UNIVERSITY OF ALBERTA
FACULTY OF ARTS
Department of Economics

Working Paper No. 2021-13

Socioeconomic and Demographic Disparities in Residential Battery Storage Adoption: Evidence from California

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December 2021

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by

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Abstract

There is growing interest in the adoption of residential battery storage because of its ability to provide bill savings, capture excess solar energy, and provide resiliency value. The resiliency benefits have become increasingly salient in light of recent large-scale power outages. However, these benefits may not accrue to all communities. We explore the presence of disparities in residential battery adoption and the allocation of subsidies under California's Self-Generation Incentive Program (SGIP) by measures of income, race and ethnicity, and a vulnerability index that captures environmental justice (EJ) concerns. We present evidence that battery adoption and subsidy allocations are concentrated in communities that have higher household income and lower EJ concerns. Regression analyses demonstrate that there are disparities in battery adoption rates by household income and race/ethnicity demographic variables, after controlling for important time-varying and regional factors. These findings persist despite the fact that the SGIP has specific funds targeting lower income households and communities, as well as funding targeting wildfire- and outage-vulnerable households. We demonstrate that these findings are partially, but not fully, driven by SGIP funding eligibility criteria that correlate with communities that have higher income, lower EJ concerns, and a lower percentage of residents of color.

Keywords: Battery Storage, Resiliency, Distributed Energy Resources, Environmental and Energy Justice

JEL Codes: H23, I30, L94, Q40, Q54

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Support from the Government of Canada's Canada First Research Excellence Fund under the Future Energy Systems Research Initiative and the Social Sciences and Humanities Research Council's (SSHRC's) Canada Research Chair program is gratefully acknowledged. I would like to thank the referees for their numerous insightful comments and suggestions.

1 Introduction

The electricity sector is facing increasing stress and risk as the result of climate change and extreme weather events. This is demonstrated by recent large-scale power outages in California and Texas that affected millions of customers and resulted in the loss of critical infrastructure and economic output (Roberts, 2019; Bohra, 2021).[1] These events are part of a broader pattern of increasing weather-related power outages which have more than doubled over the last decade in a number of regions of the United States (Allen-Dumas et al., 2019; Climate Central, 2020).

Concerns over resiliency and reliability of electricity supply have resulted in increased interest in the installation of distributed battery storage systems located at consumers' homes (CCA, 2019; Carpenter, 2021). This can allow a consumer to avoid outages on the broader electricity grid. However, the economic and resiliency benefits associated with this technology may not be evenly distributed across all individuals and communities. In this paper, we investigate if there are socioeconomic and demographic disparities in the adoption of residential battery storage systems and subsidies provided under California's Self-Generation Incentive Program (SGIP).

Disparities in the adoption of energy technologies such as rooftop solar and/or battery storage have been a growing energy and environmental justice (EJ) concern. These technologies can reduce household energy costs considerably (Borenstein, 2017). This is particularly important because utility bills have been shown to place a disproportionate burden on low-income (Drehobl and Ross, 2016) and Black households (Lybich, 2020). Further, there are growing concerns that utility costs will be shifted to households that do not invest in distributed energy resources such as rooftop solar (Boampong and Brown, 2020; Brown et al., 2020).

A growing number of studies have identified inequalities in the adoption of emerging energy technologies with a higher incidence of adoption in higher income, white majority, and lower EJ concern communities. This includes electric vehicles (Borenstein and Davis, 2016), residential rooftop solar (Vaishnav et al., 2017; Sunter et al., 2019; Lukanov and Krieger, 2019; Barbose et al., 2020, O'Shaughnessy et al. 2020), community solar (Chan et al., 2017), efficient appliances (Wada et al., 2012), and smart meters (Balta-Ozkan et al., 2013). A number of possible factors can explain the barriers to adoption for lower income households and households of color including access to financing, high upfront costs, higher

[1] In Texas, 111 deaths have been connected to the February 2021 winter storm event. These deaths have been attributed in large part to the loss of electricity (Bohra, 2021).

proportion of households that are renters, lack of peer effects and customer referrals (Lukanov and Krieger, 2019; Carley and Konisky, 2020).

To the best of our knowledge, our analysis provides the first evaluation of socioeconomic and demographic disparities in the adoption of residential battery storage, which are increasingly being paired with rooftop solar. The adoption of this technology has unique benefits beyond the technologies listed above because it allows a household to partially (or fully) avoid the consequences of power outages. With increasing large-scale power outages, the presence of inequalities in the deployment of this technology will result in communities of lower socioeconomic status bearing a heavier burden of reduced electric reliability. There are rising concerns that these communities will be negatively impacted by and/or lack access to opportunities associated with the transition to lower-carbon and emerging technologies in the energy sector (Carley and Konisky, 2020). These concerns are compounded by the growing evidence that these communities are expected to be disproportionately burdened by the consequences of climate change (USGCRP, 2018).

We utilize data from California's SGIP, a subsidy program that targets emerging distributed technologies with a particular focus on battery storage. The program has established several carve-out categories targeting households that are lower income, in "disadvantaged communities", medically vulnerable customers, and those in high fire threat districts that are more prone to wildfires or those that have experienced two or more Public Safety Power Shutoff (PSPS) events.[2] We connect these data with socioeconomic and demographic data from the U.S. Census Bureau's American Community Survey and the CalEnviroScreen (CES), an EJ screening tool that is utilized by the California government to define "disadvantaged communities" (California OEHHA, 2018).[3]

Our objective is to document observed socioeconomic and demographic patterns in communities where SGIP-funded residential battery storage investment occurs. Our analysis focuses on battery storage adoption at the zip code-level, reflecting the geographical granularity of the SGIP battery installation data. We present an array of summary statistics to detail the distribution of battery capacity and SGIP subsidies by socioeconomic and demographic characteristics across California. Using regression analyses that allow us to control for

[2]PSPS events are a preemptive measure that temporarily shutoffs off power to regions of the grid that are deemed to have the highest risk of wildfires being started by electric infrastructure (CPUC, 2021).

[3]The California Environmental Protection Agency defines "disadvantaged communities" to be those that rank in the top 25% of the CES Environmental Health Screening Tool or the top 5% of the CES Pollution Burden measure (CalEPA, 2017). This definition of "disadvantaged communities" is utilized to determine which communities are eligible for certain energy-related subsidy programs targeting communities with high EJ concerns.

percentage of homeowners and other regional and time-varying characteristics, we evaluate if there are disparities in adoption and subsidy rates by race and ethnicity and median household income.

We find that battery storage adoption is heavily concentrated in zip codes with higher median income and lower EJ concern. When looking across all zip codes, only 15% of SGIP-funded battery storage investment arises in the bottom 50th percentile of the median income distribution. Further, 75% of battery capacity investment occurs in zip codes in the 50 percent least-disadvantaged communities as defined by the CES EJ measure. Consistent with these results, 82% of the SGIP funding goes to zip codes that fall in the top 50th percentile of the median income distribution and 80% goes to zip codes in the 50 percent least-EJ concerned communities.

We demonstrate that these results are in-part driven by SGIP-funding eligibility criteria. A large proportion of the SGIP funding is allocated to communities located in regions that have the greatest risk of power shutoffs that are used as a precautionary measure to prevent electric infrastructure-induced wildfires. These zip codes have higher median income, lower EJ concern, and a lower percentage of households of color. Focusing only on these regions, we continue to find that the majority of SGIP-funded battery investment arises in the highest income and lowest EJ concern communities, but the difference is less stark.[4]

There are several SGIP carve-out subsidy policies targeting lower income households and communities that have a higher percentage of people of color. We find that these programs are relatively more successful at promoting battery investments in communities with lower median incomes, a higher percentage of residents of color, and higher EJ concerns compared to the disparities that arise when looking across all SGIP funding categories. These results suggest that these targeted subsidy programs may be a promising avenue to overcome barriers faced by these communities in the adoption of emerging energy technologies. However, these carve-out policies are small in magnitude leading to an overall negligible effect when compared to the broader SGIP-driven investment.

Our regression analyses demonstrate that there is a strong positive and statistically significant relationship between household income and the battery storage adoption rate (i.e., battery systems per household), after controlling for potentially confounding factors. For example, moving from the 10th to the 90th quartile of the median household (HH) income distribution results in a 45% increase in the storage adoption rate as a % of mean

[4]Focusing on this subset of zip codes, 72% and 62% of energy storage capacity investment occurs in communities in the top 50th percentile by median income and 50 percent least-disadvantaged communities as defined by the CES EJ measure, respectively.

adoption. Further, these regression analyses demonstrate that there are economically strong negative and statistically significant disparities in the battery adoption rates in zip codes with a larger percentage of Black, Asian, and Hispanic residents. The disparities identified for percentage of Asian and Hispanic residents persist even after we control for important regional factors that determine eligibility for key SGIP funding categories.

It is important to highlight that a large proportion of the SGIP funding has eligibility requirements related to household income or whether the customer has a serious illness or condition that could be life-threatening during a power outage. Our findings do not suggest that the SGIP is providing funding to households that do not satisfy these requirements. Rather, when looking across all zip codes in California, our findings provide evidence that households in zip codes with a lower average median income, higher EJ concern, and higher percentage of Black, Asian, and Hispanic residents are less likely to adopt battery storage and utilize the SGIP funding. This raises questions to whether the SGIP's equity-focused subsidies are sufficient to overcome barriers that households in these communities face when deciding to invest in battery storage.

Section 2 provides background information on the SGIP. Data utilized in our analysis are detailed in Section 3. Section 4 presents our empirical methodology. Section 5 presents descriptive statistics of the distribution of battery adoption and SGIP funding allocation by zip code characteristics. Our regression results are presented in Section 6. Section 7 concludes and summarizes policy implications.

2 Self-Generation Incentive Program

In the wake of the 2000 - 2001 California energy crisis, the Self-Generation Incentive Program (SGIP) was established in 2001 to provide incentives for the installation of technologies to meet all or a portion of a facility's or household's electricity demand. The objective was to help shift electricity demand from peak to off-peak periods. The distributed energy technologies covered include waste to heat, wind turbines, combined heat and power turbines, fuel cells, biogas, and battery storage (SGIP, 2016).

The SGIP provides incentives to any retail electricity customer that installs an eligible distributed technology, subject to funding limits. There are a number of budget categories that determine the size of the incentive received with varying eligibility requirements. If applications exceed the funds available for any given budget category and/or utility territory, customers are entered into a lottery (SGIP, 2020).

The focus of the SGIP and the makeup of its various budget categories have evolved over time. Starting in 2017, the SGIP shifted its focus towards energy storage where 75% of programs funds were reallocated (CPUC, 2016). In addition, a 2017 decision by the California Public Utility Commission (CPUC) required 25% of the SGIP's budget to be allocated to an equity budget category targeted at providing energy storage for low-income households (in any location) and businesses and organizations in low-income or "disadvantaged" communities (CPUC, 2017).

In September 2019, the CPUC made several changes to the SGIP (CPUC, 2019). First, the decision elevated the equity category's subsidy levels considerably to address the low levels of uptake. Second, the decision allocated (approximately) $10 million to fund projects in the San Joaquin Valley (SJV) where a large number of residents lack access to natural gas. In these communities, households often utilize propane/wood to meet their heating needs. Third, the equity resiliency budget category was established due to rising concerns of power outages as part of California's Public Safety Power Shutoffs (PSPS) that are used as preemptive measures to prevent wildfires. To qualify for the equity resiliency budget category, households must be located in California's high fire threat districts (HFTDs) where PSPS events are most likely to occur or have experienced two or more PSPS outages.[5] Like the equity budget, the equity resiliency category targets households based on measures of income. Unlike the equity budget, households that are classified as medically vulnerable or have a serious illness/condition that could be life-threatening if their electricity is disconnected can also qualify for the equity resiliency funding regardless of income.

Table 1 provides a summary of the approved SGIP funding and eligibility requirements by budget category for the period 2020 to 2024 (SGIP, 2020, 2021), with a focus on funding for residential systems when it is possible to disentangle the funding allocations. The objective of this table is to demonstrate the relative size of SGIP funding across the various budget categories. Further, over the period considered in this study (i.e., January 2017 - March 2021), the majority of SGIP-funded battery storage investment (approximately 70% of capacity) arises in or after January 2020.

Table 1 demonstrates that the largest proportion of funds (63%) are allocated to the equity resiliency fund that targets low-income households and communities or medically vulnerable customers located in HFTDs or regions that have experienced two or more PSPS events. This funding can be access by both residential and non-residential customers. The

[5] There are two HFTDs that are relevant for the determination of SGIP funding, HFTDs Tier 2 and Tier 3. Tier 2 areas have a "high risk" of wildfires, while Tier 3 HFTDs are deemed to have "extreme risk".

Table 1: SGIP Energy Storage Funding and Eligibility Summary: 2020 - 2024

Budget Category	Funding (Millions $)	Eligibility Requirements
General	$56.9	Small Residential ($\leq$10 KW)
	$81.3	Large-Scale (>10 KW).
Residential Equity	$24.4	Residential systems in disadvantaged or low-income communities or low-income residential customers.
Equity Resiliency	$512.4	Located in a Tier 2 or 3 HFTD or have experienced $\geq$ 2 PSPS Events and meet one of the following: • Eligible for the equity budget; • Medical baseline customer; or • Serious illness or condition that could be life-threatening if electricity is disconnected.
San Joaquin Valley	$9.76	Carve-out policy targeting residential customers who lack access to natural gas.

Notes. The funding reflects SGIP's (2020, 2021) budget allocations for the period 2020 - 2024. Authorized incentives total $813.4 million. 17% of funds go to the General category which is decomposed into small residential (7%) and large-scale storage (10%) subcategories. Residential Equity receives 3% of the funds. Equity Resiliency funding (for residential and non-residential systems) receives 63% of the funding. The San Joaquin Valley pilot project has been allocated $9.76 million for residential systems. The funding $'s reported above are calculated by multiplying the percent allocations by the total authorized incentives in SGIP (2020, 2021).

equity resiliency fund provides a high subsidy level of up to $1.00/Wh. The residential equity fund, targeted at low-income households (in any location) and "disadvantaged communities" as determined by the CES, is allocated only 3% of the funding and provides a subsidy of up to $0.85/Wh. Only single of multi-family residential customers are eligible for this funding. The general budget category is allocated 17% of the SGIP funding; 7% goes to small residential systems ($\leq$ 10 KWs) and 10% is allocated to large-scale (> 10 KWs) residential or non-residential systems. The subsidy for this category is considerably lower and ranges from $0.15/Wh to $0.50/Wh depending on program enrollment levels. Any retail electricity customer is eligible to apply for funding from the general budget category. Finally, the SJV pilot project is a carve-out policy that has been allocated $9.76 million for residential projects. The subsidy level is high and in-line with the equity resiliency category as it provides $1.00/Wh for eligible systems.[6]

It is important to recognize that the vast majority of SGIP-funded residential battery systems (96%) are paired with rooftop solar. This demonstrates that the decision to adopt energy storage is often coupled with the decision to adopt rooftop solar. During our period of study, California's net energy metering 2.0 policy was in place requiring households that install rooftop solar to be on a time-of-use retail rate with non-bypassable charges. While this creates potential financial incentives to install battery storage, it has been shown that the financial benefit of adding on battery storage to a rooftop solar system is not sufficient to offset the capital costs absent a sufficiently large subsidy (Verdant, 2021).

These observations suggests that absent a sufficiently large subsidy, households are adding on battery storage to rooftop solar for reasons other than pure financial benefits (e.g., energy resiliency, peer effects, other non-pecuniary benefits). Prior literature has demonstrated rooftop solar adoption occurs in communities with higher median income, fewer people of color, and higher EJ concerns (Vaishnav et al., 2017; Lukanov and Krieger, 2019; Sunter et al., 2019). In absence of a sufficiently large subsidy, the additional cost of battery storage combined with the absence of a net financial return may magnify these disparities.

3 Data

We utilize several publicly available data sets. First, we utilize data from the California Distributed Generation Statistics (2021) that publishes SGIP application-level data. This household-level data includes information on the zip code, technology, system size, customer segment, date the application was received, application review status, system cost, and SGIP incentive allocation. Second, we collect census tract-level socioeconomic and demographic data from the Census Bureau's American Community Survey (IPUMS, 2021).[7]

Third, we utilize the CalEnviroScreen (CES) 3.0 as our measure for environmental justice concerns (California OEHHA, 2018). The CES calculates a census-track level EJ measure based on 20 different socioeconomic, health, demographic, and environmental variables grouped into two categories: (1) population characteristics and (2) the pollution burden. The

[6] The funding levels reported in Table 1 do not add up to the total authorized incentives of $813.4 million. The remaining funding is allocated to non-residential projects, heat pump water heaters, and other generation technologies (SGIP, 2021).

[7] Race/ethnicity variables are complicated by the fact that individuals can self-identify as multiple races/ethnicities. For our % Black and % Hispanic residents variables, we utilize measures that capture if an individual identifies as Black alone or in combination with one or more other races and Hispanic/Latino of any race to capture the many possible Hispanic/Latino combinations in the census data.

measure ranges from 0 to 100 where a higher number represents a community with higher EJ concerns. The CES is employed by a number of California agencies to identify areas eligible for certain subsidies, including the SGIP.[8] Fourth, we use the US Census's (2021) crosswalk data file to translate the census tract-level socioeconomic, demographic, and CES measures to the zip code-level via population-weighting.[9] Fifth, we use the CPUC's SGIP Eligibility Maps to identify regions of California that are eligible to receive funding from the equity resiliency budget category because they fall within a Tier 2 or 3 HFTD or have been exposed to two or more PSPS events (CPUC, 2020).

Our analysis focuses on SGIP-funded residential battery storage between January 1, 2017 and March 31, 2021. Prior to 2017, the SGIP data does not provide information on the budget category a system was funded under. Further, there were limited SGIP-funded battery investments during this time period. Investments prior to January 1, 2017 represent 0.8% of battery capacity installed under the SGIP. We focus on residential projects because our objective is to evaluate the socioeconomic and demographic characteristics of the communities where household-level distributed battery storage capacity is adopted. Single- or multi-family residential housing received approximately 54% of SGIP funding during our sample period. We consider SGIP projects that have received payment or are in the process of receiving payment having cleared the reservation review stage. We removed projects that have been wait-listed because of enrollment limits or are in the initial phases of review because it is possible that a submitted application is eventually ruled ineligible for a specific budget category.

4 Empirical Methodology

Our empirical method proceeds in two steps. First, we carry out descriptive statistics that summarize battery storage adoption and allocation of SGIP funding by zip code-level socioeconomic and demographic characteristics. Second, we evaluate how storage adoption and SGIP funding correlates with zip code characteristics through regression analyses. Our objective is not to evaluate all possible drivers of residential battery storage adoption. Rather, our objective is to understand how battery adoption relates to key socioeconomic

[8]For a detailed review of the CES, see California OEHHA (2018) and Lukanov and Krieger (2019).

[9]More specifically, this crosswalk data file provides an estimate of each census tract's population that lies within a specific zip code. This data is then used to assign a population-based weight to the census track-level variables for the (often) multiple census tracts that intersect a given zip code. These population-weights are then used to aggregate the census track-level variables up to the zip code-level. We utilize these population-weighted zip code-level variables in the subsequent analysis.

and demographic variables, controlling for essential time-varying and regional characteristics that could confound these relationships.

As shown in Table 1, a large portion of SGIP funding is allocated to the equity resiliency budget category. A key eligibility criteria for this budget category is that households must be located in a Tier 2 or 3 HFTD, or have been expose to two or more PSPS events. Consequently, it will be important that we account for the likelihood that a household in a given zip code will satisfy one or more of these criteria. To account for this fact, we utilize geospatial files made available by the CPUC (2020) that document the regions of California that are covered by HFTD Tiers 2 and 3, and regions that have been exposed to two or more PSPS events. For each zip code, we compute an index ranging from 0 to 100 that reflects the population-weighted area that falls within a HFTD Tier 2, HFTD Tier 3, or has experience 2 or more PSPS events. For a detailed summary of how these measures are calculated, see Appendix B.

In our analysis of storage adoption, our dependent variable, Adoption $\text{Rate}_{zt} \in [0, 1]$, represents the ratio of battery storage adopters to the number of housing units in zip code z and year t. We employ a Fractional Logit model by modeling the conditional expectation of the fractional dependent variable as follows:

$$E[\,\text{Adoption Rate}_{zt}|\mathbf{X}_{zt}\,] \;=\; \frac{exp(\mathbf{X}_{zt}\beta)}{1 + exp(\mathbf{X}_{zt}\beta)}$$

where $\mathbf{X}_{zt}$ are zip code characteristics including the % of individuals that self-identify as Black, Hispanic, Asian, or American Indian or Alaskan Native (hereon, Indigenous), median household income and its squared value, % of owner occupied housing, our HFTD Tiers 2 or 3 and PSPS ≥ 2 Event indices, year controls, and utility territory controls variables.[10] The existing literature has demonstrated that home ownership is an important driver of distributed technology (e.g., rooftop solar) adoption (Sunter et al., 2019). The year controls capture time-dependent variation such as changes in SGIP subsidy policies, the cost of installing batteries, and/or changes in preferences that could impact adoption incentives. The utility territory control variables capture regional factors such as differences in retail rates and utility-specific programs to promote adoption of distributed technologies. As noted above, SGIP's equity resiliency funding is tied to whether or not a household is located in a HFTD or has experienced 2 or more PSPS events. Our population-weighted indices control

[10]We find that there is a statistically significant concave relationship between median HH income and our dependent variables. The results of the other coefficients are robust to the inclusion of only a linear income term.

for the likelihood that a given household lies within one of these regions.

We employ a fractional logit model rather than an ordinary least squares (OLS) regression because it explicitly accounts for the fact that our dependent variable is bounded between $[0, 1]$. Failure to account for this fact can lead to negative estimated dependent variable values and a model that fits the mass of observations at 0 poorly.[11] This model is estimated via quasi-likelihood estimation and permits cluster-robust standard errors at the zip code-level (Papke and Wooldridge, 1996, 2008).

In our analysis of SGIP funding, our dependent variable Incentive Rate_{zt} represents the ratio of SGIP incentive dollars received to the total number of housing units in zip code z and year t. We utilize a Poisson pseudo-maximum-likelihood (PPML) regression model with conditional expectation modeled as follows:

$$E[\,\text{Incentive Rate}_{zt}|\mathbf{X}_{zt}\,] \;=\; exp(\mathbf{X}_{zt}\beta)$$

where $\mathbf{X}_{zt}$ are the same zip code-level socioeconomic, demographic, time, and regional characteristics detailed above. The standard errors are cluster-robust at the zip code-level.

We utilize a PPML regression because Incentive Rate_{zt} is rightward skewed and includes a sizable number of zero observations. This specification is preferred over a log-linear OLS regression which is often employed to handle skewed data for several reasons.[12] First, we are interested in the conditional expectations on the incentive rate, not the log of the incentive rate. This difference is important because by Jensen's inequality $ln\,E[Y|X] \neq E[\,ln\,Y|X\,]$. This property has been shown to lead to bias in log-linearized models in the presence of heteroskedasticity (Santos Silva and Tenreyro, 2006). Second, a log-linear specification is inappropriate because our data contain a non-trivial amount of zero values on the dependent variable. Adding one to the zero-valued dependent variables before taking logs, a common approach to circumvent this issue, has been shown to lead to biased coefficient estimates (Bellego and Pape, 2019). Third, Santos Silva and Tenreyro (2006) raise concerns over the validity of the assumptions imposed on the error term in a log-linear specification and note that the PPML regression requires fewer assumptions and imposes a less rigid structure.

In both regression analyses, the coefficient estimates demonstrate the sign and statistical significance. However, because these models are non-linear regressions, we cannot directly use the coefficients to evaluate the magnitude of the effects. To illustrate the estimated

[11] We present OLS regression results and a discussion of the issues with this approach in Table A1 in the Appendix.

[12] We present the results of our Incentive Rate regression for a number of specifications, including a log-linear OLS, in Appendix Table A2.

relationships, we compute marginal effects to quantify the economic significance of the regression results. For variables that reflect percentages, the marginal effects represent the predicted change in the dependent variable when the characteristic of interest goes from 0 to 1, holding all other variables at their mean values. For the remaining variables (i.e., household median income, and our HFTD Tier 2 and 3 and PSPS $\geq$ 2 Events indices), the marginal effect reflects the effect of a one standard deviation increase in these variables from their mean values, holding all other variables at their mean values.

In addition, to facilitate a graphical interpretation of our results, we present the estimated value of our dependent variables evaluating the median income variables in increments of $5,000 and the remaining covariates at values based on the average characteristics of White, Black, Asian, and Hispanic-majority zip codes.[13] We categorize zip codes in the race-majority categories when 50% or more residents identify as being one race/ethnicity.

5 Descriptive Statistics

We begin by presenting descriptive statistics that summarize residential battery storage adoption and allocation of SGIP funding by zip code-level socioeconomic and demographic characteristics. Table 2 presents the summary statistics of the socioeconomic and demographic variables for all zip codes in California, and focusing only on zip codes that have at least one storage system adopted under the various SGIP budget categories. We present both the level of household (HH) median income and its distribution across various income bins.

Across all zip codes and years, there is an average 2.14 SGIP-funded battery storage systems adopted per 1,000 households demonstrating that residential storage is a relatively nascent technology as we are in the early stages of its deployment. The average characteristics of zip codes that had at least one storage system adopted under the general budget category closely reflect the averages across all zip codes. Alternatively, zip codes that have storage system(s) funded by the equity resiliency fund have higher average median HH incomes, a rightward shifted income distribution, a lower percentage of Black, Hispanic, and Asian residents, a higher percent of owner occupied housing, and a lower EJ concern measure. This is somewhat surprising because the eligibility of this program is at least in part targeting lower-income households and communities, with additional eligibility for medically vulnerable households regardless of HH income. As expected, zip codes that have battery adoption funded under the equity resiliency fund have the highest values for our HFTD Tier

[13] We are unable to carry out this exercise for the Indigenous race/ethnicity because few zip codes have more than 2% of individuals that self-identify as American Indian or Alaskan Native in the census data.

Table 2: Socioeconomic and Demographic Summary Statistics by Budget Category

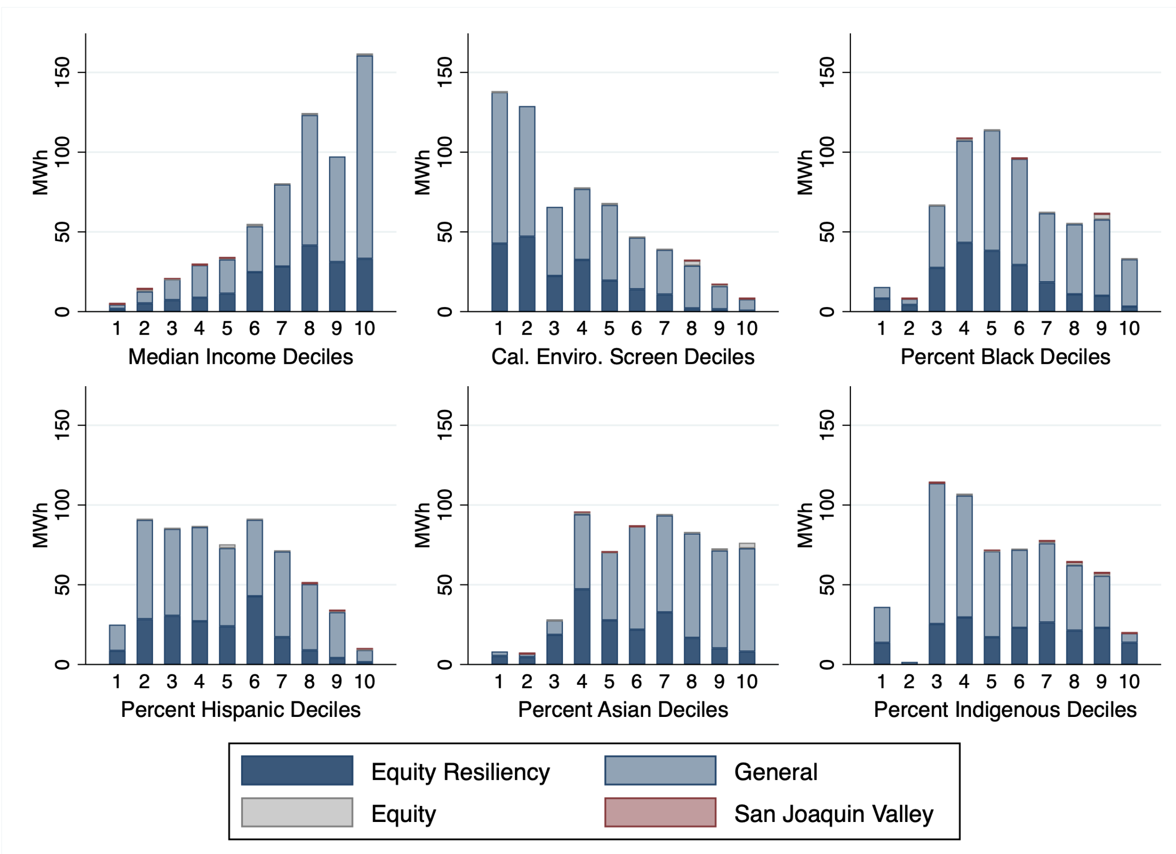
	All	SGIP Budget Category			
		General	Equity Resiliency	Equity	SJV
Median HH Income (thousands)	81.27	83.07	92.45	79.53	55.95
	(32.85)	(32.32)	(34.36)	(33.01)	(8.26)
% HH Income < 15,000	0.09	0.09	0.07	0.12	0.11
	(0.05)	(0.04)	(0.04)	(0.05)	(0.03)
% HH Income $\in [15,000, 35,000)$	0.15	0.15	0.13	0.16	0.19
	(0.07)	(0.06)	(0.06)	(0.06)	(0.05)
% HH Income $\in [35,000, 75,000)$	0.26	0.26	0.24	0.24	0.35
	(0.07)	(0.07)	(0.07)	(0.08)	(0.02)
% HH Income $\in [75,000, 150,000)$	0.29	0.29	0.30	0.26	0.27
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
% HH Income $\geq$ 150,000	0.21	0.22	0.26	0.22	0.09
	(0.14)	(0.14)	(0.14)	(0.15)	(0.03)
% Black	0.07	0.07	0.05	0.08	0.03
	(0.08)	(0.08)	(0.06)	(0.08)	(0.02)
% Hispanic	0.35	0.35	0.27	0.39	0.62
	(0.23)	(0.22)	(0.18)	(0.25)	(0.14)
% Asian	0.14	0.15	0.12	0.15	0.04
	(0.14)	(0.14)	(0.13)	(0.12)	(0.01)
% Indigenous	0.008	0.007	0.008	0.008	0.013
	(0.016)	(0.009)	(0.013)	(0.005)	(0.008)
CalEnviroScreen (EJ Concern)	26.40	25.77	19.25	29.71	41.60
	(13.99)	(13.57)	(10.36)	(13.34)	(4.78)
% Owner Occupied Housing	0.55	0.56	0.64	0.42	0.57
	(0.18)	(0.17)	(0.14)	(0.18)	(0.06)
HFTD Tier 2	11.25	10.81	25.56	1.87	0.00
	(19.77)	(18.55)	(22.67)	(4.20)	(0.00)
HFTD Tier 3	7.08	7.37	19.01	4.07	0.00
	(18.83)	(19.12)	(27.17)	(14.88)	(0.00)
PSPS $\geq$ 2 Events	1.56	1.64	4.30	0.69	0.00
	(6.23)	(6.41)	(9.63)	(3.42)	(0.00)
Storage Systems Per 1000 HHs	2.14	2.28	4.39	1.18	2.08
	(3.17)	(3.21)	(4.35)	(1.11)	(5.53)
Incentive $'s Per 1000 HHs (thousands)	20.45	21.59	51.73	19.45	35.49
	(55.73)	(56.28)	(86.43)	(17.02)	(148.61)
Number of Zip Codes	1,737	1,231	563	27	6

Notes. Standard deviations are in parenthesis. Data are weighted by the number of households in each zip code. All represents all zip codes in California. The remaining columns are zip codes with positive storage adoptions under a specific SGIP budget category.

2 and 3 and PSPS $\geq$ 2 Event measures. This reflects the fact that eligibility for this budget category is tied to HHs being located in one or more of these regions.

In contrast, zip codes that have storage system(s) adopted under the equity fund have modestly lower median HH income, a higher percentage of HH income in the lowest bins, a higher percentage of Black and Hispanic residents, lower percentage of owner occupied housing, and a higher EJ concern metric compared to all zip codes. Finally, the small number of zip codes that have SJV funded storage systems have considerably lower average median income, a leftward shifted median income distribution, a higher percentage of Hispanic and Indigenous residents, a lower percentage of Black and Asian residents, and a considerably higher EJ concern measure. These statistics suggest that these targeted categories may be more successful at inducing storage adoption in certain lower socioeconomic communities with higher EJ concerns. However, the magnitude of these programs are considerably smaller (recall Table 1).

Figure 1: MWhs of Storage Capacity by Socioeconomic and Demographic Deciles



Notes. Bar graphs present the MWhs of battery storage capacity installed at the zip code-level over our entire sample period for all SGIP budget categories by median income, CalEnviroScreen, % Black, % Hispanic, % Asian, and % Indigenous deciles.

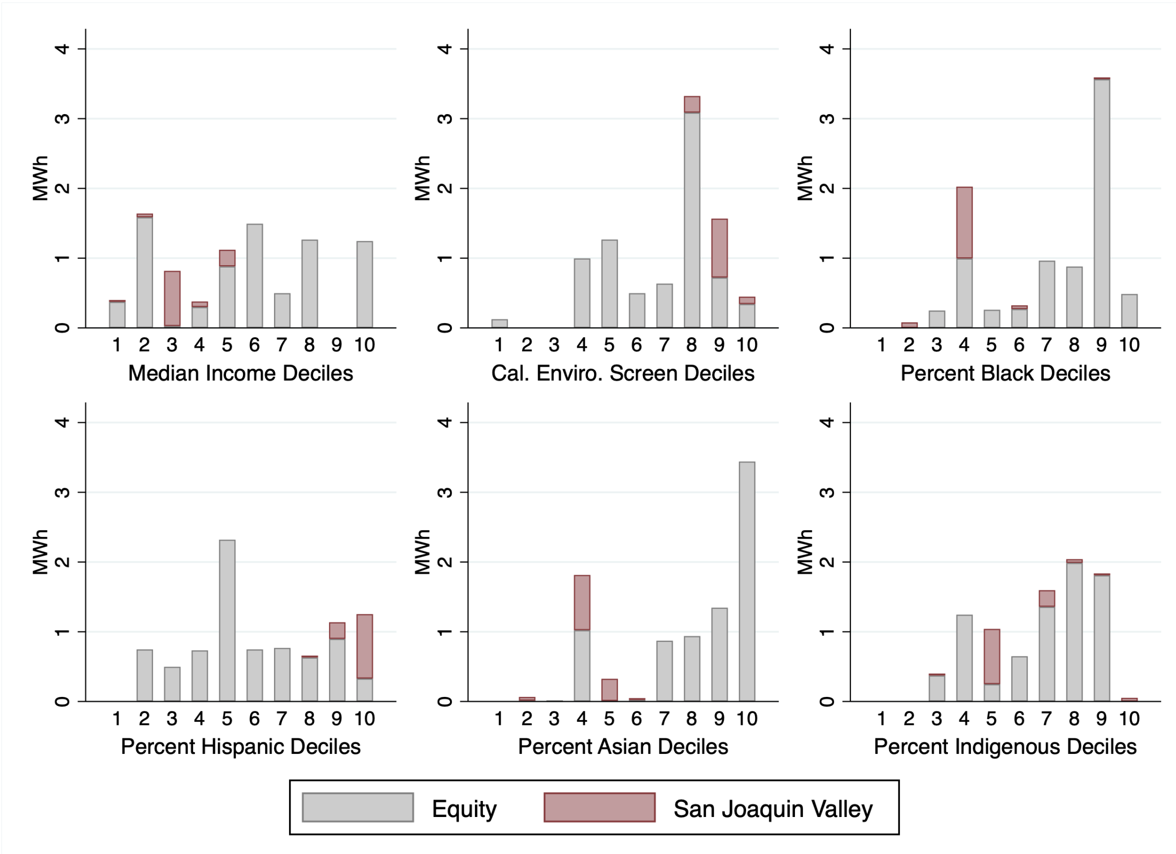
Figure 1 summarizes the MWhs of energy storage capacity by zip code-level median HH income, CalEnviroScreen (CES), and the percent Black, Hispanic, Asian, and Indigenous deciles for each budget category. The vast majority of energy storage capacity is adopted under the general budget category followed by the equity resiliency fund. Further, the majority of storage capacity is adopted in zip codes with median incomes in the top 50th percentile and CES scores in the bottom 50th percentile, demonstrating that zip codes with the highest EJ concern receive relatively limited SGIP-funded battery storage investment. 85% and 75% of energy storage capacity arises in the top and bottom 50th percentiles of the median income and CES distributions, respectively. As will be discussed in more detail below, these stark patterns are driven in part by the fact that a sizable portion of the SGIP funding comes from the equity resiliency fund which is only eligible for communities in HFTDs or that have experienced 2 or more PSPS events.

Figure 1 demonstrates a more nuanced relationship for the race/ethnicities. With the exception of percent Asian, the majority of battery investment arises in the bottom 50th percentiles for the remaining race/ethnicities. However, the distribution across deciles is relatively more uniform than those that arise when looking at median income and the CES measures. We will employ regression analyses below to evaluate these relationships in a more empirically robust manner.

Figure 2 isolates the energy storage capacity provided under the considerably smaller in magnitude equity and SJV budget categories. Figure 2 demonstrates that the SJV funding has been allocated to battery storage projects in areas with a high CES EJ measure, a high percentage of Hispanic residents, and median incomes at or below the 50th percentile. Compared to the distributions of adoption in Figure 1, storage projects funded by the equity category arise in zip codes with a relatively higher CES scores and percentage of Black, Asian, and Indigenous residents, while the median HH income of these zip codes is more uniformly distributed across income percentiles. These results continue to demonstrate that these two programs are relatively more successful at promoting battery investment in communities with lower median incomes, higher EJ concerns, and a higher percentage of people of color. Figures A.1 and A.2 in the Appendix demonstrate our results are unchanged if we consider the rated power capacity (in MWs) rather than the energy capacity (in MWhs).[14]

[14]Storage capacity is measured in both the rated power capacity (i.e., MWs) and energy capacity (i.e., MWhs). Rated power capacity reflects the amount of energy that can flow into or out of the battery at any given instant. Energy capacity is the amount of energy that can be stored. Batteries have different rated power capacity and energy capacity depending on the targeted use of the battery system. Our results are robust to the consideration of either measure.

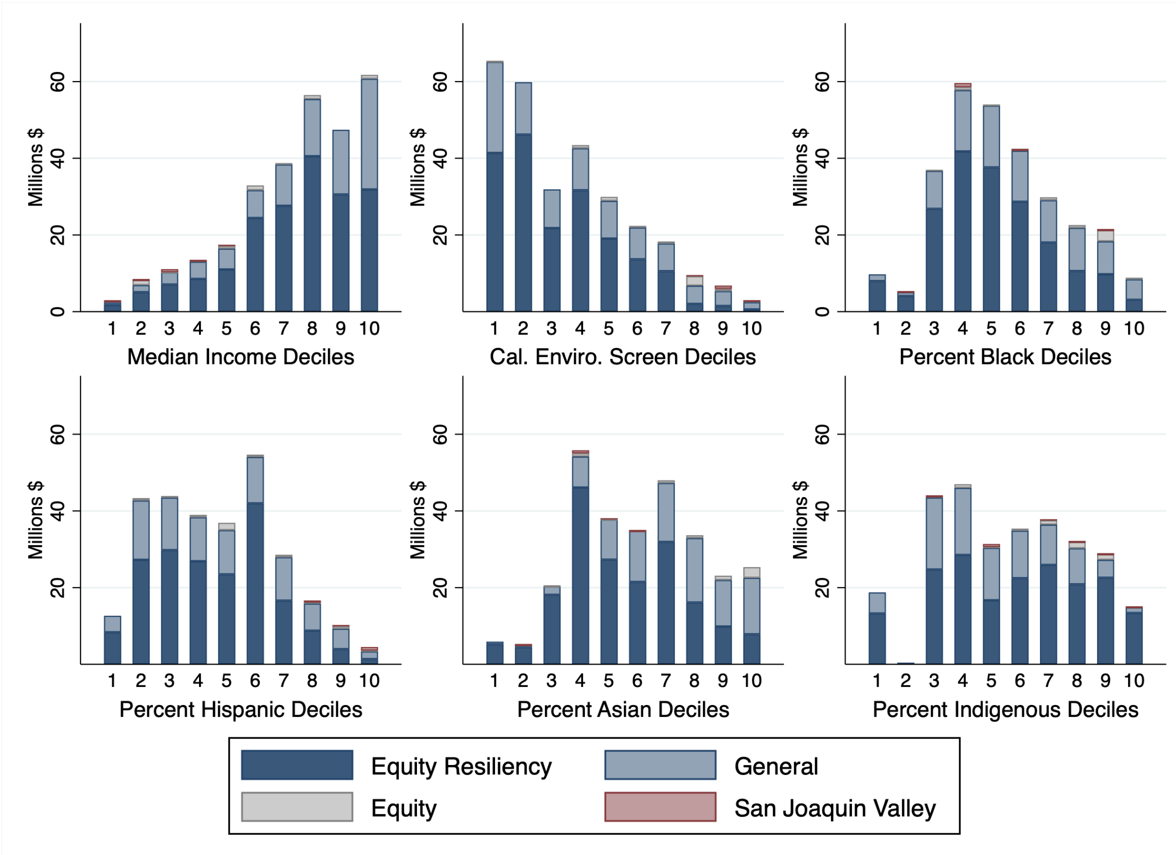
Figure 2: MWhs of Storage Capacity by Socioeconomic and Demographic Deciles - Equity and SJV Budget Categories



Notes. Bar graphs present the MWhs of battery storage capacity installed at the zip code-level over our entire sample period for the Equity and San Joaquin Valley SGIP budget categories by median income, CalEnviroScreen, % Black, % Hispanic, % Asian, and % Indigenous deciles.

Figure 3 provides the distribution of SGIP-funding by zip code-level median income, CES EJ score, and percent Black, Hispanic, Asian, and Indigenous deciles for each budget category. Consistent with the results above, the majority of the SGIP-funding flows to higher income zip codes with relatively low CES EJ scores. In particular, \$237 million (82%) and \$230 million (80%) goes to zip codes that fall in the top and bottom 50th percentile of the median income and CES distributions, respectively. The race/ethnicity patterns are consistent with those detailed above in Figure 1. In contrast to Figure 1 which shows the majority of capacity is installed under the general budget category, the majority of funding goes to the equity resiliency fund due to the higher subsidy allocated to each battery system in this category.

Figure 3: SGIP-Funding by Socioeconomic and Demographic Deciles



Notes. Bar graphs present the SGIP funding received at the zip code-level over our entire sample period for each budget category by median income, CalEnviroScreen, % Black, % Hispanic, % Asian, and % Indigenous deciles.

Figure A.3 in the Appendix presents the SGIP-funding focusing only on the equity and SJV budget categories. Analogous to Figure 2, we continue to find that these budget categories are relatively more successful at motivating adoption and providing SGIP-funding in communities with lower median income, higher EJ concerns, and a higher percentage of households of color.

The results that have been reported so far have focused on all zip codes in California. While we believe it is informative to demonstrate that there are socioeconomic and demographic disparities in SGIP-funded battery and storage adoption when looking across all zip codes, this approach masks the fact that there are eligibility criteria to receive SGIP funding. Table 1 demonstrates that the majority of the SGIP funding is allocated to the equity resiliency budget category. Recall that HHs must be in a HFTD Tier 2 or Tier 3 or have experienced two or more PSPS events, among other criteria, to receive funding under this budget category. Further, Table 2 demonstrates that zip codes that have installed storage under the equity resiliency category have higher median incomes, a higher percentage of owner occupied housing, a lower percentage of Black, Hispanic, and Asian residents, and a considerably lower EJ concern measure on average.

Consequently, to have a more complete understanding of the relationship between SGIP-funded battery storage and socioeconomic and demographic characteristics, we need to present our descriptive statistics for zip codes that were in HFTDs and/or those that experienced 2 or more PSPS events. To do so, we focus only on zip codes that had SGIP-funded battery investment under the equity resiliency budget category to capture zip codes that have households located in these regions.[15] We redefine the socioeconomic and demographic deciles using the distribution of values in this subset of zip codes.

Figure 4 presents the storage capacity (in MWhs) by zip code-level median income, the CES EJ measure, and the percent Black, Hispanic, Asian, and Indigenous declies for each budget category in zip codes that received any equity resiliency funding. Compared to the results for the full set of zip codes in Figure 1, the disparities across the median income and CES EJ measure are less severe. However, it continues to be the case that the majority of battery adoption arises in zip codes with a higher median income and lower EJ concern (i.e., lower CES values) in these regions. 72% and 62% of battery storage adoption arises in the top and bottom 50th percentiles of median income and the CES EJ measure, respectively.[16] With the exception of percent Black, the distribution of adoption by the race/ethnicity variables continue to follow the same general patterns as in the full sample. In these zip codes, the majority of battery storage capacity arises in the top 50th percentile of the percent Black distribution.

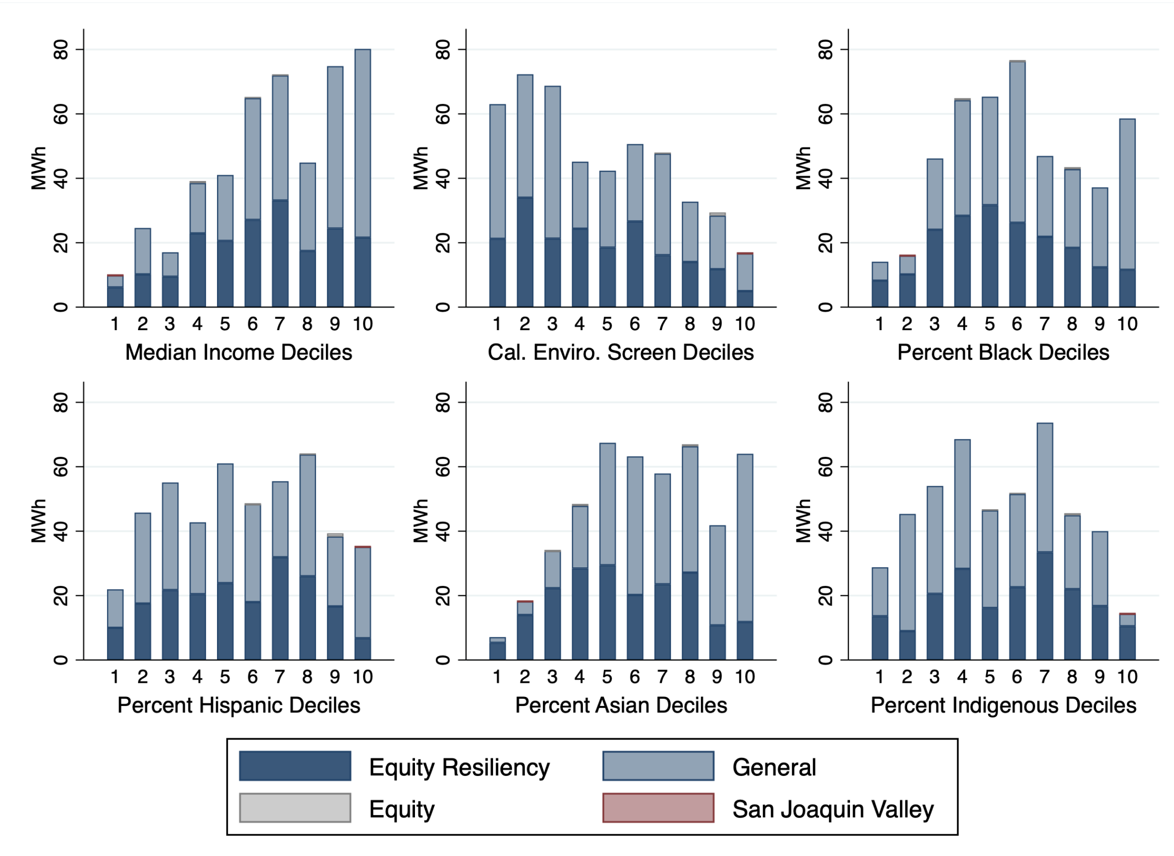
6 Regression Results

In this section, we employ the regression analyses detailed in Section 4 to evaluate if the disparities in storage adoption and SGIP-funding allocation rates by socioeconomic and demographic characteristics remain after controlling for important covariates. Throughout this section, we will report two model specifications, one that does and does not include the

[15] We also considered zip codes that had a value on the HFTD Tier 2 index that was greater than 0, above the 25th percentile, and above the 50th percentile. The conclusions are robust to these alternative definitions.

[16] Figure A.4 provides the descriptive statistics of SGIP funding by socioeconomic and demographic deciles for zip codes that received equity resiliency funding. The results parallel those in Figure 4.

Figure 4: MWhs of Storage Capacity by Socioeconomic and Demographic Deciles - Equity Resiliency Zip Codes



Notes. Bar graphs present the MWhs of battery storage capacity installed at the zip code-level over our entire sample period for zip codes that received Equity Resiliency funding by median income, CalEnviroScreen, % Black, % Hispanic, % Asian, and % Indigenous deciles.

HFTD Tier 2, HFTD Tier 3, and PSPS $\geq$ 2 Event indices. These variables are essential criteria to be eligible for the equity resiliency budget category which is the largest slice of current SGIP funding (see Table 1).

Presenting the results in this manner allows us to get at two key questions. First, are there socioeconomic and demographic disparities when looking across all zip codes in California, unconditional on eligibility criteria? This allows us to understand the relationship between SGIP-funded battery investment and key socioeconomic and demographic variables when looking across the entire state of California. Second, do these disparities persist once we control for the eligibility of the equity resiliency funding? This allows us to determine if these disparities are driven in part by the fact that only certain communities are eligible to receive this funding, and these communities have certain socioeconomic and demographic characteristics. Tables A1 and A2 in the Appendix provide additional regression results as we adjust the model specification.

Table 3 presents the results for our adoption rate fractional logit regression. First, we will focus on the specification that doesn't control for our HFTD or PSPS ≥ 2 Event indices. Columns (1) - (3) demonstrate that there is a statistically significant negative relationship between the adoption rate and % Black, % Hispanic, and % Asian. These effects are economically significant with marginal effects ranging from a 27.5% to 45.3% reduction in the SGIP-funded battery storage adoption rate relative to the mean adoption rate when these covariates change from 0 to 1. Alternatively, for % Indigenous, we find a positive and statistically and economically significant effect. Unlike the other race/ethnicity categories which span the full range of 0 to close to 1, % Indigenous takes on a value that is often less than 1%. To evaluate economic significance in a more meaningful manner, we also compute the marginal effect for % Indigenous as a one standard deviation increase from its mean value (see † in columns (2) and (3)) and find that the SGIP adoption rate increases by 3.9% relative to the mean adoption rate.

Columns (1) - (3) demonstrate that there is a statistically significant positive and concave relationship between a zip code's median HH income and the adoption rate. The marginal effect of an increase in median HH income (i.e., a one standard deviation increase above its mean value) yields a 20.9% increase in storage adoption as a % of mean adoption.[17] As expected, % owner occupied housing has a positive statistically and economically significant effect on the battery adoption rate. These findings are consistent with the literature that demonstrates that home ownership is an important driver of distributed technology adoption (Sunter et al., 2019).

Columns (4) - (6) in Table 3 present the results of our adoption rate regression, controlling for the HFTD Tier 2, HFTD Tier 3, and PSPS ≥ 2 indices. As expected, each of these variables have a positive and economically significant effect on the adoption rate. A one standard deviation increase in these variables above their mean values result in a 5.3% to 11.5% increase in the adoption rate as a % of the mean adoption rate. Median Income and % Owner Occupied continue to have positive and statistically and economically significant effects. Although the economic significance of % Owner Occupied is reduced.

[17] The marginal effect of an increase in HH median income is considerably larger if we consider a move from a lower to a higher quartile. A movement from the 10th to 90th quartile of the HH median income distribution, holding all other variables at their means, results in a 44.5% increase in storage adoption as a % of mean adoption.

Table 3: Fractional Logit Regression Results: Adoption Rate

	(1)	(2)	(3)	(4)	(5)	(6)
		Marginal Effect			Marginal Effect	
		Per 1,000 HHs	% $\overline{\text{Adoption}}$		Per 1,000 HHs	% $\overline{\text{Adoption}}$
% Black	-1.204**	-0.155	-0.275	-0.428	-0.071	-0.127
	(0.469)			(0.434)		
% Hispanic	-1.140***	-0.201	-0.358	-0.632**	-0.114	-0.203
	(0.259)			(0.249)		
% Asian	-2.715***	-0.254	-0.453	-1.680***	-0.193	-0.343
	(0.249)			(0.225)		
% Indigenous	2.063**	1.382	2.457	1.535**	0.713	1.268
	(0.894)	0.022†	0.039†	(0.764)	0.016†	0.028†
% Owner Occupied	1.897***	0.379	0.674	1.097***	0.208	0.369
	(0.286)			(0.281)		
Median Income	0.0218***	0.117	0.209	0.0232***	0.123	0.218
	(0.0031)			(0.0030)		
(Median Income)^2	-0.00005***			-0.00005***		
	(0.00001)			(0.00001)		
HFTD Tier 2				0.00876***	0.065	0.115
				(0.00138)		
HFTD Tier 3				0.00864***	0.050	0.089
				(0.00118)		
PSPS $\geq$ 2 Events				0.0190***	0.030	0.053
				(0.00247)		
Mean Adoption	0.562			0.562		
Year Controls	Yes			Yes		
Utility Controls	Yes			Yes		
# Zip Code – Years	8,130			8,130		

Notes. Statistical Significance $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Standard errors are reported in the parentheses and are clustered at the zip code-level. For the covariates % Black, % Hispanic, % Asian, % Indigenous, and % Owner Occupied, the marginal effects reflect the effect of moving the characteristic from zero to one. † denotes the marginal effect of a one standard deviation increase in % Indigenous from its mean value. For the covariates Median Income, HFTD Tier 2, HFTD Tier 3, and PSPS $\geq$ 2 Events, the marginal effects reflect a one standard deviation increase from their mean values. All marginal effects hold the other characteristics at their sample means. % $\overline{\text{Adoption}}$ reflects the marginal effects as a percentage of the mean adoption rate of 0.562.

Columns (4) - (6) demonstrate that the economic and statistical significance of the race/ethnicity variables are reduced once we control for the HFTD and PSPS Event indices. % Hispanic and % Asian remain negative and statistically and economically significant with marginal effects that represent a -20.3% and -34.3% reduction in the adoption rate as a percentage of the mean adoption rate, respectively. % Indigenous remains positive and both economic and statistically significant. However, the effect of % Black is no longer statistically significantly different from zero. These results demonstrate that part of the disparities in the adoption rate by race/ethnicity are driven by the demographics of the population in areas that are eligible to receive equity resiliency funding.

Table 4: PPML Regression Results: Incentive Rate

	(1)	(2)	(3)	(4)	(5)	(6)
		Marginal Effect			Marginal Effect	
		Per 1,000 HHs	% $\overline{\text{Incentive}}$		Per 1,000 HHs	% $\overline{\text{Incentive}}$
% Black	-2.458**	-1,188.43	-0.159	-0.658	-501.75	-0.067
	(1.119)			(0.975)		
% Hispanic	-1.321***	-1,264.94	-0.169	-0.353	-333.39	-0.045
	(0.501)			(0.500)		
% Asian	-4.977***	-1,871.53	-0.250	-2.711***	-1,231.61	-0.164
	(0.630)			(0.482)		
% Indigenous	2.883***	18,487.33	2.468	2.245***	8,204.55	1.095
	(1.028)	173.10†	0.023†	(0.844)	116.51†	0.016†
% Owner Occupied	2.810***	3,339.50	0.446	1.486***	1,415.84	0.189
	(0.479)			(0.434)		
Median Income	0.0197***	535.42	0.071	0.0227***	562.68	0.075
	(0.0047)			(0.0046)		
(Median Income)^2	-0.00005***			-0.00006***		
	(0.00002)			(0.00002)		
HFTD Tier 2				0.0172***	741.32	0.099
				(0.00213)		
HFTD Tier 3				0.0171***	560.36	0.075
				(0.00165)		
PSPS $\geq$ 2 Events				0.0214***	170.35	0.023
				(0.00490)		
Mean Incentive Rate	7,490.90			7,490.90		
Year Controls	Yes			Yes		
Utility Controls	Yes			Yes		
# Zip Code – Years	8,130			8,130		

Notes. Statistical Significance $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Standard errors are reported in the parentheses and are clustered at the zip code-level. For the covariates % Black, % Hispanic, % Asian, % Indigenous, and % Owner Occupied, the marginal effects reflect the effect of moving the characteristic from zero to one. † denotes the marginal effect of a one standard deviation increase in % Indigenous from its mean value. For the covariates Median Income, HFTD Tier 2, HFTD Tier 3, and PSPS $\geq$ 2 Events, the marginal effects reflect a one standard deviation increase from their mean values. All marginal effects hold the other characteristics at their sample means. % $\overline{\text{Incentive}}$ reflects the marginal effects as a percentage of the mean incentive rate of 7,490.90.

Table 4 presents the results for our incentive rate regression. Columns (1) - (3) present the results of our regression analysis absent the HFTD and PSPS $\geq$ 2 Event indices. The results parallel those in the adoption rate regressions above. There is a statistically significant negative relationship between % Black, % Hispanic, and % Asian and the incentive rate. This effect is economically significant with a 16% to 25% reduction in the SGIP incentive rate when these covariates move from 0 to 1, relative to the mean incentive rate. % Indigenous has a positive and significant relationship with the incentive rate. There continues to be a positive and statistically and economically significant relationship between % Owner Occupied and Median Income and the incentive rate.

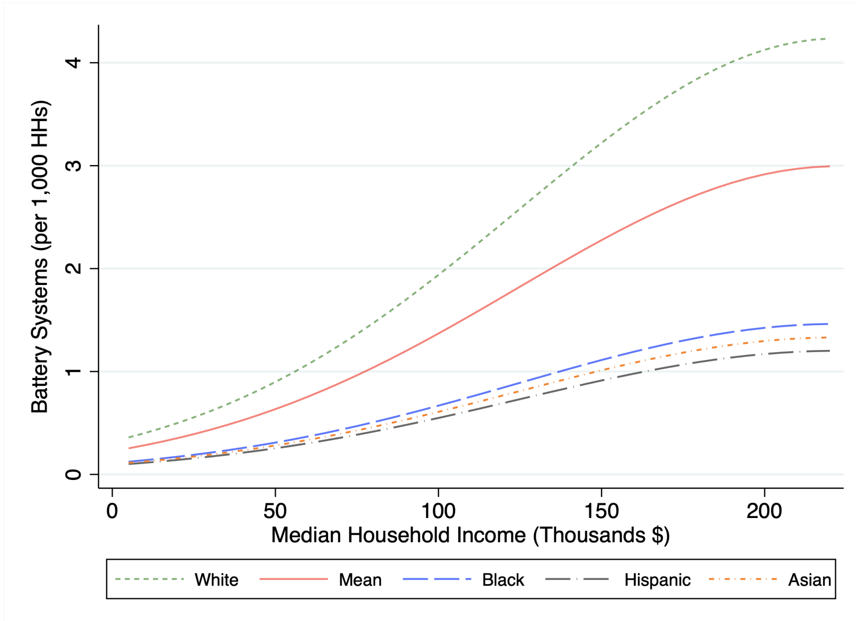
Columns (4) - (6) present the results of the incentive rate regressions, controlling for the HFTD and PSPS $\geq$ 2 Event indices. These covariates are particularly important in the incentive rate regression because the majority of SGIP funding has been allocated to the equity resiliency fund (see Table 1). This is in contrast to the MWhs of installed storage capacity (e.g., see Figure 1).[18] As expected, the HFTD Tier 2, HFTD Tier 3, and PSPS $\geq$ 2 Events covariates are all statistically significant. Importantly, % Black and % Hispanic are no longer statistically significant once these covariates are added to the regression. This could be driven by the fact that the majority of SGIP funding arises in regions that are eligible to receive equity resiliency funding, and these regions have fewer individuals that self-identify as Black or Hispanic. The remaining socioeconomic and demographic variables maintain their signs and statistical significance.

Another way to illustrate our regression results is to present the predicted adoption and incentive rates for certain socioeconomic and demographic characteristics. More specifically, we define White, Black, Hispanic, and Asian-majority zip codes as those with 50% or more households that self-identify as a specific race/ethnicity. We use our models to compute the predicted value of the adoption and incentive rates at different income thresholds, holding all other regressors at their mean values in White, Black, Hispanic, and Asian-majority zip codes. As noted above, we are unable to carry out this exercise for the Indigenous race/ethnicity because few zip codes have more than 2% of individuals that self-identify as American Indian or Alaskan Native in the census data. We also consider the average zip code which presents the predicted values of our dependent variables, evaluating the regressors at their average values across all zip codes in our sample. The results are run using the regression specifications that include the HFTD and PSPS $\geq$ 2 Event indices.

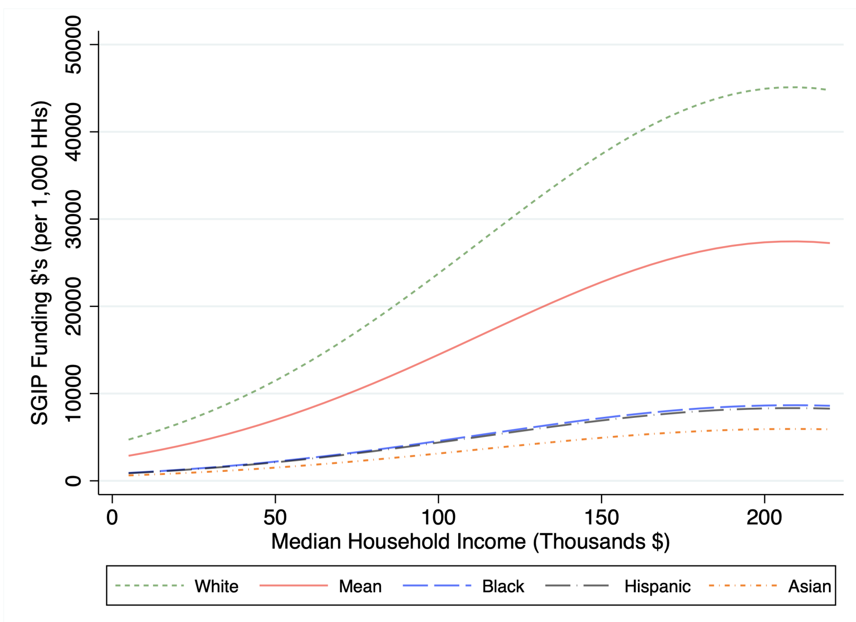
Figure 5 demonstrates that the predicted adoption and incentive rates differ considerably by income and race/ethnic-majority zip code characteristics. White-majority zip codes have unambiguously higher estimated adoption and incentive rates at all income levels, while Hispanic and Asian-majority zip codes have the lowest point-estimates on the adoption and incentive rates, respectively. Evaluated at the average median income (i.e., \$76,357), Hispanic, Asian, and Black-majority zip codes have a 72%, 69%, and 65% lower estimated adoption rates compared to White-majority zip codes. At the average median HH income, estimated SGIP funding is \$17,428 per 1,000 HHs in White-majority zip codes compared to only \$3,220, \$2,298, and \$3,348 in Hispanic, Asian, and Black-majority zip codes, respectively.

[18] This decoupling of MWhs of capacity and % of funding by category arises because the majority of storage systems adopted under the SGIP falls under the general budget category which has considerably less funding per Watt-hour of storage capacity.

Figure 5: Estimated Adoption and SGIP Incentive by Race/Ethnicity and Median Income



(a) Adoption Rate



(b) Incentive Rate

Notes. (a) and (b) present the estimated adoption and incentive rates from the fractional logit and PPML regressions, respectively, evaluated at intervals of $5,000 and the remaining covariates at their mean values in White, Black, Asian, and Hispanic-majority zip codes. Average reflects the estimated adoption and incentive rates evaluating the covariates at the sample average values.

It is important to acknowledge that there is considerable variability in the estimated adoption and incentive rates segmented by race categories within a $5,000 income bin. This should be kept in mind when interpreting the estimated adoption and incentive rates in Figure 5. However, these figures demonstrate broad patterns and relationships in the data that suggest that there are disparities in battery storage adoption and incentive rates by income and race and ethnicity at the zip code-level after controlling for important regional and time-vary factors.

Taken together, the regression results demonstrate that there is a strong relationship between a zip code's median income and battery storage adoption and SGIP-funding allocations. This is consistent with the descriptive results report in Figures 1 and 3. Further, these results demonstrate that there is a negative relationship between % Black, % Hispanic, and % Asian and SGIP-funded battery adoption rates. Although the results for % Black are sensitive to the inclusion of variables that control for the eligibility for equity resiliency funding. This suggests that disparities in battery adoption rates exist for these race/ethnicities. Interestingly, there is a positive relationship between % Indigenous and storage capacity adoption and incentive rates throughout. Unfortunately, without household-level data, or at least more granular location information on SGIP funded projects, we are unable to dig deeper into the source of this positive relationship.

7 Conclusion and Policy Implications

Residential battery storage has experienced a period of rapid growth in California. With the growing concerns over the inequitable burdens of climate change, electricity network resiliency, and energy and environmental justice (EJ), it is essential to evaluate if there are disparities in the adoption of and subsidies for residential battery storage.

Despite the fact that a subset of the Self-Generation Incentive Program (SGIP) funds are tied to household income, we find the majority of SGIP-funded battery storage is adopted in zip codes with higher average median incomes and low EJ concerns. When looking across all zip codes in California, 85% and 75% of battery capacity is installed in zip codes with average median income and an EJ concern metric in the top and bottom 50th percentiles, respectively. As a result, 82% ($237 million) and 80% ($230 million) of the utilized SGIP funding goes to zip codes that fall in the top and bottom 50th percentiles of the average median income and EJ concern distributions.

We demonstrate that these patterns are partially driven by the fact that a large proportion of SGIP funding is tied to being located in regions with the highest vulnerability to wildfires. These zip codes tend to have higher median incomes, a larger proportion of homeowners, lower EJ concerns, and a lower percentage of households of color. While the disparities across median income and EJ concern are reduced, we demonstrate that these disparities continue to exist when focusing on these regions.

We present descriptive evidence that carve-out programs targeted at specific "disadvantaged" and low income communities help reduce disparities in battery deployment. This suggests that these types of programs may prove to be a valuable avenue to ensuring equitable deployment of battery storage. However, because these programs are small in magnitude and target a small number of communities, we are limited in our ability to draw broad conclusions about their performance.

Regression analyses demonstrate that the strong relationship between median income and battery adoption and subsidy rates persists even after controlling for potentially confounding factors. Further, we find statistically significant evidence of disparities in battery storage adoption rates by race and ethnicity. Zip codes with a higher percentage of Black, Asian, and Hispanic residents are less likely to install battery storage. For example, the predicted battery adoption rates decrease by 20% and 34% relative to the mean adoption rate as we move to Hispanic and Asian-majority zip codes. Alternatively, we find a positive relationship between the percentage of households that self-identify as Indigenous and SGIP-funded battery adoption. The effects identified for Hispanic, Asian, and Indigenous race/ethnicities persist even after controlling for important regional and time-varying factors (e.g., such as being eligible for SGIP's equity resiliency funding).

We find that SGIP-funded residential battery storage is almost always coupled with rooftop solar. It has been shown that the financial returns for adding on battery storage to a rooftop solar system is not sufficient to offset the additional costs (Verdant, 2021). This suggests that absent a sufficiently large subsidy, the decision to invest in energy storage is driven by other non-financial factors (e.g., resiliency value, other non-pecuniary benefits). These observations suggests that the barriers to adoption such as access to financing, high upfront costs, lower home ownership, and/or a lack of peer effects that have been shown to play an important role in the adoption of rooftop solar (Bollinger and Gillingham, 2012; Lukanov and Krieger, 2019) may be magnified in this setting.

While residential battery storage is a relatively infant industry at its beginning stages, numerous states have designed programs to enhance its development (Twitchell 2019; EIA, 2020). Previous literature has demonstrated that lags in deployment for certain communities can enhance disparities relative to other communities over time because of "peer" and "seeding effects" that speed up deployment (Graziano and Gillingham, 2015; Sunter et al., 2019). Consequently, when designing programs to support residential battery storage investment, it is important to ensure that these programs are designed to promote widespread access to its various benefits.

It is important to acknowledge that our analysis is limited by the geographical granularity of the battery storage data, which is only available at the zip code-level. Zip codes vary in size and population and can mask potentially important socioeconomic and demographic patterns. Availability of more geographically granular data (e.g., at the census block group-level) would enhance researchers' abilities to evaluate and quantify disparities in battery adoption and SGIP funding allocations.[19] These data would be further enriched by household-level information for individuals that receive SGIP-funding and/or invest in battery storage. These data could be used to isolate key drivers of battery investment and allow researchers to establish testable hypotheses of the barriers that non-adopters of battery storage face.

[19] In addition, having more granular location-specific information would help identify whether or not a specific household is located in a HFTD or has experienced 2 or more PSPS events. This would provide a more accurate measure of the likelihood that a household is eligible for equity resiliency funding.

References

Allend-Dumas, M., KC, B. and C. Cunliff (2019). Extreme Weather and Climate Vulnerabilities of the Electric Grid: A Summary of Environmental Sensitivity Quantification Methods. Oak Ridge National Laboratory. ORNL/TM-2019/1252.

Balta-Ozkan, N., Davidson, R., Bicket, M., and L. Whitmarsh (2013). "Social Barriers to the Adoption of Smart Homes," *Energy Policy*, 63: 363 - 374.

Barbose, G., Forrester, S., Darghouth, N., and B. Hoen (2020). Income Trends Among U.S. Residential Rooftop Solar Adopters. Lawrence Berkeley National Laboratory.

Bellego, C. and L.-D. Pape (2019). "Dealing with Logs and Zeros in Regression Models," Working Papers 2019-13, Center for Research in Economics and Statistics.

Boampong, R. and D. Brown (2020). "On the Benefits of Behind-the-Meter Rooftop Solar and Energy Storage: The Importance of Retail Rate Design," *Energy Economics*, 86: 10482.

Bohra, N. (2021). Almost 70% of ERCOT Customers Lost Power During Winter Storm, Study Finds. The Texas Tribune. March 29, 2021.

Bollinger, B. and K. Gillingham (2012). "Peer Effects in the Diffusion of Solar Photovoltaic Panels," *Marketing Science*, 31(6): 873 - 1025.

Borenstein, S. (2017). "Private Net Benefits of Residential Solar PV: The Role of Electricity Tariffs, Tax Incentives, and Rebates," *Journal of the Association of Environmental and Resource Economists*, 4: S85 - S122.

Borenstein, S. and L. Davis (2016). "The Distributional Effects of US Clean Energy Tax Credits," *Tax Policy and the Economy*, 30(1): 191 - 234.

Brown, M., Soni, A., Lapsa, M., and K. Southworth (2020). Low-Income Energy Affordability: Conclusions from a Literature Review. Oak Ride National Laboratory. ORNL/TM-2019/1150.

California Distributed Generation Statistics (2021). Self Generation Incentive Program (SGIP) Data. Date Accessed: April 4, 2021.

California OEHHA (2018). CalEnviroScreen 3.0 (June 2018). California Office of Environmental Health Hazard Assessment.

CalEPA (2017). Designation of Disadvantaged Communities Pursuant to Senate Bill 535. California Environmental Protection Agency. April 2017.

Carley, S. and D. Konisky (2020). "The Justice and Equity Implications of the Clean Energy Transition," *Nature Energy*, 5: 569 - 577.

Carpenter, S. (2021). Traffic to Rooftop Solar Websites Surges as Texans Seek Freedom From Grid. Forbes. February 18, 2021.

CCA (2019). CCA Resilience Initiatives. California Community Choice Association.

Chan, G., Evans, I., Grimley, M., Ihde, B., and P. Mazumder (2017). "Design Choices and Equity Implications of Community Shared Solar," *The Electricity Journal*, 30(9): 37 - 41.

Climate Central (2020). Power Off: Extreme Weather and Power Outages. Climate Central. September 30, 2020.

CPUC (2016). Decision Revising the Self-Generation Incentive Program Pursuant to Senate Bill 861, Assembly Bill 1478, and Implementing Other Changes. California Public Utility Commission. Decision 16-06-055. Rulemaking 12-11-005.

CPUC (2017). Decision Establishing Equity Budget for Self-Generation Incentive Program. California Public Utility Commission. Decision 17-10-004. Rulemaking 12-11-005.

CPUC (2019). Decision Establishing Self-Generation Incentive Program Equity Resiliency Budget, Modifying Existing Equity Budget Incentives, Approving Carry-Over of Accumulated Unspent Funds, and Approving $10 Million to Support the San Joaquin Valley Disadvantaged Community Pilot Projects. California Public Utility Commission. Decision 19-09-027. Rulemaking 12-11-005.

CPUC (2020). Participating in Self-Generation Incentive Program. SGIP Eligibility Maps (December 2020). California Public Utility Commission.

CPUC (2021). Decision Adoption Phase 3 Revised Additional Guidelines and Rules for Public Safety Power Shutoffs (Proactive De-Energizations) of Electric Facilities to Mitigate Wildfire Risk Caused by Utility Infrastructure. Decision 21-06-034. Rulemaking 18-12-005.

Drehobl, A. and L. Ross (2016). Lifting the High Energy Burden in America's Largest Cities: How Energy Efficiency Can Improve Low Income and Underserved Communities. American Council for an Energy-Efficient Economy.

EIA (2020). Battery Storage in the United States: An Update on Market Trends. United States Energy Information Administration.

Graziano, M. and K. Gillingham (2015). "Spatial Patterns of Solar Photovoltaic System Adoption: The Influence of Neighbors and the Built Environment," *Journal of Economic Geography*, 15(4): 815 - 839.

Gaughan, A., Stevens, F., Huang, Z., Nieves, J., Sorichetta, A., Lai, S., Ye, X., Linard, C., Hornby, G., Hay, S., Yu, H., and A. Tatem (2016). "Spatiotemporal Patterns of Population in Mainland China, 1990 to 2010," *Nature: Scientific Data*.

Krieger E., Casey, J., and S. Shonkoff (2016). "A Framework for Siting and Dispatch of Emerging Energy Resources to Realize Environmental and Health Benefits: Case Study on Peaker Power Plant Displacement," *Energy Policy*, 96: 302 - 313.

Lukanov, B. and E. Krieger (2019). "Distributed Solar and Environmental Justice: Exploring Demographic and Socio-Economic Trends of Residential PV Adoption in California," *Energy Policy*, 134: 110935.

Lyubich, E. (2020). "The Race Gap in Residential Energy Expenditures," Energy Institute at Haas Working Paper 306.

IPUMS (2021). Integrated Public Use Microdata Series. American Community Surveys 2015 - 2019. Date Accessed: March 10, 2021. Available at: https://usa.ipums.org/usa/.

Papke, L. and J. Wooldridge (1996). "Econometric Methods for Fractional Response Variables with an Application to 401(k) Plan Participation Rates," *Journal of Applied Econometrics*, 11(6): 619 - 632.

Papke, L. and J. Wooldridge (2008). "Panel Data Methods for Fractional Response Variables with an application to Test Pass Rates," *Journal of Econometrics*, 145(1-2): 121 - 133.

O'Shaughnessey, E., Barbose, G., Wiser, R., Forrester, S., and N. Darghouth (2020). "The Impacts of Policies and Business Models on Income Equity in Rooftop Solar Adoption," *Nature Energy*, 6: 84 - 91.

Roberts, D. (2019). California's Deliberate Blackouts were Outrageous and Harmful. They're Going to Happen Again. Vox Energy and Enviroment. October 24, 2019.

Santos Silva, J. and S. Tenreyro (2006). "The Log of Gravity," *Review of Economics and Statistics*, 88(4): 641 - 658.

SGIP (2016). 2016 Self-Generation Incentive Program Handbook – V1.

SGIP (2020). 2020 Self-Generation Incentive Program Handbook – V9.

SGIP (2021). 2021 Self-Generation Incentive Program Handbook – V2.

Soricheta, A., Hornby, G., Stevens, F., Gaughan, A., Linard, C., and A. Tatem (2015). "High-Resolution Gridded Population Datasets for Latin America and the Caribbean in 2010, 2015, and 2020," *Nature: Scientific Data*.

Sunter, D., Castellanos, S., D. Kammen (2019). "Disparities in Rooftop Photovoltaics Deployment in the United States by Race and Ethnicity," *Nature Sustainability*, 2(1): 71 - 76.

Twitchell, J. (2019). "A Review of State-Level Policies on Electrical Energy Storage," *Current Sustainable Renewable Energy Reports*, 6:35 - 41.

USGCRP (2018). *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II*, (eds.) Reidmiller, D.R., C.W. Avery, D.R. Easterling, K.E. Kunkel, K.L.M. Lewis, T.K. Maycock, and B.C. Stewart, U.S. Global Change Research Program, Washington, DC, USA.

U.S. Census (2021). 2010 ZIP Code Tabulation Area (ZCTA) Relationship File Record Layouts. United States Census Bureau. Date Accessed: March 1, 2021.

Vaishnav, P., Horner, N., and I. Azevedo (2017). "Was it Worthwhile? Where have the Benefits of Rooftop Solar Photovoltaic Generation Exceeded the Cost?" *Environmental Research Letters*, 12: 094015.

Verdant (2021). Net-Energy Metering 2.0 Lookback Study. Submitted to: California Public

Utilities Commission - Energy Division.

Wada, K., Akimoto, K., Sano, F., Oda, J., and T. Homma (2012). "Energy Efficiency Opportunities in the Residential Sector and their Feasibility," *Energy*, 48(1): 5 - 10.

WorldPop (2020). Population Counts. Unconstrained Top-Down Data. Available at: www.worldpop.org/project/categories?id=3.

Appendix

A HFTD and PSPS Indices

We utilize the CPUC's (2020) geospatial shapefiles that define the locations of HFTD Tiers 2 and 3, and regions that have experienced two or more PSPS events. Our objective is to construct a zip code-level measure to proxy for the likelihood that a household falls within one or more of these regions. A challenge we face is that the HFTD regions are often located in rural, less populated, regions. To account for this fact, we compute a population-weighted measure of the area covered by each of these regions for each zip code in California.

We employ methods established by the geography literature to determine the population weights across all of California. We utilize the 2020 WorldPop data set that provides a population weight for approximately every 1,000 meters in California (WorldPop, 2020).[20] The WorldPop data set employs granular census data (at the block group level), projects land cover topology layers (e.g., rivers, elevation, etc.), utilizes the geography literature's estimates on where humans live by land use types, and employs empirical methods to project the census population onto a more granular scale. For additional details on these methods, see Sorichetta et al. (2015) and Gaughan et al. (2016).

The WorldPop data set provides population weight points for (approximately) every 1,000 meters. Since our objective is to calculate a measure of the population-weighted area covered by HFTD Tier 2, HFTD Tier 3, or that has been exposed to two or more PSPS events, we project this data from a point-based measure to a spatial measure using Inverse Distance Weighting Interpolation to fill the gaps between the points to assign a population weight to all locations in California. This yields a 1,000-by-1,000 meter grid of population estimates across the state.

We use the gridded population estimate to compute our indices as follows. It is without loss of generality to focus on the HFTD Tier 2 measure. For a given zip code z, define $j = 1, 2, ..., \overline{J}_z$ to be the number of WorldPop grid cells contained within zip code z. The population weight for each WorldPop cell is $w_j \geq 0$. Define A_j to be the area of WorldPop cell j in zip code z that lies within a HFTD Tier 2. Define B_j to be the total area within WorldPop cell j in zip code z:

$$\text{HFTD Tier } 2_z \;=\; \frac{\sum_{j=1}^{\overline{J}_z} w_j \, A_j}{\sum_{j=1}^{\overline{J}_z} w_j \, B_j}.$$

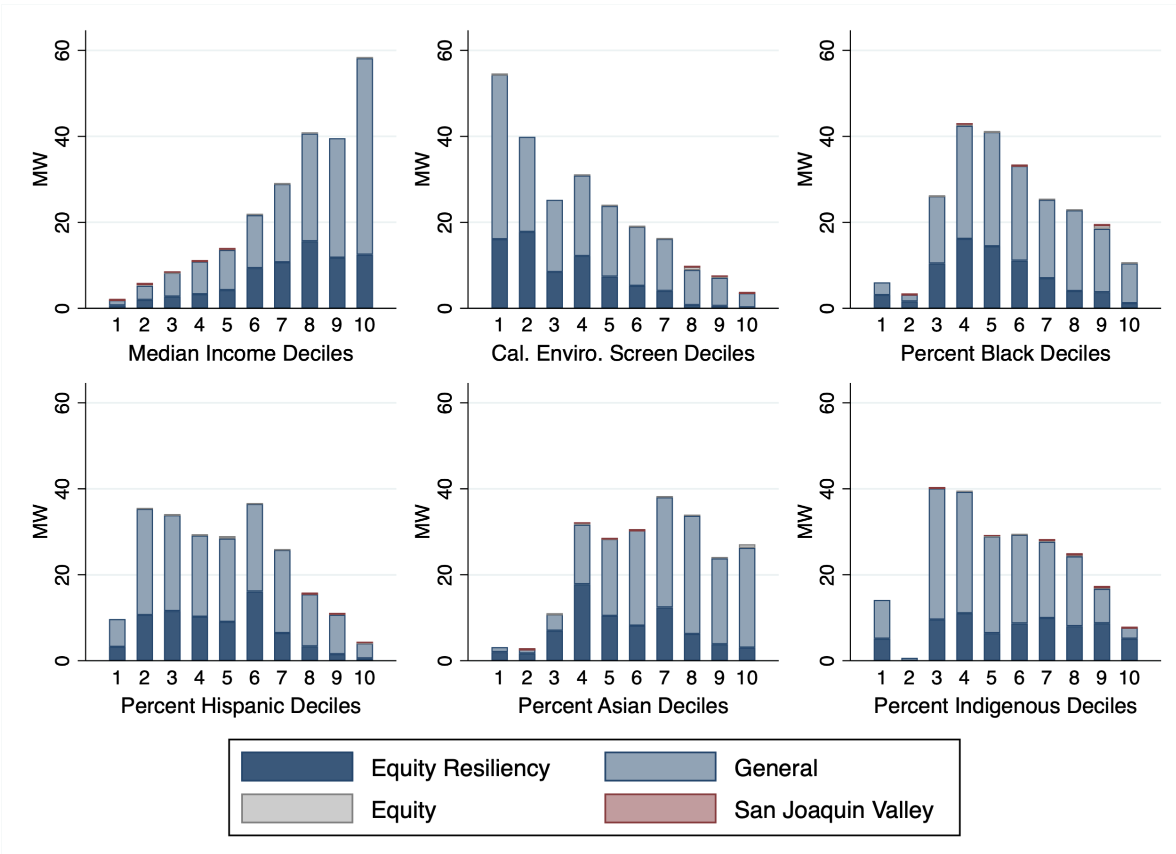
This approach provides a population-weighted area covered by each measure for each zip code in our sample. An analogous approach is employed for the HFTD Tier 3 and PSPS two or more measures. For the PSPS ≥ 2 Event measure, it is important to acknowledge that the CPUC's (2020) geospatial file often locates individual households rather than large geographical areas. As a result, the magnitude of this index will be smaller than the HFTD measures which capture large geographical areas. However, for zip codes that have a larger

[20]More specifically, we use the 2020 unconstrained top-down data set at a 1,000 meter resolution.

proportion of households that have experienced PSPS events, the PSPS $\geq$ 2 Event measure will take on a larger value.

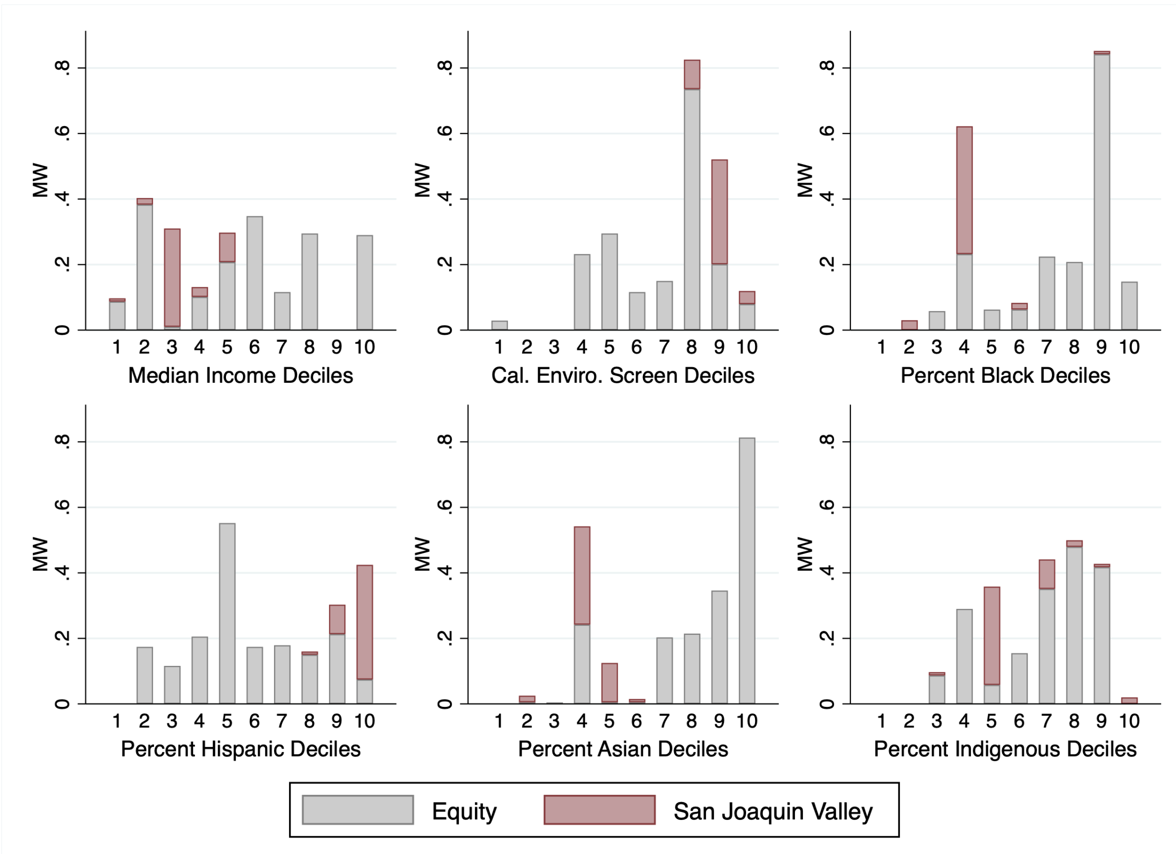
B Additional Results

Figure A.1: MWs of Storage Capacity by Socioeconomic and Demographic Deciles



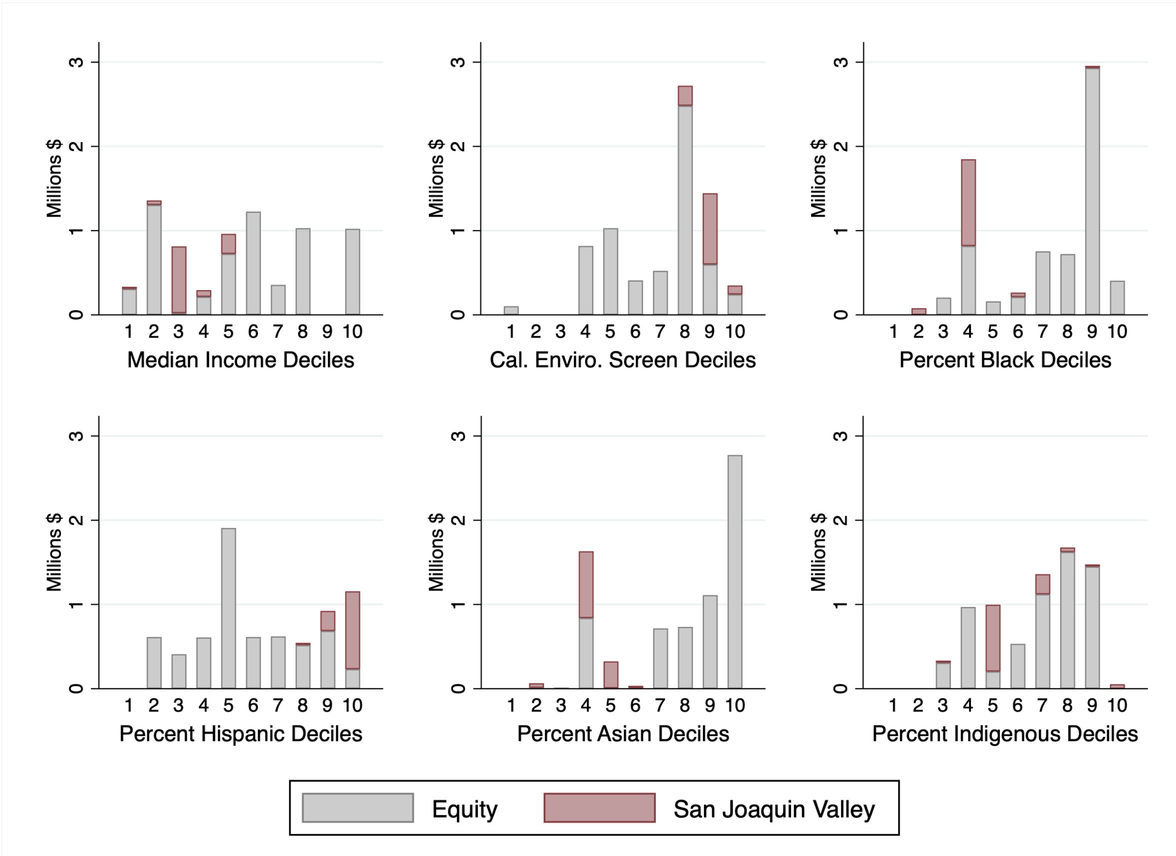
Notes. Bar graphs present the MWs of battery storage capacity installed at the zip code-level over our entire sample period for all SGIP budget categories by median income, CalEnviroScreen, % Black, % Hispanic, % Asian, and % Indigenous deciles.

Figure A.2: MWs of Storage Capacity by Socioeconomic and Demographic Deciles - Equity and SJV Budget Categories



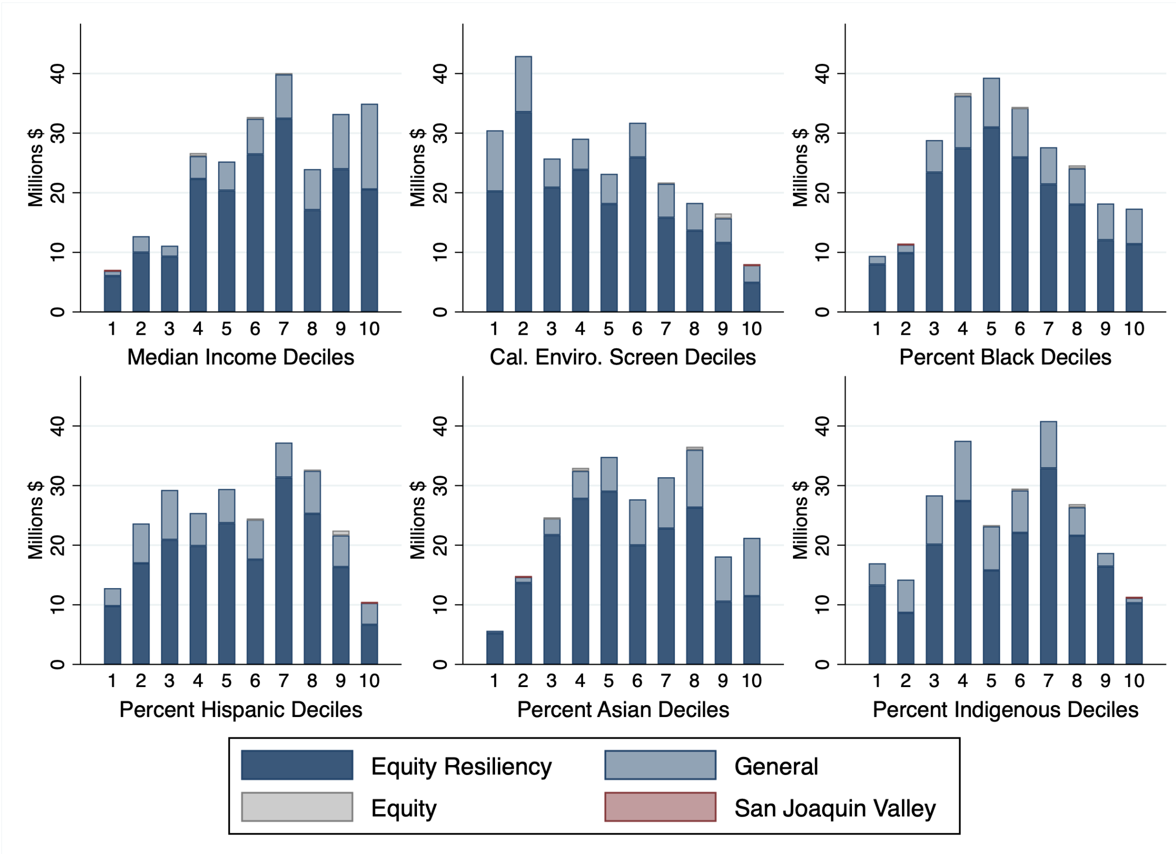
Notes. Bar graphs present the MWs of battery storage capacity installed at the zip code-level over our entire sample period for the Equity and San Joaquin Valley SGIP budget categories by median income, CalEnviroScreen, % Black, % Hispanic, % Asian, and % Indigenous deciles.

Figure A.3: SGIP-Funding by Socioeconomic and Demographic Deciles - Equity and SJV Budget Categories



Notes. Bar graphs present the SGIP funding received at the zip code-level over our entire sample period for each budget category by median income, CalEnviroScreen, % Black, % Hispanic, % Asian, and % Indigenous deciles.

Figure A.4: SGIP-Funding by Socioeconomic and Demographic Deciles - Equity Resiliency Zip Codes



Notes. Bar graphs present the SGIP funding received at the zip code-level over our entire sample period for each budget category for zip codes that received Equity Resiliency funding by median income, CalEnviroScreen, % Black, % Hispanic, % Asian, and % Indigenous deciles.

Table A1 presents the results of our Adoption Rate Fractional Logit regression analysis with varying control variables in columns (1) - (5), and considering an ordinary least squares (OLS) regression in column (6). Columns (1) - (5) demonstrate that the sign and statistical significance are in general robust, but their magnitudes decrease. The most consequential effect is when the HFTD and PSPS ≥ 2 Events control variables are added reflecting the fact that the SGIP equity resiliency funding is tied to being in these regions.

Column (6) presents the OLS regression results which indicates limited statistically significant for the race/ethnicity variables. However, the OLS regression fails to account for the fact that the dependent variable is constrained to be in the set $[0, 1]$ with a mass of observations at zero. Further, the predicted Adoption Rate using the OLS regression results in approximately 30% of predicted values being negative indicating it performs relatively poorly at modeling the relationships between the covariates and the dependent variable.

Table A1: Adoption Rate Regression Results - Robustness

Model	(1) Frac. Logit	(2) Frac. Logit	(3) Frac. Logit	(4) Frac. Logit	(5) Frac. Logit	(6) OLS
% Black	-3.264***	-1.821***	-1.204**	-1.204**	-0.428	0.00013
	(0.688)	(0.546)	(0.469)	(0.469)	(0.434)	(0.00016)
% Hispanic	-1.267***	-0.867***	-1.139***	-1.140***	-0.632**	0.00002
	(0.235)	(0.253)	(0.258)	(0.259)	(0.249)	(0.00010)
% Asian	-3.498***	-2.878***	-2.711***	-2.715***	-1.680***	-0.00082***
	(0.318)	(0.271)	(0.249)	(0.249)	(0.225)	(0.00014)
% Indigenous	2.579**	2.355**	2.060**	2.063**	1.535**	0.00143
	(1.002)	(1.021)	(0.892)	(0.894)	(0.764)	(0.0012)
% Owner Occupied		2.016***	1.895***	1.897***	1.097***	0.0004***
		(0.294)	(0.286)	(0.286)	(0.281)	(0.00013)
Median Income	0.0310***	0.0288***	0.0217***	0.0218***	0.0232***	0.00001**
	(0.00372)	(0.00337)	(0.00305)	(0.00306)	(0.00295)	(0.000002)
(Median Income)^2	-0.00007***	-0.00007***	-0.00005***	-0.00005***	-0.00005***	0.000001
	(0.000015)	(0.000013)	(0.000012)	(0.000012)	(0.00001)	(0.000001)
HFTD Tier 2					0.00876***	0.000005***
					(0.00138)	(0.000001)
HFTD Tier 3					0.00864***	0.000009***
					(0.00118)	(0.000002)
PSPS ≥ 2 Events					0.0190***	0.00003***
					(0.00247)	(0.000007)
Year Controls	No	No	No	Yes	Yes	Yes
Utility Controls	No	No	Yes	Yes	Yes	Yes
Zip Code – Years	8,130	8,130	8,130	8,130	8,130	8,130
Pseudo–R^2	0.038	0.043	0.057	0.111	0.120	
R^2						0.109
χ^2	489.4***	574.3***	989.4***	1,957.2***	2,314.2***	
F-Stat						37.88***

Notes. Statistical Significance $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Standard errors are reported in the parentheses and are clustered at the zip code-level. Columns (1) – (5) reflect the Fractional Logit regression. Column (6) reflects Ordinary Least Squares (OLS).

Table A2 presents the results of our Incentive Rate PPML regression analysis with varying control variables in columns (1) - (5), and considering an OLS log-linear regression in column (6). Columns (1) - (4) demonstrate that the sign and statistical significance are robust to the addition of control variables, but their magnitudes decrease. % Black and % Hispanic are no longer statistically significant once the HFTD and PSPS ≥ 2 Events control variables are added.

Column (6) presents the log-linear OLS regression with the dependent variable Log(Incentive Rate_{zt}) that is a common approach to handle rightward skewed data. Compared to column (5), % Black and % Hispanic are more statistically significant and the remaining patterns persist with the exception that % Indigenous is not statistically significant. For reasons discussed in Section 4, the log-linear regression has a number of issues that are accounted for in the PPML regression.

Table A2: Incentive Rate Regression Results - Robustness

Model	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) Log - OLS
% Black	-6.107***	-3.559***	-2.458**	-2.458**	-0.658	-0.366**
	(1.538)	(1.281)	(1.119)	(1.119)	(0.975)	(0.163)
% Hispanic	-1.679***	-1.050**	-1.321***	-1.321***	-0.353	-0.211***
	(0.434)	(0.481)	(0.501)	(0.501)	(0.500)	(0.0667)
% Asian	-6.373***	-5.356***	-4.977***	-4.977***	-2.711***	-0.826***
	(0.735)	(0.652)	(0.630)	(0.630)	(0.482)	(0.116)
% Indigenous	3.430***	3.346***	2.883***	2.883***	2.245***	0.112
	(1.126)	(1.138)	(1.028)	(1.028)	(0.844)	(0.362)
% Owner Occupied		2.847***	2.810***	2.810***	1.486***	0.290***
		(0.496)	(0.479)	(0.479)	(0.434)	(0.0907)
Median Income	0.0318***	0.0289***	0.0197***	0.0197***	0.0227***	0.00404***
	(0.00570)	(0.00513)	(0.00473)	(0.00473)	(0.00457)	(0.00145)
(Median Income)^2	-0.00008***	-0.00008***	-0.00005***	-0.00005***	-0.00006***	0.00002***
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.000007)
HFTD Tier 2					0.0172***	0.00553***
					(0.00213)	(0.000590)
HFTD Tier 3					0.0171***	0.00874***
					(0.00165)	(0.000852)
PSPS ≥ 2 Events					0.0214***	0.0125***
					(0.00490)	(0.00284)
Year Controls	No	No	No	Yes	Yes	Yes
Utility Controls	No	No	Yes	Yes	Yes	Yes
Zip Code – Years	8,130	8,130	8,130	8,130	8,130	8,130
Pseudo–R^2	0.165	0.194	0.255	0.573	0.641	
R^2						0.336
χ^2	261.1***	315.9***	549.7***	1,783.4***	2,012.0***	
F-Stat						100.6***

Notes. Statistical Significance $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Standard errors are reported in the parentheses and are clustered at the zip code-level. Columns (1) – (5) reflect the Poisson pseudo-maximum-likelihood (PPML) regression. Column (6) reflects an Ordinary Least Squares (OLS) log-linear regression with the dependent variable Log(Incentive Rate_{zt}). When Incentive Rate is zero, we use the common approach of adding 1 to account for the fact that log(0) is undefined (Bellego and Pape, 2019).

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