (GWdc) in the third quarter of 2023 alone. This increase is largely attributed to proactive federal policies aimed at clean energy, underscoring the strategic role of solar power within the U.S. energy policy framework and positioning the nation as a potential leader in the renewable sector.

However, despite the rapid growth in solar power, the United States encounters significant challenges in maximizing this potential. Contrary to countries like India and China, where solar energy has been leveraged to alleviate poverty in underprivileged areas, the U.S. has witnessed a skewed deployment of solar PV systems, predominantly within higher-income communities. A body of research indicates that solar adoption in the U.S. over the past decade has not been equitable across different socioeconomic groups (Darghouth et al. (2022) and Gao and Zhou (2022)). Findings from the Lawrence Berkeley National Laboratory reveal that in 2022, the median household income of solar adopters in the U.S. was approximately $117,000—well above the median for the middle-income bracket. This figure stands in contrast to the national median household income of $69,000, and $86,000 for owner-occupied households. Moreover, research conducted by the National Renewable Energy Laboratory (NREL) indicates that less than half of U.S. community solar projects have included low-income participants (NREL, 2021), signaling a gap in the accessibility of solar investments.

The disparity in solar adoption has elicited numerous explanations, notably the hesitation of lower-income groups to invest in solar technology. Despite reduced costs and the availability of governmental incentives, a significant barrier persists—the federal clean energy tax credit under the Inflation Reduction Act (IRA). Offering up to a 30% tax credit for solar panel installations, the IRA is a milestone in legislative efforts to helping the United States meet its climate goals and strengthen energy security. However, it contains a significant oversight: the tax credit is non-refundable. This characteristic means that entities like government bodies and low-income homeowners, who often have limited tax liability, cannot fully benefit from the tax credit. This situation inadvertently excludes them from participating in the clean energy transition, while wealthier individuals can leverage the credit to decrease both their energy costs and tax responsibilities. Consequently, this lack of tax liability serves as an 'invisible barrier', continuing to prevent disadvantaged groups from accessing the benefits of this policy.

In this paper, we delve into this systematic bias underlying the disparities in solar technology

[1] https://www.irena.org/Data/View-data-by-topic/Capacity-and-Generation/Country-Rankings

adoption. We start by analyzing the significance of this policy for households and assessing the population impacted by it. Using tax credit data from the Internal Revenue Service (IRS) alongside individual-level data from the Annual Social and Economic Supplements (ASEC), the results uncover significant disparities in tax credit utilization between different income groups. Our analysis reveals a striking 74% difference in the use of tax credits between low- and higher-income households. Additionally, we find that 28% of homeowner households are ineligible for solar tax credits due to tax liability constraints. These findings underscore a critical imbalance in the uptake of tax credits, suggesting that despite their aim to make solar energy accessible across socio-economic strata, these incentives do not achieve equitable utilization in practice.

To delve deeper into this bias, we develop and estimate a structural model of the solar installation market to identify systemic factors contributing to these disparities in solar PV adoption. Furthermore, using previous estimates, we assess the welfare implications of different policy designs and offer policy recommendations. Our cost-benefit analysis evaluates whether the social value of emissions avoided due to the program outweighs its costs. In our demand estimation model, prospective solar PV buyers choose between different options in a market characterized by oligopolistic competition and differentiated products, with household preferences linked to income levels. We employ a BLP model incorporating micro moments (Petrin (2002)) to estimate the model, revealing a negative relationship between price and demand. Additionally, the coefficient of tax benefits (1.64) is lower than the price coefficient (2.98), aligning with conventional economic theory, as the marginal utility of tax credits diminishes due to delayed payment and restricted usage. Our results also show that wealthier individuals have lower price sensitivities, indicating their higher propensity to invest in solar technology despite higher initial costs.

Building on these estimates, we conduct counterfactual analysis to evaluate the policy's effectiveness. We find that converting the tax credit from non-refundable to refundable results in a 23.8% increase in market sales. This increase is particularly pronounced among low-income households, where market share surges by 123.6%, which is seven times higher than the growth rate in high-income households at 16.3%. This stark difference illustrates the enhanced accessibility in low income communities provided by refundable credits.

Beyond quantifying the effect of the solar tax credit on household adoption, I undertake several welfare analyses. Initially, it measures the consumer surplus generated by the current policy. Additionally, by leveraging recent estimates of the social cost of pollution from Holland et al. (2016) and Sexton et al. (2021), the social value of emissions avoided—such as SO2, CO2, NOx, and PM2.5—under various policy designs is approximated. The findings reveal that the value of avoided emissions is significantly higher in low-income communities compared to their high-income counterparts. Specifically, the results show that installing a PV system in low-income communities yields greater environmental benefits, averaging $600 per system compared to $537 in high-income communities, with an additional $63 in avoided damages per system. Furthermore, optimal siting of rooftop solar installations could result in $X billion (work in progress) annually in avoided pollution damages. By examining how changes in the tax credit structure affect environmental outcomes, particularly avoided pollution damages, the study assesses the policy's efficiency in directing investments to the highest-value locations. The results indicate that current policies fail to maximize the environmental benefits of solar power installations, highlighting the need for more effective fiscal instruments to drive substantial environmental improvements and address global sustainability challenges.

This paper contributes to the growing body of literature on the distributional consequences of energy policies, particularly within the context of the clean energy transition. Previous studies have examined the distributional impacts of carbon pricing (Mankiw (2009); Metcalf (2009); Grainger and Kolstad (2010)), fossil fuel extraction dynamics (Blonz et al. (2023)), renewable energy policy (Reguant (2019)), and residential energy subsidies (Hahn and Metcalfe (2021)). For instance, Sunter et al. (2019) found that rooftop solar adopters are predominantly higher-income and White households. Other studies, such as Nemet et al. (2017), Barbose and Darghouth (2018), and O'Shaughnessy et al. (2021), have documented significant price variations in solar installations. Sexton et al. (2021) explored the distribution of environmental benefits from rooftop solar adoption. This paper builds on these works by estimating a structural model to evaluate market outcomes and welfare distribution, uncovering the mechanisms driving distributional disparities.

The broader empirical literature on policy evaluation in the residential solar market is also relevant to this study. Bollinger and Gillingham (2012), along with Bollinger et al. (2022), used data from California and Connecticut to analyze the impact of subsidies and peer effects on solar adoption, revealing significant peer influence. De Groote and Verboven (2019) found that upfront incentive programs are more effective than long-term ones due to substantial future discounting. These insights into policy evaluation provide a foundation for understanding the dynamics of solar adoption and the effectiveness of different incentive structures.

The study also touches on tax policy, specifically comparing the effects of refundable and non-refundable tax credits using empirical methods. Using Canadian data,Simpson and Stevens (2015) and Philipps (2001) has shown that converting non-refundable tax credits to refundable ones can benefit many families, especially low-income ones. Distinct from these studies, this paper models solar adoption behavior using a structural model incorporating consumer heterogeneity. Previous findings suggest that policy changes yield varied benefits across income groups, underscoring the importance of modeling diverse household preferences rather than assuming homogeneity in OLS models. We contribute to this strand of literature by using a structural model incorporating consumer heterogeneity to fill this knowledge gap. In addition, this study is unique in using U.S. data to compare non-refundable and refundable tax credits.

The primary contribution of this paper is the comparison of two common policy instruments — refundable and non-refundable tax credits—on adoption rates and emission avoidance. This is the first study to use a structural model to quantify both direct and indirect outcomes of these policies. Although the focus is on a specific environmental and energy policy, the method can be applied to other similar policies to evaluate their efficiency and the necessity of policy changes through counterfactual analysis. Another significant contribution is the evidence of systematic inequality in the current policy scheme, challenging the notion that disparities are solely due to differing willingness to adopt. Additionally, this paper undertakes a comprehensive evaluation program, considering adoption rates, consumer welfare (price changes), and heterogeneous pollution avoidance across U.S. zip codes, thereby assessing the environmental benefits—the ultimate goal of promoting clean energy installations. Finally, this study adds to the growing literature applying empirical methods from industrial organization to analyze environmental policies (Kellogg and Reguant (2021)). This interconnected analysis emphasizes the critical role of targeted fiscal instruments in achieving optimal environmental and distributional outcomes in the renewable energy sector.

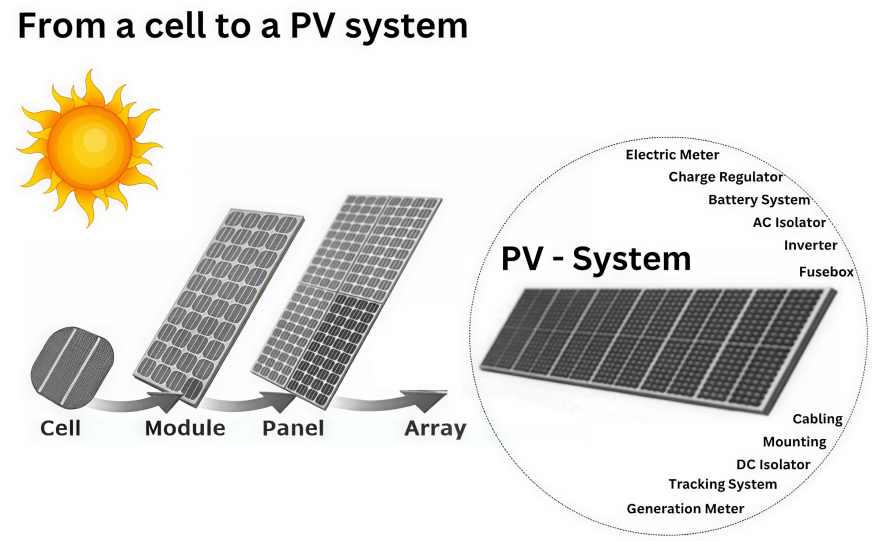
This paper is structured as follows. Section 2 provides an overview of the residential solar energy industry and the relevant policy background. Section 3 details the data utilized in the subsequent empirical analysis. In Section 4, we present reduced-form evidence on the distributional effects within the solar market, laying the groundwork for more in-depth analysis. Our model and estimation strategy are introduced in Section 5, with the model results discussed in Section 6. Section 7 explores the implementation of various policy counterfactuals and analyzes their outcomes. The final section offers concluding remarks.

2 Industry Background

2.1 Technology and Supply

Photovoltaic (PV) solar systems represent a groundbreaking innovation in energy technology, harnessing the power of sunlight to generate electricity. At the heart of these systems lie solar cells, constructed predominantly from semiconductor materials such as silicon, adept at absorbing sunlight and converting its energy into electrical current through the liberation of electrons. In the residential realm, arrays of interconnected modules or panels comprise the typical setup, channeling the generated current through metallic conductors to electrical wiring. This electricity finds its destination either in the local utility grid or within the confines of the home, facilitating domestic consumption (see Figure 1). Complementing the solar cells, inverters play a pivotal role in converting the direct current (DC) produced by the cells into alternating current (AC), suitable for household applications.

The efficiency and energy output of a PV system hinge significantly upon the composition of its solar cells and the extent of solar exposure. Factors such as the duration of sunlight exposure, along with the orientation and inclination of panels relative to the ground, significantly influence a system's performance. Notably, within my sample, the typical residential setup boasts a capacity of 8.9 kW, yielding approximately 10,500 kWh of electricity annually—a surplus that exceeds the average annual energy consumption of a typical U.S. household by 109%.



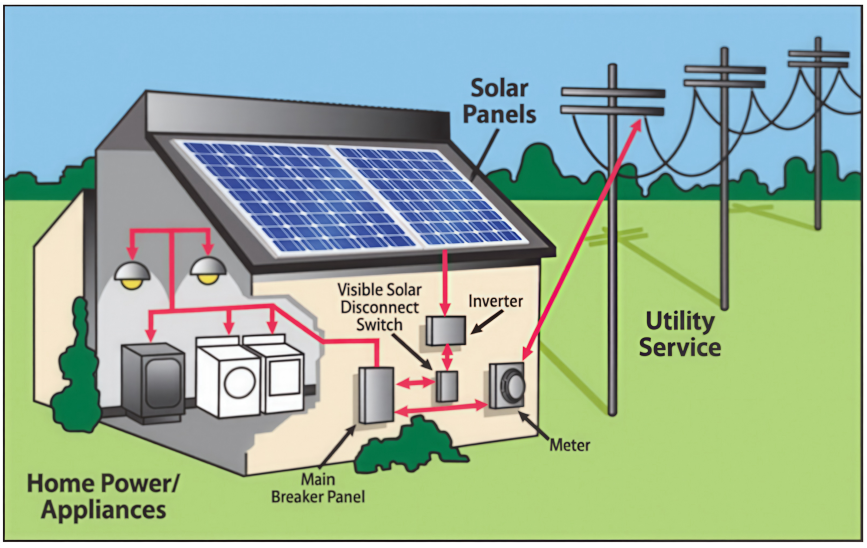


Figure 1: PV System Technology

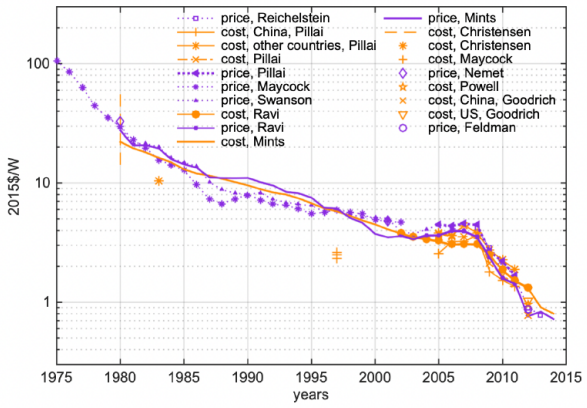
The evolution of solar panel technology has been marked by a transformative journey. Initially confined to niche applications due to their low efficiency and prohibitive costs, solar panels have undergone a remarkable metamorphosis. Advancements in efficiency and the economies of scale have substantially mitigated these early barriers, rendering PV solar increasingly accessible for both commercial and residential utilization. Observing the trajectory of manufacturing costs reveals a consistent decline, monitored by the energy industry (see Figure 2). At the same time, there is a large body of academic work that decomposes this trend into various factors. For example, Kavlak et al. (2018) observe a consistent reduction in PV module costs, noting a 20% decline with each doubling of cumulative capacity since the 1970s. Their analysis underscores enhanced module efficiency, robust research and development funding, and economies of scale as primary drivers of this trend across varying epochs. Building upon this narrative, Louwen and Van Sark (2020) identify a seminal inflection point in 2008, correlating with the influx of Chinese manufacturers into the module market. Their findings underscore the role of economies of scale and learning-by-doing in precipitating this structural shift. Moreover, data sourced from the National Renewable Energy Laboratory (NREL) underscores the broader decline in component costs, encompassing both modules and ancillary expenses like labor. These cost dynamics reverberate in installation prices, evidenced by data from the Lawrence Berkeley National Laboratory (2019). Over the past two decades, PV system installation costs in the United States have exhibited a consistent decline of 5-7% annually, predominantly driven by reductions in manufacturing expenses.

As expounded upon in subsequent sections, this downward trajectory in module prices furnishes a source of exogenous variation in local installation costs, serving as a instrumental variable in identifying households' price elasticity of demand for solar panels.

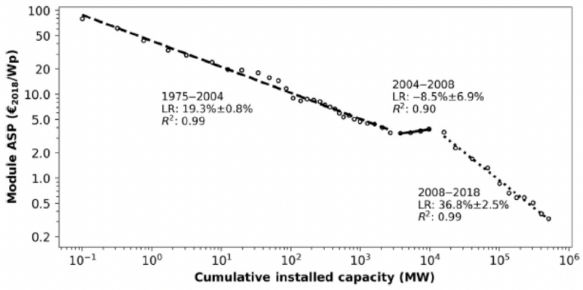
The PV system sector comprises a diverse array of stakeholders, including module, inverter, and ancillary component manufacturers, as well as system installers catering to end-users, and electric utilities wielding control over electricity pricing and the integration of renewables into the grid. Across the United States, the landscape is marked by a myriad of utility markets, with investor-owned utilities (IOUs) serving a significant portion of municipalities alongside smaller municipal electric companies.

Over my sample period, the United States witnessed a proliferation of 12,529 PV system installers. Predominantly, these entities consist of local electricians or construction firms, with a median installation count of two per firm.

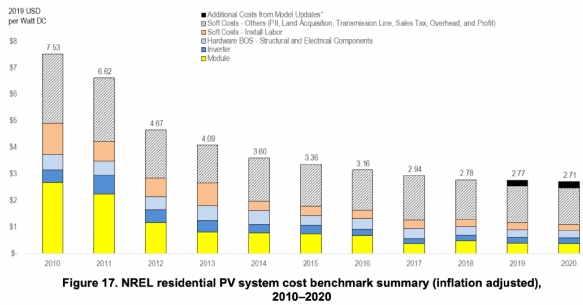
In this paper, I primarily focus on the demand-side of the market rather than the supply-side for two reasons. Firstly, the primary objective is to assess the impact of government subsidies on demand dynamics. Secondly, the competitive landscape within the installation segment, characterized by a substantial number of installers in the States, suggests a degree of competitiveness that diminishes the significance of individual firms' pricing strategies. These two insights together affirm the importance of focusing on demand-side stimuli to understand market evolution and the effectiveness of policy instruments.



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



(b) Louwen and van Sark (2020)



(c) National Renewable Energy Laboratory

Figure 2: Declining Manufacturing Costs

2.2 Residential Clean Energy Credit (RCEC)

In the realm of renewable energy, residential solar markets have seen a robust framework of tax incentives and subsidies designed to encourage the adoption of solar technology. These financial mechanisms reduce the upfront costs and increase the return on investment for homeowners choosing to install solar systems. Various state-specific incentives, such as rebates, property tax exclusions, and sales tax exemptions, complement federal policies. Amid these, the Residential Clean Energy Credit, or RCEC, stands out as the cornerstone of federal solar incentives.

The Residential Clean Energy Credit, first introduced under the Energy Policy Act of 2005, has played a crucial role in fostering the growth of the renewable energy industry in the United States. This credit is for homeowners who install residential solar panels, solar water heating systems, and fuel cells. And it was expanded in 2008 to include small residential wind turbines and geothermal heat pumps. Neither renters nor landlords are eligible, though there is a parallel program for commercially owned systems. The main category of qualified expenditures is solar credits, which constitute over 95% of all credits (as shown in Figure 3). This makes them the primary focus of this study due to their representative role.

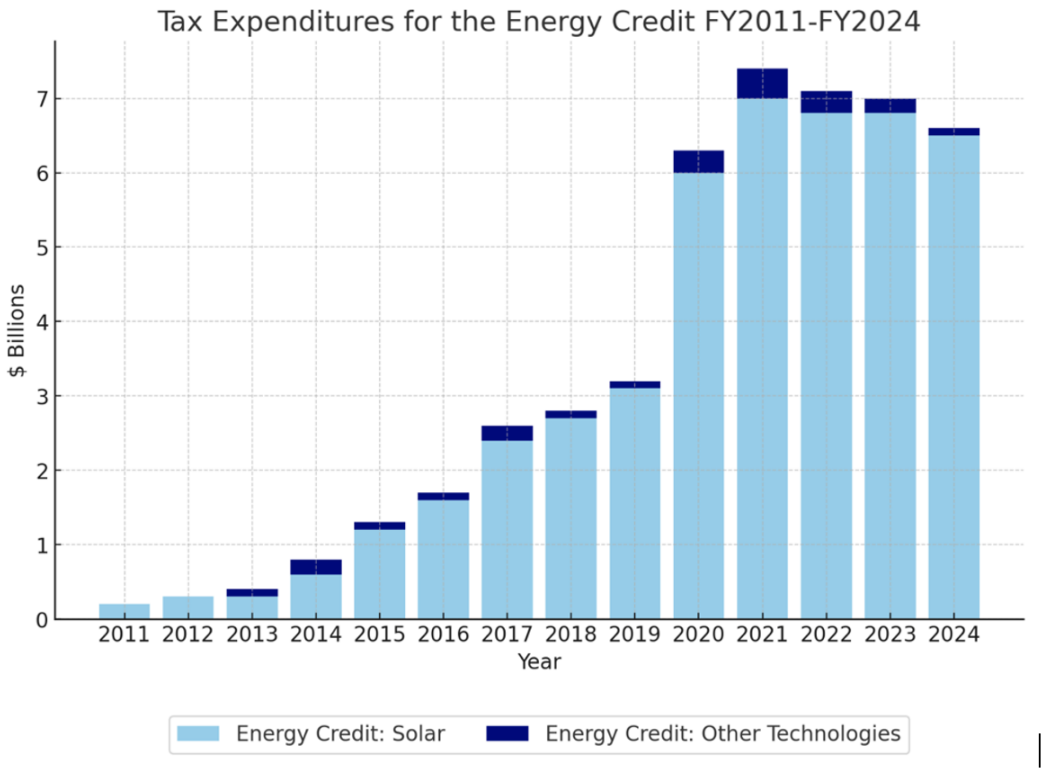


Figure 3: Tax Expenditure across years

The RCEC works by providing a dollar-for-dollar reduction in the income tax that a person or company would owe to the federal government. It is applicable to the cost of solar PV systems and includes a range of eligible expenses, such as solar panels, installation costs, and even some

additional equipment like inverters and batteries if they meet specific criteria.

Initially set at 30% for both residential and commercial sectors, the RCEC has undergone several extensions and modifications, contributing significantly to the solar sector's expansion by making solar installations more financially accessible. It was extended multiple times, most notably through legislation in 2008 during the financial crisis, and later through the Inflation Reduction Act signed in 2022. This act not only extended the RCEC but also increased its percentage back to 30% through 2032, after which it will begin to phase down to 26% in 2033 and 22% in 2034 (as shown in Figure 4).

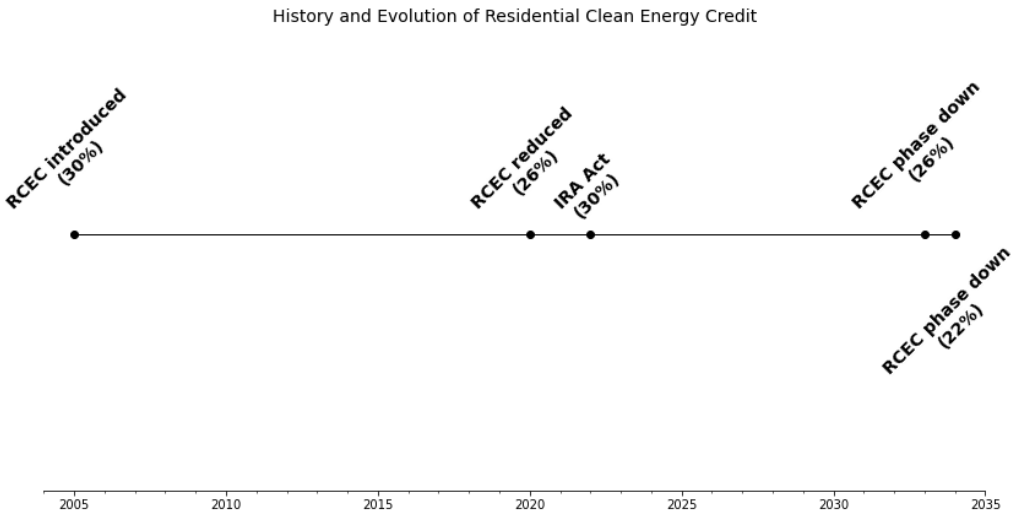


Figure 4: Tax Expenditure across years

The impact of the RCEC on the U.S. solar industry has been profound. Since 2006, the industry has grown exponentially, evidenced by a more than 10,000% increase in solar deployment, which has driven down costs and created hundreds of thousands of jobs. The policy's stability has allowed for long-term planning and continued investment in solar technologies, making solar energy an increasingly significant part of America's energy portfolio.

In addition to fostering domestic solar projects, the RCEC has been influential in promoting technological innovation and driving economic growth within the renewable energy sector. By reducing the initial cost burden of solar installations, the RCEC has not only made solar power more accessible to a broader range of Americans but also contributed to the country's goals for energy independence and environmental sustainability.

Overall, the Residential Clean Energy Credit stands as a prime example of effective government incentives in the renewable energy sector, demonstrating significant success in promoting solar energy adoption across the United States. Its ongoing adaptation and extension continue to support the nation's transition towards more sustainable energy solutions.

For the purposes of my analysis, I focus specifically on the effect of the RCEC on household

adoption behavior. This focus is critical because, unlike the state-specific or city-specific benefits, the impacts of the RCEC can be directly measured and are more uniformly applicable across different states and economic conditions. Other incentives like property tax exemptions, while beneficial, vary widely by locality and are often entangled with other local fiscal policies, making their effects more idiosyncratic and challenging to isolate.

Thus, by examining the RCEC's influence, this study aims to provide a clear, quantifiable understanding of how federal financial incentives impact individual and collective decisions to invest in solar energy. This focus will allow for a detailed exploration of the broader implications of fiscal policies on sustainable energy adoption, offering insights into how similar incentives might be optimized to support environmental goals and economic savings for households across the nation.

2.3 Solar Installations

Figure 5 plots the annual installations of residential solar photovoltaic (PV) systems across the United States, measured in megawatts of capacity. It includes critical milestones marked by vertical lines: the introduction of the Residential Clean Energy Credit (RCEC) in 2005 and its significant enhancement in 2009 under the American Recovery and Reinvestment Act. This data, sourced from the "Tracking the Sun" database, represents a comprehensive sample of installations and shows a rapid increase in solar adoption during this period. This growth can be attributed to several factors, including substantial reductions in the cost of solar panels, favorable retail electricity tariffs encouraging distributed generation, state-level subsidies, and notably, the federal Residential Clean Energy Credit (Borenstein (2017)).

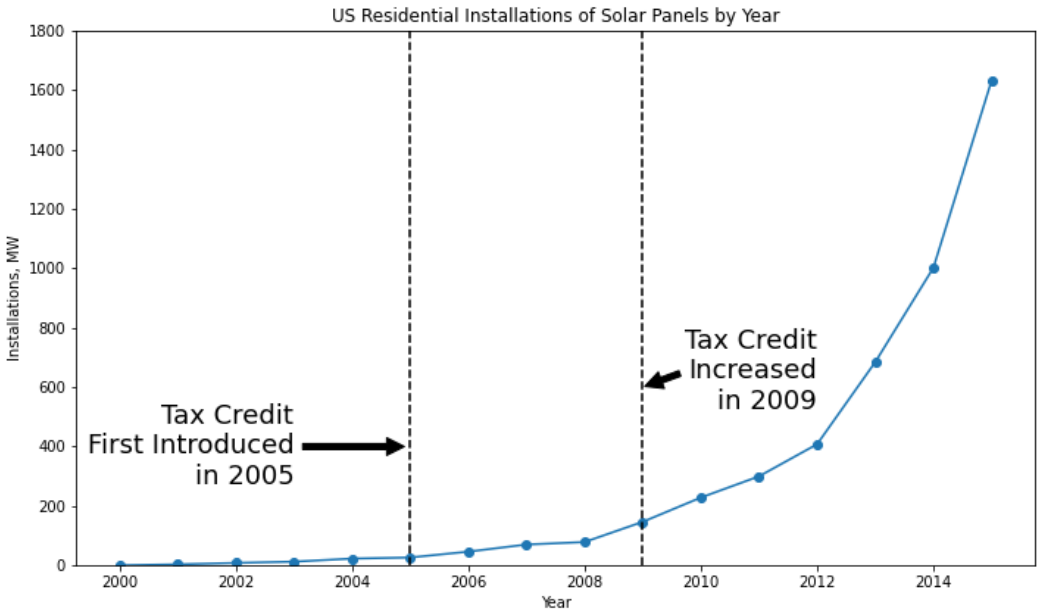


Figure 5: Solar Installation across years

The past two decades have witnessed pivotal changes in the RCEC, notably in 2006 when it became available, offering a 30% credit on qualifying expenses up to a $2,000 limit for most categories. This credit was extended in 2009 to eliminate the credit cap for all eligible investments except fuel cells, significantly increasing the program's generosity, as these systems generally involve substantial costs.

To examine the impact of these federal tax credits on the growth of the U.S. residential solar industry, I employed a regression discontinuity in time (RDiT) approach. My primary hypothesis posits a positive relationship between the introduction and subsequent enhancement of the RCEC and the installed solar PV capacity (measured in KW/month). Given the policy's structure—a dollar-for-dollar reduction in federal income taxes for qualifying individuals or companies—it is reasonable to anticipate a positive influence on solar PV installations during the years when the 30% credit was accessible (2006-2015) compared to earlier years (1997-2005) when the credit was either unavailable or less generous.

The analysis predominantly utilizes data from the "Open PV Project," a collaborative initiative between the Lawrence Berkeley National Laboratory and the National Renewable Energy Laboratory. This dataset encompasses monthly solar PV data at the state level from 2000 to 2020, strategically chosen to include approximately three years before and after the policy's introduction and expansion. To mitigate potential confounding effects, I incorporated controls for year, month, and state to adjust for seasonal and geographical variations.

The RDiT model, supplemented with simple controls, yielded a significant positive coefficient for the post-2006 period, indicating an uptick in installed solar PV capacity. In Figure 6 , a noticeable gap in the total PV installation size between 2006 and 2009 underscores this positive trend. The regression results, detailed in Table 1 using quadratic approximations, estimate an increase of 0.008 megawatts in PV installations following the policy introduction and an additional 0.0028 megawatt rise after the credit limit removal.

Table 1: Effect of REEPC Policy on Solar Installations: Regression Discontinuity Evidence

	Coefficient	Standard Error
	REEPC Introduction	
First-order polynomial time trend	0.0035*	(0.0022)
Second-order polynomial time trend	0.0082**	(0.0042)
Third-order polynomial time trend	0.0101***	(0.0043)
	REEPC Expansion	
First-order polynomial time trend	0.0007**	(0.0004)
Second-order polynomial time trend	0.0028***	(0.0008)
Third-order polynomial time trend	0.0029***	(0.0008)

Despite observing a positive correlation, it is difficult to attribute the entire growth to the federal tax credit. Solar panel installations are growing quickly throughout this period, but it is hard to make causal statements based on these before- and- after comparisons. We simply don't know how much of this growth would have occurred absent the federal tax credit. Probably the best

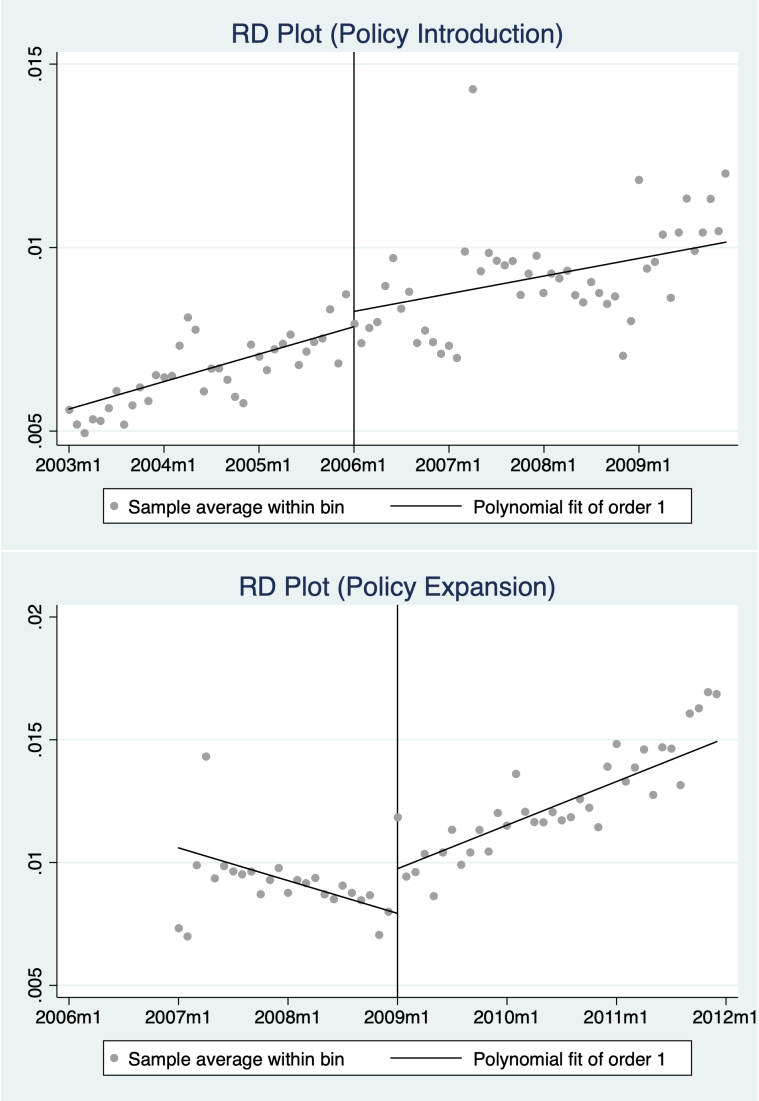


Figure 6: RD Plot

evidence to date on the impact of subsidies on residential solar panel adoption comes not from the federal tax credit, but from variation over time in state-level subsidies. In particular, Hughes and Podolefsky (2015) show that households were responsive to rebates offered under the California Solar Initiative. While it is challenging to generalize these findings nationally, they underscore the complexity of isolating the effects of federal subsidies.

In subsequent sections, this paper will explore in greater depth the role of tax incentives in influencing household decisions regarding solar adoption. We will employ a structural model to address the limitations inherent in reduced-form analysis, aiming to provide a more nuanced understanding of these dynamics.

3 Data

To analyze households' adoption behavior and measure their responsiveness to solar incentives, I utilize installation records from the Lawrence Berkeley National Laboratory's Tracking the Sun, combined with zip code-level energy tax credit information from the IRS's annual statistics and detailed demographic and household characteristic data from the American Community Survey. Additionally, the Residential Energy Consumption Survey (RECS) data supplements this analysis by providing individual-level insights into solar adoption, incorporating detailed demographic information such as income, household size, and the number of children.

These datasets will enable a comprehensive analysis of solar adoption trends, the utilization of tax credits, and the demographic characteristics of affected communities.

3.1 Solar Installation Data

The Lawrence Berkeley National Laboratory (LBNL)'s Tracking the Sun dataset serves as a cornerstone for this study, providing a comprehensive overview of individual-level solar panel installations across various states, complete with detailed characteristics such as size and efficiency. This rich dataset, published in September 2022, encompasses approximately 2.5 million solar energy systems installed from 2000 through 2021, representing an impressive 77% of the U.S. market (Barbose et al., 2022). Specifically, the data for the year 2021 includes about 340,000 systems, capturing 68% of the market share. By aggregating this data to the ZIP code level, this research leverages the granularity of the dataset to analyze the nuanced impacts of solar panel incentives like tax credits through a BLP structural model.

The dataset's inclusion of detailed information on each solar panel—ranging from brand and size to efficiency and technology—enables a thorough analysis of consumer preferences within the solar panel market. This level of detail facilitates a deeper understanding of how solar policies, particularly tax credits, affect different demographics, with a focus on the unequal benefits received by low-income households.

3.2 Energy Tax Credit Data

While the Tracking the Sun dataset offers comprehensive insights into solar panel installations, including their specifications and geographic distribution, it lacks direct data on energy tax credit utilization and consumer demographics within its sample period. To bridge this gap, the research employs the dataset's ZIP code-level buyer location information as a springboard to connect energy tax credit usage and demographic characteristics. This information is meticulously compiled from two pivotal sources: the IRS's Statistics of Income (SOI) dataset and the American Community Survey (ACS) data spanning from 2010 to 2020. The ZIP code, serving as the IRS tax record data's most granular geographic unit, facilitates a precise merge of neighborhood demographic details from the ACS, enriching the analysis with a layered understanding of the socio-economic backdrop against which solar panel installations occur.

The main variable we extract from the Internal Revenue Service's Statistics of Income (SOI) dataset are the number and amounts of energy tax credit claims at the ZIP code level, spanning

from 2007 to 2020. This dataset offers a unique lens through which to understand the geographic and socio-economic distribution of these incentives. By integrating this fiscal data with the detailed installation records from the Tracking the Sun dataset, the research delves into the nexus of policy incentives, economic capacity, and renewable energy adoption, highlighting how financial mechanisms influence the landscape of solar energy uptake across diverse communities.

3.3 Household and Neighborhood Demographic Data

To enhance the granularity of our analysis of solar installation patterns, we enrich our primary dataset with neighborhood demographic information sourced from the American Community Survey (ACS). The primary dataset, Tracking the Sun, does not capture consumer demographic specifics during the study's sample period. It does, however, provide the location of each installation at the zipcode level. Leveraging this locational data, we access and incorporate demographic characteristics from the ACS for the years 2011 to 2020. The ACS facilitates this integration by providing demographic data at the zipcode level, a geographic unit utilized by the US Census, thus enabling a robust merging of installation locations with corresponding neighborhood demographic profiles.

The main demographic variables extracted from the ACS include median household income and the Gini Index, both at the zipcode level. These enhancements to our dataset enable a more nuanced understanding of the socio-economic and demographic factors influencing solar technology adoption, thereby enriching the analytical depth of our study.

3.4 Individual Level Income and Tax Liability Data

To further refine our analysis, we integrate individual-level data using the Annual Social and Economic Supplements (ASEC) of the Current Population Survey (CPS). This dataset is pivotal for our exploration of the non-refundable nature of the Solar Investment Tax Credit (ITC). A critical aspect of our study addresses the extent to which taxpayers' liabilities limit their ability to fully benefit from the ITC. Specifically, we analyze the incidence of tax liability capping, which restricts the full utilization of the credit.

From the ASEC, we extract variables including gross income, federal tax liability prior to any credits, and homeownership status. Our analysis is confined to homeowners, as the ownership of a home is typically a prerequisite for the installation of solar photovoltaic (PV) systems. We limit our examination to federal tax liabilities, thereby excluding state tax considerations, as the ITC is a federal policy affecting only federal tax obligations.

By merging this individual tax data with solar installation data from Tracking the Sun, which details the total cost of each solar panel installation, we can discern the proportion of taxpayers who are either fully or partially capped by their tax liabilities. This investigation reveals the number of households unable to reap the full benefits of the tax credit due to their financial circumstances.

These enhancements to our dataset provide a detailed view of the demographic and economic characteristics influencing eligibility for the ITC. This granularity is crucial for assessing the policy's impact and underscores the need for potential reforms to make solar energy more accessible, thereby enriching the analytical depth and policy relevance of our study.

4 Distributional Analysis

Having provided an overview of Solar Investment Tax Credit, we now turn to our main research question. How does the use of these credits vary across income levels? In this section, we delve into the distributional effects in residential solar panels. To start with, we use detailed data from the RECS to calculate the adoption rate across different states and among various income strata. Subsequently, we examine the impact of tax liabilities as a potential barrier to credit utilization. By integrating data from the American Economic Community Survey (AECS), we calculate the proportion of households whose tax burden limits their ability to fully benefit from the tax credits. This assessment sheds light on the restrictive influence of non-refundable tax credits on solar adoption among lower-income households. Finally, we turn to data from the Internal Revenue Service (IRS) to evaluate the distribution of tax credit benefits among income groups, comparing the average credit received across different income thresholds. In scrutinizing the structural nuances of the U.S. residential solar market, particularly the non-refundable energy tax credits, this empirical evidence section aims to provide a comprehensive understanding of solar panel adoption patterns and the consequential socio-economic implications.

We begin our exploration by examining the geographic distribution of solar panel adoption across the United States. Utilizing data from the Residential Energy Consumption Survey (RECS) 2020, we observe a distinct variation in adoption rates by state, with significant concentrations noted in the Southwest and Northeast, as shown in Figure 7. This geographical variance likely reflects regional differences in sunlight availability, state-level incentives, and economic factors.

In parallel, our economic analysis focuses on income distribution among adopters. Analyzing the data further, we find a pronounced skew towards wealthier households. The data from Figure 8 illustrates that higher-income groups are substantially more likely to install solar panels. This trend suggests that financial capacity significantly influences the adoption of solar technologies, reinforcing the role of economic accessibility in the deployment of renewable energy solutions.

To quantify the effects of income on the likelihood of adopting solar panels more precisely, we applied logistic regression with various model specifications. As shown in Table 2, we began with a basic model that included fixed effects for location and the building's construction year to account for regional and infrastructural variabilities. Subsequent models incorporated progressively detailed controls:

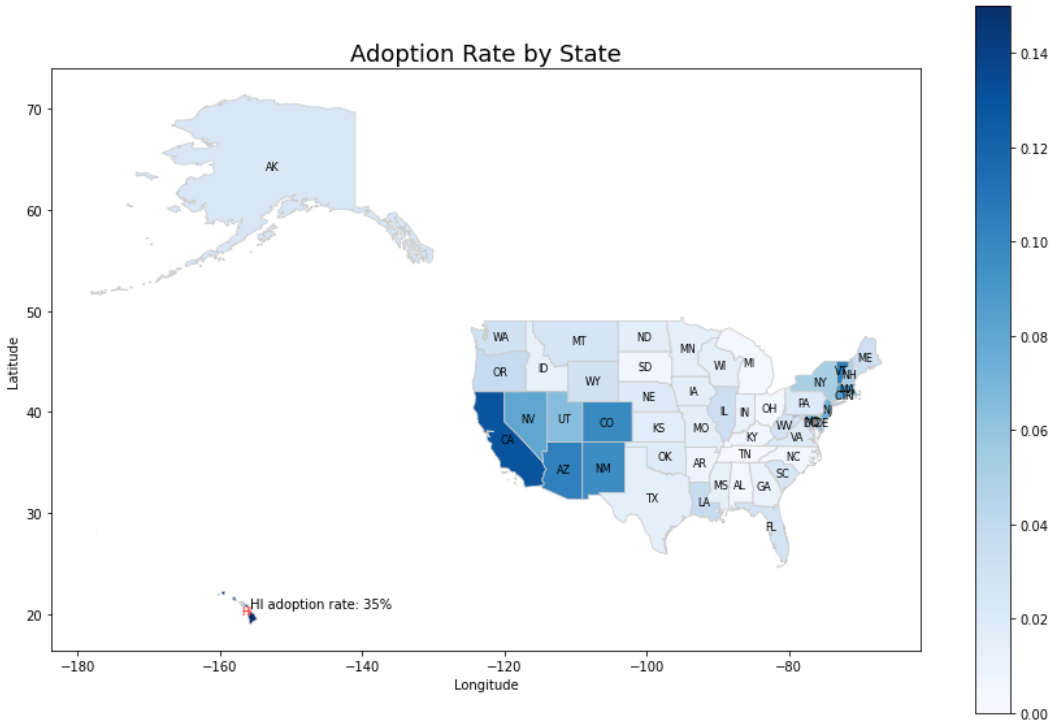


Figure 7: Solar Adoption Rates by State

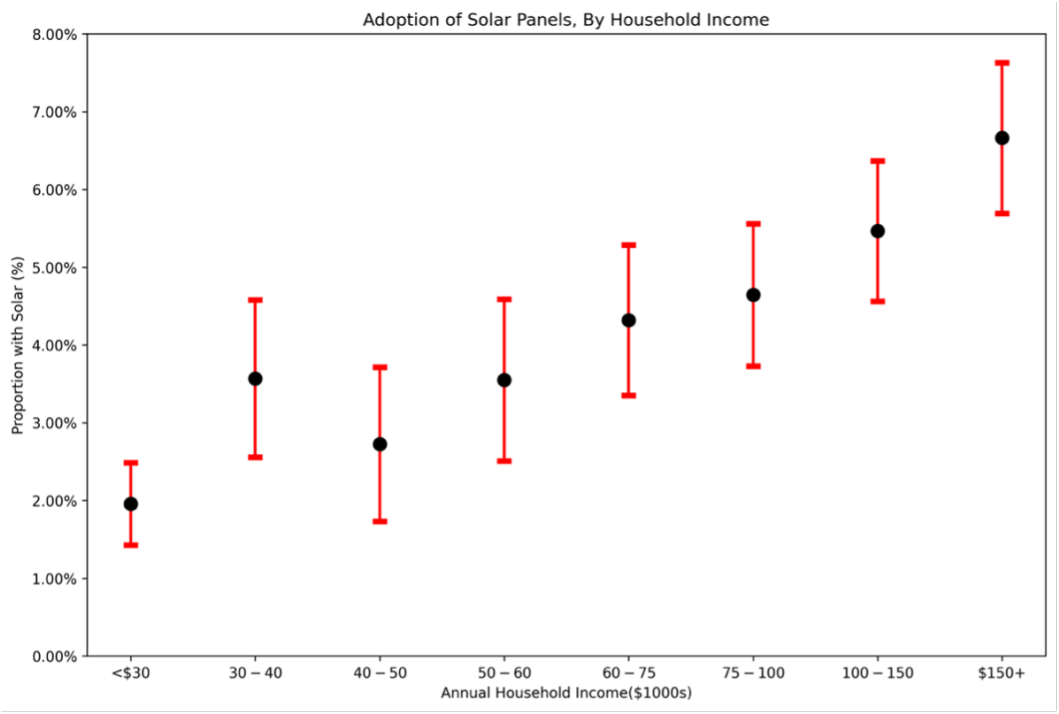


Figure 8: Solar Adoption Rates by Income

1. **Household Demographics**: Variables such as homeowner's age, sex, employment status, education level, race, and household size were controlled to understand demographic influences on adoption rates.

2. **Housing Characteristics**: This included detailed elements like the type of housing unit, the number of bedrooms and bathrooms, presence of a swimming pool, and appliance counts (refrigerators, ovens, microwaves, dishwashers, TVs, etc.), as well as construction materials and insulation levels.

3. **Regional Weather Conditions**: Considering the building's climate zone and historical weather data (heating degree days and cooling degree days), we adjusted for environmental factors that could affect the utility and efficiency of solar panels.

4. **Household Electricity Consumption Habits**: We controlled for factors such as the months a swimming pool is used, the age and usage frequency of major appliances, which could reflect energy consumption patterns and potential for energy savings through solar adoption.

Table 2: Effect of Income on Solar Installations: Logistic Regression Results

	Whether adopted solar panels				
	(1)	(2)	(3)	(4)	(5)
	(Odds Ratio)				
Income	1.08***	1.07***	1.04**	1.04**	1.04**
	(0.015)	(0.017)	(0.018)	(0.018)	(0.019)
Household Electricity Consumption Habits					✓
Weather Condition Controls				✓	✓
Housing Characteristics			✓	✓	✓
Household Demographics		✓	✓	✓	✓
Location Fixed Effect	✓	✓	✓	✓	✓
Built Year Fixed Effect	✓	✓	✓	✓	✓
Sample size	14,932	14,932	14,932	14,932	14,932
Adjusted R^2	0.1433	0.1552	0.1860	0.1876	0.2132

These detailed controls, derived from the comprehensive RECS data, enabled a nuanced analysis of the factors affecting solar panel adoption. Our most robust model (column 5) indicates that an additional $10,000 in household income is associated with a 4.08% increase in the odds of a household adopting solar panels, translating to an odds ratio of 1.0408. These findings are consistent with prior research that emphasizes socioeconomic disparities within the residential solar market, such as the work by Borenstein and Davis (2016), which highlighted distributional effects and the economic accessibility of clean energy technologies.

We now turn our attention to a contributing factor of the observed income disparity in solar adoption: the non-refundability of the Solar Investment Tax Credit. A critical examination is directed at understanding the extent to which tax liability thresholds affect households' eligibility for

this credit. Analyzing detailed data from the American Economic Community Survey (AECS) for the year 2023, which includes individual income and tax liability figures, alongside the cost data for solar panels from "Tracking the Sun," we illustrate these dynamics in Figure 9. This figure displays the correlation between income levels and tax liabilities, with two horizontal lines indicating the upper and lower bounds of solar credit values, equating to 30% of solar panel costs.

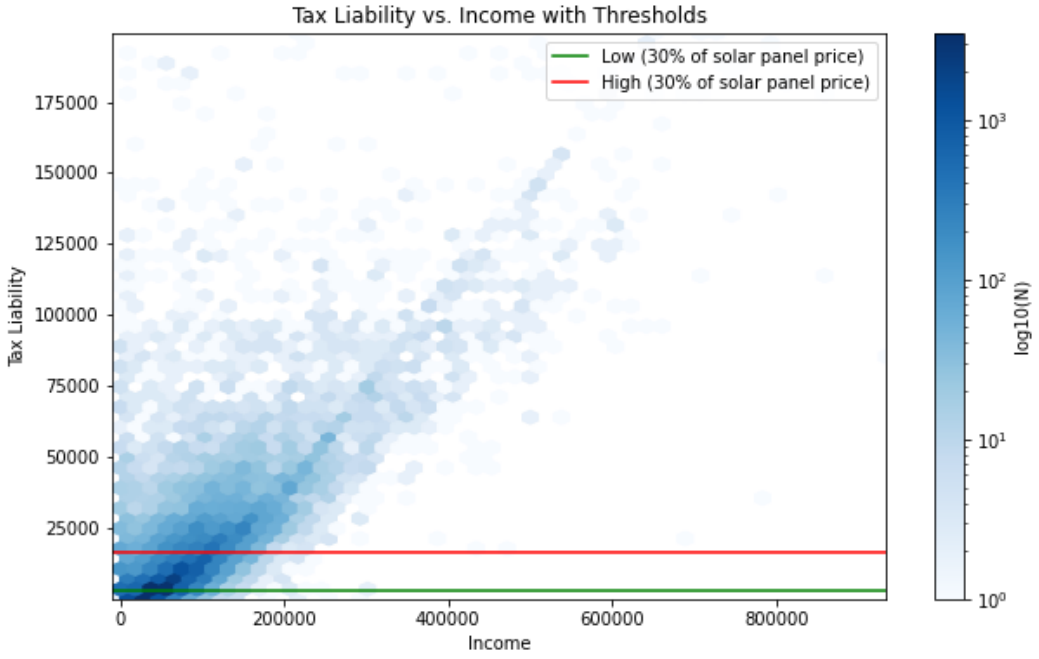


Figure 9: Tax Liability v.s. Income with Thresholds

The graph provides a visual representation of the policy's impact: households falling below the green line are precluded from receiving any credits, while those below the red line qualify for only a partial credit. A rudimentary quantitative analysis reveals a significant finding: nearly one-third of households are ineligible for any credit, while roughly 70% are constrained to receiving only a portion. These households, demarcated by the green and red lines, respectively, embody the tangible consequences of the policy's structural limitations.



Figure 10 presents a striking disparity in the utilization of tax credits across different income brackets, utilizing IRS annual statistics of zip-code level energy tax credit data. This analysis reveals a significant underutilization of tax credits in lower-income communities, with a notable 72% deficiency compared to their higher-income counterparts. Such a stark contrast underscores the potential barriers to accessing energy-efficient technologies in economically disadvantaged areas.

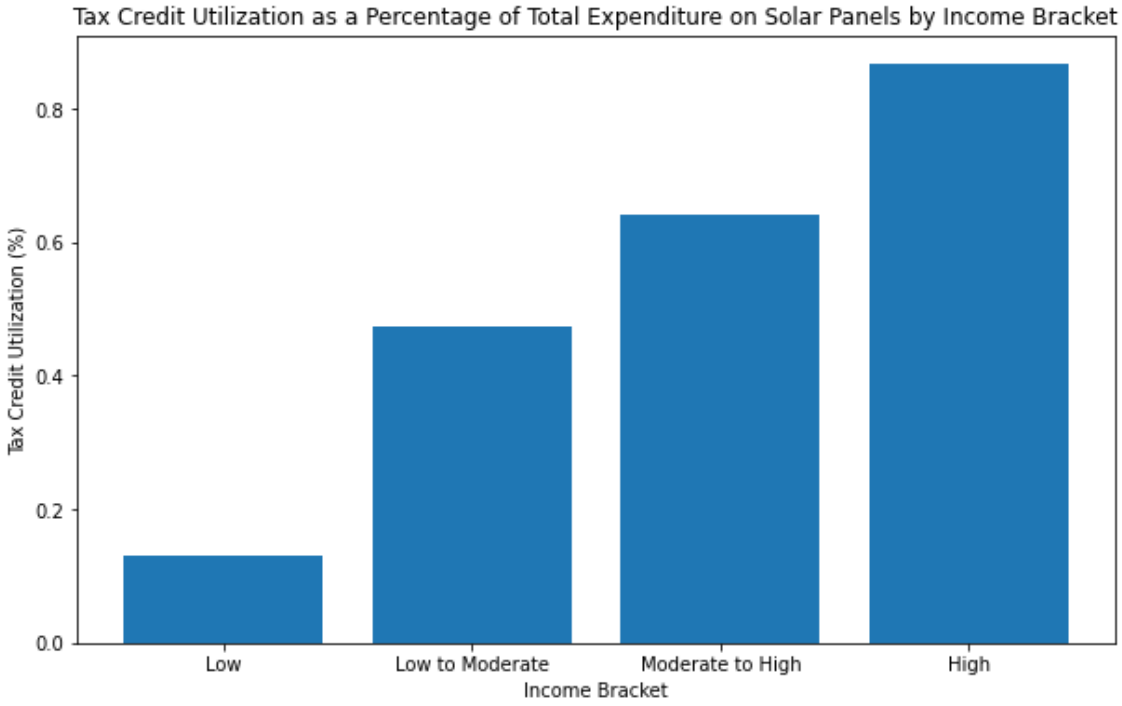


Figure 10: Tax Utilization by Income

To quantify the influence of income on tax credit utilization with greater precision, we applied a regression model as follows:

$$\text{Tax Credit Utilization}_{jt} = \alpha \text{ Median Household Income }_{jt} + \beta \text{ Average Price }_{jt} + \eta X_j + \gamma_t + \epsilon_{it}$$

where

- The dependent variable: the annual percentage of energy tax credits relative to total solar panel expenditures in each zip code.
- X_i controls macro characteristic in each zipcode like Gini Index.
- γ_t is the time fixed effect.

In Table 3, we present three different specifications. Initially, we start with a basic model that excludes controls for year and state fixed effects, focusing exclusively on fundamental income and price variables. In subsequent iterations, we progressively incorporate more controls, including the Gini index as a macro control. These additions facilitate a more nuanced examination of the regional and infrastructural factors that may influence the utilization rates of tax credits.

Table 3: Effect of Income on Tax Credit Utilization:Linear Regression Results

	Tax Credit Utilization		
Median Household Income	0.003226***	0.002891***	0.003289***
	(0.000224)	(0.000256)	(0.000360)
Gini Index		-0.1381*	-0.01488
		(0.065567)	(0.092458)
Constant	0.302157***	0.275502***	0.529256***
	(0.013091)	(0.011964)	(0.0642153)
Year FE	N	N	Y
State FE	N	N	Y
Obs	42193	42193	42193
Adj. R^2	0.0038	0.0038	0.0745
F-stat	207.24	165.32	89.16

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

The most robust specification (presented in column 3 of Table 3) demonstrates that a $1,000 increase in median household income correlates with a 0.3482% rise in the proportion of tax credit utilization relative to solar panel expenditures. This relationship remains statistically significant across various model specifications. Moreover, we extend our analysis by categorizing median household income into four dummy variables (Table 4). The results indicate a pronounced disparity in tax credit utilization among these categories. Notably, using the highest income bracket as the reference group, households in the low-income bracket exhibit a substantial decrease in tax credit utilization, with a rate reduction of approximately 79.602%.

Table 4: Effect of Income on Tax Credit Utilization:Linear Regression Results

	Tax Credit Utilization		
Low Income	-0.408295***	-0.631826***	-0.759626***
	(0.028904)	(0.039756)	(0.074759)
Low to Moderate Income	-0.077993**	-0.241055***	-0.342401***
	(0.026717)	(0.034464)	(0.037327)
Moderate to High Income	0.098576***	-0.039152	-0.152811***
	(0.022747)	(0.030016)	(0.030205)
Gini Index		-0.761080***	-0.835235***
		(0.061784)	(0.086125)
Constant	0.472484***	0.290587**	0.582427***
	(0.016613)	(0.012491)	(0.064990)
Year FE	N	N	Y
State FE	N	N	Y
Obs	42193	42193	42193
Adj. R^2	0.0010	0.0034	0.0744
F-stat	110.35	125.77	84.748404

Standard errors in parentheses
* p<0.05, ** p<0.01, *** p<0.001

These findings highlight a significant discrepancy in tax credit uptake among different income groups. While these credits are designed to broaden access to solar energy across socio-economic strata, the empirical evidence suggests a disparity in their actual utilization. Such a pattern intimates that, in their present form, these tax incentives fail to equitably distribute support for solar technology adoption.

This underutilization reflects broader systemic issues that past studies have identified, specifically concerning the impacts of the Federal Investment Tax Credit on the overall adoption of renewable energy technologies and the associated effects on power sector emissions within the United States, as well as the uneven distribution of clean energy tax credits across different income groups (Mai et al. (2016); Borenstein and Davis (2016); Comello and Reichelstein (2016)). The congruence of our findings with this body of literature underscores the critical need for policy adjustments to ensure that tax credits fulfill their intended role in fostering equitable clean energy transitions.

Collectively, these findings unveil a multifaceted challenge: while the RCEC stands as a significant federal instrument to incentivize residential solar investments, its efficacy is marred by disparities in distribution and utilization. By offering empirical evidence of these inequities, we lay the groundwork for the subsequent theoretical modeling. This study, thereby, calls upon policymakers to recalibrate the existing framework, potentially through the introduction of refundable tax credits and amplified credit values, to bolster adoption rates among the economically disadvantaged. The resultant policy suggestions from this research aspire to catalyze a shift towards a more sustainable and equitable energy paradigm.

5 Model

Motivated by the data patterns in the previous section, we develop a structural model to investigate the determinants influencing the household adoption of solar panels, incorporating the significant role of tax considerations. This model is inspired by the framework of Berry et al. (1993) and Petrin (2002). However, it is tailored specifically to the nuances of the solar panel market by incorporating the unique impacts of tax credits and liabilities, distinguishing it from previous models.

5.1 Demand

We consider a set of markets $t = 1, \ldots, T$, each comprising $i = 1, \ldots, I_t$ consumers and $j = 1, \ldots, J$ solar panel products. The utility that household i derives from choosing solar panel j in market t is given by

$$u_{ijt} = -\alpha_i p_{jt} + \boldsymbol{x}_{jt}^{\top}\boldsymbol{\beta} + \eta \min(TaxCredit_{jt}, TaxLiability_{it}) + \xi_{jt} + \epsilon_{ijt}, \tag{1}$$

where:

- α_i represents the marginal utility of income for consumer i.
- p_{jt} denotes the price of solar panel j in market t.
- $\boldsymbol{x}_{jt}$ is a vector of solar panel attributes, such as efficiency and size.
- β captures the preference coefficients for these attributes.
- η captures the sensitivity of consumer utility to the tax benefit.
- The term $\min(TaxCredit_{jt}, TaxLiability_{it})$ represents the realized tax benefit, which is the lesser of the tax credit available for solar panel j in market t and the tax liability of household i.
- ξ_{jt} is the unobserved utility from solar panel j in market t.
- ϵ_{ijt} captures the idiosyncratic taste shock.

Household i chooses solar panel j over other options if and only if $u_{ijt} \geq u_{ikt}$ for all $k \in J$. The decision framework accounts for the essential consideration of tax implications in the adoption process.

Consumer heterogeneity in preferences for solar panels is captured through observed and unobserved characteristics:

$$\alpha_i = \bar{\alpha} + \Pi D_i + \Sigma v_i, \tag{2}$$

where D_i represents observed demographics, including income, and v_i captures individual-specific unobserved factors.

The key innovation part of this model, tax benefits, depends on product prices and individual characteristics, particularly tax liability. To gain a deeper understanding of how the marginal utility of tax benefits is calculated, we explicitly define the functions associated with these benefits. The tax benefits a household ultimately receives are determined by two key factors: the tax credits available for specific products and the household's tax liability. This relationship can be modeled as follows:

$$\begin{aligned}\min(TaxCredit_j, TaxLiability_i) &= \min(30\% \times Price_j, TaxLiability_i) \\ &= \begin{cases} 30\% \times Price_j & \text{if } TaxLiability_i > 30\% \times Price_j \\ TaxLiability_i & \text{if } 30\% \times Price_j > TaxLiability_i \end{cases}\end{aligned}$$

Thus we can rewrite the utility function as:

$$\begin{aligned}u_{ijt} &= -\alpha_i p_{jt} + \boldsymbol{x}_{jt}^\top \boldsymbol{\beta} + \eta \min(TaxCredit_{jt}, TaxLiability_{it}) + \xi_{jt} + \epsilon_{ijt} \\ &= \begin{cases} -\alpha_i p_{jt} + \boldsymbol{x}_{jt}^\top \boldsymbol{\beta} + \eta 30\% \times Price_j + \xi_{jt} + \epsilon_{ijt} & \text{if } TaxLiability_i > 30\% \times Price_j \\ -\alpha_i p_{jt} + \boldsymbol{x}_{jt}^\top \boldsymbol{\beta} + \eta TaxLiability_{it} + \xi_{jt} + \epsilon_{ijt} & \text{if } 30\% \times Price_j > TaxLiability_i \end{cases} \\ &= \begin{cases} (-\alpha_i p_{jt} + \eta 30\% p_{jt}) + \boldsymbol{x}_{jt}^\top \boldsymbol{\beta} + \xi_{jt} + \epsilon_{ijt} & \text{if } TaxLiability_i > 30\% \times Price_j \\ -\alpha_i p_{jt} + \boldsymbol{x}_{jt}^\top \boldsymbol{\beta} + \eta TaxLiability_{it} + \xi_{jt} + \epsilon_{ijt} & \text{if } 30\% \times Price_j > TaxLiability_i \end{cases} \\ &= \begin{cases} -\bar{\alpha}_i 70\% p_{jt} + \boldsymbol{x}_{jt}^\top \boldsymbol{\beta} + \xi_{jt} + \epsilon_{ijt} & \text{if } TaxLiability_i > 30\% \times Price_j \\ -\alpha_i p_{jt} + \boldsymbol{x}_{jt}^\top \boldsymbol{\beta} + \eta TaxLiability_{it} + \xi_{jt} + \epsilon_{ijt} & \text{if } 30\% \times Price_j > TaxLiability_i \end{cases}\end{aligned}$$

Given the random shock following the extreme value distribution, the equilibrium CCP to choose alternative j takes the logit form (here normalizing utility to outside option as zero and assuming that α_i and β_i are the same for all households):

$$s_j = \frac{\exp\Big(-\alpha_i p_j + \boldsymbol{x}_j^\top \boldsymbol{\beta} + \eta \min(TaxCredit_j, TaxLiability_i) + \xi_j \Big)}{1 + \sum_{j \in J} \exp\big(-\alpha_i p_l + \boldsymbol{x}_l^\top \boldsymbol{\beta} + \eta \min(TaxCredit_l, TaxLiability_i) + \xi_l\big)}$$

Integrating across the households, the market share for product j is

$$s_j = \int_i \frac{\exp\Big(-\alpha_i p_j + \boldsymbol{x}_j^\top \boldsymbol{\beta} + \eta \min(TaxCredit_j, TaxLiability_i) + \xi_j \Big)}{1 + \sum_{j \in J} \exp\big(-\alpha_i p_l + \boldsymbol{x}_l^\top \boldsymbol{\beta} + \eta \min(TaxCredit_l, TaxLiability_i) + \xi_l\big)} dF_i$$

where F_i is the CDF of the household demographic variable.

5.2 Supply

The supply of solar panels is characterized by firms engaging in Bertrand competition. Firms set prices p_{jt} based on costs, demand factors, and government policies, including subsidies and tax credits. The profit maximization problem for a firm offering solar panel j in market t is formulated as:

$$\max_{p_j : j \in J_f} \sum_{j \in J_f} s_j(\mathbf{p}) \left(p_j - c_j\right) \tag{3}$$

where c_j is the cost of solar panel j, and s_j denotes the market share.

The first-order conditions of the profit function are as follows:

$$s_j(\mathbf{p}) + \sum_{j \in J_f} \frac{\partial s_j(\mathbf{p})}{\partial p_j} \left(p_j - c_j\right) = 0 \tag{4}$$

Writing the above first-order condition in matrix form:

$$\mathbf{p} - \mathbf{c} = \eta = \Delta^{-1}(\mathbf{p})\mathbf{s}(\mathbf{p})$$

where $\Delta^{-1} = -\mathcal{H} \odot \frac{\partial \mathbf{s}(\mathbf{p})}{\partial \mathbf{p}}$ is the element-by-element product. $\mathcal{H}$ is the ownership matrix where (j,k) element equal to one means that the same firm produces product j and k, and $\frac{\partial \mathbf{s}(\mathbf{p})}{\partial \mathbf{p}}$ is the derivatives and (j,k) element is equal to $\frac{\partial s_j(\mathbf{p})}{\partial p_k}$. Denote θ to be the full parameters to be estimated. Then I can recover the marginal cost $c_j = p_j - \eta_j(\theta)$, which allows me to construct the supply side moments.

5.3 Identification and micromoments

The main challenging Identification issue is in the heterogeneity part of i, particularly in estimating the marginal utility of tax benefits. The identification approach for other terms follows the methodology established by Berry et al. (1993). Building on Petrin (2002)'s framework, I utilize data at the zipcode level, including the total amount of energy tax credits and the number of individuals claiming these credits as recorded by the IRS. This data is then aggregated to the state level.

I construct micro-moments that align with the average tax credits per household, contingent on claiming the tax credit. Additionally, these moments facilitate a match between the model's predicted tax credits—based on the probability of purchasing solar panels—and the observed averages from survey respondents. The relevant micro moments are expressed as:

$$E[\min(TaxCredit_j, TaxLiability_i)|\text{i purchases product j }]$$

To enhance the robustness of the analysis, I have incorporated micro-moments for each state across multiple years. These are subsequently matched with market share data sourced from the Tracking the Sun database. Altogether, I have compiled 25 micro-moments, providing sufficient variation to robustly estimate the marginal utility parameter η.

5.4 Estimation

In this section, I describe the estimation of parameters in demand. We adopt a two-step estimation procedure akin to the method outlined by Berry et al. (1993) and Petrin (2002). for differentiated products markets, tailored to accommodate the unique features of the solar panel market. The first step involves recovering the product-level unobservables ξ_{jt}, while the second step estimates the preference parameters β and η. I supplement the macro moments with micro-moments the IRS data provides.

5.4.1 The macro moments

The first set of moments matches the market-level disturbances ($\xi_j(\theta)$). The unobserved demand disturbances are assumed to be uncorrelated with observed demand-side variables of all solar panels in that year. Then demand side moment is

$$\mathbb{E}\left[\xi_j(\theta) Z_j^D\right] = 0$$

where Z^D is the demand side instruments. The instruments used for demand estimations are:

- Silicon Price × Size (3 IVs)
  1. Price of Ferrosilicon 50% Si × Solar Panel Size
  2. Price of Ferrosilicon 75% Si × Solar Panel Size
  3. Silicon metal × Solar Panel Size
- BLP instruments for Size and Efficiency (6 IVs)
- Electricity Price (5 IVs)
- Differentiation instruments for Size and Efficiency (5 IVs) following Gandhi and Houde (2019).

The second set of moments matches the model's share predictions $s_j(\delta(\theta), \theta)$, to the shares in the data, S_j :

$$s_j(\delta(\theta), \theta) = S_j \tag{5}$$

where $\delta_j(\theta) = x_j\beta + \eta \min(TaxCredit_j, TaxLiability_i) + \xi_j$ is the mean utility. The other nonlinear part of utility is denoted as $\mu_{ij} = \alpha_i p_j + \Pi D_i + \Sigma\nu_i$. This set of moments enters the estimation in finding a fixed point of mean utility.

5.4.2 The micro moments

The set of micro-moments, as mentioned above, matches the model predictions of solar tax credits from the macro sales data and those from the IRS statistics:

$$\mathbb{E}\left[\text{ Tax Credits } \mid \{\text{i purchases PV system }\}\right],$$

5.4.3 The objective function

The program with macro moment $g_1(\theta)$ and micro-moment $g_2(\theta)$ can be summarized as following:

$$\begin{aligned} \min_{\theta} q(\theta) &\equiv g(\theta)' \tilde{W} g(\theta) \\ g(\theta) &= \begin{bmatrix} g_1(\theta) \\ g_2(\theta) \end{bmatrix}; \\ \xi_j &= \delta_j - x_j\beta - \min(TaxCredit_j, TaxLiability_i) \\ \eta_j &= \Delta^{-1}(\theta)\mathbf{s} \\ S_j &= s_j\left(\delta_j; \theta\right) \end{aligned} \tag{6}$$

where the weighting matrix is

$$\tilde{W} = \begin{bmatrix} W_1 & 0 \\ 0 & W_2 \end{bmatrix} = \begin{bmatrix} (Z_D Z_D')^{-1} & 0 \\ 0 & W_2 \end{bmatrix} \tag{7}$$

where W_2 at the lower right part matches the average claimed tax cerdits per household in each market from the IRS data.

The estimation procedures are similar to Petrin (2002), and I summarise them as follows:

1. Guess a value of θ.

2. Given θ, solve the nonlinear equation 5 to get the mean utility $\hat{\delta}_j(\theta)$.

3. Solve the linear IV problem for β, η through the GMM objective function.

4. Update θ, and iterate until convergence.

I deal with variance of linear part of parameters $\theta_1 = [\alpha']'$ and variance of non-linear parameters $\theta_2 = [\beta, \eta]'$ separately. The variance of θ_2 comes from the GMM objective function. Since $\theta_1 = C\delta(\theta_2)$ (C here comes from the expression of mean utility), the variance for the linear parameters can be derived using the Delta method:

$$\text{var}(\theta_1) = \nabla(C\delta(\theta_2))' \Sigma_{\theta_2} \nabla(C\delta(\theta_2))$$

and $\text{se}(\theta_1) = \text{var}(\theta_1)^{1/2}$.

6 Results

Table 5 presents the demand system estimates derived from the BLP model, which disentangles the effects of demographic characteristics, income, and tax benefits on consumer preferences for solar panels. This model elaboration captures nuances in consumer behavior with respect to energy-efficient investments.

Table 5: Demand System Estimates

	w/o Demographic	w/ Income	w/ Income & Tax Benefits
Price	-3.06**	-2.98***	-3.12***
	(1.50)	(1.15)	(1.69)
Size	6.88***	2.91***	2.80***
	(2.14)	(0.81)	(0.60)
Efficiency	-3.42	7.60***	1.49
	(14.47)	(2.46)	(2.04)
Tax Benefit		1.64***	2.59**
		(0.47)	(1.86)
Price*Income			0.35***
			(0.13)

In the first column, without demographic factors, the model explores basic price elasticity and reveals a robust negative relationship between price and demand, consistent with conventional economic theory which posits that an increase in price leads to a decrease in demand. This relationship is quantitatively significant, indicating strong price sensitivity among consumers. The positive coefficients for size and efficiency suggest that, ceteris paribus, consumers favor larger and more efficient solar panels, likely due to long-term savings on energy costs.

As tax variables are introduced in the second column, the model captures an uplift in utility from tax benefits, which significantly enhances the demand for solar panels. This key finding—the positive coefficient for tax benefits—serves as a cornerstone of this study, highlighting the strong impact of fiscal incentives on renewable energy adoption. It underscores the policy relevance of tax credits as an effective mechanism to boost consumer investment in solar technology. Additionally, the persistence of similar coefficients for price, size, and efficiency across both the first and second columns suggests that these factors consistently influence consumer choices. This robust effect of tax incentives offers crucial insights for tailoring effective energy policies that can engage broader segments of the population.

Here, we observed that the coefficient of tax benefits (1.64) is lower than the price coefficient (2.98), and this magnitude relationship remains consistent across various model specifications. There are two primary explanations for this relationship. First, households typically receive tax benefits one year after making a purchase, reducing the present value of the tax credits compared to immediate cash savings at the time of purchase. Second, the solar tax credit is restricted to specific purposes related to solar installations and cannot be used as freely as cash. This usage restriction further diminishes the utility of a one-dollar tax credit compared to one dollar in cash.

The third column integrates both income and tax benefits, further refining the model's accuracy by accounting for interactions between price and income. The emergence of a positive coefficient for the interaction term (Price*Income) suggests that higher income brackets exhibit decreased price sensitivity. This may imply that wealthier consumers, less constrained by budgetary limitations, are more willing to invest in solar technology despite higher initial costs.

The detailed examination of these variables provides critical insights into market dynamics and consumer decision-making processes in the solar panel industry. Understanding these relationships helps policymakers and businesses tailor strategies that effectively target various demographic and income groups, optimizing the uptake of solar energy solutions. Such strategies could include scaling tax incentives based on income levels to make solar technology accessible and appealing across all socioeconomic segments.

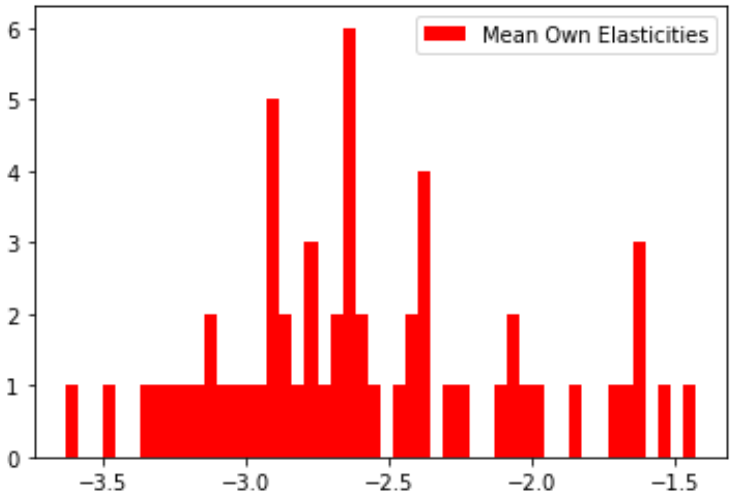
Figure 11 presents the elasticity distribution implied by the demand estimation. Looking at the market's total elasticity, we find that overall demand is less sensitive than individual product demands. The mean own elasticity shows a kind of normal distribution, averaging at -2.57.

The cross-price elasticities, on the other hand, are relatively small, mostly less than -0.1. This indicates that changes in the price of one brand have a minimal impact on the demand for another brand. Notably, these cross-price elasticities are larger among more similar solar panel brands, reflecting a higher degree of substitutability among these products.

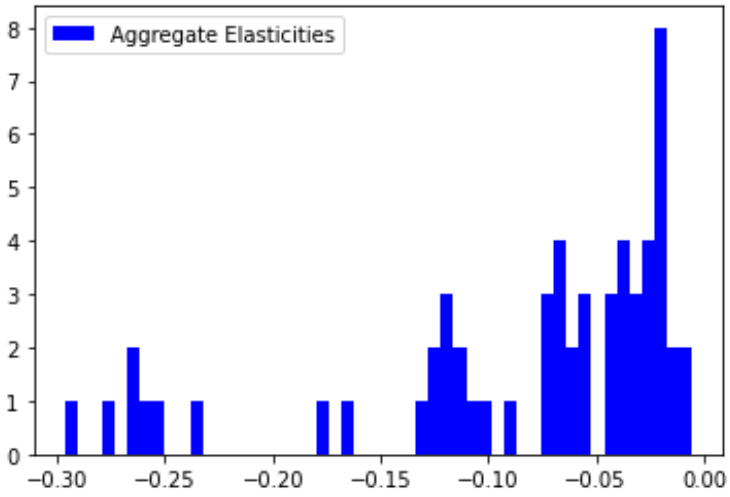
To better understand the estimates, Table 6 presents a sample of own and cross-price elasticities for the top 10 models of a sample region. Here I chose the CBSA 41740 (San Diego-Carlsbad, CA metropolitan area) market in 2020 for illustration. The demand estimates reveal that the own-price elasticities are significantly larger, averaging around -2.2, indicating a high sensitivity of demand to price changes within each brand. This high sensitivity suggests that consumers are likely to reduce their purchase volume substantially in response to price increases.

For instance, the cross-price elasticity between Jinko Solar, Model JKM320M and LG Electronics, Model LG350 is slightly higher compared to other brand pairs, suggesting that consumers view these brands as closer substitutes. Similarly, Jinko and Sanyo also exhibit relatively higher cross-price elasticities, reinforcing the idea that consumers are more likely to switch between these brands when faced with price changes.

Overall, the estimated elasticities align well with those found in the existing literature on demand estimation for residential solar panels. The data underscores the significant role of price in driving demand for solar panels, while also highlighting the competitive dynamics within the market where brand differentiation plays a crucial role.



(a) Mean Own Elasticity



(b) Aggregate Elasticity

Figure 11: Elasticity

Table 6: Elasticity for Selected Solar Panel Brands of CA in 2020

	Jinko Solar JKM320M	Q CELLS Q.PEAK	Q CELLS $BLK-SC$	LONGi LR6	SANYO ELECTRIC SA17	LG LG350	LG LG320	Q CELLS $BLK-G6+$	SunPower X21	LG LG345
Jinko Solar, JKM320M	-2.6450	0.1695	0.1275	0.0864	0.1040	0.1090	0.0001	0.0616	0.0058	0.0748
Hanwha Q CELLS, Q.PEAK	0.2095	-2.2943	0.1393	0.0937	0.1006	0.0999	0.0007	0.0703	0.0085	0.0765
Hanwha Q CELLS, $BLK-SC$	0.1935	0.1710	-2.1905	0.0940	0.0979	0.0957	0.0021	0.0713	0.0102	0.0755
LONGi Green Energy, LR6	0.1953	0.1714	0.1400	-2.2507	0.0983	0.0962	0.0019	0.0713	0.0100	0.0757
SANYO ELECTRIC, SA17	0.2211	0.1730	0.1371	0.0924	-2.4716	0.1023	0.0004	0.0686	0.0077	0.0764
LG Electronics, LG350	0.2324	0.1722	0.1344	0.0907	0.1026	-2.5721	0.0002	0.0666	0.0070	0.0760
LG Electronics, LG320	0.0007	0.0028	0.0067	0.0040	0.0008	0.0005	-1.1173	0.1143	0.0013	0.0734
Hanwha Q CELLS, $BLK-G6+$	0.1802	0.1661	0.1374	0.0922	0.0942	0.0913	0.0047	-2.1655	0.0122	0.0734
SunPower, X21	0.0238	0.0280	0.0276	0.0180	0.0147	0.0135	0.0975	0.0179	-1.5903	0.0124
LG Electronics, LG345	0.2094	0.1732	0.1393	0.0937	0.1006	0.0998	0.0007	0.0703	0.0085	-2.3900

Finally, we turn to the supply side to investigate differences in marginal costs. Figure 12 presents the marginal cost distribution implied by the demand estimation based on data from 2010 to 2020. The median marginal cost for residential photovoltaic (PV) systems during this period is approximately $26,489. This distribution highlights significant variation in costs, with a notable concentration around the median value.

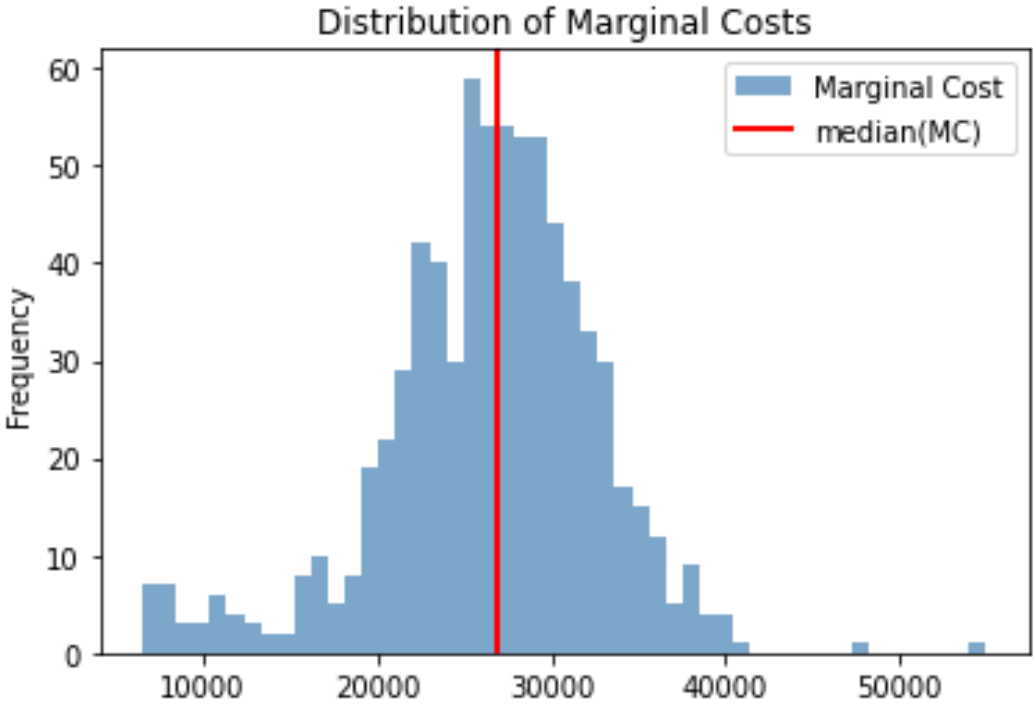


Figure 12: Distribution of Marginal Cost for Solar Panels

Recent data from the National Renewable Energy Laboratory (NREL) indicate that costs associated with residential PV systems have steadily declined over the past decade, driven primarily by reductions in module, inverter, logistics, and customer acquisition costs. These decreases were substantial enough to offset increases in other areas, such as balance of system costs. According to the Solar Energy Industries Association (SEIA), the cost of installing solar has dropped by more than 70% in the last decade (NREL)[2].

The distribution in Figure 12 reflects these broader market trends, emphasizing the impact of policy measures and technological advancements that have contributed to cost reductions. Specifically, the solar credits under the Inflation Reduction Act, which is the focus of this paper, have introduced manufacturing tax incentives that lower component prices for domestic manufacturers. These incentives have played a significant role in reducing overall costs for residential PV systems.

[2]https://solarbuildermag.com/news/residential-solar-pv-system-costs-track-15-percent-lower-in-2023-utility-scale-not-so-lucky/

Moreover, this distribution suggests that while the median marginal cost is around $26,489, there are economies of scale and efficiency improvements that could further drive down costs, especially for large-scale adopters. Understanding these cost dynamics is crucial for policymakers aiming to enhance the adoption of solar technologies, as it underscores the potential financial benefits of targeted subsidies and incentives to lower upfront costs for consumers.

By examining these demand estimates and cost structures over the last decade, we gain a deeper understanding of the economic barriers and opportunities within the residential solar market. This analysis not only highlights the impact of recent policy measures and technological advancements but also provides a robust foundation for the subsequent counterfactual analysis.

7 Counterfactual Scenarios

To evaluate policy effectiveness and explore alternative scenarios, we conduct counterfactual analysis. This analysis considers the impact of making the tax credit, for two aspects:

1. **Adoption Rate:** This analysis considers the impact of making the tax credit for solar panel adoption refundable, expanding its reach to households with lower tax liabilities.
2. **Environmental Benefit Focus:** Here, we examine optimal policy configurations prioritizing environmental benefits, such as carbon emission reductions, over direct adoption rates. This scenario aims to align solar panel adoption incentives with broader environmental goals.

In this section, we conduct experiments by making the modification of the tax credit's non-refundability, thereby making it accessible to all households irrespective of their income levels. Secondly, we alter the focus of the incentive structure from a purely adoption-driven approach to one that is primarily environmentally oriented. For both aspects, we utilize parameter estimates derived from the preceding empirical analysis to recalibrate the equilibrium pricing models under the newly proposed frameworks. Subsequently, we assess the resultant market dynamics, such as changes in adoption rates and environmental impacts.

It is crucial to note that these computations assume constancy in several variables: solar panel characteristics, marginal costs, and demographic characteristics are presumed to remain unchanged from those recorded in the existing data set. This assumption allows for a focused analysis of policy impact by controlling for external variations.

These focuses in this part are designed to provide deep insights into how adjustments in policy mechanisms could simultaneously enhance the uptake of solar panels and improve environmental outcomes. The findings are expected to contribute to the broader discourse on effective strategies for promoting renewable energy adoption and achieving sustainability targets.

The common approach to solve the equilibrium price is to treat equation 9 as a fixed point and iterate on the equation. The problem is that the equation is not necessarily a contraction mapping. Instead, follow the faster and more reliable method by Morrow and Skerlos(2011) and Conlon and Gortmaker (2020) who reformulate equation 9 by breaking up the demand derivatives into two parts: a diagonal J × J matrix Λ , and a J × J dense matrix Γ :

$$\begin{aligned}\frac{\partial \boldsymbol{s}}{\partial \boldsymbol{p}}(\boldsymbol{p}) &= \Lambda(\boldsymbol{p}) - \Gamma(\boldsymbol{p}) \\ \Lambda_{jj} &= \int \frac{\partial u_{ij}}{\partial p_j} s_{ij} dF_i \\ \Gamma_{jk} &= \int \frac{\partial u_{ij}}{\partial p_j} s_{ij} s_{ik} dF_i\end{aligned}$$

The problem then can be reformulated as a different fixed point that is specific to mixed logit demands:

$$\begin{aligned}\boldsymbol{p} &= \boldsymbol{c} + \zeta(\boldsymbol{p}) \\ \text{where } \zeta(\boldsymbol{p}) &= \Lambda(\boldsymbol{p})^{-1}[\mathcal{H} \odot \Gamma(\boldsymbol{p})](\boldsymbol{p} - \boldsymbol{c}) - \Gamma(\boldsymbol{p})^{-1}\boldsymbol{s}(\boldsymbol{p})\end{aligned}$$

Morrow and Skerlos (2011) argue that numerical methods based on equation 17 can have entirely different properties from equation 9 because they are different functions, and these two functions coincide only at stationary prices.

7.1 Focus One: Adoption Rate

Table 7 presents a counterfactual analysis to compare market outcomes before and after converting non-refundable tax credits to refundable ones, utilizing estimates from the most comprehensive model with full demographic details.

The analysis reveals that median photovoltaic (PV) panel prices decrease from $28,031 under the non-refundable scenario to $22,261 under the refundable scenario, representing a reduction of $5,770 or 20.6%. This price drop coincides with a significant increase in total market PV sales, which rise from 221,518 units to 274,132 units, marking a 23.8% increase.

This growth is particularly pronounced among low-income households, where market share escalates by 123.6%, more than seven times the growth rate of 16.3% observed in high-income communities. This stark contrast demonstrates the enhanced accessibility afforded to the most vulnerable groups by the refundable credits.

We hypothesize that the higher growth rate in low-income communities stems from the low utilization of tax credits under the current non-refundable scheme. Since making the credit refundable does not directly alter the price but removes the cap imposed by tax liability, low-income households benefit more significantly as they were previously unable to fully utilize the non-refundable credits. In contrast, high-income households, which were less affected by the cap, see less pronounced benefits, as supported by the analysis in Section 4.

Table 7: CF1: Market outcome after making tax credits refundable

	Refundable	Non-refundable	Difference	Growth Rate (%)
Median Price	22,261	28,031	-5,770	-20.6%
Total Market Sales	274,132	221,518	52,614	23.8%
Sales (Low Income)	14,576	6,520	8,056	123.6%
Sales (Median Income)	53,432	37,751	15,681	41.5%
Sales (High Income)	206,124	177,247	28,877	16.3%

Table 8 presents a detailed analysis of the welfare outcomes from making tax credits refundable as opposed to their original non-refundable state, drawing on methods from demand estimation for differentiated products as utilized in studies like those by J. Li (2019), illustrating nuanced impacts across different social strata.

The transition to refundable tax credits results in a increase in total consumer surplus of 32.8%, with the increase of around $X (work in progress) million. This suggests that consumers overall benefit from the refundability of the tax credits, particularly under conditions considering demographic variations.

The impact on consumer surplus varies significantly among different income groups. Low-income households experience substantial benefits from the refundability, with a 381% increase due to their previously limited ability to fully utilize non-refundable credits. Medium-income households see smaller gains with a 140% growth rate, while high-income households observe minimal changes, with a slight decrease of 8%. This outcome indicates that the policy disproportionately favors those at the lower end of the income spectrum, addressing equity concerns in the adoption

of solar technology.

The subsidy expenditure, which reflects the total cost to the government or other bodies providing the subsidies, sees dramatic increases to $X (work in progress). This significant rise underscores the economic cost of making tax credits refundable. The distribution of these subsidies also shifts, with low-income households receiving the largest increases, underscoring the policy's targeted benefit towards enabling more equitable access to solar technologies.

Table 8: CF1: Welfare Outcome of making tax credit refundable

	Refundable	Non-refundable	Difference	Growth Rate (%)
Total Consumer Surplus (USD)	4,075,314	3,068,432	1,006,882	32.8%
Low Income Households	248,928	51,777	197,151	380.8%
Medium Income Households	1,695,699	709,014	986,685	139.2%
High Income Households	2,130,687	2,307,641	-176,954	-7.7%

Finally, the average subsidy per solar panel increases/ decreases (work in progress) substantially, demonstrating the higher per-unit cost of subsidies under the refundable system. While this shift clearly benefits consumers, particularly those from lower-income households, by enhancing their purchasing power and enabling greater access to solar technology, it also imposes considerable costs on subsidy providers and slightly impacts producers negatively. This policy adjustment, despite its expense, aligns with broader environmental goals by facilitating increased solar adoption across all economic demographics, supporting sustainability efforts.

Overall, the refundability of tax credits introduces substantial benefits across various income groups, with low-income households witnessing the most dramatic improvements. This shift not only democratizes access to solar technology but also suggests a broader acceptance and integration of renewable energy solutions in economically diverse demographics. By making the tax credits refundable, the policy removes financial constraints that previously hindered low-income households from investing in environmentally sustainable technologies.

7.2 Focus Two: Environmental Benefits

In this section of our counterfactual analysis, we shift our focus from general market outcomes to the environmental impacts of implementing refundable tax credits for solar technology. While existing literature often examines the role of solar policies in promoting solar panel adoption, it rarely addresses their ultimate environmental benefits. This analysis aims to fill that gap by evaluating whether current solar policies direct investments to locations that maximize environmental improvement. This is crucial because the goal of promoting clean energy extends beyond merely increasing the number of solar panels installed. It is essential to consider where these panels are placed to ensure they generate the highest possible environmental benefits. By optimizing the location of solar panels, we can achieve greater reductions in pollution and better overall outcomes for public health and the environment.

To understand the environmental efficiency of federal solar policy, we use econometric models of marginal electricity generator pollution emissions developed by Holland et al. (2016) and Sexton et al. (2021) to derive empirically valid estimates of the spatially varying environmental benefits of solar capacity. These estimates, which monetize avoided environmental damages for each of 30,105 U.S. zip codes, are compared to the value of federal solar subsidies to provide a comprehensive evaluation of solar policies. By exploring how changes in the tax credit structure influence environmental outcomes, specifically avoided pollution damages, we estimate spatially heterogeneous emissions avoided per unit of solar generation and integrate these changes into an assessment model to map emissions into damages. This approach allows us to attribute values to potential solar capacity in each U.S. zip code, considering solar irradiance and weather characteristics, with the goal of determining whether policy adjustments promoting solar panel adoption can also achieve broader environmental objectives, such as reducing the ecological footprint of energy consumption.

7.2.1 Solar Generation

To estimate the avoided damages resulting from solar panel installations, we first need to calculate the changes in electricity demand that these panels bring to the grid. This involves using the System Advisor Model (SAM) developed by the National Renewable Energy Laboratory (NREL). SAM is a sophisticated simulation tool designed to predict the performance and financial feasibility of renewable energy projects, including solar photovoltaics (PV).

SAM provides detailed analyses by integrating solar irradiance data at a 4-square-kilometer resolution with weather information from over 1,000 weather stations across the contiguous United States. This high-resolution data ensures that the model can accurately predict solar panel output by considering the specific solar radiation and climatic conditions of each location.

The model takes into account various factors such as the angle of the solar panels, shading, and the efficiency of the panels and inverters. For our analysis, we assume standard system settings to ensure comparability of results across different locations. Specifically, we align the tilt of the panels with the local latitude, which is a common practice to optimize solar exposure and maximize energy production. Additionally, we orient the panels southward, which is generally the best direction to capture the most sunlight throughout the day in North America.

By using SAM, we can estimate the system generation for solar panels in each of the 30,105 zip codes we are analyzing, thereby providing a robust estimate of the changes in electricity demand.

Figure 13 summarizes the modeled annual solar generation for each zip code across the United States. Mean annual generation for a 4kW system is 6,357 kWh. It varies by a factor of 2 from 4,344 kilowatt-hours (kWh) in Arlington, Washington, to 8,647.4 kWh in Lone Pine, California. The within-state standard deviation varies from 55.7 kWh to 636.6 kWh. The mean within-state standard deviation is 239 kWh. The graph shows that solar energy generation is highest in the Southwest, indicating significant regional variability in solar potential across the country.



Figure 13: Total annual electricity generation per 4 kWsolar capacity

7.2.2 Marginal Emissions

Next, to estimate the emissions avoided by each unit of solar energy generated, it is crucial to identify which power plants respond to the marginal reduction in net load. In my analysis, I focus on plant-level emissions because the power plants operating on the margin can vary significantly depending on the time and location of solar energy production. By applying the reduced-form regression models developed by Holland et al. (2016) and Sexton et al. (2021) , we can accurately determine these marginal emissions.

This approach involves regressing the hourly emissions of each power plant on the hourly electricity demand within each subregion of the power plant grid interconnection. This method allows us to capture the dynamic response of power plants to changes in electricity demand induced by solar energy generation. We analyzed data from 1,486 power plants across the United States, covering a comprehensive range of pollutants, including CO2, SO2, NOX, and PM2.5.

The emissions data were obtained from the Environmental Protection Agency's (EPA) Continuous Emissions Monitoring System (CEMS), which provides high-frequency, plant-level emissions data. By incorporating detailed hourly demand and emissions data, our regression models can identify the specific plants that adjust their output in response to the introduction of solar power and quantify the resulting changes in emissions.

To gather data on hourly emissions of CO2, NOX, and SO2, we utilized the Continuous Emissions Monitoring System (CEMS) database maintained by the US Environmental Protection Agency (EPA). This dataset includes emissions information from 1,451 power plants across the United States for the years 2007 to 2016, providing a substantial volume of 114.4 million hourly

observations for each pollutant.

Since the CEMS does not directly report hourly PM2.5 emissions, we estimated these values by calculating plant-specific PM2.5 emission intensities per unit of electricity generated. These intensities were then multiplied by the hourly generation data recorded in the CEMS. The PM2.5 emission intensities were derived from the EPA's 2011 National Emissions Inventory, which offers annual emission data.

In addition to emissions data, we obtained hourly electricity consumption records from the Federal Energy Regulatory Commission (FERC) Form 714 filings, which cover 200 planning areas throughout the United States. This consumption data was aggregated into eGRID subregions to provide a comprehensive overview of regional electricity demand patterns.

Finally, to complement the emissions and consumption data, we incorporated solar irradiance information from the National Solar Radiation Database. This database offers detailed hourly measurements of solar irradiance at the zip-code level for all utility-scale solar facilities in the country. These irradiance values were aggregated by eGRID subregions, weighted according to the solar capacity installed in each area, resulting in a weighted-average solar irradiance for every subregion and hour.

Specifically, we estimate:

$$\begin{aligned} y_{it} = &\sum_{b=1}^{24}\sum_{j=1}^{j(i)}\sum_{m=1}^{12} \beta_{ijbm}\text{LOAD}_{tj} \times \text{HOUR}_b \times \text{eGRID}_j \times \text{MOY}_m + \gamma_{ijbm}\sum_{j=1}^{j(i)} s_{jt} \\ &+ \sum_{b=1}^{24}\sum_{m=1}^{120}\sum_{d=1}^{2} \alpha_{ibmd}\text{HOUR}_b \times \text{MOS}_m \times \text{DAY}_d + \epsilon_{it}, \end{aligned} \tag{8}$$

In this model, y_{it} represents the pollutant emissions at plant i during time t. $LOAD_{tj}$ is a continuous variable representing the electricity demand in eGRID subregion j at time t. The variables HOUR, eGRID, and MOY are indicator variables for each hour of the day, each eGRID subregion within the network of plant i, and each month of the year, respectively. This setup produces a vector of marginal emissions coefficients, β_{ijhm}, for each plant and pollutant, with a dimensionality of 24 * j(i) * 12. Additionally, MOS and DAY serve as indicators for each month and for weekdays, respectively.

To account for potentially correlated, unreported generation, we include an index of contemporaneous solar generation in each subregion, s_{jt}. This index is calculated by summing the product of plant-specific solar irradiance and plant capacity for all utility-scale solar installations within the subregion for each hour of the sample period. The model also includes an idiosyncratic error term, ϵ_{it}. We estimate Equation (8) using ordinary least squares (OLS) regression.

This detailed analysis enables us to estimate the environmental benefits of solar energy more accurately. By understanding which power plants are displaced by solar generation, we can provide more precise estimates of the reductions in harmful emissions, thereby offering valuable insights for

policymakers on the potential environmental benefits of expanding solar energy capacity.

7.2.3 Exposure and Damages

With modeled solar generation by zip code and estimated emissions responses from each plant in 7.2.1 and 7.2.2, we can estimate annual changes in pollutant emissions from solar capacity additions in each zip code. To monetize these emissions changes, we use the updated version of Air Pollution Emission Experiments and Policy analysis model (AP3). AP3 is an advanced air pollution model that translates emissions into concentrations, concentrations into exposure, and exposure into health impacts. This model, utilizes data from the EPA's National Emissions Inventory and employs a reduced complexity air quality model to estimate annual average pollution concentrations by county. AP3 also incorporates demographic and economic data to evaluate the health impacts of pollution exposure, primarily focusing on mortality risks, which are valued using the EPA's recommended statistical life value, adjusted for inflation. The social cost of carbon, updated to 2016 figures by the U.S. Interagency Working Group, is used to value CO2 emissions at $41 per ton.

The model estimation yields over 13.7 million parameter estimates, covering each plant's emissions across different times and conditions. It provides a unique estimation for each hour of the day and month of the year for each pollutant and for each regional load within the plant interconnection. We validate our empirical model by aggregating these estimates to confirm that a 1 MW change in hourly load across the interconnection induces a corresponding response in fossil fuel generation.

From our analysis, we derive the avoided annual total damages and pollutant-specific damages for a 4 kW solar system in each zip code. On average, the avoided damages amount to $568 per system per year, or $7,084 over the system's lifetime, which represents about half the average installation cost. The largest share of these avoided damages comes from reduced SO2 emissions (56%), followed by CO2 (30%), NOX (10%), and PM2.5 (4%).

Figure 14 illustrates the spatial distribution of these avoided damages, showing that the highest benefits are observed in the Midwest and Mid-Atlantic states, such as Delaware, Indiana, Maryland, New Jersey, and Virginia, where avoided damages per 4 kW system can reach approximately $1,100 annually. Conversely, the lowest benefits are in the West and Northeast, with states like Connecticut, Massachusetts, Rhode Island, and Washington seeing avoided damages around $80 annually. In California, which hosts two-thirds of the nation's rooftop solar capacity, the annual avoided environmental damages range from $92 in Klamath on the northern coast to $277 in Desert Hot Springs, located about 100 miles east of Los Angeles.

Solar resources are most abundant in the Southwest, as Figure 13 demonstrates. However, Figure 14 shows that avoided damages are lowest in the Western region. In contrast, the highest avoided damages are observed in the Midwest and Mid-Atlantic regions, where the power generation fleet is considerably more polluting than in the West.

The disparity in avoided damages can be attributed to the composition of the energy generation mix in these regions. In the Western Interconnection (WECC), which serves the Mountain West and West Coast, coal accounted for only 27% of electricity generation in 2014, with natural gas units supplying 30%. On the other hand, the Midwest Reliability Organization, which manages the

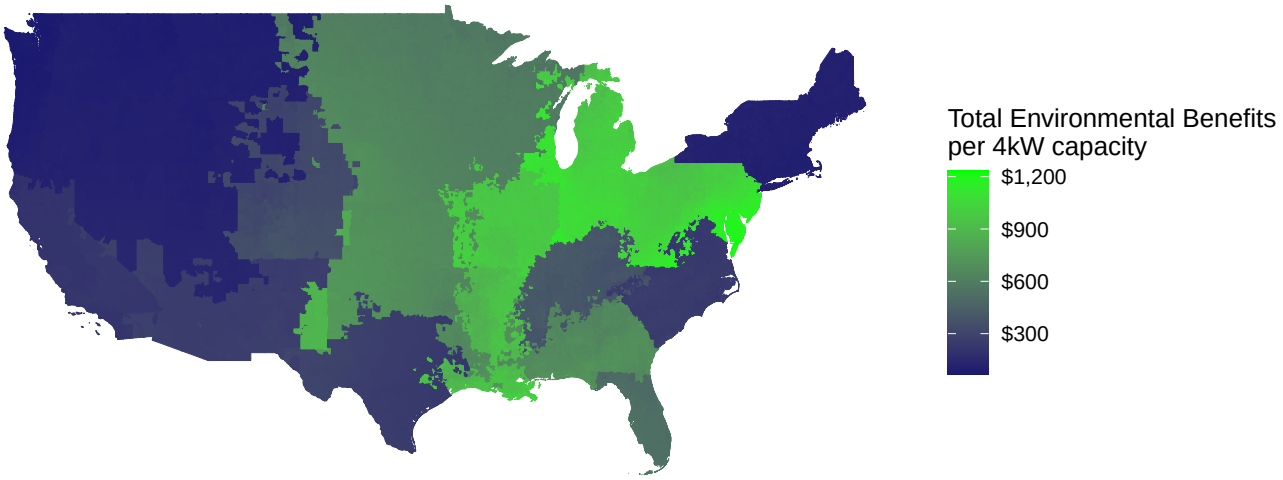


Figure 14: Total annual avoided environmental damages per 4 kW solar capacity

Midwest grid within the Eastern Interconnection, relied heavily on coal, which constituted 60% of its generation, while natural gas unitscontributed just 5% (NREL 2017).

This significant dependence on coal in the Eastern Interconnection means that marginal responding plants are more likely to be coal-fired, which are typically dirtier compared to natural gas plants. Consequently, the Midwest and Mid-Atlantic regions experience greater avoided damages from reduced coal emissions. Additionally, the reduction of pollution emissions in the Eastern Interconnection positively impacts densely populated areas such as Washington, DC, Boston, Philadelphia, and New York. Reducing emissions in these regions translates to substantial public health and environmental benefits.

The heterogeneity in the value of emissions reductions across the United States is depicted in Figure 14 , which illustrates the variation in damages from 1 ton emissions. This figure underscores the importance of considering regional differences when evaluating the environmental benefits of solar energy installations.

Overall, the analysis highlights that while solar resource availability is a crucial factor, the composition of the regional energy mix and population density play significant roles in determining the environmental and public health benefits of solar power. These insights are vital for policymakers aiming to maximize the impact of renewable energy policies by targeting areas where emissions reductions can achieve the highest value.

7.2.4 Income and Heterogeneous Environmental Benefits

Based on the estimates provided above, we categorized the 30,105 zip codes in the United States into three distinct income groups: low, medium, and high, based on percentiles. We then calculated the average avoided pollution damages for each group, as detailed in Table 9. The data reveals that the mean avoided pollution damage is $600 for low-income households, $584 for medium-income households, and $537 for high-income households.

The results show that installing a PV system in low-income communities yields greater environmental benefits compared to high-income communities, with an additional $63 in avoided damages per system. Current literature extensively documents that solar panel adoption is more prevalent among high-income households. However, our findings challenge this trend by highlighting that the existing policy framework is not only inequitable but also inefficient from an environmental standpoint.

This disparity indicates that the current non-refundable tax credit policies are not effectively directing investments to the locations where they would achieve the highest environmental benefits. Consequently, opportunities for maximizing the potential of solar power are being missed. The higher avoided damages in low-income areas suggest that these regions would benefit more from solar installations compared to higher-income areas.

This inefficiency highlights the necessity for policy reforms that would facilitate a more strategic allocation of solar investments. According to the Environmental Defense Fund, low-income communities often face higher levels of pollution and have more to gain from cleaner energy solutions. By making tax credits refundable and more accessible to low-income households, these reforms could better target areas with the highest potential for environmental impact.

To determine the effectiveness of such policy reforms, we conducted an analysis comparing the environmental benefits before and after the introduction of refundable tax credits across different income groups. Table 6 illustrates significant changes in emission levels for each pollutant, emphasizing the impact of the policy shift. By analyzing these changes, we can see how making tax credits refundable could significantly enhance the environmental benefits in low-income communities, which are currently underserved by the existing policy framework.

Table 9 presents the results of environmental benefits. When examining the total annual dollars of avoided pollution damages, the average environmental benefit per zip code increases from $568 to $615, representing an 8% rise. Disaggregating these effects by income group reveals notable disparities. For low-income communities, the average avoided damages increase from $600 to $664, a 10.7% rise. Medium-income communities see a more modest increase from $584 to $608, or 4.1%. High-income communities experience a rise from $537 to $564, a 5% increase. The rate of increase in low-income communities is more than double that in high-income households, indicating that this policy change will primarily benefit low-income communities and enhance environmental equity.

Table 9: Market Outcome of Environmental Benefits: Avoid Pollution Damages

	Non-Refundable	Refundable		
	Mean (dollars)	Mean (dollars)	Diff	% Change
Total Annual Dollars				
Total	568.4	615.3	46.9	8.3 %
Low Income	599.5	663.7	64.2	10.7 %
Medium Income	584.0	607.9	23.9	4.1 %
High Income	536.9	563.5	26.6	5.0 %
Part A: Avoided CO2 (dollars)				
Total	170.3	173.5	3.2	1.9 %
Low Income	176.8	204.9	28.1	15.9 %
Medium Income	164.6	144.5	-20.1	-12.2 %
High Income	167.9	186.4	18.5	11.0 %
Part B: Avoided NOx (dollars)				
Total	55.0	56.1	1.1	2.0 %
Low Income	56.3	59.7	3.4	6.0 %
Medium Income	57.5	58.0	0.5	0.9 %
High Income	52.8	50.7	-2.1	-4.0 %
Part C: Avoided $PM_{2.5}$ (dollars)				
Total	23.2	23.5	0.3	1.3 %
Low Income	21.8	23.7	1.9	8.7 %
Medium Income	24.4	24.0	-0.4	-1.6 %
High Income	24.2	23.1	-1.1	-4.5 %
Part D: Avoided SO2 (dollars)				
Total	320.0	362.2	42.2	13.2 %
Low Income	344.5	375.4	30.9	9.0 %
Medium Income	337.4	384.4	47	13.9 %
High Income	292.0	303.3	11.3	3.9 %

Specifically, examining the categories of emissions:

- **CO2 Emissions:** There is a nuanced reduction pattern. The average avoided CO2 emissions increase from \$170 to \$174, a 1.9% increase in avoidance. While medium-income households experience a slight decrease, low and high-income households show an increase in avoided emissions. This indicates that while the policy is effective in reducing overall carbon footprints, the consumption patterns of higher-income households might require different strategies to achieve similar reductions.
- **NOx Emissions:** There is a noticeable decrease following the policy change. The average avoided NOx emissions increase from \$55 to \$56, a 2% increase in avoidance. The reductions are particularly significant among low-income households, which see an increase of 6%, underscoring the policy's effectiveness in enabling lower-income brackets to adopt cleaner technologies.
- **PM2.5 Emissions:** There is a mild decrease in PM2.5 emissions. While medium and high-income households show a moderate decrease, low-income households exhibit an increase in avoided emissions, overall generating positive benefits.
- **SO2 Emissions:** This category shows the most significant reduction pattern. SO2 emissions decline substantially, with total avoidance increasing from \$320 to \$362, a 13.2% increase. This increase is mainly driven by pollution avoidance in low-to-moderate income groups. This suggests that the policy not only supports the adoption of solar panels but also contributes to reducing sulfur compounds that are known for causing respiratory problems and acid rain.

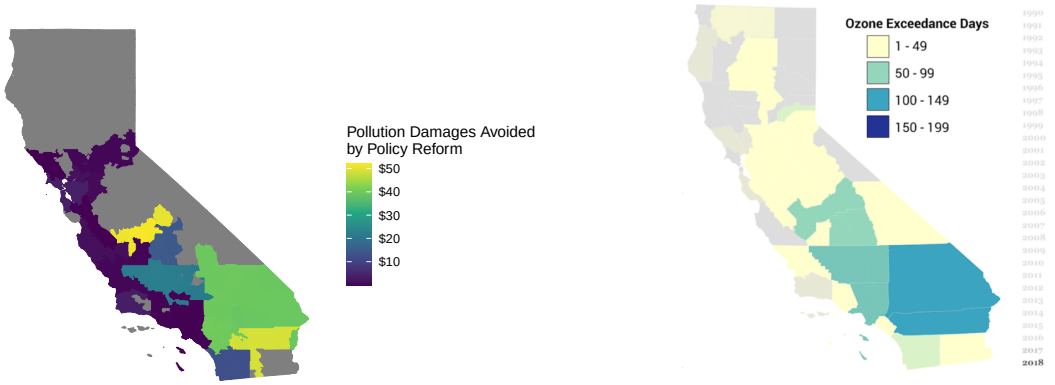
The results suggests that making tax credits refundable has a dual benefit: it supports broader adoption of solar technologies and contributes to significant reductions in harmful emissions. The effectiveness of this policy in reducing environmental impacts aligns with global sustainability goals, providing a strong argument for the continuation and expansion of such incentives.

However, the increase in NOx and PM2.5 emissions among high-income households highlights a critical area for policy adjustment. It suggests that while the policy is effective overall, it may need to be tailored or accompanied by additional measures that target consumption behaviors specific to higher-income groups, perhaps by integrating more stringent standards or combining tax credits with other disincentives for high-emission technologies.

Finally, we present a visual representation of the environmental benefits brought by the policy reform, using California as a sample to illustrate this impact. In the left graph of Figure 15 , we plot the total avoided damages, highlighting the environmental benefits derived from changing non-refundable tax credits to refundable credits in California. The green/yellow colors indicate regions with higher environmental benefits, making these areas greener, while the dark colors denote regions with lower benefits. Notably, we observe that the greatest benefits are concentrated in the southeast of California, particularly in San Bernardino County and its neighboring counties.

To understand the significance of these benefits, the right graph of Figure 15 shows the Days With Unhealthy Ground-Level Ozone Concentrations in California Counties in 2019. Counties in the Inland Empire recorded the highest number of days with unhealthy ground-level ozone concentrations, followed by neighboring counties in Southern California and the Central Valley. Data indicates that residents in San Bernardino County experienced nearly five out of every 10 days in

2019 with unhealthy air (180 days). Riverside County recorded 64 days with unhealthy air, while Tulare County had 59 days. In contrast, 15 counties did not record any unhealthy air days, and nine counties lacked data.



(a) Environmental Benefits brought by Policy Reform in CA

(b) Days With Unhealthy Ground-Level Ozone Concentrations in CA

Figure 15: Policy Analysis in CA

Air pollution poses a serious threat to public health, being linked to adverse birth outcomes, obesity, cardiovascular and respiratory diseases, and cancer. It can also affect cognitive and behavioral development. By comparing the two graphs, it becomes evident that the policy reform's main benefits are directed towards the most unhealthy regions, helping to alleviate current environmental problems. This targeted benefit is crucial in addressing air quality issues and improving public health outcomes in the areas most affected by pollution.

Moreover, this analysis underscores the potential of policy reforms to drive significant environmental improvements. By making tax credits refundable, not only is the adoption of solar technologies encouraged, but there is also a substantial reduction in harmful emissions, aligning with broader sustainability goals. This dual benefit reinforces the importance of such policy measures in fostering both economic and environmental health.

In conclusion, this counterfactual analysis highlights the transformative potential of making solar tax credits refundable. This policy adjustment significantly enhances consumer access to renewable technologies and reduces emissions across all examined pollutants. By aligning economic incentives with environmental goals, it creates a sustainable framework benefiting both consumers and producers—consumers enjoy increased surplus, while producers experience heightened demand and profitability.

The analysis illustrate the importance of such policy shifts in driving environmental progress. Current policies do not effectively direct investments to the highest-value locations, missing opportunities to optimize the environmental benefits of solar power installations. This inefficiency underscores the need for fiscal instruments that can catalyze substantial environmental improvements, which are essential for addressing global sustainability challenges. Therefore, these findings support the continuation and enhancement of policies that leverage economic tools to combat en-

vironmental degradation.

Our analysis provides a compelling argument for integrating economic incentives with environmental objectives. It demonstrates a clear pathway to achieving significant emissions reductions while simultaneously enhancing consumer and producer welfare. This balance is crucial for the long-term sustainability of environmental policies, ensuring they remain both economically viable and ecologically effective.

By making solar tax credits refundable and accessible to low-income households, policymakers can ensure that solar energy investments are both equitable and environmentally effective. This approach promotes fairness in the distribution of clean energy benefits and enhances the overall efficiency of solar power deployment, leading to greater reductions in pollution and more substantial environmental gains nationwide.

In summary, the analysis clearly demonstrates the advantages of policy reforms that make solar tax credits refundable and more accessible. These reforms can redirect investments to areas where they are most needed, optimizing environmental benefits and promoting a more equitable distribution of clean energy resources. This strategic approach is essential for maximizing the environmental and health benefits of solar energy, particularly in communities that need them the most.

8 Conclusion

Recognizing these distributional injustices, recent legislative initiatives have sought to rectify these disparities for businesses and other entities like nonprofits and local and tribal governments. On March 5th, 2024, the U.S. House of Representatives announced a significant amendment in the reconciliation bill, introducing a direct pay option under section 48 (ITC 48). This amendment extends the solar investment tax credit (ITC) benefits to entities without sufficient tax liabilities, including governments and NGOs, thus widening the scope of potential participants in renewable energy deployment. However, residential solar, which accounts for over 20 percent of the total solar capacity installed in the U.S., remains outside the scope of these provisions, highlighting a critical area for policy enhancement.

This study makes a great contribution to the understanding of structural inequities in the U.S. residential solar market by rigorously analyzing the impacts of non-refundable energy tax credits. Leveraging comprehensive data from the IRS and the Annual Social and Economic Supplements (ASEC), we uncovered a stark 74% discrepancy in tax credit utilization between low and higher-income households, with 28% of homeowner households being ineligible for solar tax credits due to insufficient tax liabilities.

Our structural model, inspired by the Berry, Levinsohn, and Pakes (1995) framework, offers a robust quantification of the adverse impacts of the current tax policies on solar adoption rates among economically vulnerable populations. By making these tax credits refundable, we demonstrated a potential increase in adoption rates by 5.81% among low-income households, alongside substantial reductions in emissions across all examined pollutants. This finding underscores the dual economic and environmental benefits of such policy reforms.

The demand system estimates presented in this study further elucidate the significant role of tax benefits in enhancing consumer demand for solar panels. The strong positive relationship between tax benefits and solar adoption, particularly among lower-income groups, highlights the efficacy of fiscal incentives in driving renewable energy investments. This analysis not only reinforces the importance of economic accessibility in the deployment of renewable energy solutions but also provides a clear policy direction for enhancing solar adoption.

Our counterfactual analyses provide critical insights into the potential impacts of alternative policy frameworks. The Refundable Tax Credit Scenario reveals that making tax credits refundable can dramatically increase market share and consumer surplus, especially among low-income households. This policy change effectively removes financial barriers, thereby democratizing access to solar technology and enhancing its affordability. The Environmental Benefit Focus Scenario demonstrates that refundable tax credits significantly reduce harmful emissions, aligning economic incentives with broader environmental objectives.

This study's primary contribution lies in its rigorous analysis of the distributional impacts of non-refundable energy tax credits and the innovative application of a structural model to quantify these effects. By integrating detailed demographic and income data, our model provides a nuanced understanding of how tax policies influence solar adoption across different socioeconomic groups. The counterfactual analyses further illuminate the potential for policy reforms to enhance both economic and environmental outcomes.

Our work extends the existing literature by providing empirical evidence on the critical role of tax policy in promoting equitable access to renewable energy. The findings underscore the necessity for policymakers to address the limitations of non-refundable tax credits and consider the broader implications of making these credits refundable.

The policy implications of our findings are profound. Making tax credits refundable not only democratizes access to solar technology but also aligns economic incentives with environmental goals, providing a sustainable framework that benefits all stakeholders involved. Policymakers should consider these insights to recalibrate existing frameworks, potentially introducing refundable tax credits and amplifying credit values to foster greater adoption rates among economically disadvantaged households. This approach would also support broader environmental objectives, contributing to significant reductions in harmful emissions and promoting a more equitable transition to renewable energy.

In conclusion, this study provides a comprehensive and empirically grounded analysis of the U.S. residential solar market, offering actionable insights for policy enhancement. By addressing structural barriers and recalibrating fiscal instruments, policymakers can drive substantial progress towards a more inclusive and sustainable energy future. This research not only contributes to the academic discourse on energy justice and policy design but also serves as a critical guide for practical policy implementation, aiming to achieve an equitable and environmentally sustainable transition to renewable energy.

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