Equity in Solar PV Adoption in New Mexico

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Keywords: Solar photovoltaic, Clean energy transition, Adoption equity, Distributional equity

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Executive Summary

The state of New Mexico passed the Energy Transition Act (ETA) in 2019 which sets statewide renewable energy standard to achieve 100% carbon-free electricity by 2045. This legislative move reflects the state's commitment to addressing climate change. New Mexico's unique demographic and economic landscape, characterized by its diverse population, dependence on the oil and gas industry, and substantial renewable energy resources, underscores the importance of ensuring an equitable energy transition. The focus of this research is on understanding the adoption patterns of residential solar photovoltaic (PV) systems and their implications for equity in this transition.

We construct a comprehensive dataset on solar installations collected from state agencies and utility companies to examine current trends and the distribution of solar PV adoption across New Mexico. We analyze how solar adoption varies by geographical location, income levels, and racial and ethnic groups. Additionally, we evaluate the impact of state solar tax credit on promoting solar adoption among different segments of the population and its distributional effects.

Our key findings are:

- Residential solar PV installation in New Mexico has grown exponentially, fueled by decreasing costs and supportive tax incentives. However, this growth is unevenly distributed, with higher adoption rates observed in urban areas, higher-income neighborhoods, and White-majority census tracts.
- There is minimal racial disparity in solar adoption within New Mexico. The predominant sources of existing adoption inequality stem from disparities in income and education level.
- State-level incentives have effectively mitigated adoption inequality. However, the distribution of the tax credit benefits is concentrated among wealthier households with higher electricity consumption level.

This study documents the current landscape of solar PV adoption in New Mexico and provides the first evidence that the state solar tax incentive effectively promotes equitable solar adoption. We recommend the continuous monitoring and adjustment of incentive programs to ensure they remain inclusive and effective in reducing disparities in solar adoption. The findings also highlight the need for innovative and targeted policy designs to reduce structural barriers to solar adoption, enhance the distributional equity of state incentives, and reduce potential informational barriers for disadvantaged groups.

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1 Introduction

1.1 Energy transition in New Mexico

In 2019, the state of New Mexico (NM) passed its Energy Transition Act (ETA), which sets a statewide Renewable Portfolio Standard (RPS). The RPS mandates that 50% of the electricity supplied by investor-owned utilities (IOUs) and rural electric cooperatives (rural co-ops) must come from zero-carbon resources by 2030, with a further goal of achieving 80% by 2040. The ultimate objective is to have 100% carbon-free electricity supplied by IOUs and rural co-ops by 2045 and 2050, respectively (Figure 1) (Candelaria et al. 2019). The ETA exemplifies the state's commitment to achieving carbon neutrality in the era of climate change. Ensuring a just and equitable transition towards clean energy is especially important in the NM context given its unique socioeconomic status.

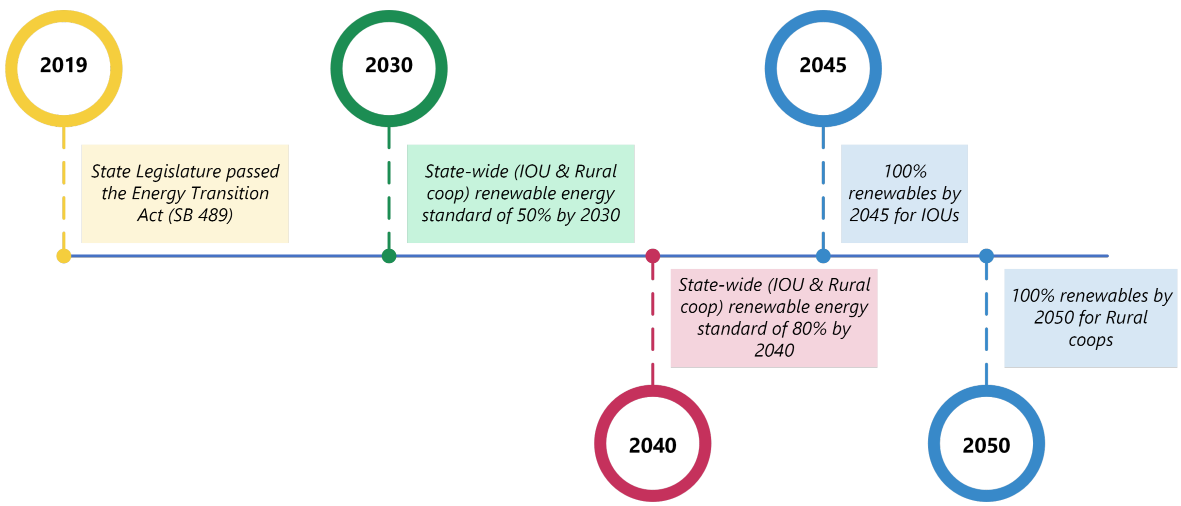

Figure 1: Timeline of the Energy Transition Act (Senate Bill 489)

NM is notable for its distinctive demographic composition and climate. Ranking 5th in land area at 121,590 square miles and 36th in population with 2.1 million residents, NM has one of the lowest population densities in the nation (U.S. Census Bureau 2022).[1] NM is also a majority-minority state, with over 50% of the population identifies as Hispanic and 11.2% as Native American (U.S. Census Bureau 2020). Around 86% of the population lives in disadvantaged census tracts defined as overburdened and under-served by the Climate and Economic Justice Screening Tool (CEJST).[2]

[1] NM is the 46th most densely populated state in the nation (U.S. Census Bureau 2022).

[2] Author's calculation. Disadvantaged communities are defined as overburdened in one or several of the following aspects: climate change, energy, health, housing, legacy pollution, transportation, waste and wastewater, and workforce development. See https://screeningtool.geoplatform.gov/en/methodology for a detailed definition of for each of the aspects.

In terms of the state's economy, NM Ranks 41st in GDP per capita among the U.S. states.[3] NM's economy has been significantly reliant on the oil and gas (O&G) industry since the discovery of the Permian Basin oil fields in the 1920s. The O&G industry contributes to around 10% of NM's annual Gross Domestic Product (GDP) and 25% to 30% of the state's tax revenue (New Mexico Legislative Finance Committee 2023; U.S. Energy Information Administration 2023b). This dependency on the fossil fuel industry also poses a challenge to the equitable energy transition.

NM is also well-suited to achieve 100% renewables as it boasts abundant wind, solar, and geothermal potential. The state's eastern high plains offer significant wind energy opportunities, while NM ranks third in solar energy potential and sixth in geothermal energy potential nationally. In 2022, renewable sources accounted for 42% of the state's total electricity generation, well on track to achieve the 2030 50% renewable target (U.S. Energy Information Administration 2023c).

The interplay between NM's unique demographics, O&G dependency, and abundant renewable energy resources underlines the importance of exploring equitable energy transition pathways (Figure 2). In this research, we focus on solar photovoltaic (PV) and investigate the current state of residential solar PV adoption in NM and its equity implications.

1.2 Equity in energy transition

In the context of energy transition, the definition of equity encompasses multiple dimensions. The literature can be categorized into three main aspects of equity, namely *access equity*, *adoption equity*, and *distributional equity*. In the following, we review the literature on equitable energy transition with a particular focus on residential solar PV. We also explain the relevance of considering the different aspects of equity in the NM context.

1.2.1 Access equity

Access equity refers to the availability and accessibility of clean energy technologies for all communities, regardless of income, race, or geographic location. Brockway et al. (2021) find using California data that existing grid infrastructure may not be sufficiently robust to handle the increased load from widespread solar PV installations without significant upgrades. This can lead to inequitable access, where certain regions or communities might have lesser ability to connect their solar systems to the grid due to these capacity issues. This finding is relevant in the NM context as solar installations are concentrated in urban areas where the grid infrastructure limits solar installations in some neighborhoods. For example, in parts of Albuquerque and Rio

[3]Data source: Statista, Real per capita gross domestic product of United States in 2023, by state https://www.statista.com/statistics/248063/per-capita-us-real-gross-domestic-product-gdp-by-state/.

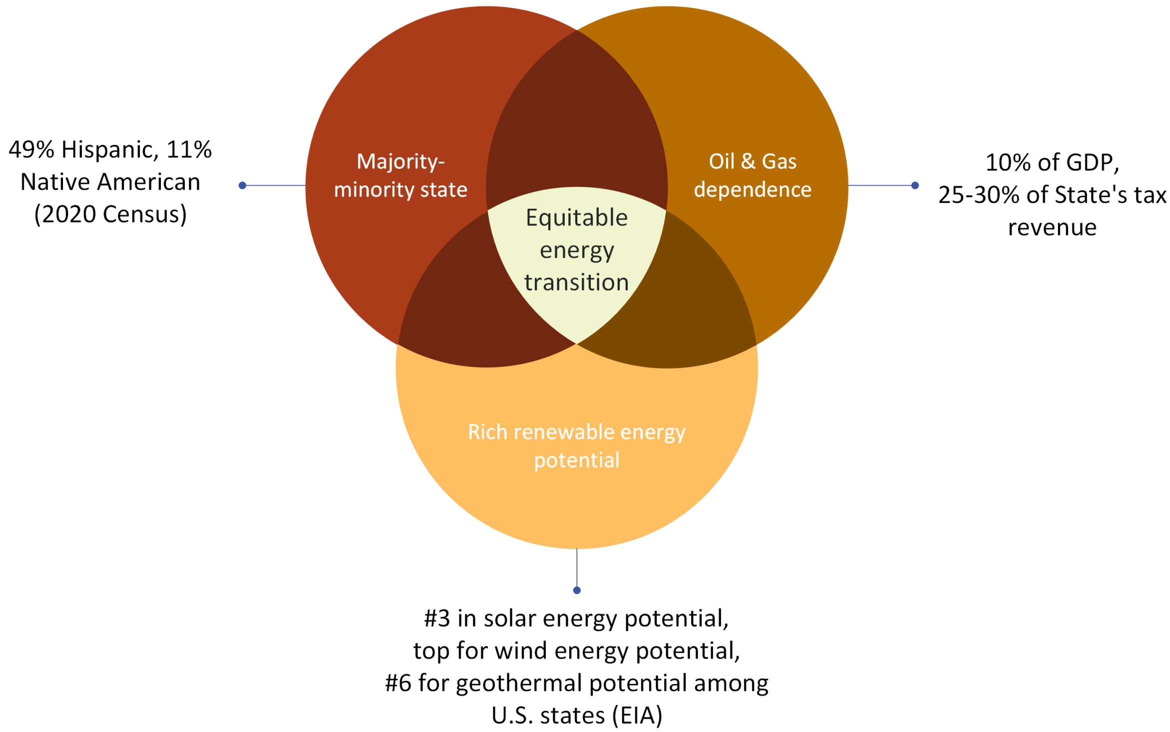

Figure 2: The socioeconomic background of energy transition in New Mexico

Rancho, the feeder grids are already at maximum capacity.[4] Residents in those communities cannot be approved for new solar installations with grid interconnection until the infrastructure is upgraded.[5]

In addition to grid constraints, other technical barriers, including the lack of suitable roof space or home ownership and restrictions of homeowner associations (HOA), or financial barriers, such as high upfront cost, can also limit the access of some households to solar PV.

1.2.2 Adoption equity

Adoption equity in the context of solar PV systems refers to the equitable distribution of solar technology across various socio-economic groups, particularly focusing on income levels, and racial and ethnic groups. Research has consistently highlighted disparities in solar adoption related to these factors. For instance, Gao and Zhou (2022) observe a reduction in racial and ethnic disparities in solar PV adoption between 2012 and 2019, yet noted that Asian-, Black-, and Hispanic-majority census tracts still lag behind White-majority tracts in the number of

[4] See https://pnm.maps.arcgis.com/apps/webappviewer/index.html?id=cbd3bad85fc64f2180dda652e957bacd for areas with maximum feeder capacity.

[5] In 2021, 2022, and 2023, the Public Service Company of New Mexico (PNM) put 96, 70, and 29 new solar applications on hold, respectively, due to a lack of feeder capacity (PNM 2021; PNM 2022; PNM 2023).

installations. Darghouth et al. (2022) identify a significant income-related inequality in U.S. rooftop solar adoption, with more affluent households having a higher likelihood of installing solar systems. They also found that areas with greater racial diversity, higher education levels, and higher owner-occupancy rates showed more equitable solar adoption. Moreover, Reames (2021) suggests that although communities of color have marginally lower rooftop solar potential, this does not account for the substantial disparities in adoption rates, highlighting the influence of other non-physical factors.

Researchers also point to supply-side barriers impacting solar equity. O'Shaughnessy, Barbose, et al. (2021) note that solar installers tend to offer fewer quotes to low-income households, thereby reducing their chances of adopting solar technology. This indicates the presence of significant market-driven barriers that could deter solar adoption among economically disadvantaged groups.

The literature has also examined the effectiveness of various policies to improve equity in solar adoption. Gao and Zhou (2022) emphasize that while local and utility-level policies designed to foster solar adoption among diverse populations have benefitted low-income households, their impact remains limited in Black-majority census tracts, suggesting the necessity of addressing non-financial barriers. Meanwhile, Darghouth et al. (2022) argues that decreasing costs of solar PV reduce price-related adoption inequities, but emphasize the need to tackle structural barriers and support diverse installation practices to enhance equity. Financial mechanisms like grants, rebates, and tax credits have been highlighted by O'Shaughnessy (2022) as effective tools in encouraging solar adoption among low- and moderate-income households. Additionally, innovative business models such as solar leasing have been shown to significantly boost adoption rates in these communities (O'Shaughnessy et al. 2021).

Examining the issue of adoption equity is particularly relevant in NM given its high share of minority and disadvantaged populations and significant variance in income and education levels. NM also implements generous solar incentives, such as state solar tax credits and utility net energy metering (NEM) policies. Therefore, it is important to evaluate whether these policies alleviate or exacerbate adoption equity in the NM context.

1.2.3 Distributional equity

Distributional equity refers to whether the benefits of clean energy incentives are uniformly distributed across different demographic groups. The issue of distributional inequality is not limited to incentives for solar adoption. Borenstein and Davis (2016) use tax filing data to examine the uptake of four major clean energy tax credits: weatherization (Nonbusiness Energy Property Credit), residential solar (Residential Energy Efficient Property Credit), alternative fuel vehicles (Alternative Motor Vehicle Credit), and electric and plug-in hybrid vehicles (Qualified Plug-In Electric Drive Motor Vehicle Credit). They find significant inequities in the distribution of tax credits, with the top income quintile receiving about 60% of all clean energy tax credits, while the bottom three income quintiles receive about 10%. Jacobsen (2024) uses survey data from the Residential Energy Consumption Survey (RECS) and finds significant racial and ethnic disparities in the receipt of energy efficiency incentives in the U.S., driven primarily by differences in home-ownership rates. As NM provides state solar tax credits to households, understanding the distributional effect of existing credits provides insights into efficient and equitable policy design.

1.3 Policy background

Incentives to promote solar PV adoption in the residential sector have been implemented at different regulatory levels, from the federal government to service-providing utilities. These incentives play important roles in the households' decision-making of going solar. All incentives are essentially financial, which either lowers the upfront cost of solar investment or reduces the payback period of solar. In the remainder of this section, we review the incentives available to NM households since 2005 for solar PV investments. Figure 3 summarizes the various incentives and their respective policy time spans. For each incentive, we describe the incentive structure, time of initiation and expiration, and eligibility.

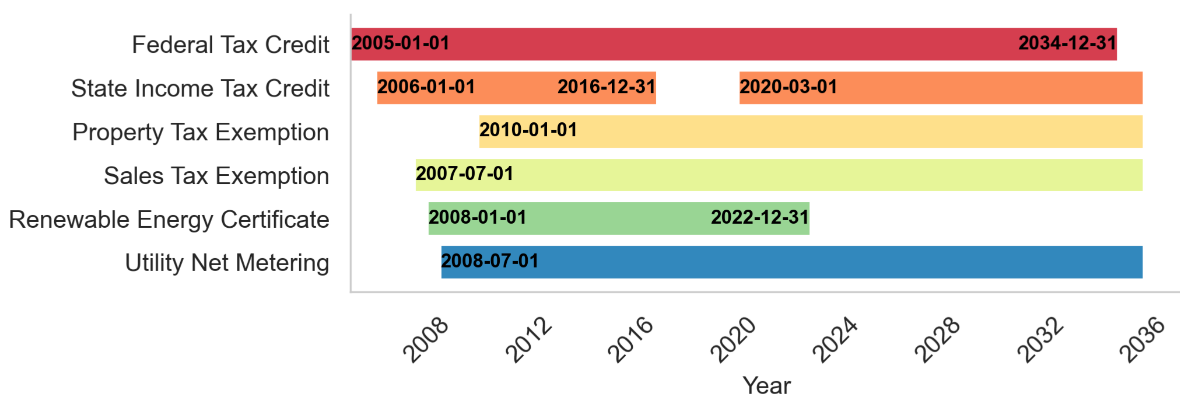

Figure 3: Incentives for residential solar PV in New Mexico

Note: For policies with no definitive end dates, the end date is not displayed in the timeline.

1.3.1 Federal incentives

The federal tax credit for solar panel installations, also known as the Investment Tax Credit (ITC), was initially introduced in the Energy Policy Act in 2005. It provided a tax credit of 30% for residential and commercial solar energy installations. ITC was extended multiple times and maintained a 30% credit for solar installations through 2019. The tax credit percentage was stepped down in 2020, where the systems installed in 2020 and 2021 were eligible for a 26% tax credit (Office of Energy Efficiency & Renewable Energy 2023). ITC was originally set to phase down after 2022 (with a credit rate of 26% in 2022, 22% in 2023, 0% by 2024) before the introduction of the Inflation Reduction Act (IRA) in 2022. IRA extended the ITC, now known as the Residential Clean Energy Credit, which provides a 30% tax credit from 2022 through 2032. The credit rate will phase down to 26% in 2033 and 22% in 2034, unless otherwise noted. The federal tax credit places no limit on the total amount claimed, and any credit exceeding tax liability can be carried forward to future tax years until 2034 (Internal Revenue Service 2023).

1.3.2 State incentives

Solar tax credit

Since the early 2000s, the role of renewable energy in mitigating greenhouse gas emissions and addressing climate change has become increasingly evident. In response to this growing awareness, NM introduced the Solar Market Development Tax Credit (SMDTC) in 2006. From January 1, 2006, until December 31, 2016, the SMDTC provided a 10% tax credit on the total installation costs of solar PV systems, with a cap of $9,000 per taxpayer per taxable year.

Recognizing the continued importance of fostering renewable energy adoption, NM reinstated this incentive in 2020 with the introduction of the New Solar Market Development Tax Credit (NSMDTC). Effective from March 1, 2020, this revised program also offers a 10% tax credit on the total installation costs, but with a reduced maximum credit amount of $6,000. To manage fiscal impacts, the total tax credit issuance was initially capped at $8 million for the tax years 2020 and 2021, and increased to $12 million annually from 2022. Due to high demand, this cap has been reached consistently each year, leading to a further increase to $30 million in 2024.[6]

The program features no income threshold for eligibility, and initially, any unused credit exceeding the taxpayer's liability could be carried over for up to five consecutive years. However, in a significant policy evolution, the tax credit became refundable in 2024, enhancing its accessibility by allowing taxpayers to receive a refund for any credit amount that surpasses their tax liability (New Mexico Energy, Minerals and Natural Resources Department 2020).

Property tax exemption

Under House Bill 233, enacted by the NM legislature in 2010, residential solar systems are not treated as physical improvements and therefore do not increase the value of the property for property tax purposes. However, future assessments can include the value of a solar energy system if the property is sold (Stewart 2010). This exemption provides a financial incentive for

[6] In 2021, 2022, and 2023, the credit cap was reached. https://nm-emnrd.maps.arcgis.com/apps/dashboards/e882d2ccd57e4a99bc6d2a4314fcd3bb

homeowners since installing solar PV increases property value on the housing market without incurring additional property taxes.

Sales tax exemption

The NM Gross Receipts Tax Exemption policy for solar energy systems, effective since 2007, allows businesses to deduct receipts from selling solar equipment or installation services (New Mexico Taxation & Revenue Deparment 2021). Essentially, for consumers, there is no sales tax on top of the cost of solar installation, which reduces the financial burden on solar adopters.

1.3.3 Utility incentives

Renewable energy certificates

The NM Renewable Energy Certificate (REC) policy for solar PV is part of the state's broader Renewable Portfolio Standard (RPS). The RPS requires that IOUs must secure 50% of their capacity through carbon-free renewables by 2030 and 100% by 2045. For rural electric cooperatives, the goals are 40% by 2025, 50% by 2030, and 100% by 2050. The IOUs in NM thus offered REC purchase agreements to solar owners for a limited time to count residential solar generation toward the utilities' renewable portfolio. The Public Service Company of New Mexico (PNM) offered a Solar Renewable Energy Certificate (SREC) program that awards residential systems a stepped purchased rate for the energy generated. This program was discontinued at the end of 2022 (Public Service Company of New Mexico 2023b). The El Paso Electric Company (EPE) offered a tiered REC purchase rate for systems installed before 2017, which ended on December 31, 2020 (El Paso Electric Company 2016a; El Paso Electric Company 2016b).[7]

Net energy metering

Utility companies in NM, including IOUs, rural cooperatives, and public utilities, are mandated by the NM Public Regulatory Commission (NMPRC) to offer NEM programs to solar customers. Under NEM, solar customers who generate excess electricity with their solar panel systems can send it back to the grid and receive credits. These credits can be used to offset future electricity use.[8] However, the details of the NEM program vary by utility. For example, PNM offers a differentiated net metering program based on system capacity. For small PV systems (inverter capacity lower than 10 kW-AC), any excess generation for the month (when monthly usage is lower than total monthly generation) is credited to the customer's account and can be used for future billing cycles, never expiring unless the account is closed. Excess generation from large PV systems (inverter capacity greater than 10 kW-AC) is paid each month at the predetermined energy purchase rate for that month (Public Service Company of New Mexico

[7] Details on the purchase agreements can be found on the respective company's websites.

[8] For example, if the solar panels generate more electricity during the day than the household consumes, the excess electricity is sent back to the grid, and the meter runs backward, creating a credit. At night, when solar panels do not produce electricity, the household consumes electricity from the grid and the meter runs forward.

2023a). EPE offers net metering for all systems within a billing cycle, but all excess generation for the month is paid out to customers at the predetermined purchase rate (El Paso Electric Company 2023a; El Paso Electric Company 2023b). The purchase rate for the credits is typically lower than the retail electricity price for all utilities.[9] The differences in NEM incentives provide a quasi-experimental setting to study how NEM policy design incentivizes residential solar adoption.

2 Current trends and distribution of residential solar PV in NM

In this section, we utilize detailed solar installation data collected from state agencies and utilities at the system level to illustrate the trends and distribution of solar installations in NM. Our focus is on the distribution of installations across geographical areas, income groups, and racial and ethnic groups for both installation counts and system capacities. The unit of analysis is at the individual system level.

2.1 Data description

To provide a comprehensive overview of solar installations in NM, we assemble a unique dataset from various public and restricted sources. This dataset includes solar PV system-level characteristics, housing characteristics, census tract-level demographics, and spatial data on climate and community types. The following sections detail the dataset components.

2.1.1 Installation data

We obtain system-level solar installation data from three sources: the New Mexico Energy, Minerals, Natural Resources Department (EMNRD), the NMPRC document archive eDocket database, and individual utilities.

EMNRD oversees the state solar tax credit claims under the SMDTC and NSMDTC programs. Their data includes all systems that were approved for the state tax credits between the programs' active periods (2006-2016 and 2020 onwards). This data, acquired through a non-disclosure agreement, provides details on the installation location, grid connection date, system size, installer name, system cost, and approved state credit amount, encompassing 20,159 unique residential systems.

The NMPRC eDocket database contains records of annual compliance filings from state-regulated utilities (IOUs and rural cooperatives) under Rule 17.9.570.13(G) NMAC.[10] This rule

[9]For example, in 2023, the PNM power purchase rate ranged from 3 to 12 cents per kilowatt hour (kWh), depending on the month, while the retail rate was 7.8 cents per kWh for the first 450 kWh per month, increasing to 15 cents per kWh thereafter.

[10]Details of Rule 17.9.570 can be found here: https://www.srca.nm.gov/parts/title17/17.009.0570.html.

mandates utilities to report the name and location of interconnected solar systems, annual purchases from these systems, and any rejected interconnection applications. Due to varying data quality, we obtain data of the two largest IOUs in the state, PNM and EPE, and one rural cooperative, Socorro Electric Coop (SEC). Together, they account for over 90% of solar customers in NM, providing data on system location, interconnection date, and installed capacity for 50,416 residential systems.

Public utilities, not subject to NMPRC rulings, provided solar system data directly. We obtain data from the Los Alamos Department of Public Utilities (LADPU) for the 427 residential solar systems in their service area.

2.1.2 Housing characteristics data

We scrape housing characteristics data from Zillow using the addresses in the installation data. This data includes variables such as year built, number of bedrooms and bathrooms, estimated home value (Zestimate), living area size, lot size, parking features, heating and cooling technologies, and geographic coordinates.[11] Housing information was available for 65,125 systems in the combined installation dataset.

2.1.3 Census tract-level demographics data

Using the geographical information from the housing data (longitude and latitude), each system was placed in a census tract using the Census Bureau's tract shape file. We gathered census tract-level demographic variables from the 2010 and 2020 Decennial Census and the American Community Survey from 2010 to 2022. The demographic data includes the following variable categories: 1) housing characteristics (total housing units, occupancy rate, owner occupancy rate, average number of rooms and housing size, main energy source, mortgage rate, housing value, and age of housing); 2) racial composition (racial diversity, percentages of white, Native American, and Hispanic populations); and 3) other demographics (percentage of male population, age distribution, education level, total population, area median income, and urban/rural classification).

2.1.4 Other relevant data

We complement the main dataset with utility-level average annual electricity prices from the Energy Information Administration (EIA) (U.S. Energy Information Administration 2023a), spatial weather data from Solargis, including Global Horizontal Irradiation (GHI) and average annual

[11] NM is a non-disclosure state, meaning the actual transaction price of homes is not public information.

temperature (Solargis 2023), and the community disadvantage status from the CEJST (Council on Environmental Quality 2022).

In summary, our comprehensive dataset contains 54,462 unique solar installations (full sample) in NM, 49,993 of which have detailed geographical information (restricted sample). We use the full sample in the subsequent analysis when geographical information is not required and use the restricted sample when spatial analysis is needed.

2.2 Installation time trend

NM has experienced exponential growth in residential solar installations since 2000. As shown in Figure 4, the total installation capacity in 2023 (280 MW) almost doubled that in 2020 (141 MW). By 2023, residential solar accounted for 14.8% of the state's total solar capacity (Solar Energy Industries Association 2023).

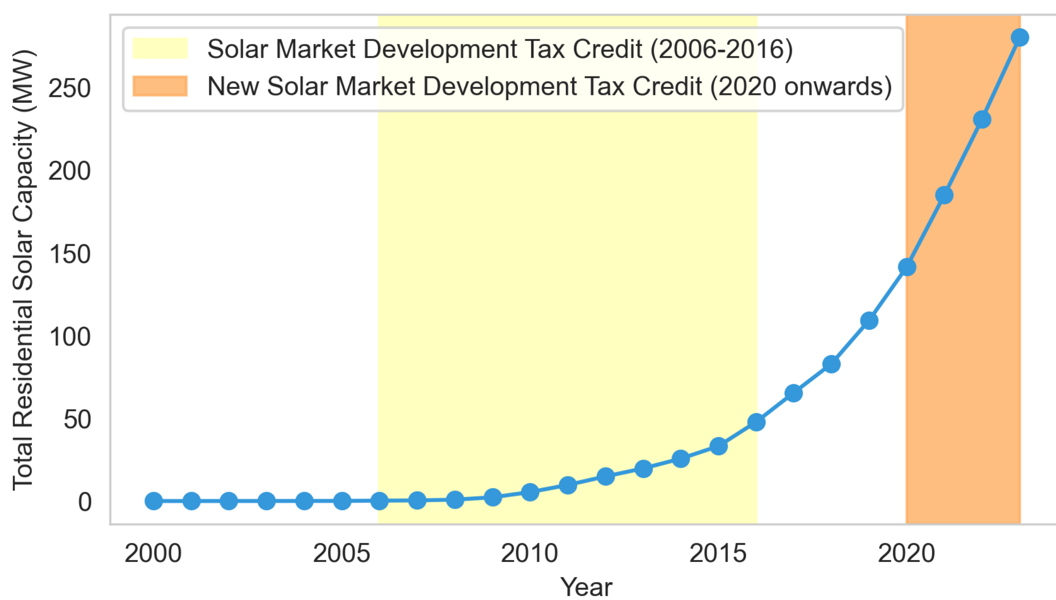

Figure 4: Cumulative residential solar capacity from 2000 to 2023

Note: The line chart shows the cumulative residential solar capacity since 2000 in megawatts (MW). The shaded areas illustrate the policy period of the first and second state solar tax credits.

The rapid growth in residential solar can be partially attributed to the significant reduction in the cost of solar panels. Figure 5 shows the annual installation count in relation to the unit price of the installation. The installation price per kilowatt (kW) of solar PV capacity in 2023 is less than one-third of the price in 2007, making solar an affordable energy source for many households.

State solar tax credits, combined with federal and other incentives, have also facilitated the growing adoption of solar. Figures 4 and 5 show that in years with tax credits, the adoption level is high, especially when unit prices are lower.

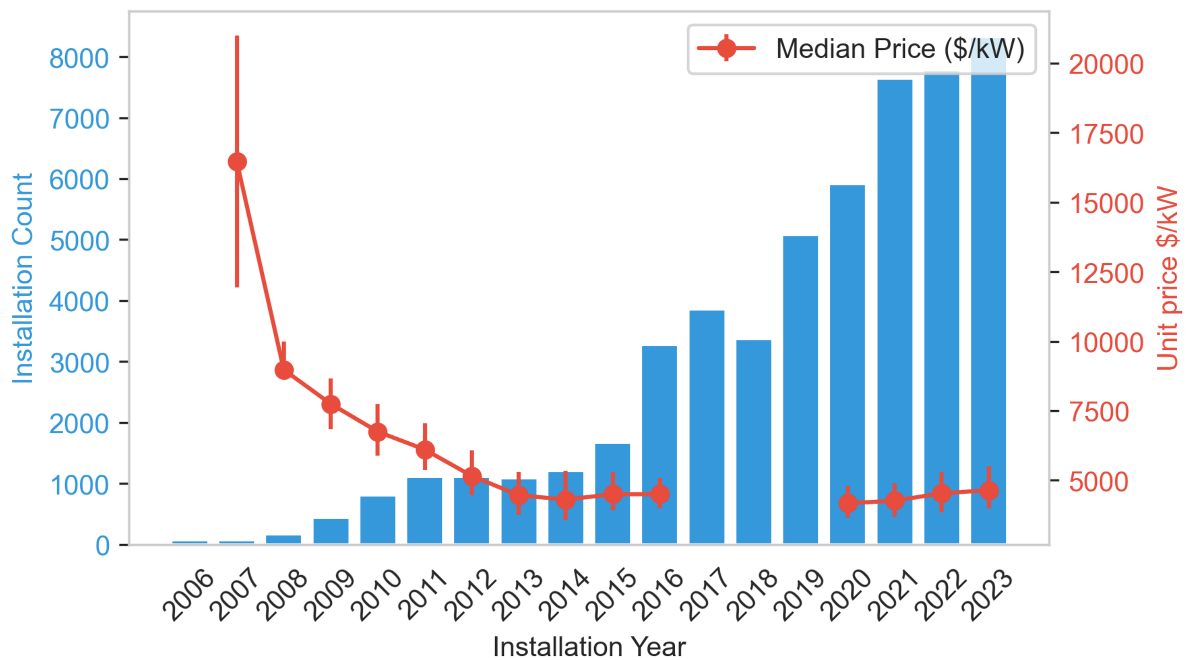

Figure 5: Annual solar installation count and unit price in New Mexico

The error bars show the 25% to 75% range of the unit prices ($/kW). The installed price ranges exclude any systems with battery storage. In the years 2017 to 2019, the state's solar tax credit program was not available. Therefore, price information is missing for those years.

2.3 Distribution of solar installation

2.3.1 Spatial distribution

The growth in solar adoption is not uniformly distributed across NM. Figure 6 shows the total installations by census tract per thousand people. It is evident that current solar installations are concentrated in the most populous cities of NM, namely Albuquerque, Santa Fe, and Las Cruces, even after adjusting for population density.[12] This pattern suggest a potential urban/rural disparity in solar adoption.

[12] Figure A.1 shows the absolute installation count per census tract.

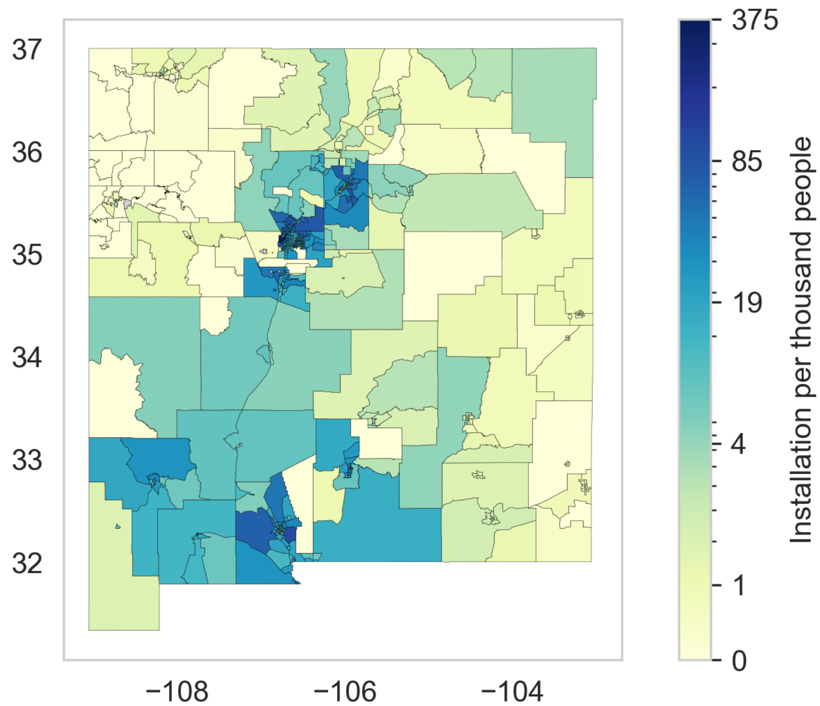

Figure 6: Installation per thousand people by 2020 census tract

Note: The total installation count is up to the end of 2023 for each census tract. The census tracts areas are defined in the 2020 Decennial Census. The tract-level population is taken at the 2022 level from the American Community Survey 1-year data. The legend is in logarithm scale.

Figure 7 illustrates the distribution of installations with respect to disadvantaged census tracts within NM. Disadvantaged census tracts are defined as "census tracts that are overburdened and underserved" by the Justice40 Initiative (U.S. Federal Government 2021). While 86% of the population in NM lives in disadvantaged communities, less than 29% of the solar installations are within those communities (orange dots in the figure).

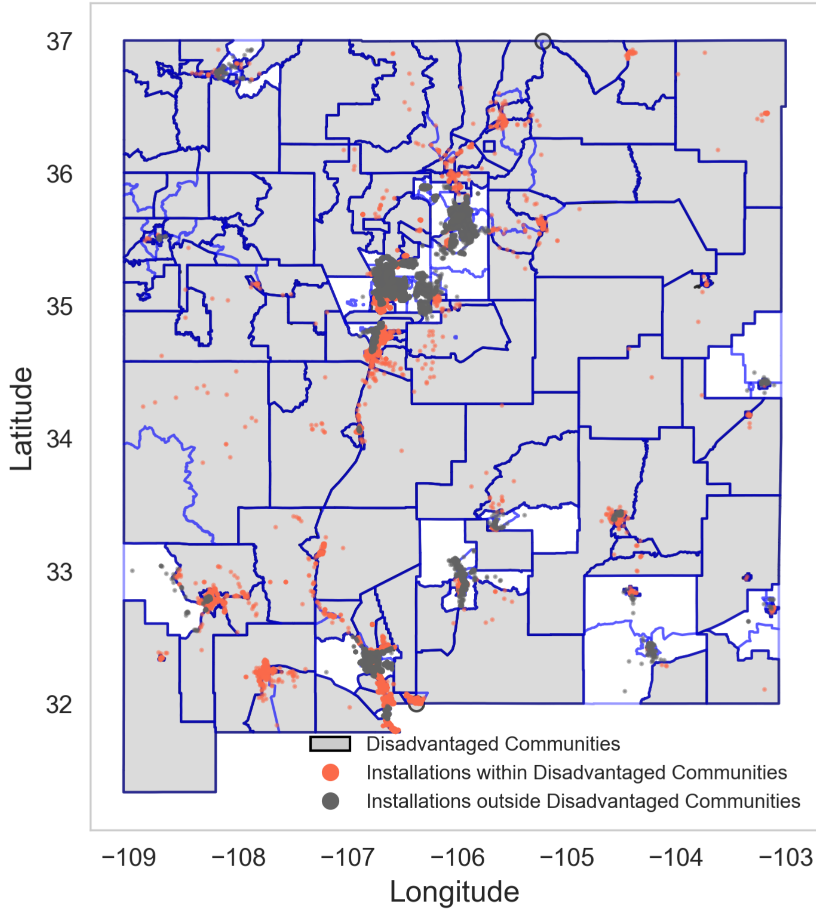

Figure 7: Installation within and outside disadvantaged communities

Note: Disadvantaged communities shape file retrieved from the Climate and Economic Justice Screening Tool https://screeningtool.geoplatform.gov/en/#10.84/36.2534/-104.868. Census tracts that are overburdened and underserved are highlighted as being disadvantaged on the map.

2.3.2 Income distribution

Consistent with existing research, census tracts in NM with higher area median income (AMI) also have higher per capita solar installation. Figure 8 reveals a positive correlation between AMI and installation per thousand population.

This AMI-installation relationship is more distinct when comparing across income quartiles. Figure 9 show the total installation count in each census tracts by income group. We observe distinct patterns in the distribution across different income levels. The histogram for the bottom income quartile reveals a highly left-skewed distribution, indicating a concentration of census tracts with fewer installations. Conversely, the top income quartile demonstrates a more evenly

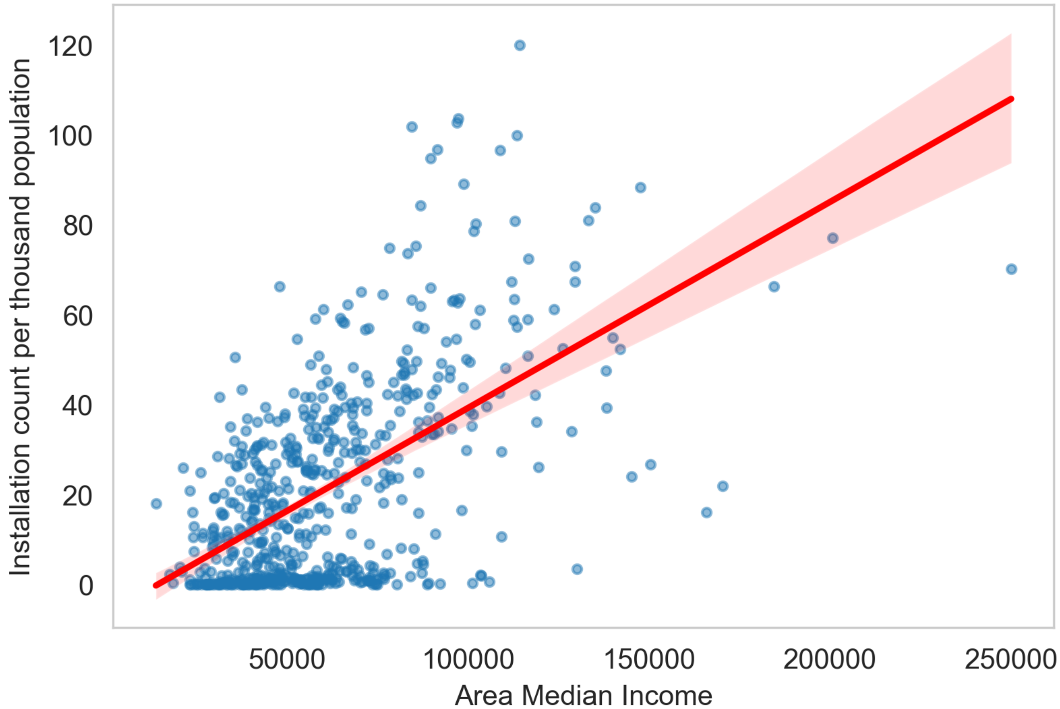

Figure 8: Installation per thousand people by area median income

Note: The population and area median income (AMI) are based on 2022 data from the American Community Survey 1-year data. Census tracts with an AMI higher than 250,000 are capped at 250,000. The shaded area around the regression line represents the 95% confidence interval.

spread distribution across various levels of installation counts, suggesting a broader uptake of solar technology among higher-income tracts.

2.3.3 Racial and ethnic distribution

NM features a racially and ethnically diverse composition. According to the 2020 Census, 51% of the population identifies as White alone (U.S. Census Bureau 2020). Other significant groups include American Indian and Alaska Native (10%), Black or African American (2.2%), Asian (1.8%), individuals identifying as Some Other Race alone (15.0%), and those identifying as two or more races (19.9%). The state's population is nearly evenly divided between Hispanic (47.7%) and non-Hispanic (52.3%), with White non-Hispanics making up 36.5%.

Of the 612 census tracts in NM in the 2020 Decennial Census, 64% are White-majority (where more than 50% of the population identifies as White alone), and 38% are Hispanic-majority. An analysis of the total installation count by majority status (Figure 10) shows a notable concentration of installations in White-majority census tracts over the years. The dispar-

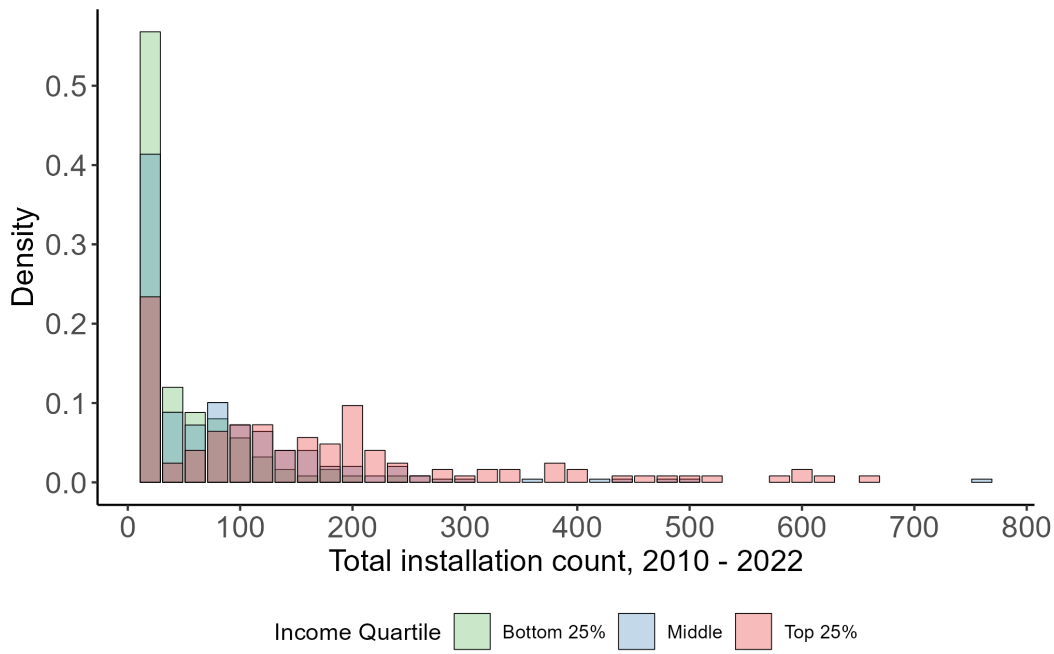

Figure 9: Census tract total installation by income quartile

Note: The income quartile classification is based on the average census tract area median income from 2010 - 2022. The total installation is the sum of installation in each census tract from 2010 - 2022. We normalize the frequency with the count of census tracts in each income quartile group. There are 124 census tracts in the top income quartile, 249 census tracts in the middle quartiles, and 125 census tracts in the bottom quartile.

ity between Hispanic-majority and non-Hispanic-majority tracts is less pronounced, with non-Hispanic tracts having slightly higher installation counts. This trend is further elaborated in Figure A.2, which divides the census tracts into five bins based on population shares, rather than majority status.

2.3.4 Capacity distribution

The capacity of installed systems varies among solar households. Figure 11 displays the density and cumulative distribution function (CDF) of system capacities (in kW). Most system capacities are clustered between 2 kW and 8 kW, with half of the systems below 5 kW and 95% below 10 kW.

The choice of system capacity typically reflects prior and projected electricity usage, which can be influenced by many factors, including household size, number of people in the house-

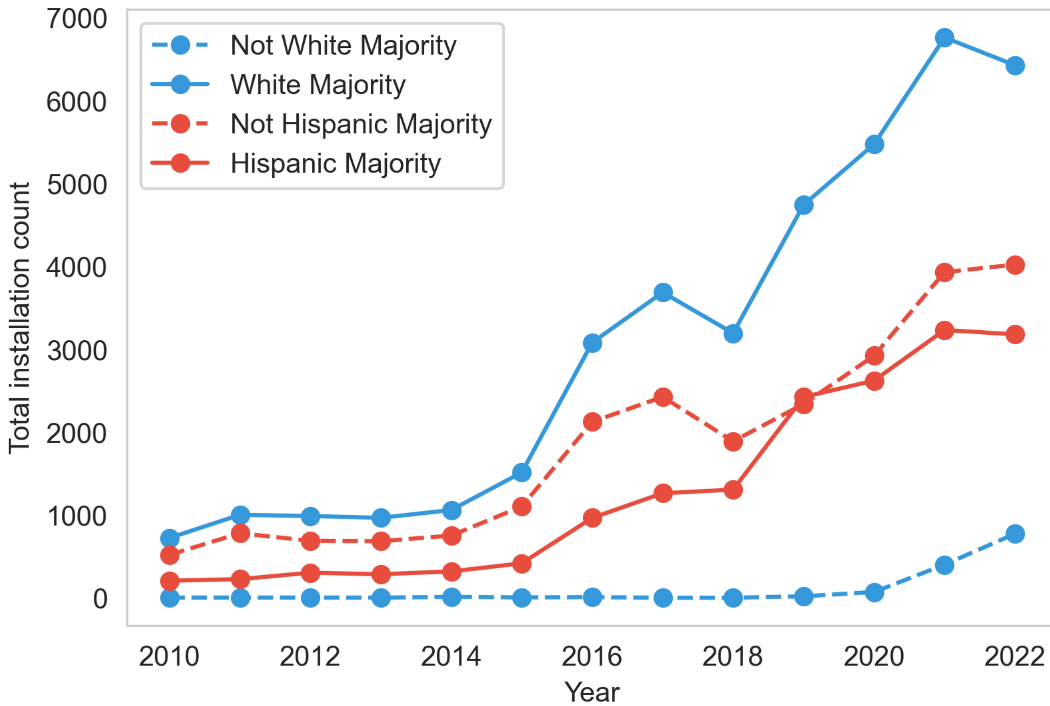

Figure 10: Annual installation by racial majority group

Note: White majority refers to census tracts where more than 50% of the population identifies as White alone. Hispanic majority refers to census tracts where more than 50% of the population identifies as Hispanic.

holds, type of cooling and heating technology, etc. The system capacity may also depend on utility incentives. Households served by utilities that offer more generous net-metering incentives are more likely to adopt a system with higher capacity as NEM increases the financial incentive of solar PV (Borenstein 2017). Figure 12 depicts the relationship between installed system capacity (in kW) and the size of the living area of the home (in square feet) by utility company. It shows that as the housing size increases, the installed system capacity tends to increase. However, the intensity of this correlation varies by utility. Systems within the PNM service area have the highest slope compared to those served by EPE or other utilities. This difference could be attributed to variations in utility-level incentives (e.g., NEM policies) or correlations between utility service areas and other factors such as urban/rural or installer characteristics. It is notable that the shares of systems installed within the PNM, EPE, and other service areas are 77.9%, 16.7%, and 5.4%, respectively.

Figure 13 shows the spatial distribution of median installed capacity. The map indicates that rural areas with low installation counts (Figure 5) tend to have higher median installed capacities.

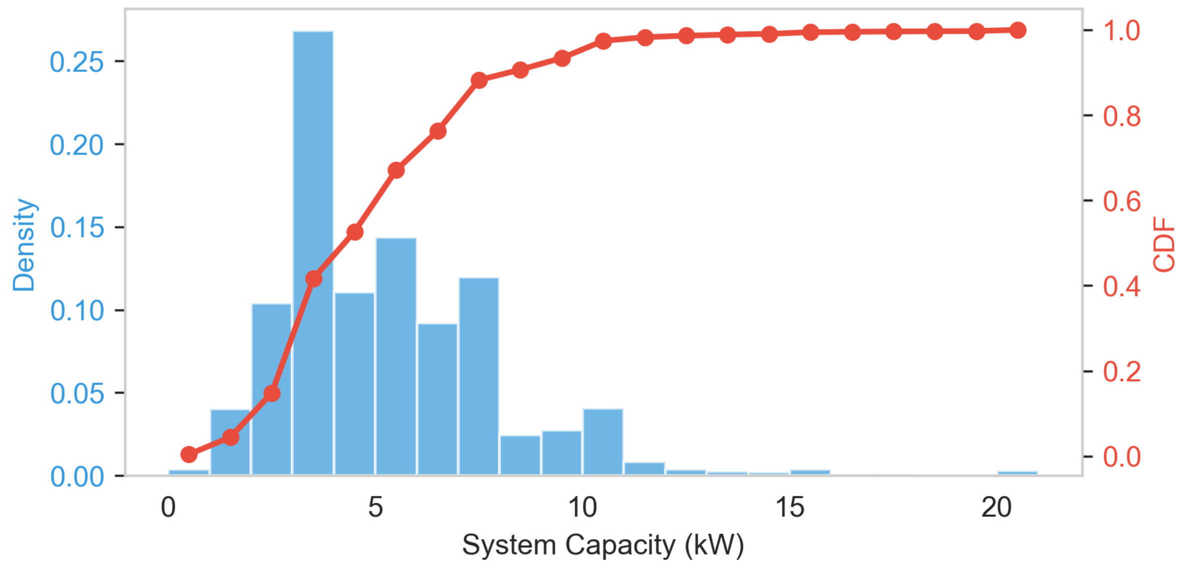

Figure 11: Distribution of installed solar PV system capacity

Note: Systems with capacity greater or equal to 20kW are grouped together.

In summary, residential solar adoption in NM has grown exponentially since 2000, driven by decreasing solar panel costs and supportive tax incentives. However, this growth has been unevenly distributed across different geographical, income, and demographic groups. Urban areas, higher-income neighborhoods, and White-majority tracts have seen higher adoption rates compared to their rural, lower-income, and non-White-majority counterparts. The capacity of installed systems also varies, with larger systems more common in larger homes and areas with stronger utility incentives. These trends and distributions directly motivate the empirical analyses we carry out in the following sections.

3 Adoption equity analysis

An important aspect of solar equity is the adoption equity across different demographic and socioeconomic groups. In this section, we investigate the equity of solar adoption by examining the impact of key factors on both the extensive margin (the likelihood of solar PV adoption within census tracts) and the intensive margin (the magnitude of solar PV installations). This analysis is essential for understanding how census tract characteristics influence solar adoption. Additionally, we focus on estimating the effectiveness of the state solar tax credit in promoting the equitable adoption of solar PV.

Our primary research question is: How do demographic and socioeconomic characteristics

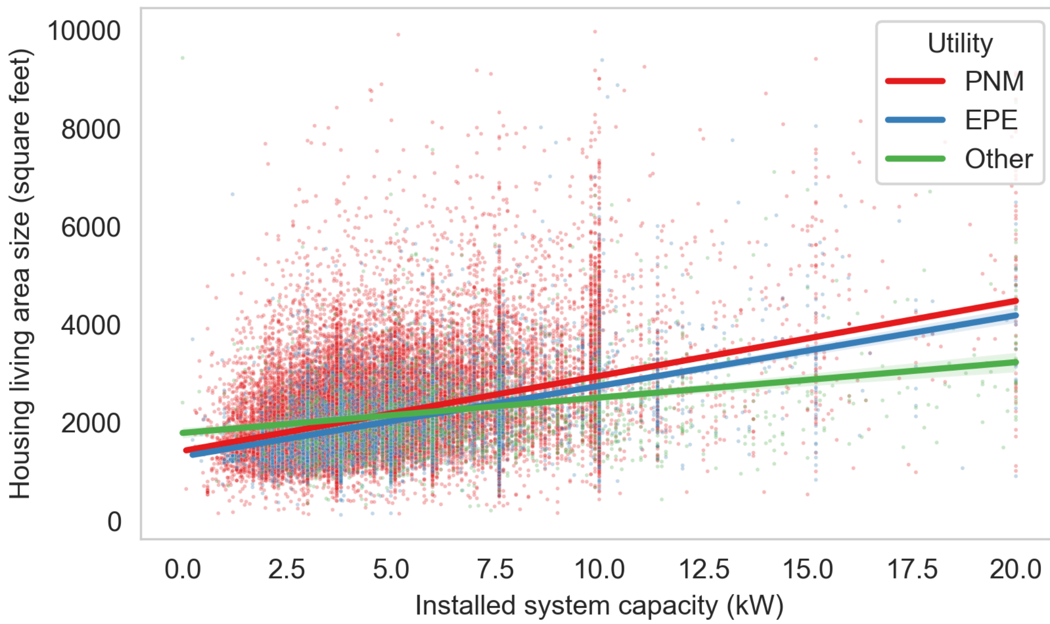

Figure 12: Linear relationship between installed capacity and housing size

Note: Each colored dot in the graph represent on system within the corresponding utility service area. PNM stands for the Public Service Company of New Mexico, EPE stands for El Paso Electric, and Other includes all other utilities in NM.

affect the likelihood and magnitude of solar PV adoption? This question is important for two reasons. First, it helps identify whether existing adoption patterns disproportionately favor certain demographic groups, potentially exacerbating social inequalities. Second, by analyzing the effectiveness of NM's solar tax credit programs, SMDTC and NSMDTC, we can evaluate whether these incentives successfully mitigate disparities related to income, race, ethnicity, and education.

3.1 Data description

We conduct our aggregate analysis at the 2010 census tract level. New Mexico had 499 census tracts in the 2010 Decennial Census, which increased to 612 in the 2020 Census. We normalize all data to the 2010 tract level to create a balanced panel dataset spanning from 2010 to 2022, ensuring consistency and comparability across the entire study period. The normalization method is detailed in Appendix A.1.

The key variable we use to estimate the adoption disparities is the aggregate count of newly installed residential solar PV systems each year at the census tract level. We merge the aggregated installation data with other census tract-level variables that may impact solar adoptions,

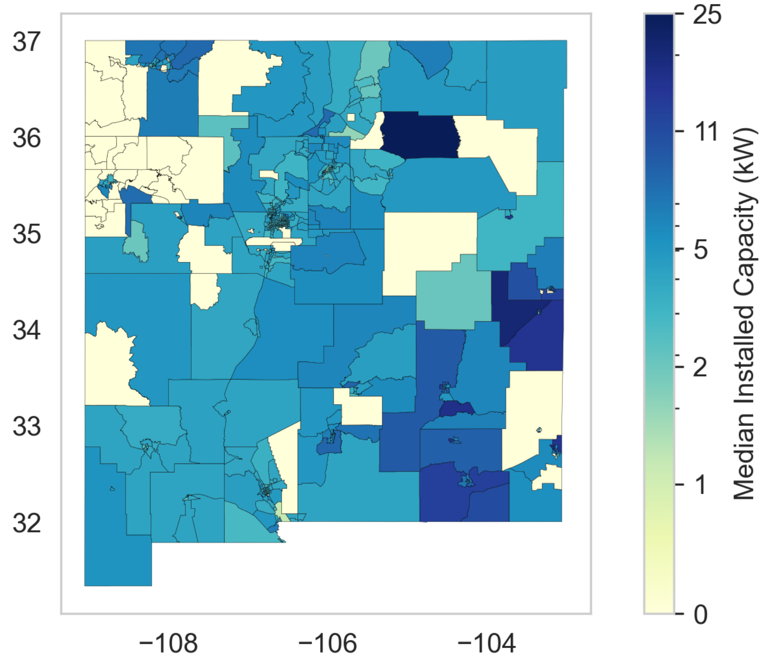

Figure 13: Median system capacity by census tract

Note: The median system capacity for all installed systems within the census tract area. The census tracts areas are defined in the 2020 Decennial Census. The legend is in logarithm scale.

including racial composition, education level, area median income, and disadvantaged status. We include controls for housing characteristics, spatial weather patterns, electricity providers, and state credit incentives.

The dataset comprises 498 tracts in NM from 2010 through 2022 after excluding one census tract with a zero population across all study years. Table 1 provides detailed explanations of variables used in the empirical analysis and their respective data sources.

We empirically investigate the disparity in solar PV adoptions across different demographic groups from two perspectives: 1) the impact of key factors on the extensive margin, which is the likelihood of solar PV adoption within census tracts over different years, and 2) the impact of key factors on the intensive margin, which represents the magnitude of solar PV installations. We discuss the details of our methodology and findings in the following sections.

3.2 The extensive margin of adoption

To estimate adoption equity on the extensive margin, we use the aggregated installation data to generate a binary dependent variable indicating the presence of any new solar installation within a census tract-year. Figure 14 shows the number of census tracts with solar installation in

Table 1: Variable descriptions and data sources

Variable	Description	Data sources
Dependent variables		
Count	Installed system count	EMNRD, NMPRC, and individual utilities
Explanatory variables		
Installation price	New Mexico average installation price, cent/W	Lawrence Berkeley National Lab Tracking the Sun database
Housing characteristics		
Total housing unit	Total housing units	U.S. Census Bureau (DP04)
Owner occupied	Owner occupied rate	U.S. Census Bureau (DP04)
Electricity	Share of of housing with electricity as main the heating source	U.S. Census Bureau (B25040)
Built year group	Median housing age year group Built after 2020 = 1; Built between 2010 and 2019 = 2; Built between 2000 and 2009 = 3; Built between 1990 and 1999 = 4; Built between 1980 and 1989 = 5, Built between 1970 and 1979 = 6; Built between 1960 and 1969 = 7; Built between 1950 and 1959 = 8; Built between 1940 and 1949 = 9; Built in 1939 or earlier = 10.	Authors' calculation based on Census Bureau (DP04)
Racial composition		
Racial diversity	Racial diversity index calculated as the sum of squared percentage of each race	Authors' calculation based on Census Bureau (DP05)
White	Share of one race White population	U.S. Census Bureau (DP05)
Hispanic	Share of Hispanic population	U.S. Census Bureau (DP05)
Non-Hispanic White	Share of Non-Hispanic White population	U.S. Census Bureau (DP05)
Electricity provider variables		
Utility type	IOU only = 1; Cooperative only = 2; Public utility only = 3; IOU & Cooperative = 4; IOU & Public utility = 5; Cooperative & Public utility = 6; IOU & Cooperative & Public utility = 7	Homeland Infrastructure Foundation -Level Data (HIFLD)
PNM	Dummy for PNM service area Yes = 1, other = 0	Public Service Company of New Mexico
Electricity price	Average annual electricity price (cent/kWh)	Authors' calculation based on U.S. Energy Information Administration
Weather variables		
Temperature	Average temperature	Solargis
GHI	Global Horizontal Irradiance (W/m^2)	Solargis
Other demographic variables		
Bachelor	Share of population (25 years and over) with bachelor's or higher degree	U.S. Census Bureau (S1501)
Income	Area median income (inflation-adjusted $)	U.S. Census Bureau (S1903)
Population	Total population	U.S. Census Bureau (DP05)
Disadvantage	Disadvantage rate	Climate and Economic Justice Screening Tool
Urban	Share of urban housing units	U.S. Census Bureau (H2)
Credit	Dummy for state credit incentives Yes = 1, other = 0	Authors' compilation

Note: See Appendix A.1 for details on the author-calculated variables.

each year. In 2022, 403 census tracts had at least one installation, while 95 census tracts had no installations. This represents a substantial increase in the extensive margin compared to 2010 where the with and without installation ratio is 221 to 277.

Table A.1 presents summary statistics for all variables over the sample period. We observe large standard deviations of income and housing value, indicating significant variability across the dataset and a wide financial disparity across census tract. To account for these skewed distributions, we take the logarithm of these variables in the regression analysis.

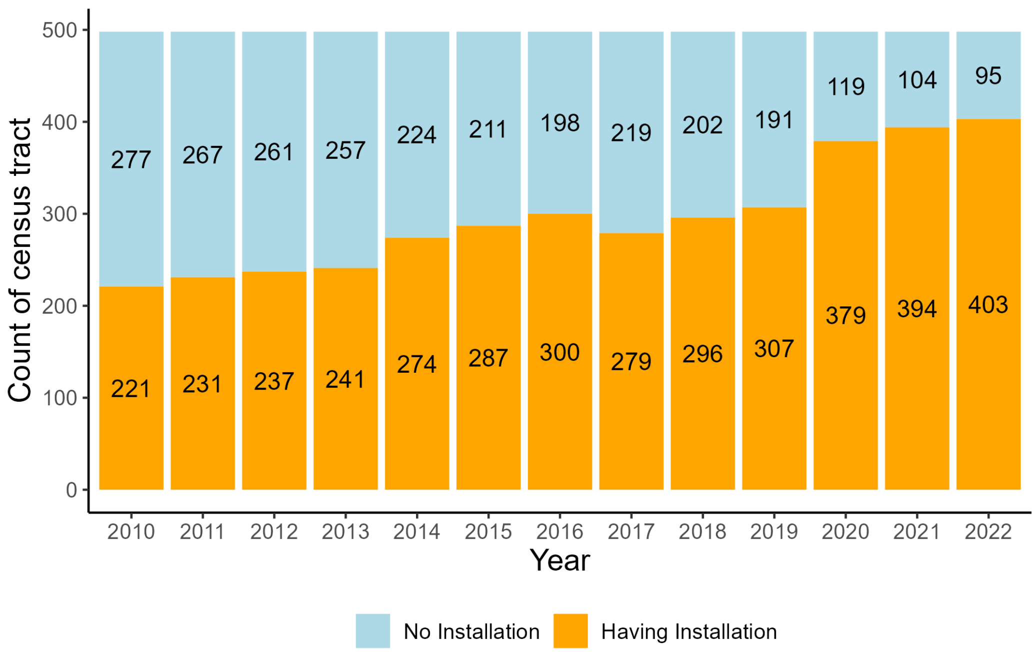

Figure 14: Number of census tract with/without solar installation by year

We compare the impact of various demographic and socioeconomic characteristics on the probability of having solar installations through a linear probability model (LPM) with county and year-fixed effects. Considering the limitations of the LPM, such as the linearity assumption, we use the fixed effect Logit model as a robustness check. The LPM is specified as follows:

$$W_{it} = \alpha_0 + \alpha_1 H_{it} + \alpha_2 WH_{it} + \alpha_3 \log(\text{INC}_{it}) + \alpha_4 EDU_{it} + \alpha_5 DIS_i + \gamma C_{it} + \lambda_t + \nu_j + \epsilon_{it}, \quad (1)$$

where W_{it} is the binary variable indicating whether there is any solar adoption within census tract i in year t. We consider five key explanatory variables from race and ethnicity, financial, and education perspectives. Specifically, H represents the share of the Hispanic population, WH represents the share of the White population, INC is the area median household income, EDU is the share of the population with a bachelor's degree or higher, and DIS is a dummy variable indicating whether a census tract is disadvantaged. C is the vector of control variables, which includes total population, average solar installation price, housing characteristics, and share of urban housing units. Other unobserved policies and incentives at the county level are accounted for through county fixed effect ν_j. We specify the year fixed effect λ_t as continuous to capture the time trend.

Table 2 presents the model results for the extensive margin of solar adoption (full results in Table A.2). Comparing the outputs of the LPM with the average marginal effects of the Logit model, we find that the LPM sufficiently captures the impact of key characteristics on the likelihood of solar adoption. There is a general increasing trend in solar adoption over the study period. The probability of new solar installation is positively correlated with the Hispanic population share, White population share, and education, although these correlations are relatively modest. Income has the highest impact on the likelihood of adoption; a 1% increase in the area median income increases the likelihood of having any installations by 12 percentage points.

The extensive margin analysis indicates that demographic and socioeconomic factors, particularly income, significantly influence the likelihood of solar adoption. Next, we will examine the intensive margin to understand how these factors impact the scale of solar PV installations within census tracts.

Table 2: Regression results for the extensive margin of solar adoption

	Dependent Variable: Having Installation (binary)			
	Linear Probability	Logit Marginal Effect	Linear Probability	Logit Marginal Effect
Hispanic	0.001**	0.001***	0.001*	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
White	0.003***	0.003***	0.003***	0.005***
	(0.000)	(0.000)	(0.000)	(0.001)
Log Area Median Income	0.120***	0.140***	0.134***	0.146***
	(0.019)	(0.018)	(0.020)	(0.019)
Bachelor	0.003***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Disadvantaged	0.003	0.013	0.001	0.013
	(0.013)	(0.012)	(0.013)	(0.012)
Observations	6,472	6,446	6,472	6,446
R-squared	0.522		0.523	
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Control	Main	Main	All	All
Year trend	0.043***	0.048***	0.0470***	0.0443***

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

3.3 The intensive margin of adoption

Given the disparities in extensive margin of residential solar PV adoption across census tracts, our next step is to assess the magnitude of adoption within solar-adopting census tracts to identify whether certain demographic and socioeconomic groups are installing more systems. This analysis will provide insights into the adoption equity on the intensive margin. We use the count of solar installations within a census tract-year as the dependent variable.[13] Table A.3 presents summary statistics for the main variables, conditional on having at least one installation within a tract-year over the sample period.[14]

The average number of residential solar PV installations per census tract-year is 10.64, with installation counts ranging from a minimum of 1 to a maximum of 155, and a standard deviation of 14.84. We aim to identify the key demographic and socioeconomic factors leading to this variability in installation count through a count model. Given the presence of over-dispersion in our dependent variable, we choose the Negative Binomial (NB) model over the Poisson model. The NB regression with county and year fixed effect model is specified as follows:

$$\begin{aligned}\log(\mu_{it}) =& \beta_0 + \beta_1 H_{it} + \beta_2 WH_{it} + \beta_3 \log(\text{INC}_{it}) + \beta_4 EDU_{it} + \beta_5 DIS_i + \beta_6 CR_t \\ &+ \delta C_{it} + \theta_t + \phi_j + \eta_{it}\end{aligned} \tag{2}$$

In this regression, we assume that the installed system count follow a Negative Binomial distribution, and $\mu_{i,t}$ is the average system count in census tract i in year t. CR_t is a dummy variable that equals 1 for year t if state tax credit is available and 0 if not. Other covariates are the same as in equation (1).

Table 3 displays the intensive margin of solar adoption estimation within the census tract-year. We also estimate an OLS regression with the system count as the dependent variable (model (2)) for comparison with the marginal effect from the NB model. Descriptive analysis in Figures 10 and 6 suggest that solar installations are concentrated in census tracts with high White population shares (greater than 50%), but decreases as White population shares exceeds 80%. To confirm this pattern, we introduce a quadratic term of White population rate into the OLS model as the third model specification (model (3)). Following Ros and Sai (2023), we add lagged system count into the NB model (model (4)) to capture any potential non-contemporaneous relationship between the explanatory variables and solar installation counts.

[13] We use the absolute count of installations instead of per capita installation because we want to control for the effect of population while examining the impact of other explanatory variables on solar adoption.

[14] We focus on the intensive margin of adoption in this step of the analysis, that is, the magnitude of adoption conditional on having any adoption. We also show the full sample result as a robustness check for the overall effect in Table A.5.

This dynamic model can be expressed as

$$\begin{aligned}\log(\mu_{it}) = &\beta_0 + \beta_1 H_{it} + \beta_2 WH_{it} + \beta_3 \log(\mathrm{INC}_{it}) + \beta_4 EDU_{it} + \beta_5 DIS_i + \beta_6 CR_t \\ &+ \beta_7 Count_{i,t-1} + \delta C_{it} + \theta_t + \phi_j + \eta_{it},\end{aligned} \tag{3}$$

where $Count_{i,t-1}$ is the lagged system count.

Table 3: Regression results for the intensive margin of solar adoption

	Dependent Variable: System Count (if > 0)			
	(1)	(2)	(3)	(4)
	NB	OLS	OLS with quadratic term	NB with lagged count
	Marginal Effect			Marginal Effect
Hispanic	0.027**	0.022	0.016	0.034**
	(0.012)	(0.018)	(0.018)	(0.014)
White	-0.039	0.050	0.414**	0.079
	(0.025)	(0.037)	(0.198)	(0.159)
$(\text{White})^2$			-0.004**	
			(0.002)	
Log Area Median Income	4.064***	4.051***	3.987***	3.704***
	(0.663)	(0.949)	(0.950)	(0.732)
Bachelor	0.102***	0.106***	0.106***	0.067***
	(0.017)	(0.025)	(0.025)	(0.018)
Disadvantage	-1.822***	-1.110**	-1.105**	-1.768***
	(0.384)	(0.563)	(0.563)	(0.418)
Credit	6.491***	7.145***	7.274***	2.439***
	(0.609)	(0.952)	(0.954)	(0.667)
Lagged System Count				0.364***
				(0.020)
Control	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year	All	All	All	2011 - 2022
Observations	3,849	3,849	3,849	3,628
R-squared		0.45	0.45	
Note:				*p<0.05; **p<0.01; ***p<0.001

To evaluate the impact of the main demographic characteristics on solar installations in NM, we compare results of different model specifications in Table 3.[15] We highlight several key findings:

First, we found that the Hispanic population in NM does not experience a disadvantage in solar PV adoption; rather, it has a slight advantage. This is contrary to findings from other studies using national samples, which suggest significant disparities (Darghouth et al. 2022; Gao and Zhou 2022). While the Hispanic population rate does show a statistically significant

[15] The full result is shown in Table A.4.

positive impact on installation counts in NB models (models (1) and (4)), the overall numerical effect remains small, indicating that ethnic factors do not play a significant role in shaping solar PV adoption across census tracts in NM.

Second, the result shows that being White does not confer a significant advantage in solar PV adoption, evident by the small and statistically insignificant coefficients for the White population rate in both OLS and NB models. However, model (3) indicates a significant non-linear relationship. The positive first-order coefficient suggests that higher percentages of White residents correlate with increased solar adoption, but the negative second-order coefficient indicates that this effect diminishes at higher white rates. This non-linear relationship explains why the average effect may appear insignificant, capturing the complexity of how demographic factors influence solar adoption.

Third, the consistent result across all model specifications reveals that demographic factors such as income, educational attainment, and residence in underserved communities continue to influence disparities in solar PV adoption, with income showing the most significant impact. Specifically, a one percent increase in the area median income within a census tract correlates with approximately four additional solar installations per year. Conversely, tracts categorized as disadvantaged experience fewer installations, typically around two less annually, compared to non-disadvantaged tracts. These findings align with literature that highlights the role of higher income and educational levels in fostering greater environmental awareness and investment capacity in solar technologies (Darghouth et al. 2022; O'Shaughnessy, Barbose, et al. 2021). In contrast, disadvantaged areas encounter significant barriers, leading to reduced adoption rates. Furthermore, the availability of solar tax credits has been found to boost installations across all demographic groups, underscoring the effectiveness of financial incentives in promoting solar energy adoption (Borenstein 2017).

Lastly, we observe a statistically significant positive impact from the lagged system count on current period installations in model (4), indicating that NM is still experiencing a growth phase in solar installations. The positive coefficient (0.364) suggests that higher installation numbers in one period are likely to lead to even more in the following period. While we do not delve into specific mechanisms, we refer to insights from the literature to gain some plausible explanations. The growing trend in solar installation may be attributed to peer effects, which reduce the uncertainty and lead to increased trust in the reliability of solar PV, consequently resulting in higher installations (O'Shaughnessy, Grayson, and Barbose 2023). Additionally, learning-by-doing among installers may lead to decreased costs over time (O'Shaughnessy 2019). When combined with state tax credits, these reduced costs make solar installations more financially accessible for households, further encouraging adoption. However, it is important to note that as the market matures and potentially approaches saturation, the positive impact of previous installations might diminish, possibly even turning negative.

Given the significantly positive impact of income on solar installations, we further explore how this impact varies across different income brackets. We calculate the average AMI over the study period and segment the census tracts into three groups: the top income quartile, the bottom income quartile, and the middle. Table A.6 presents the NB model estimation results for each group, revealing several notable observations.

First, within the bottom income quartile, solar installations appear to be largely uninfluenced by key demographic factors. While the Hispanic population rate shows a positive and statistically significant effect, its overall numerical impact is small. Interestingly, being classified as disadvantaged within the bottom income quartile is correlated with an additional two installations per year, which contrasts with results from the full sample. This suggests little disparity in solar adoption among this income group.

Second, in the top income quartile, the white population rate negatively impacts solar installations. Specifically, a 1 percent increase in the white population correlates with an average decrease of 0.57 solar installations. This negative trend may be attributed to the non-linear effects of white population rate on solar installations. As shown in Figure 15, census tracts in the top income quartile generally have higher shares of white populations. Moreover, racial diversity has a strong positive impact on installations, i.e., areas with less racial diversity in the top quartile tend to have more installations, which might also capture some of the effect of the higher white rate.

Third, the top income quartile exhibits greater sensitivity to financial factors compared to the other income groups. Contrary to expectations, income significantly boosts solar installations in this group; a 1 percent increase in AMI correlates with approximately six additional installations. Financial responsiveness also extends to installation costs and state incentives. A one-dollar increase in the average installation price per watt leads to six fewer installations, while the availability of state solar incentives is associated with an average increase of 11.6 installations. These findings indicate that households in top quartile areas demonstrate heightened financial sensitivity when making solar investment decisions and show a higher uptake of the state tax incentive compared to other income groups.

This analysis of the intensive margin of solar PV adoption across different census tracts suggests significant disparities influenced by demographic and socioeconomic factors, with income being the leading cause. This finding motivates us to assess the effectiveness of NM's solar tax credit incentives in reducing adoption disparities related to income and other demographic factors.

3.4 Effectiveness of the state solar tax credit

To evaluate whether state-level solar incentives alleviate or exacerbate disparities, we divide the observations into three groups based on the availability of solar incentives. The first group

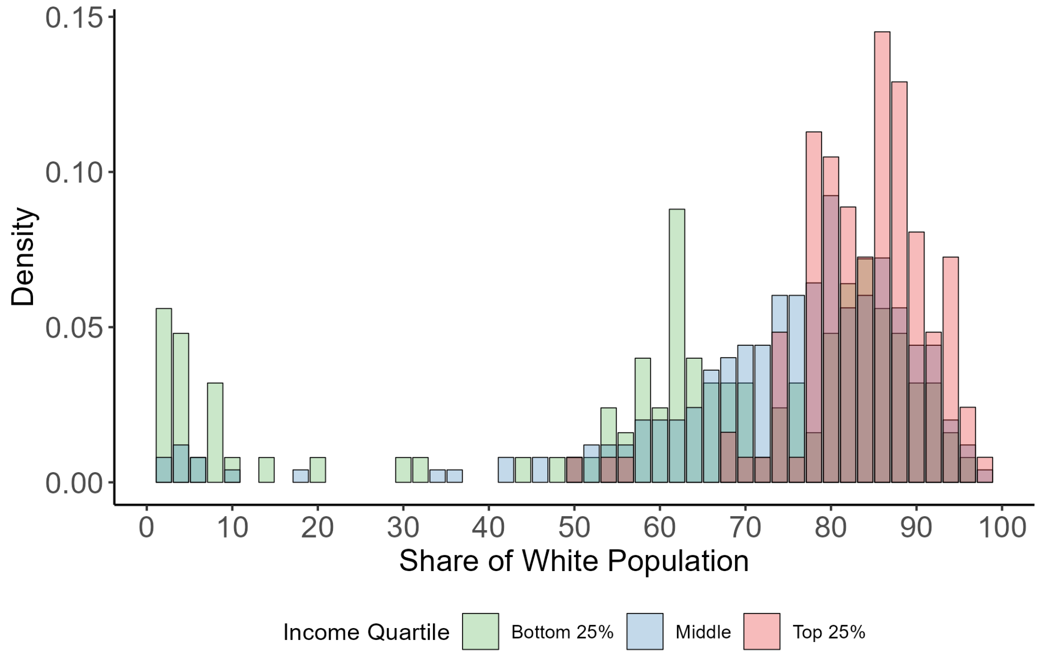

Figure 15: White population rate in census tracts by income quartile

Note: The income quartile classification is based on the average census tract area median income from 2010 to 2022. The share of White population in each census tract is the average of White population rate from 2010 to 2022. We normalize the frequency with the count of census tracts in each income quartile group. There are 124 census tracts in the top income quartile, 249 census tracts in the middle quartiles, and 125 census tracts in the bottom quartile.

includes data from 2010 to 2016 when the initial solar tax credit, SMDTC, was available. The second group comprises data from 2017 to 2019 when state-level solar incentives were absent. The last group spans from 2020 to 2022, when the solar tax credit was reintroduced as NSMDTC (Figure 4). Table 4 shows the estimation results of equation (2) for each period. The dependent variable is the census tract-year installation count if greater than zero because the tax credit has a higher impact on intensive margin of adoption. We discuss the effects of the state solar tax credit on adoption disparities by race and income separately.

The comparison of the racial variable coefficients across three periods indicate that the state solar tax credits significantly mitigate racial disparities in solar adoption. When state incentives were available, no significant racial disparities were observed. In contrast, during periods without these incentives, a 1 percentage point increase in the White population correlated with an average increase of 0.3 solar installations. This pattern underscores the effectiveness of state

Table 4: Negative binomial marginal effects for system count by state credit availability

	Dependent variable: System count (if > 0)		
	(1)	(2)	(3)
	SMDTC	No credit	NSMDTC
	2010-2016	2017-2019	2020-2022
Hispanic	0.011	0.063**	-0.016
	(0.009)	(0.032)	(0.032)
White	0.014	0.343***	-0.000
	(0.028)	(0.110)	(0.053)
Log area median income	3.722***	5.950***	-2.600
	(0.504)	(1.920)	(1.664)
Bachelor	0.111***	0.026	0.072*
	(0.013)	(0.040)	(0.040)
Disadvantage	-0.560**	-1.600*	-3.388***
	(0.280)	(0.918)	(0.975)
Log population	4.256***	2.526	3.151
	(0.767)	(2.764)	(2.436)
Electricity	0.013	0.204***	-0.112**
	(0.015)	(0.052)	(0.047)
Electricity price	0.218*	0.301	0.732
	(0.119)	(0.416)	(0.474)
Installation price	-1.336***	-4.248***	-36.52***
	(0.131)	(0.805)	(8.084)
Log total housing unit	0.403	9.155***	5.507**
	(0.765)	(2.846)	(2.422)
Urban	-0.021***	0.061***	0.086***
	(0.004)	(0.016)	(0.015)
Owner occupied	0.017***	0.226***	0.263***
	(0.006)	(0.035)	(0.034)
Built year group	0.111	-1.143***	-1.641***
	(0.089)	(0.286)	(0.298)
PNM	-0.103	-2.906***	-3.915***
	(0.265)	(0.834)	(0.971)
GHI	0.011**	0.038**	0.044**
	(0.005)	(0.016)	(0.017)
Racial Diversity	-0.728	-19.86**	7.222
	(2.268)	(8.461)	(4.960)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	1,791	882	1,176

Note: *p<0.05; **p<0.01; ***p<0.001

incentives to help create a more equitable environment for solar adoption across different racial groups.

The coefficients of the income variable highlight a significant increase in income-related adoption disparity when the tax credit was removed, as indicated by a statistically significant coefficient of 5.950. With the reintroduction of the NSMDTC in 2020, this impact diminished, with the income coefficient turning insignificant and negative (-2.600). This reversal suggests that the state tax credits have effectively reduced income-based disparities.

Several other observations can be made from the regression analysis:

While individuals with higher educational attainment were generally more likely to adopt solar PV, this trend has weakened as solar energy has become more widely adopted. A similar pattern is observed in population centers, where new adoption is now more dispersed rather than concentrated solely in populous areas. However, disparities between disadvantaged and non-disadvantaged communities, as well as between homeowners and renters, persist even with the tax credit in place.

To conclude, the state solar tax credit has been highly effective in narrowing the adoption gap related to the primary causes of disparity, namely income and race. However, it has been less effective in reducing other barriers, such as disadvantaged status and home ownership.

4 Distributional equity analysis

Another important aspect of solar equity is distributional equity, which pertains to whether the benefits of clean energy incentives are uniformly distributed across different demographic groups. In this section, we focus on the distributional equity of the state solar tax credit programs, SMDTC and NSMDTC, as they are the most prominent and salient forms of financial incentives for households. Given that solar tax credits are financed through tax dollars, understanding their distributional effects and potential regressivity is crucial for evaluating the efficiency and equity of these policies. Furthermore, the main motivation for solar tax credits is to promote solar adoption by reducing the financial burdens on households and to facilitate energy transition. Since the electricity produced by residential solar panels crowds out kWh for kWh of electricity from other generation sources in the grid regardless of the location and household characteristics (unless off-grid), having only a subset of households benefiting from the credit can be viewed as inequitable.

Our main research question is: Conditional on adopting solar, how do household and tract-level characteristics affect the probability of receiving state tax credits? Studying this question is crucial for several reasons. Firstly, it helps identify whether existing policies inadvertently favor certain demographic groups over others, which can exacerbate social inequalities. If solar incentives disproportionately benefit higher-income households or specific racial or ethnic groups, it indicates a need to redesign these policies to be more inclusive and equitable. Secondly, by understanding the factors that influence the distribution of these incentives, policymakers can develop targeted strategies to enhance the accessibility of solar energy for underrepresented and disadvantaged communities, contributing to a more just and sustainable energy transition. Lastly, evaluating the regressivity of solar tax credits ensures that public funds are used efficiently and equitably, promoting broader societal support for clean energy initiatives. Overall, this research provides valuable insights into designing more equitable and effective solar incentive programs.

We would like to emphasize a few details about the state solar tax credit in New Mexico. First, the tax credit is 10% of the total installation cost, with a cap of $9,000 in the first period and $6,000 in the second. Second, the tax credit can only be approved if the household applies for it (obviously), and approval for the tax credit requires an extensive set of documents from installers, utilities, permitting agencies, county assessors, and homeowners. Third, a household only qualifies for the tax credit if the system is owned and not leased. These specific incentive structures may also affect which types of households eventually receive the credit.

Our main hypotheses to be tested given the incentive structure are the following:

H1 Households with more expensive systems, reflected by higher installed capacity, are more likely to claim the tax credit. This is because, with the flat 10% credit, systems with a higher price tag can receive a higher absolute return.

H2 Less wealthy families are more likely to claim the tax credit as they have a higher marginal utility of wealth. Since we do not observe income or wealth at the household level, we use housing value as a proxy.

H3 Households in census tracts with higher education levels and lower Hispanic rates are more likely to claim credits as the application process may pose information and language barriers.

4.1 Data and descriptive analysis

We use the system-level data described in section 2.1 for the years when tax credits were available (2006-2016 and after 2020). Since the demographics data spans from 2010 to 2022, we restrict our sample to the overlapping years: 2010-2016 and 2020-2022.

Figure 16 shows the number of newly installed systems each year that received or did not receive solar tax credits within PNM, EPE, SEC, and LADPU service areas. It also shows the total credit amount claimed each year by all residential solar systems. During the first phase of the tax credit program (SMDTC), the majority of installations benefited from the 10% credit. In contrast, in the second phase (NSMDTC), more than half of the installations did not receive the credit. This gap can partially be explained by the annual funding cap implemented with NSMDTC. In 2020 and 2021, the cap was $8 million, increasing to $12 million in 2022 and 2023.[16] The aggregate cap was reached in 2021 and 2022, resulting in 190 and 226 tax credit

[16] In 2024, Governor Lujan Grisham signed House Bill 252 into law to raise the annual aggregate cap to $30 million per year (Lente 2024).

application rejections, respectively. Among the systems approved for tax credits, around 1% and 3% of the applications exceeded the individual system cap in the first and second phase, respectively.

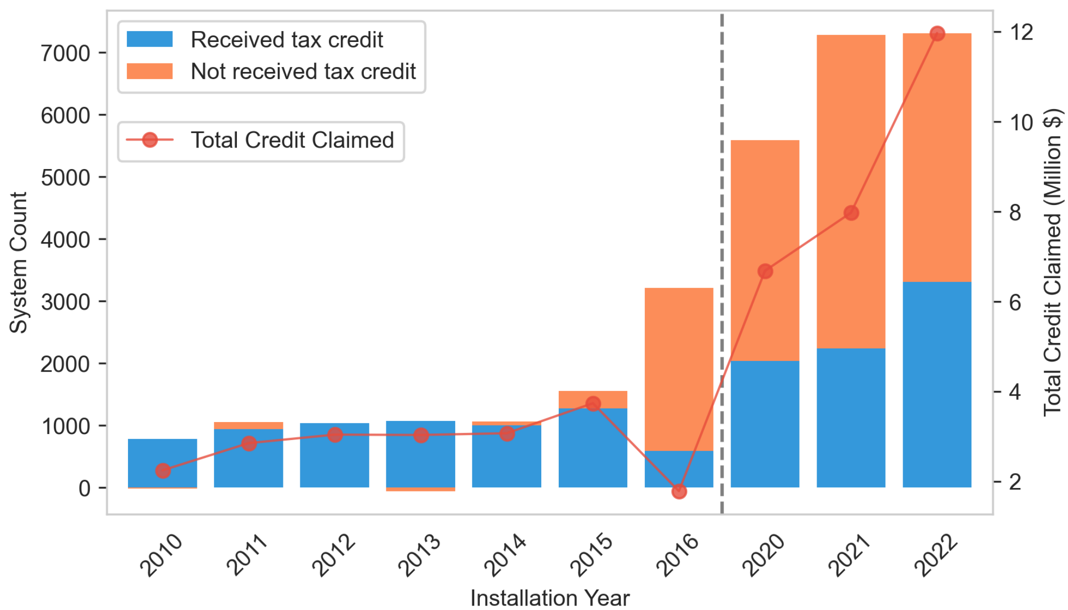

Figure 16: Installed systems by credit claim status and total credit claimed between 2010 and 2022

Note: The total system counts only include systems within PNM, EPE, SEC, and LADPU service areas. The number of systems receiving credits is also for this subset of utilities only. The total credit claimed accounts for all residential systems. In 2010 and 2013, the number of systems that did not receive tax credits (orange bars) was negative. This could be due to data errors between different data sources or credit claim delays.

Figure 17 illustrates the concentration of total tax credit claims and the average amount claimed per system. Total credits concentrate in census tracts with high solar installations (Figure A.1). In contrast, the average tax credit is highly correlated with the median installed capacity of the tract (Figure 13).

To answer the research question, we need to match the two data sources of solar installations to identify which systems received solar credits. The EMNRD data contains a wealth of information but only for systems that received tax credits, while the utility data includes the universe of all systems installed. We match the recorded address of the installed systems between the two data sources. Since the recorded address for the same system may vary across data sources, some of the systems in the EMNRD data cannot be found in the utility dataset despite our best efforts. Table A.7 shows the result of the matching, which, although imperfect, remains statistically insignificant. We also dropped any households with living areas of less than 100 square feet to avoid extreme outliers. The resulting dataset includes 26,735 unique systems.

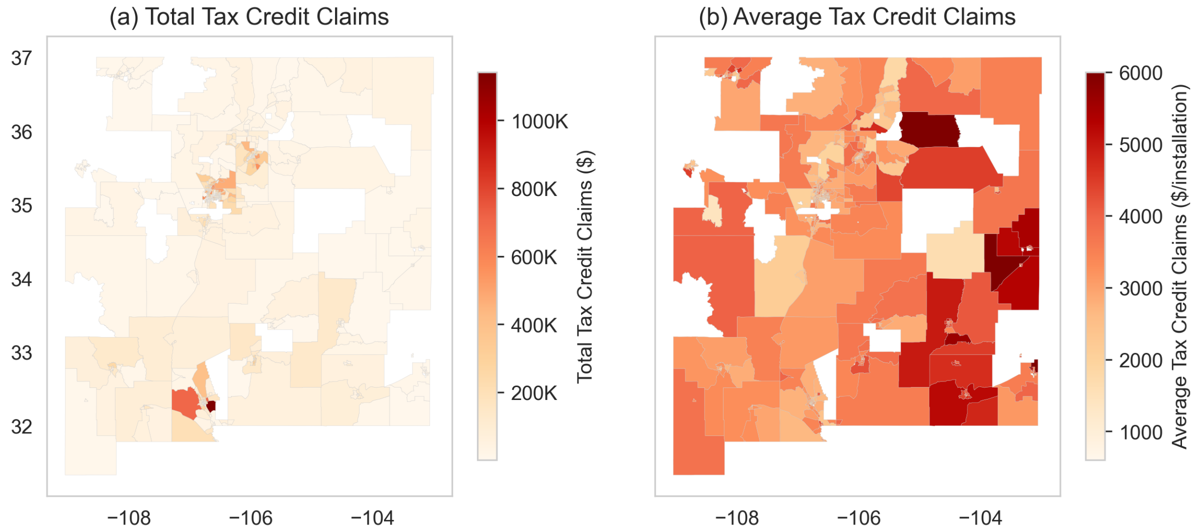

Figure 17: Total and average tax credit claim by census tract

Note: The total credit claimed sums up all historical amounts of credit received in the census tract by 2022. The average credit claim uses the total amount divided by the number of systems that received tax credits.

Table A.8 shows the summary statistics of the matched dataset, and Figure A.3 displays the correlation matrix of the key variables.

4.2 The extensive margin of tax credit claim

The dependent variable in our analysis is whether a household received a tax credit upon adopting solar energy. We use the linear probability model (LPM) as a preliminary step to decompose the effect of various household and tract-level characteristics on the probability of claiming credit. We run the Logit model as a robustness check. The model is specified as follows:

$$\text{SolarTaxCredit}_{hlt} = \alpha + \beta_1 X_{ht} + \beta_2 C_{lt} + \gamma_t + \delta_c + \theta_u + \varepsilon_{lt}, \tag{4}$$

where $\text{SolarTaxCredit}_{hlt}$ is a binary variable indicating whether household h in census tract l received a solar tax credit in year t, X_{ht} is a vector of household-level variables for household h in year t, C_{lt} is a vector of census tract-level variables for the census tract l in year t, γ_t is the year fixed effect, δ_c is the county fixed effect, θ_u is the utility fixed effect, standard errors are clustered at the census tract level.

We test five model variations: (1) including only household-level variables, (2) including both household- and census tract-level variables, (3) with year fixed effects, (4) with year and utility fixed effects, and (5) with year and county fixed effects.

Model (1) examines how household-level characteristics alone affect the probability of claiming the credit. Model (2) examines whether the tax credit benefits concentrate in communities with certain demographic characteristics. Model (3) controls for time-varying unobserved factors, such as changes in solar PV price trends and societal awareness and acceptance of solar PV. Model (4) controls for time-invariant utility-specific characteristics, including utility type (IOU, coop, or public utility), solar incentives, and infrastructure. Model (5) controls for county-specific characteristics, including regulatory environment and geographic factors not captured by the demographic controls. The results of these models are presented in Table 5. The regression result of the Logit model with the same model specifications is reported in Table A.9.

We find that households with higher system capacity, higher housing values, and older residences are more likely to obtain tax credits. Housing value has the most significantly positive impact: a 1 percent increase in housing value increases the probability of claiming the credit by 15.6 percentage points in model (5), contrary to our initial hypothesis (H2). Additionally, households in census tracts with higher education levels, higher owner-occupancy rates, lower mortgage rates, and lower Hispanic populations are more likely to receive tax credits. Conversely, disadvantaged census tracts have fewer tax credit claims.

These results provide evidence that tax credits are concentrated among wealthier households, all else being equal, similar to findings in the literature related to other green energy incentive programs (Borenstein and Davis 2016). Figure 18 illustrates the percentage of systems claimed tax credit by housing value quintile. It is evident that the rate of credit claims increases for higher housing value quintiles, with more than 65% of households in the top quintile claiming the credit, compared to only around 25% in the bottom quintile.

The positive coefficient of education level and negative coefficient of Hispanic population share suggest potential information barriers to ethnic minorities and populations with lower education levels in the tax credit program, confirming our initial hypothesis H3. The negative coefficient of the mortgage rate suggests that more solar systems may be under leasing contracts in these census tracts, which do not qualify for the tax credits.

We estimate model specification (5) of equation (4) for the two tax credit program phases separately to examine whether some of the distributional effects change over time. Table 6 reports the regression results. Figure A.4 shows the time trend of the household-level explanatory variable coefficients.

Under SMDTC, none of the housing characteristics significantly impacted the probability of claims. However, census tract characteristics such as higher educational levels, higher owner occupancy rates, higher median age, and lower percentage of white population increased the probability of credit claims. In contrast, under NSMDTC, housing value has a significantly positive impact on the outcome. Moreover, census tracts with higher Hispanic populations and those that are disadvantaged have fewer claims.

Table 5: Regression results on state credit claim

	Dependent variable: State Credit				
	(1)	(2)	(3)	(4)	(5)
System capacity	-0.005***	0.003*	0.010***	0.009***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log Zestimate	0.294***	0.148***	0.117***	0.134***	0.156***
	(0.009)	(0.012)	(0.011)	(0.012)	(0.015)
Year built	-0.002***	-0.000	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log Housing size (sq ft)	0.047***	0.029*	0.004	-0.005	-0.016
	(0.014)	(0.014)	(0.013)	(0.013)	(0.015)
# of Bedrooms	-0.036***	-0.017***	-0.009*	-0.010*	-0.010*
	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
% population with bachelor degree (>25)		0.183***	0.260***	0.213***	0.187***
		(0.033)	(0.031)	(0.034)	(0.037)
Owner occupancy rate		-0.383***	0.141***	0.136***	0.139***
		(0.021)	(0.025)	(0.025)	(0.025)
Mortgage rate		-0.298***	-0.287***	-0.272***	-0.228***
		(0.031)	(0.030)	(0.031)	(0.031)
Log Area Median Income		0.067***	-0.015	-0.005	-0.005
		(0.014)	(0.014)	(0.014)	(0.014)
Log Population		0.054***	0.016*	0.015*	0.024**
		(0.007)	(0.007)	(0.007)	(0.007)
Log Median Age		0.048*	0.009	0.008	0.023
		(0.022)	(0.021)	(0.021)	(0.021)
% population identified as White		0.064	0.017	-0.011	-0.067
		(0.038)	(0.036)	(0.038)	(0.040)
% population identified as Hispanic		-0.090***	-0.105***	-0.145***	-0.142***
		(0.024)	(0.023)	(0.025)	(0.029)
Urban share		-0.061***	-0.031**	-0.021	-0.008
		(0.012)	(0.011)	(0.012)	(0.012)
Within disadvantaged census tracts		-0.039***	-0.034***	-0.032***	-0.042***
		(0.009)	(0.009)	(0.009)	(0.009)
Year Fixed Effects	No	No	Yes	Yes	Yes
Utility Fixed Effects	No	No	No	Yes	No
County Fixed Effects	No	No	No	No	Yes
Observations	25234	25234	25234	25234	25234
R^2	0.086	0.157	0.232	0.233	0.235
Adjusted R^2	0.086	0.156	0.231	0.232	0.234
Residual Std. Error	0.475	0.456	0.435	0.435	0.435
F Statistic	476.601***	313.067***	317.205***	282.905***	209.254***

Note: *p<0.05; **p<0.01; ***p<0.001
Standard errors are clustered at the census tract level and are robust

The change over time in the key characteristics affecting credit claims highlights discernible differences between early and late adopters of solar PV. Early adopters are likely to be more tech-savvy and have a preference for clean energy. For them, the likelihood of claiming the credit depends on their awareness of the program, which is potentially correlated with education level,

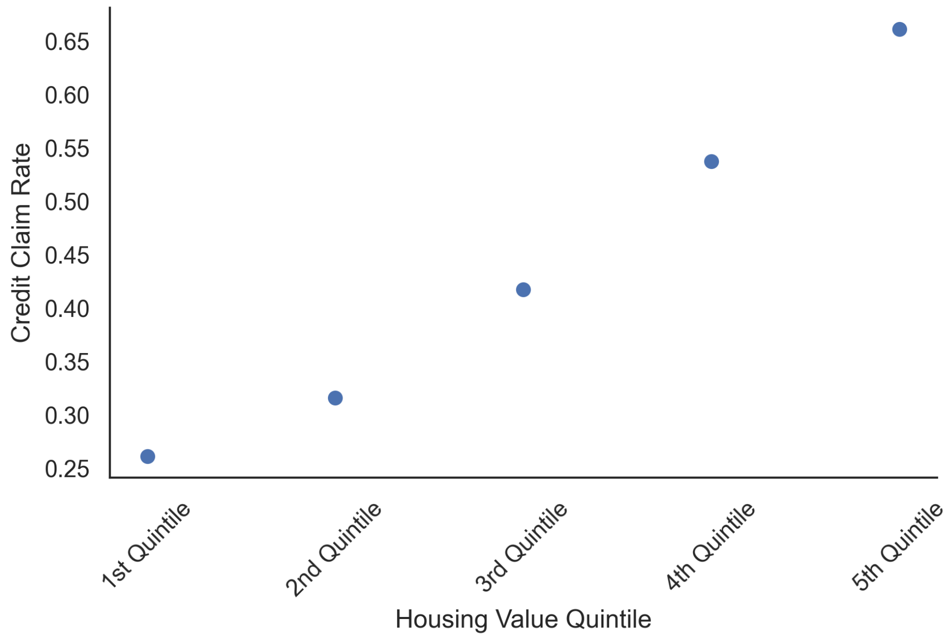

Figure 18: Credit claim rate by housing value quintile

and their financial savviness, potentially correlated with age and racial status. Additionally, if the system is under a leasing contract, potentially correlated with the mortgage rate, it is less likely to receive credit. Late adopters, on the other hand, could be more motivated by the financial gains of installing solar. Therefore, they are more sensitive to the financial benefits of the tax credit, as shown by the significant positive effect of system capacity in the second period.

The findings also reveal persistent equity issues, as disadvantaged and Hispanic-majority census tracts are less likely to benefit from tax credits under the NSMDTC. A notable difference between SMDTC and NSMDTC is the introduction of an aggregate cap under NSMDTC. This cap negatively affects distributional equity by imposing a negative effect on areas that are disadvantaged and have higher Hispanic populations. Thus, these results support the recent policy change to increase the aggregate cap and allowing for retroactive tax credit applications from rejected applications due to the cap being reached (Lente 2024).

4.3 The intensive margin of tax credit claim

We further explore the distributional equity on the intensive margin. We examine the research question: conditional on receiving tax credits, which household characteristics lead to higher claimed amounts? To answer this question, we estimate the following OLS regression with the claimed amount as the dependent variable:

Table 6: Regression results on state credit claim by program period

	Dependent variable: State Credit	
	First round, SMDTC (before 2016)	Second round, NSMDTC (after 2020)
System capacity	0.002	0.010***
	(0.002)	(0.002)
Log Zestimate	0.024	0.251***
	(0.021)	(0.020)
Year built	-0.001**	-0.001***
	(0.000)	(0.000)
Log Housing size (sq ft)	0.033	-0.062**
	(0.021)	(0.020)
# of Bedrooms	0.004	-0.016**
	(0.007)	(0.006)
% population with bachelor degree (>25)	0.207**	0.170***
	(0.065)	(0.045)
Owner occupancy rate	0.091**	0.026
	(0.033)	(0.048)
Mortgage rate	-0.300***	-0.095
	(0.047)	(0.051)
Log Area Median Income	0.026	-0.008
	(0.023)	(0.019)
Log Population	0.028*	0.024*
	(0.012)	(0.010)
Log Median Age	0.182***	-0.003
	(0.035)	(0.029)
% population identified as White	-0.252***	0.007
	(0.069)	(0.051)
% population identified as Hispanic	-0.004	-0.152***
	(0.052)	(0.036)
Urban share	0.007	-0.033*
	(0.019)	(0.016)
Within disadvantaged census tracts	-0.006	-0.038***
	(0.016)	(0.011)
Year Fixed Effects	Yes	Yes
County Fixed Effects	Yes	Yes
Observations	8326	16908
R^2	0.382	0.112
Adjusted R^2	0.380	0.111
Residual Std. Error	0.386	0.453
F Statistic	160.188***	71.071***
Note:		*p<0.05; **p<0.01; ***p<0.001

$$\log(\text{TaxCreditAmount})_{ht} = \alpha + \beta X_{ht} + \gamma C_{lt} + \delta_t + \varepsilon_{lt}, \tag{5}$$

where $\text{TaxCreditAmount}_{ht}$ is the dollar amount tax credit approved for household h in year t, X_{ht} is a vector of household level explanatory variables, C_{lt} is a vector of census tract demographic controls, δ_t is the year fixed effect, and ε_{lt} is the error term clustered at the census tract level.

β is the vector of coefficients of interest. We test three model specifications for the full sample: (1) with only household-level variables, (2) adding census tract controls, and (3) incorporating year-fixed effects. We also run subsample analysis for the SMDTC and NSMDTC separately. Table A.10 provides the summary statistics, and Table 7 displays the regression results.[17]

Table 7: Regression results of linear models for tax credit claim amount

	Dependent variable: Log(Tax credit claimed)				
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Full sample	SMDTC	NSMDTC
System capacity	0.109***	0.112***	0.115***	0.130***	0.108***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
Log Zestimate	0.049***	0.070***	0.059***	0.237***	−0.086***
	(0.010)	(0.013)	(0.013)	(0.021)	(0.016)
Year built	−0.001***	−0.001***	−0.001***	−0.002***	−0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Log Housing size (sq ft)	0.083***	0.057***	0.054***	−0.036	0.135***
	(0.015)	(0.015)	(0.015)	(0.024)	(0.019)
No. of Bedrooms	0.026***	0.027***	0.028***	0.028***	0.018***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.006)
Census Tract Controls	No	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes	Yes
Observations	11,034	11,034	11,034	4,940	6,094
R^2	0.435	0.448	0.461	0.458	0.507
Adjusted R^2	0.435	0.447	0.459	0.455	0.505
Note:					*p<0.1; **p<0.05; ***p<0.01

The regression results highlight two primary factors influencing the intensive margin of solar tax credit claims. First, higher system capacity consistently leads to higher tax credit claims across all model specifications. This trend is expected, as the tax credit amounts to 10% of the total installation cost, and systems with greater capacity generally incur higher costs. It is also important to note that system capacity typically reflects the household's electricity consumption. Therefore, this result implies that energy-intensive solar adopters receive higher subsidies.

Secondly, households with higher property values claim larger tax credits in both the full sample and SMDTC regressions. However, in the NSMDTC subsample, this correlation is reversed. This observation reinforces equity concerns within the subsidy program, as it suggests that wealthier households are not only more likely to claim credits, as shown in the extensive margin analysis, but also claim higher amounts. Under NSMDTC, although wealthier households are still more likely to claim credits, the absolute amount claimed is lower when they do.

We follow Borenstein and Davis (2016) to illustrate the concentration of solar credit claims

[17] Full regression results are detailed in Table A.11.

by income quintile and calculate the concentration index for the full sample period, SMDTC, and NSMDTC. Figure 19 shows the concentration curves for the three samples. The 45-degree line represents perfect equality; the more convex the curve, the more regressive the policy, favoring wealthier households. The curves indicate that NSMDTC is more equitable than SMDTC. The concentration index, calculated as the ratio of the area between the concentration curve and the 45-degree line over the total area under the 45-degree line, for the full sample, SMDTC, and NSMDTC are 0.444, 0.498, and 0.405, respectively.[18] Borenstein and Davis (2016) showed that the concentration index for the federal Residential Energy Credit, which is the federal solar tax credit, is 0.606, higher than what we find at the state level.

It is important to note a caveat in how the concentration index is calculated: the income quintile is based on census tracts, not individual households, as we only observe census tract-level AMI. Given that income levels vary within census tracts and households adopting solar are likely on the higher end of the income distribution, our calculated concentration index is likely a lower bound estimation. Nevertheless, it shows significant concentration of the tax credits among more affluent groups.

These insights indicate that while the tax credit scheme is effective in promoting solar adoption, it tends to favor wealthier households. This observation calls for reviewing policy designs to ensure that solar energy benefits are more equitably distributed, thereby supporting broader access to renewable energy across different socioeconomic groups. Further research is also warranted to explore the reasons behind price variations in solar system installations across different households.

5 Conclusion and policy implications

This research aims to understand the landscape of residential solar PV adoption in New Mexico through the lenses of two aspects of equity: adoption equity and distributional equity. For adoption equity, we examine whether the rate of adoption is equitable across census tracts with varying racial, ethnic, income, and education compositions, both at the extensive and intensive margins. For distributional equity, we focus on whether the state solar tax credit is equitably distributed across solar households.

In terms of adoption equity, we find little disparity between racial and ethnic groups, contrary to findings from other research on solar equity in other parts of the U.S. Moreover, the existence of the state solar tax credit diminishes any remaining disparities across racial and ethnic groups. However, significant income disparity remains at both the extensive and intensive

[18] If we use the full credit claim data from EMNRD for the study period, the concentration index for the full sample, SMDTC, and NSMDTC are 0.387, 0.449, and 0.356, respectively. This suggests that solar adopters are shifting towards low-income populations as the market matures, and the distributional inequality gap is shrinking. Figure A.5 shows the year trend of the concentration index.

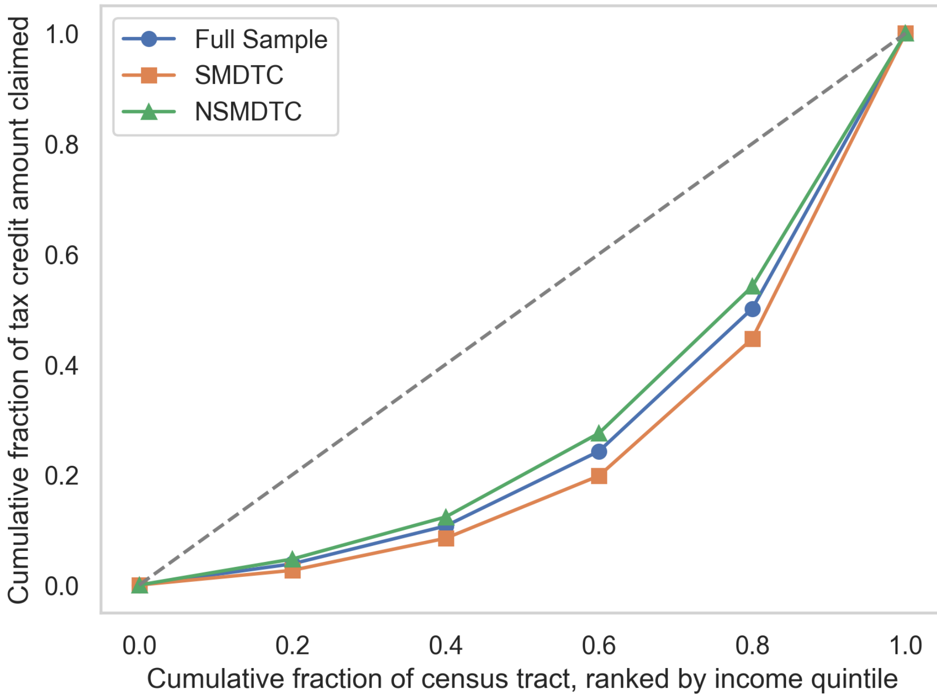

Figure 19: Concentration curves of solar tax credit

Note: The 45-degree line indicates perfect equality. The concentration index can be calculated as the ratio of the area between the concentration curve and the 45-degree line over the total area under the 45-degree line. The index would take values between -1 and 1. An index value of zero indicates perfect equality.

margins. Census tracts that are overburdened on other socioeconomic aspects are also correlated with lower solar adoption. Although the solar tax credit reduces some of these disparities, it is not sufficient to alleviate them fully. Education disparity only exists among early adopters and higher-income areas and has relatively small effects on solar adoption rates.

Conditional on solar adoption, the results reveal significant disparities in the distribution of solar tax credits in New Mexico. Credit claims are concentrated among households adopting large solar capacities and with higher housing values. Communities with higher education levels, higher owner-occupied housing rates, lower mortgage rates, and lower Hispanic population shares also see higher rates of tax credit claims. The introduction of the aggregate cap under the NSMDTC has exacerbated these inequities, favoring wealthier households and negatively affecting disadvantaged and Hispanic-majority census tracts.

We conclude with the following remarks. First, although the findings highlight persistent equity issues, especially stemming from income disparity and disadvantaged status, this inequality is smaller compared to what the literature has found. The diverse racial and ethnic composition in New Mexico may have contributed to greater solar adoption equity compared to other states.

Second, we show that disadvantaged and Hispanic-majority census tracts are less likely to benefit from tax credits under the NSMDTC, potentially due to the information barrier of the application process and the aggregate cap being imposed. However, we acknowledge that the NSMDTC has undergone some recent changes, including raising the aggregate cap and allowing for retroactive credit claims for rejected applications from 2021 to 2023 due to the cap being met (Lente 2024), and changing the tax credit from nonrefundable to refundable (New Mexico Energy, Minerals and Natural Resources Department 2020). These policy changes will likely relieve some of the distributional issues. Yet, since leased systems do not qualify for tax credits, and lower-income households are more likely to lease systems rather than own them, we will still see a concentration of credit claims among wealthier households. Additionally, there is a need for targeted outreach and support to disadvantaged communities to ensure they are aware of and can overcome the information barriers to these incentives.

To enhance the equity of solar tax credits and other incentives, we recommend the continuous monitoring of existing policy impacts and adjusting it based on adoption rates and feedback from underserved communities. Introducing specific incentives or additional support for low-income households and those in disadvantaged areas can help reduce the financial and informational barriers to solar adoption. Implementing educational campaigns and providing resources to ensure that all communities are aware of available incentives and how to access them are also essential steps.

Future research should explore the long-term impacts of recent policy changes on the equity of solar adoption, the effectiveness of targeted outreach programs in increasing solar adoption in disadvantaged communities, and comparative studies across different states to identify best practices in promoting equitable solar adoption. Additionally, estimating the effect of community solar programs on equity, particularly how these programs can enhance access to solar energy for households that cannot afford individual installations or do not own their homes, is a vital area for future research.

While this study provides valuable insights, it is limited by the availability of data on individual household characteristics. Future studies with more granular data could provide a deeper understanding of the equity issues in solar adoption. By addressing these aspects, policymakers can better design and implement solar incentive programs that promote equitable access and adoption across all socioeconomic groups, ensuring a just and inclusive energy transition in New Mexico.

A Appendix

A.1 Variable calculation methods

Census tract mapping

To map 2020 Decennial Census-level data into 2010 Decennial, we refer to the 2020 Census Redistricting Data (P.L. 94-171) Block Relationship files [19]. We use the land area of the overlapping part (in square meters) divided by the total land area of 2010 tract to calculate the share of 2020 tract land overlapping into each 2010 tract, and then build a 612×499 matrix. Then, we convert each census tract-level variable into a 612×1 matrix, and multiply with the mapping matrix to get the 499×1 data matrix.

Built year group

We define the house built year group as follows: Built after 2020 = 1; Built between 2010 and 2019 = 2; Built between 2000 and 2009 = 3; Built between 1990 and 1999 = 4; Built between 1980 and 1989 = 5; Built between 1970 and 1979 = 6; Built between 1960 and 1969 = 7; Built between 1950 and 1959 = 8; Built between 1940 and 1949 = 9. To determine the built year group of the median house in each census tract-year, we use the total number of housing units provided by the U.S. Census Bureau DP04 table. We identify the built year group of the median housing unit by ranking the built year groups from earliest to latest. The built year group of the median unit is then assigned to the entire tract-year.

Racial diversity

The racial diversity is defined as:

$$\text{Racial diversity} = \sum_i \left(\frac{\text{Population identified as race } i}{\text{Total one-race population}} \right)^2 \tag{A.1}$$

where i = White, Black or African American, American Indian and Alaska Native, Asian, Native Hawaiian and Other Pacific Islander, and other race.

Electricity price

We determine the electricity provider for each census tract and the company's ownership each year using data from the Homeland Infrastructure Foundation Level Data (HIFLD). Additionally,

[19] https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.2020.html

we obtain the electricity price for each company annually from the Energy Information Administration's Table 6 (T6). We then calculate the tract-year electricity price as the average electricity price of all providers in each tract for each year.

Credit

We generate $Credit$ for each year to show the state solar incentive availability as follows.

$$\text{Credit} = \begin{cases} 0 & \text{if Year} = 2017, 2018, 2019 \\ 1 & \text{otherwise.} \end{cases}$$

A.2 Supplementary Figures

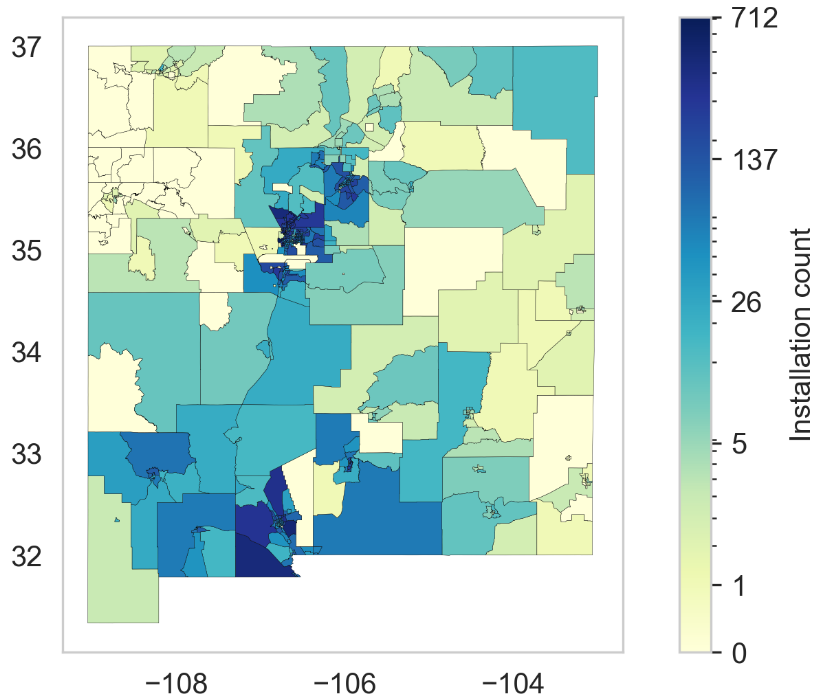

Figure A.1: Total installation count by census tract

Note: The total installation count is up to the end of 2023 for each census tract. The census tracts are defined in the 2020 Decennial Census. The legend is on logarithmic scale.

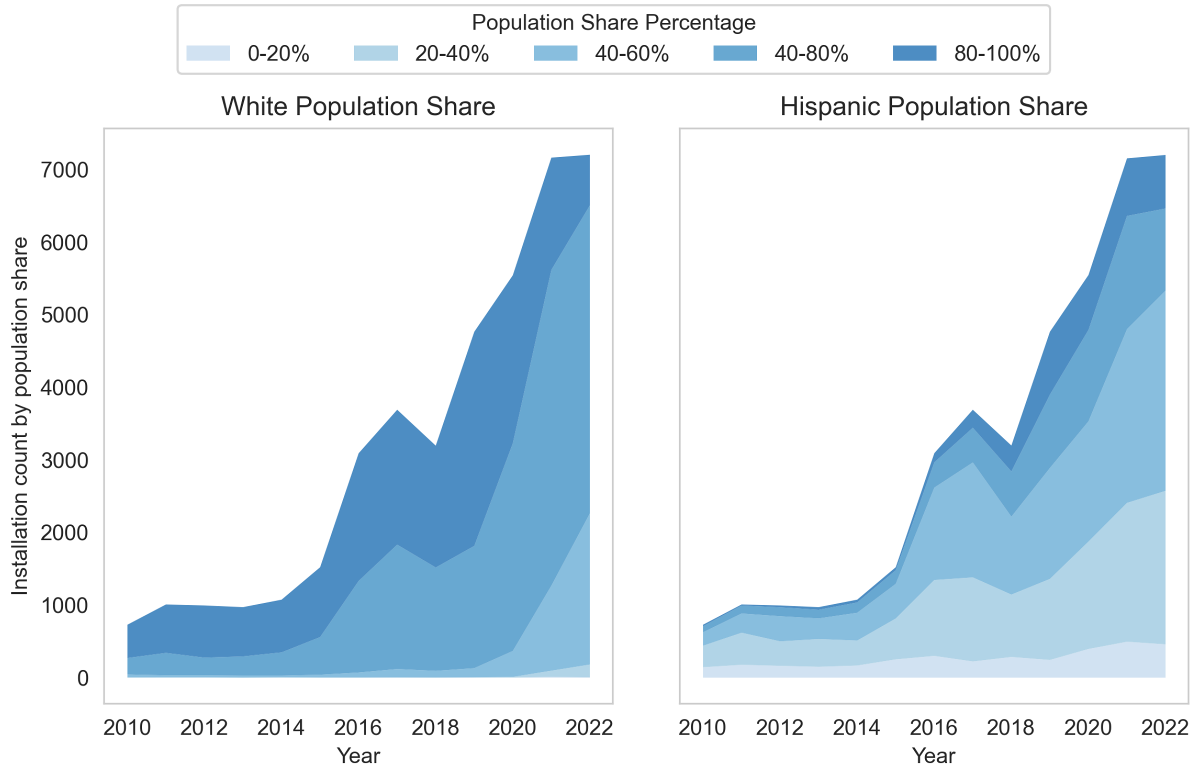

Figure A.2: Installation by racial population share

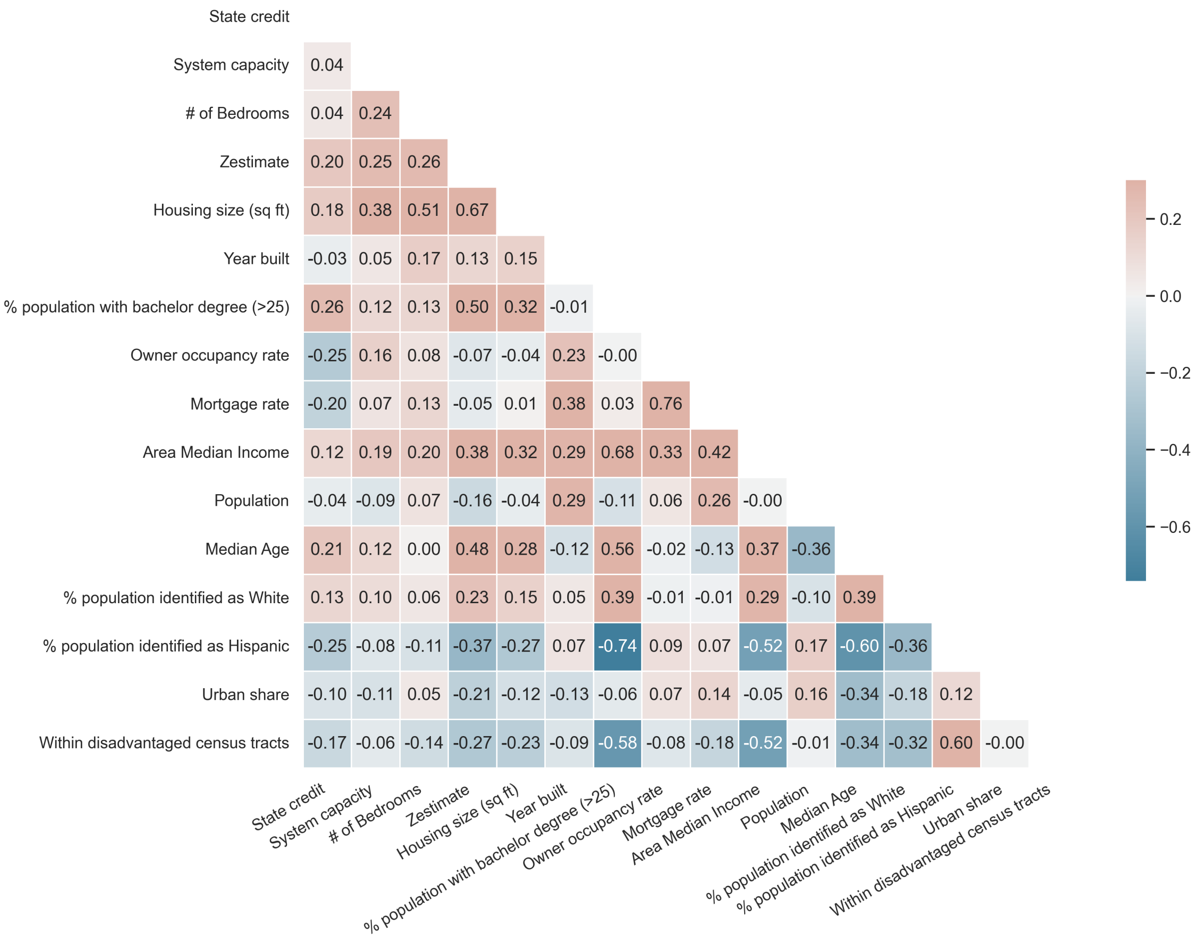

Figure A.3: Correlation matrix between regression variables in the distributional equity analysis

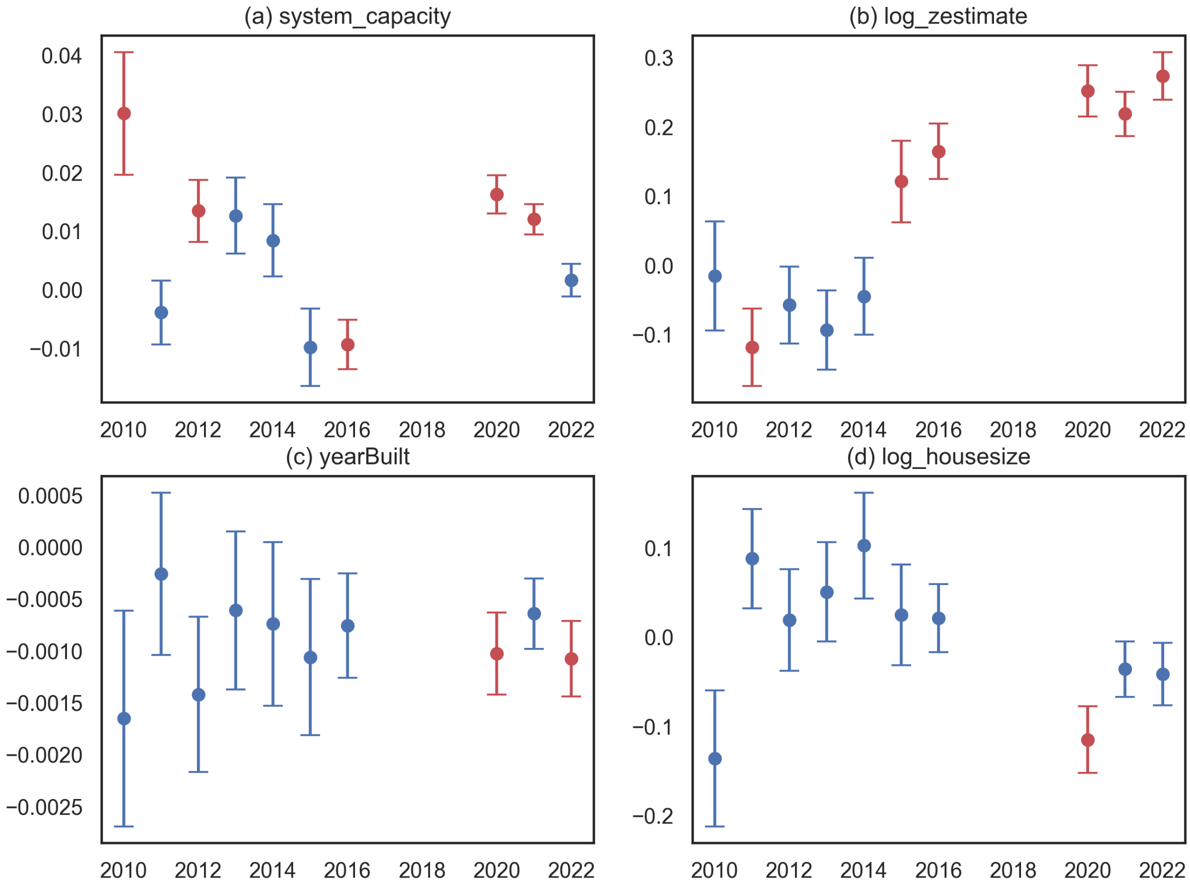

Figure A.4: Coefficient trend by year for household-level explanatory variables

Note: Red and blue error bars show statistically significant and insignificant coefficient estimates, respectively.

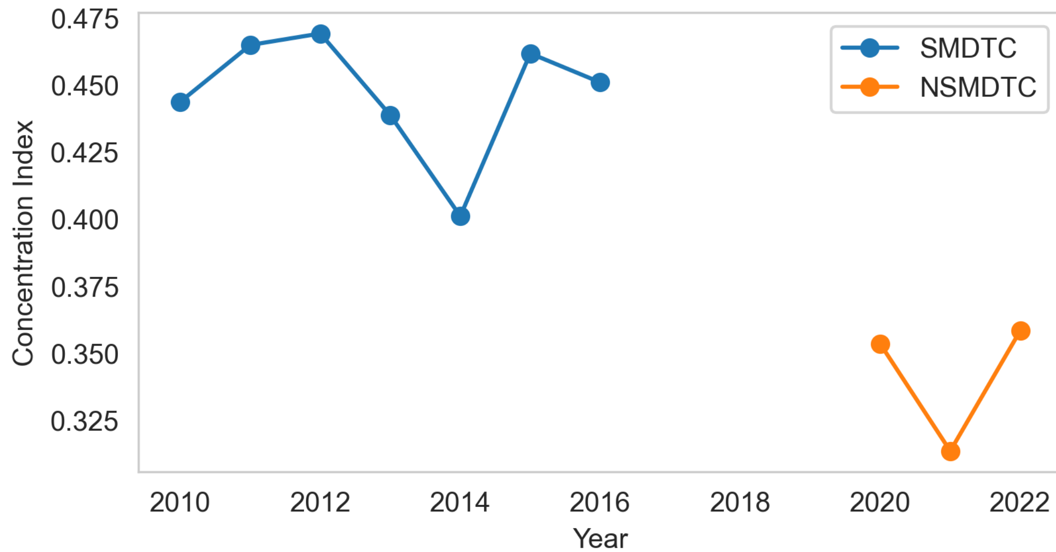

Figure A.5: Concentration index of state tax credit distribution by year

Note: The concentration indices are calculated using the EMNRD credit claim data from 2010 to 2022.

A.3 Supplementary Tables

Table A.1: Summary statistics of regression model (1)

	N	Mean	Std. Dev.	Median	Max	Min
Having installation	6474	0.59	0.49	1	1	0
Owner occupied	6474	45.33	22.72	47.27	100	0
Electricity	6474	17.64	14.86	12.21	100	0
Built year group	6474	5.18	1.45	5	10	1
Utility type	6474	2.72	1.71	2	6	1
PNM	6474	0.41	0.49	0	1	0
Electricity price	6474	13.01	1.83	13.08	21.11	7.78
Installation price	6474	5.68	1.33	5.30	9	4.30
Temperature	6474	14.03	2.83	14.40	18.90	3.68
GHI	6474	2034.01	59.10	2035.95	2189.54	1816.68
Bachelor	6474	25.92	16.48	21.95	81.78	0
Income	6474	49333.93	21219.96	45054	174019.73	7278.34
Population	6474	4022.10	1805.60	3819	17497	71.02
Racial diversity	6474	0.65	0.16	0.66	1	0.22
White	6474	72.31	21.71	78.43	100	0.16
Non-Hispanic White	6474	39.99	21.77	40.54	95.78	0
Hispanic	6474	45.82	23.42	44.31	100	0
Total housing unit	6474	1781.76	824.98	1680.50	8278	0
Disadvantage	6474	0.54	0.50	1	1	0
Urban	6474	73.28	38.64	98.08	100	0
Credit	6474	0.77	0.42	1	1	0

Table A.2: Full results for regression model (1)

	Dependent Variable: System Count			
	Linear Probability	Logit Marginal Effect	Linear Probability	Logit Marginal Effect
Hispanic	0.001**	0.001***	0.001*	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
White	0.003***	0.003***	0.003***	0.005***
	(0.000)	(0.000)	(0.000)	(0.001)
Log Area Median Income	0.120***	0.140***	0.134***	0.146***
	(0.019)	(0.018)	(0.020)	(0.019)
Bachelor	0.003***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Disadvantaged	0.003	0.013	0.001	0.013
	(0.013)	(0.012)	(0.013)	(0.012)
Log population	0.022	0.043*	0.037	0.072***
	(0.023)	(0.022)	(0.025)	(0.024)
Electricity	-0.002***	-0.001***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
Electricity price	-0.012***	-0.010**	-0.010**	-0.010**
	(0.005)	(0.005)	(0.005)	(0.005)
Installation price	0.020***	0.030***	0.021***	0.029***
	(0.007)	(0.006)	(0.007)	(0.006)
Log total housing unit	0.142***	0.091***	0.132***	0.066***
	(0.022)	(0.022)	(0.023)	(0.023)
Credit			0.103***	0.124***
			(0.011)	(0.011)
Urban			-0.000	0.000
			(0.000)	(0.000)
Owner Occupied			-0.001***	0.000
			(0.000)	(0.000)
Built year group			0.006	0.006
			(0.004)	(0.004)
Permit Number			0.024	0.007
			(0.015)	(0.014)
GHI			0.000	-0.000
			(0.000)	(0.000)
Racial diversity			-0.008	-0.230***
			(0.039)	(0.049)
Observations	6,472	6,446	6,472	6,446
R-squared	0.522		0.523	
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year trend	0.043***	0.048***	0.0470***	0.0443***

Note: $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Table A.3: Summary statistics of regression model (2)

	N	Mean	Std. Dev.	Median	Max	Min
Count	3849	10.64	14.84	5	155	1
Owner occupied	3849	48.94	22.95	51.7	95.45	0
Electricity	3849	15.42	11.81	11.83	89.3	0
Built year group	3849	5.11	1.52	5	9	1
Utility type	3849	2.19	1.54	1	6	1
PNM	3849	0.55	0.5	1	1	0
Electricity price	3849	13.39	1.5	13.32	21.11	8.35
Installation price	3849	5.49	1.23	5.17	9	4.3
Temperature	3849	14.25	2.72	14.5	18.9	3.68
GHI	3849	2044.98	59.81	2046.8	2189.54	1816.68
Bachelor	3849	31.74	16.96	29.31	81.78	0.04
Income	3849	54284.29	22928.66	49896	174019.73	7278.34
Population	3849	4257.71	1885.79	3977	17497	71.02
Racial diversity	3849	0.65	0.15	0.66	1	0.25
White	3849	77.83	12.54	80.07	100	3.06
Non-Hispanic White	3849	43.27	20.02	44.01	90.48	0
Hispanic	3849	48.12	21.21	45.89	99.66	1.78
Total housing unit	3849	1897.37	800.37	1819.12	8278	24.06
Disadvantage	3849	0.42	0.49	0	1	0
Urban	3849	81.52	32.74	100	100	0
Credit	3849	0.77	0.42	1	1	0

Table A.4: Full results for regression model (2)

	Dependent Variable: System Count (if > 0)			
	(1)	(2)	(3)	(4)
	NB Marginal Effect	OLS	OLS with quadratic term	NB with lagged count Marginal Effect
Hispanic	0.027**	0.022	0.016	0.034**
	(0.012)	(0.018)	(0.018)	(0.014)
White	-0.039	0.050	0.414**	0.079
	(0.025)	(0.037)	(0.198)	(0.159)
$(\text{White})^2$			-0.004**	
			(0.002)	
Log Area Median Income	4.064***	4.051***	3.987***	3.704***
	(0.663)	(0.949)	(0.950)	(0.732)
Bachelor	0.102***	0.106***	0.106***	0.067***
	(0.017)	(0.025)	(0.025)	(0.018)
Disadvantage	-1.822***	-1.110**	-1.105**	-1.768***
	(0.384)	(0.563)	(0.563)	(0.418)
Credit	6.491***	7.145***	7.274***	2.439***
	(0.609)	(0.952)	(0.954)	(0.667)
Log population	6.400***	6.786***	6.768***	5.011***
	(1.005)	(1.374)	(1.374)	(1.107)
Electricity	-0.002	0.017	0.017	-0.009
	(0.018)	(0.026)	(0.026)	(0.020)
Electricity price	0.179	-0.390*	-0.368*	0.277
	(0.156)	(0.219)	(0.220)	(0.174)
Installation price	-4.243***	-3.289***	-3.351***	-3.953***
	(0.225)	(0.292)	(0.293)	(0.301)
Log total housing unit	1.319	0.113	0.151	1.735
	(0.996)	(1.356)	(1.355)	(1.104)
Urban	0.017**	0.017**	0.004	0.002
	(0.006)	(0.008)	(0.008)	(0.006)
Owner occupied	0.059***	0.138***	0.137***	0.026*
	(0.009)	(0.012)	(0.012)	(0.010)
Built year group	-0.818***	-1.016***	-1.030***	-0.417***
	(0.118)	(0.174)	(0.174)	(0.129)
PNM	-1.886***	-4.576***	-4.574***	-0.720*
	(0.365)	(0.574)	(0.574)	(0.402)
GHI	0.016***	0.014*	0.014*	0.014**
	(0.005)	(0.008)	(0.008)	(0.006)
Racial diversity	9.026***	-2.366	14.46	5.242
	(2.109)	(3.239)	(9.526)	(7.607)
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Observations	3,849	3,849	3,849	3,628
R-squared		0.45	0.45	0.755
Note:				*p<0.05; **p<0.01; ***p<0.001

Table A.5: Results for regression model (2) with full sample (all census tract-year)

	Dependent Variable: System Count	
	(1)	(2)
	NB Marginal Effect	OLS
Hispanic	0.025***	0.037***
	(0.009)	(0.011)
White	0.111***	0.013
	(0.013)	(0.011)
Log Area Median Income	3.682***	3.002***
	(0.466)	(0.568)
Bachelor	0.075***	0.123***
	(0.013)	(0.017)
Disadvantage	-1.656***	-0.653*
	(0.283)	(0.368)
Credit	6.868***	7.091***
	(0.502)	(0.658)
Log population	3.221***	3.917***
	(0.660)	(0.684)
Electricity	-0.025**	-0.035**
	(0.013)	(0.015)
Electricity price	0.093	-0.605***
	(0.112)	(0.134)
Installation price	-3.731***	-2.853***
	(0.179)	(0.183)
Log total housing unit	2.887***	0.504
	(0.644)	(0.639)
Urban	0.003	0.008*
	(0.004)	(0.005)
Owner occupied	0.030***	0.101***
	(0.006)	(0.007)
Built year group	-0.512***	-0.961***
	(0.087)	(0.114)
PNM	-1.323***	-3.517***
	(0.276)	(0.410)
GHI	0.011***	0.015***
	(0.004)	(0.005)
Racial diveristy	-2.070*	2.812***
	(1.149)	(1.088)
Observations	6,472	6,472
R-squared		0.439
Year FE	Yes	Yes
County FE	Yes	Yes
Year	All	All
Sample	All	All
Note:	*p<0.05; **p<0.01; ***p<0.001	

Table A.6: Negative binomial marginal effects for system count by income quartile

	Dependent variable: System count		
	(1)	(2)	(3)
	Bottom 25%	Top 25%	Middle quartiles
Hispanic	0.057**	0.127***	0.014
	(0.022)	(0.040)	(0.013)
White	0.106*	-0.570***	0.255***
	(0.056)	(0.080)	(0.039)
Log area median income	0.904	6.111***	1.665*
	(1.046)	(2.072)	(0.878)
Bachelor	0.006	0.293***	0.078***
	(0.031)	(0.047)	(0.020)
Disadvantage	2.182**	4.710	-0.301
	(1.017)	(11.47)	(0.361)
Credit	3.086***	11.62***	4.869***
	(0.850)	(1.478)	(0.669)
Log population	2.684*	13.82***	4.870***
	(1.390)	(2.797)	(1.207)
Electricity	0.010	0.114*	-0.049**
	(0.022)	(0.068)	(0.020)
Electricity price	-0.060	0.581	0.185
	(0.191)	(0.500)	(0.182)
Installation price	-2.785***	-6.111***	-3.374***
	(0.322)	(0.679)	(0.254)
Log total housing unit	0.129	-1.363	1.556
	(1.389)	(2.812)	(1.209)
Urban	0.005	-0.025*	0.022***
	(0.009)	(0.015)	(0.007)
Owner occupied	0.050***	0.026	0.079***
	(0.014)	(0.029)	(0.011)
Built year group	-0.851***	-0.276	-0.678***
	(0.184)	(0.329)	(0.135)
PNM	-0.178	-1.579**	-2.181***
	(0.691)	(0.783)	(0.466)
GHI	-0.008	0.046***	-0.016**
	(0.015)	(0.015)	(0.007)
Racial Diversity	-5.223	45.57***	-11.48***
	(4.601)	(6.325)	(3.268)
Year FE	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Observations	674	1,235	1,940
Year	All	All	All

Note: *p<0.05; **p<0.01; ***p<0.001

Table A.7: Comparison of systems claimed tax credit in the EMNRD and utility datasets

Utility	EMNRD Count	Utility Claim Count	Difference
PNM	14350	13435	-915
EPE	3322	2866	-456
SEC	91	72	-19
LADPU	207	193	-14

Note: T-statistic: 0.0759, P-value: 0.9419

Notes: The t-test compares the mean counts of tax credit claims between the EMNRD dataset and the utility datasets (PNM, EPE, SEC, LADPU) where state credit is claimed. The result suggests that the number of tax credit claims recorded in the EMNRD dataset is not significantly different from those recorded in the utility datasets.

Table A.8: Summary statistics of regression model (4)

	N	Mean	Std. Dev.	Min	Max
Dependent variable					
State credit	26735	0.44	0.50	0	1
Household-level variables					
System capacity	26735	5.09	2.51	0	43
# of Bedrooms	25951	3.33	0.78	0	17
Zestimate	26087	483442.77	348557.87	49600	14324300
Housing size (sq ft)	26735	2201.28	975.74	100	24517
Year built	26397	1989.18	21.99	1750	2024
Census tract-level variables					
% population with bachelor degree (>25)	26735	0.37	0.17	0	0
Owner occupancy rate	26735	0.61	0.23	0	1
Mortgage rate	26735	0.41	0.17	0	0
Area Median Income	26735	69062.99	27312.01	12014	250000
Population	26735	4904.32	2235.43	274	15722
Median Age	26735	41.07	8.80	20	82
% population identified as White	26735	0.83	0.09	0	1
% population identified as Hispanic	26735	0.47	0.21	0	1
Urban share	26735	0.86	0.28	0	1
Within disadvantaged census tracts	26735	0.26	0.44	0	1

Table A.9: Regression results of logistic models for state credit claim

	Dependent variable: State credit			
	(1)	(2)	(3)	(5)
System capacity	-0.025^{***}	0.014^{**}	0.049^{***}	0.040^{***}
	(0.006)	(0.006)	(0.007)	(0.007)
Log Zestimate	1.328^{***}	0.695^{***}	0.597^{***}	0.817^{***}
	(0.044)	(0.059)	(0.062)	(0.080)
Year built	-0.008^{***}	-0.001	-0.003^{***}	-0.004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Log Housing size (sq ft)	0.189^{***}	0.143^{**}	0.031	-0.082
	(0.063)	(0.067)	(0.071)	(0.080)
# of Bedrooms	-0.157^{***}	-0.080^{***}	-0.047^{**}	-0.052^{**}
	(0.021)	(0.023)	(0.024)	(0.024)
% population with bachelor degree (>25)		0.751^{***}	1.268^{***}	0.933^{***}
		(0.155)	(0.164)	(0.192)
Owner occupancy rate		-1.929^{***}	0.572^{***}	0.554^{***}
		(0.106)	(0.147)	(0.149)
Mortgage rate		-1.268^{***}	-1.309^{***}	-0.959^{***}
		(0.154)	(0.166)	(0.175)
Log Area Median Income		0.344^{***}	-0.099	-0.051
		(0.066)	(0.076)	(0.078)
Log Population		0.250^{***}	0.085^{**}	0.137^{***}
		(0.036)	(0.039)	(0.040)
Log Median Age		0.269^{***}	0.034	0.097
		(0.103)	(0.109)	(0.113)
% population identified as White		0.375^{**}	0.158	-0.307
		(0.180)	(0.191)	(0.212)
% population identified as Hispanic		-0.438^{***}	-0.552^{***}	-0.742^{***}
		(0.115)	(0.123)	(0.155)
Urban share		-0.285^{***}	-0.145^{**}	-0.022
		(0.057)	(0.060)	(0.064)
Within disadvantaged census tracts		-0.188^{***}	-0.192^{***}	-0.223^{***}
		(0.045)	(0.047)	(0.048)
Year Fixed Effects	No	No	Yes	Yes
County Fixed Effects	No	No	No	Yes
Observations	25,234	25,234	25,234	25,234
Log Likelihood	−16,174.720	−15,186.560	−14,116.800	−14,063.310
Akaike Inf. Crit.	32,361.440	30,405.120	28,283.590	28,204.620
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A.10: Summary statistics of regression (5)

	count	mean	std	min	max
Tax credit amount	11565	2824.47	1292.94	110	9000
System capacity	11565	5.21	2.63	0	43
# of Bedrooms	11304	3.36	0.79	0	17
Zestimate	11348	562241.67	360527.71	90500	4680500
Housing size (sq ft)	11565	2398.00	1046.81	240	24517
Year built	11442	1988.36	21.63	1850	2022
% population with bachelor degree (>25)	11565	0.42	0.17	0	0
Owner occupancy rate	11565	0.55	0.27	0	1
Mortgage rate	11565	0.37	0.17	0	0
Area Median Income	11565	72866.17	28833.53	16569	250000
Population	11565	4805.21	2289.56	464	15722
Median Age	11565	43.21	9.04	20	66
% population identified as White	11565	0.85	0.09	0	1
% population identified as Hispanic	11565	0.41	0.19	0	1
Urban share	11565	0.83	0.31	0	1
Within disadvantaged census tracts	11565	0.18	0.38	0	1

Table A.11: Full results for regression model (5)

	Dependent variable: Log(Tax credit claimed)				
	(1)	(2)	(3)	(4)	(5)
	Full sample	Full sample	Full sample	SMDTC	NSMDTC
System capacity	0.109***	0.112***	0.115***	0.130***	0.108***
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
Log Zestimate	0.049***	0.070***	0.059***	0.237***	−0.086***
	(0.010)	(0.013)	(0.013)	(0.021)	(0.016)
Year built	−0.001***	−0.001***	−0.001***	−0.002***	−0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Log Housing size (sq ft)	0.083***	0.057***	0.054***	−0.036	0.135***
	(0.015)	(0.015)	(0.015)	(0.024)	(0.019)
No. of Bedrooms	0.026***	0.027***	0.028***	0.028***	0.018***
	(0.005)	(0.005)	(0.005)	(0.008)	(0.006)
Population share with bachelor degree (>25)		−0.378***	−0.358***	−0.611***	−0.097**
		(0.038)	(0.038)	(0.070)	(0.042)
Owner occupancy rate		−0.165***	−0.194***	−0.082*	−0.005
		(0.020)	(0.026)	(0.042)	(0.054)
Mortgage rate		0.136***	0.119***	−0.046	0.080
		(0.035)	(0.035)	(0.062)	(0.054)
Log Area Median Income		0.091***	0.092***	0.167***	−0.022
		(0.016)	(0.016)	(0.028)	(0.021)
Log Population		−0.037***	−0.044***	−0.073***	−0.016
		(0.008)	(0.009)	(0.014)	(0.011)
Log Median Age		0.024	0.018	0.020	0.012
		(0.025)	(0.025)	(0.046)	(0.030)
White rate		−0.248***	−0.175***	−0.439***	0.035
		(0.045)	(0.045)	(0.076)	(0.053)
Hispanic rate		−0.194***	−0.159***	−0.425***	−0.011
		(0.030)	(0.030)	(0.054)	(0.033)
Urban share		−0.017	−0.014	0.050**	−0.056***
		(0.013)	(0.013)	(0.021)	(0.015)
Within disadvantaged census tracts		0.017	0.012	−0.015	0.022*
		(0.012)	(0.011)	(0.020)	(0.013)
Census Tract Controls	No	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes	Yes
Observations	11,034	11,034	11,034	4,940	6,094
R^2	0.435	0.448	0.461	0.458	0.507
Adjusted R^2	0.435	0.447	0.459	0.455	0.505
Note:					*p<0.1; **p<0.05; ***p<0.01

References

Borenstein, S. (2017). Private net benefits of residential solar PV: The role of electricity tariffs, tax incentives, and rebates [Publisher: The University of Chicago Press]. *Journal of the Association of Environmental and Resource Economists*, *4*, S85–S122. https://doi.org/10.1086/691978

Borenstein, S., & Davis, L. W. (2016). The distributional effects of US clean energy tax credits [Publisher: The University of Chicago Press]. *Tax Policy and the Economy*, *30*(1), 191–234. https://doi.org/10.1086/685597

Brockway, A. M., Conde, J., & Callaway, D. (2021). Inequitable access to distributed energy resources due to grid infrastructure limits in california [Publisher: Nature Publishing Group]. *Nature Energy*, *6*(9), 892–903. https://doi.org/10.1038/s41560-021-00887-6

Candelaria, J. R., Small, N. P., Stewart, M., Caballero, P. R., & Egolf, B. (2019). Senate Bill 489 energy transition act. https://www.nmlegis.gov/Sessions/19%20Regular/bills/senate/SB0489.pdf

Council on Environmental Quality. (2022). Climate and economic justice screening tool [Accessed: 2024-06-04]. https://screeningtool.geoplatform.gov/en/

Darghouth, N. R., O'Shaughnessy, E., Forrester, S., & Barbose, G. (2022). Characterizing local rooftop solar adoption inequity in the US [Publisher: IOP Publishing]. *Environmental Research Letters*, *17*(3), 034028. https://doi.org/10.1088/1748-9326/ac4fdc

El Paso Electric Company. (2016a). Medium system renewable energy certificate purchase. https://www.epelectric.com/files/html/Renewable/Sign_up_forms/NM/Rate_No._34-4th_revision.pdf

El Paso Electric Company. (2016b). Small system renewable energy certificate purchase. https://www.epelectric.com/files/html/Renewable/Sign_up_forms/NM/Rate_No._33-5th_revision.pdf

El Paso Electric Company. (2023a). New mexico interconnection process facilities up to 10kw. https://www.epelectric.com/renewables-tech/distributed-generation/new-mexico-interconnection-of-facilities-less-than-10-kw

El Paso Electric Company. (2023b). New mexico interconnection process for facilities greater than 10 kw and up to 100 kw. https://www.epelectric.com/renewables-tech/distributed-generation/new-mexico-interconnection-of-facilities-greater-than-10-kw-and-less-than-100-kw

Gao, X., & Zhou, S. (2022). Solar adoption inequality in the u.s.: Trend, magnitude, and solar justice policies. *Energy Policy*, *169*, 113163. https://doi.org/10.1016/j.enpol.2022.113163

Internal Revenue Service. (2023). Residential clean energy credit. https://www.irs.gov/credits-deductions/residential-clean-energy-credit

Jacobsen, G. D. (2024). Race, ethnicity, and the distribution of energy efficiency incentives. *Energy Economics*, *130*, 106933. https://doi.org/10.1016/j.eneco.2023.106933

Lente, D. J. (2024). House Bill 252 adjust income tax brackets. https://nmlegis.gov/Legislation/Legislation?chamber=H&legtype=B&legno=252&year=24

New Mexico Energy, Minerals and Natural Resources Department. (2020). New solar market development tax credit incentive. https://www.emnrd.nm.gov/ecmd/tax-incentives/solar-market-development-tax-credit-smdtc/

New Mexico Legislative Finance Committee. (2023). Oil and nature gas revenue. https://www.nmlegis.gov/Entity/LFC/Documents/Finance_Facts/finance%20facts%20oil%20and%20gas%20revenue.pdf

New Mexico Taxation & Revenue Deparment. (2021). New mexico statutes annotated, chapter 7 - taxation, article 9 - gross receipts and compensating tax, section 7-9-112. https://www.srca.nm.gov/parts/title03/03.002.0247.html

Office of Energy Efficiency & Renewable Energy. (2023). Homeowner's guide to the federal tax credit for solar photovoltaics. https://www.energy.gov/eere/solar/homeowners-guide-federal-tax-credit-solar-photovoltaics

O'Shaughnessy, E. (2019). Non-monotonic effects of market concentration on prices for residential solar photovoltaics in the united states. *Energy Economics*, *78*, 182–191. https://doi.org/10.1016/j.eneco.2018.11.010

O'Shaughnessy, E. (2022). Rooftop solar incentives remain effective for low- and moderate-income adoption. *Energy Policy*, *163*, 112881. https://doi.org/10.1016/j.enpol.2022.112881

O'Shaughnessy, E., Barbose, G., Wiser, R., & Forrester, S. (2021). Income-targeted marketing as a supply-side barrier to low-income solar adoption. *iScience*, *24*(10), 103137. https://doi.org/10.1016/j.isci.2021.103137

O'Shaughnessy, E., Barbose, G., Wiser, R., Forrester, S., & Darghouth, N. (2021). The impact of policies and business models on income equity in rooftop solar adoption [Number: 1 Publisher: Nature Publishing Group]. *Nature Energy*, *6*(1), 84–91. https://doi.org/10.1038/s41560-020-00724-2

O'Shaughnessy, E., Grayson, A., & Barbose, G. (2023). The role of peer influence in rooftop solar adoption inequity in the united states. *Energy Economics*, *127*, 107009. https://doi.org/10.1016/j.eneco.2023.107009

PNM. (2021). Annual 2021 compliance filing pursuant to NMPRC rule 17.9.570.13g NMAC.

PNM. (2022). Annual 2022 compliance filing pursuant to NMPRC rule 17.9.570.13g NMAC.

PNM. (2023). Annual 2023 compliance filing pursuant to NMPRC rule 17.9.570.13g NMAC.

Public Service Company of New Mexico. (2023a). Interconnection benefits. https://www.pnm.com/solar-interconnection-benefits#netmetering

Public Service Company of New Mexico. (2023b). Solar renewable energy certificate purchase programs. https://www.pnm.com/documents/28767612/28775078/schedule_32.pdf/6da5a011-bf9f-4ebe-bdb7-f9d1559e097c?t=1683639426098

Reames, T. G. (2021). Exploring residential rooftop solar potential in the united states by race and ethnicity [Publisher: Frontiers]. *Frontiers in Sustainable Cities*, *3*. https://doi.org/10.3389/frsc.2021.666411

Ros, A. J., & Sai, S. S. (2023). Residential rooftop solar demand in the u.s. and the impact of net energy metering and electricity prices. *Energy Economics*, *118*, 106491. https://doi.org/10.1016/j.eneco.2022.106491

Solar Energy Industries Association. (2023). New Mexico solar. https://www.seia.org/state-solar-policy/new-mexico-solar

Solargis. (2023). Solar resource maps and gis data for 200+ countries. https://solargis.com/maps-and-gis-data/overview

Stewart, M. (2010). House Bill 233 no solar panels as property tax improvements. https://www.nmlegis.gov/Sessions/10%20Regular/bills/house/HB0233.html

U.S. Census Bureau. (2020). 2020 Decennial Census. https://www.census.gov/programs-surveys/decennial-census/decade/2020/2020-census-main.html

U.S. Census Bureau. (2022). State population totals and components of change: 2020-2022. https://www.census.gov/data/tables/time-series/demo/popest/2020s-state-total.html

U.S. Energy Information Administration. (2023a). Electric sales, revenue, and average price. https://www.eia.gov/electricity/sales_revenue_price/index.php

U.S. Energy Information Administration. (2023b). New Mexico state energy profile. https://www.eia.gov/state/print.php?sid=NM

U.S. Energy Information Administration. (2023c). Profile analysis. https://www.eia.gov/state/analysis.php?sid=NM

U.S. Federal Government. (2021). *Justice40 initiative* [Accessed: 2024-06-03]. https://www.whitehouse.gov/environmentaljustice/justice40/