



DETERMINANTS OF RESIDENTIAL SOLAR PHOTOVOLTAIC ADOPTION

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Working Paper No. 2018-1
February 7, 2018

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Determinants of Residential Solar Photovoltaic Adoption

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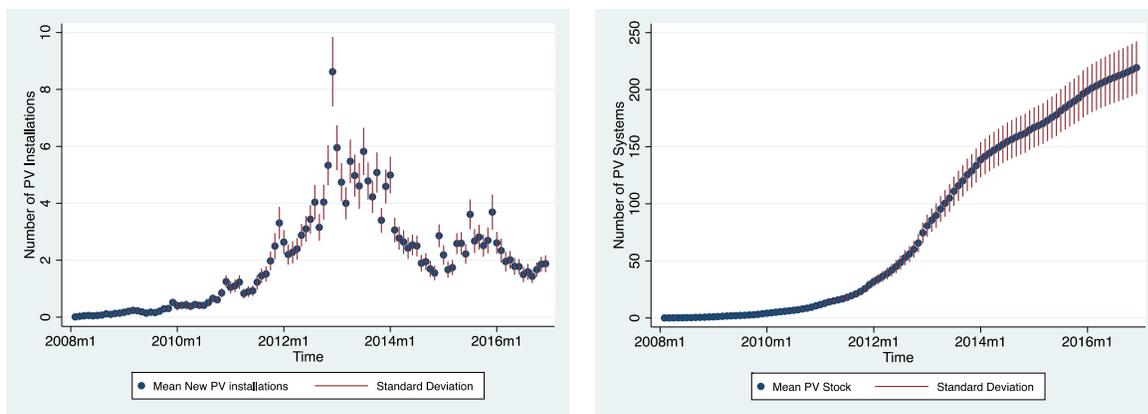
Acknowledgements

We thank the State of Hawaii Division of Consumer Advocacy for their financial support of this project. We thank the University of Hawaii Economic Research Organization for their administrative support and James Jones for his data gathering assistance.

Executive Summary

This study analyzes the role of demographic factors in residential solar photovoltaic (PV) system adoption for Oahu and Maui Counties from 2008 to 2016. We use building permit data to spatially identify residential PV systems. We join this with demographic data at the census tract level as well as information on solar radiation. After accounting for residences that have multiple building permits, there are a total of 50,615 PV permits. Figure 1 below shows the average number of new PV installations per month in a census tract as well as the accumulation within the average tract over our time period.

Figure 1. Average New PV Installations per Month (left) and Average Number of Homes with PV (right) Per Tract for both Oahu and Maui, 2008 – 2016



Source: CCH, 2017; Maui Department of Public Works, 2017.

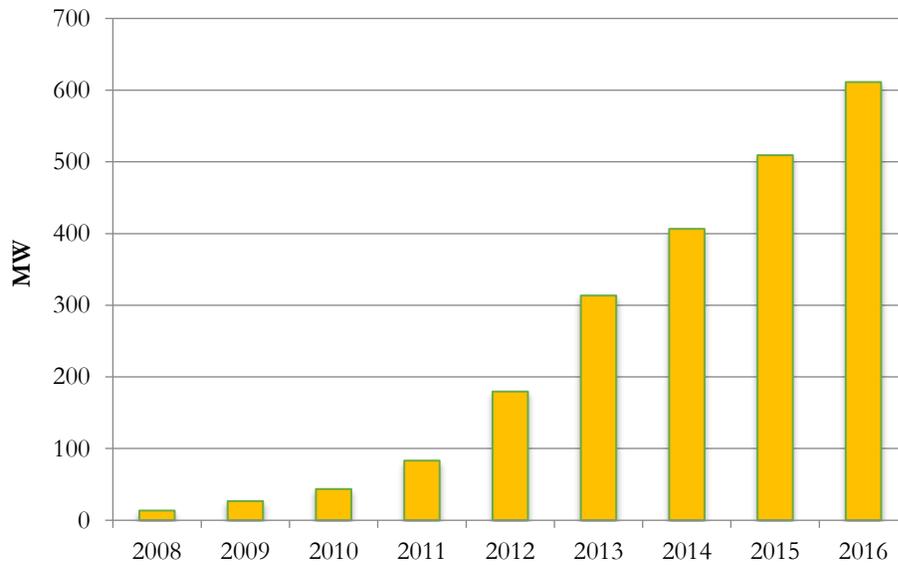
We find that owner-occupied housing units, single-family residences, and income are the most influential factors in explaining the differences in PV adoption between census tracts. We find that a 1% increase in owner-occupancy corresponds to a 9-12% increase in the share of households with PV. We find that a 1% increase in the share of single-family dwellings corresponds to a 2-4% increase and that a \$10,000 increase in the median income in a tract corresponds to a 0.6-1% increase.

Owner-occupancy is particularly important because landlords and renters suffer from what is referred to as a “principal-agent” problem, where renters lack autonomy over decision-making regarding capital investments and landowners face a disconnect between cost and benefits of capital investments in rental assets. These findings confirm that there are clearly distributive impacts of PV support policies, where benefits are largely accruing to higher income groups. The question of how to bring about the benefits of renewable energy technologies to a broader set of residents requires additional analysis of rate-setting procedures and rate design. The current solution to bringing in renters and underserved communities is community-based renewable energy (CBRE) programs, though its efficacy will certainly depend on the relative rates in comparison to alternatives like utility-scale projects.

1. Introduction

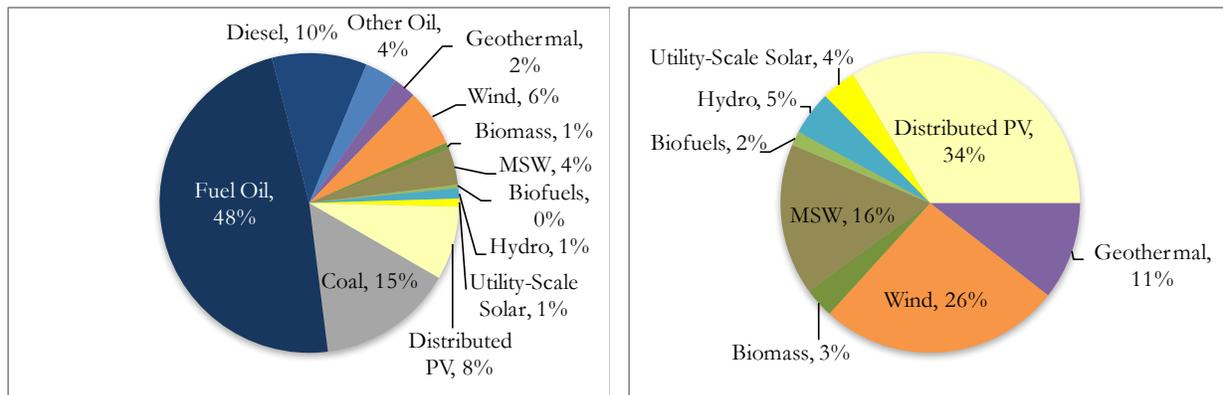
Hawaii is a leader in distributed solar photovoltaic (PV) adoption. It has the highest rate of PV-based electricity penetration in the U.S. and rivals global frontrunners (Trabish, 2016). The policy impetus towards large-scale adoption of renewable energy in Hawaii comes from its Renewable Portfolio Standard (RPS), with a target of 40% net electricity sales from renewable sources by the year 2030 and 100% by 2045. Rooftop PV provides the largest share of renewable energy in Hawaii's electricity generation portfolio. Much of the growth in PV has been through residential systems, as nearly 17% of homes, and 32% of single-family homes on Oahu have PV (Trabish, 2016). The adoption of distributed PV by Hawaii's households has been motivated by a combination of Hawaii's high electricity prices, federal and state solar PV income tax credits, net-energy metering (NEM) and other grid-supply arrangements, as well as strong solar resources (Coffman et al., 2016). Figures 1 and 2 below show the adoption of distributed PV from 2008 to 2016 and Hawaii's electricity generation profile.

Figure 1. PV Installed Capacity, 2008 – 2016



Source: Hawaiian Electric Companies, 2017a; KIUC 2008-2016.

Figure 2. Electricity Generation and Renewable-Based Electricity Generation Portfolio, 2016



Source: EIA, 2017; Hawaiian Electric Companies, 2017b; KIUC, 2017.

There has been steady growth in PV system adoption and by 2016 distributed PV totaled 600 MW and accounted for 8% of total generation (EIA, 2017a; Hawaiian Electric Companies, 2017a and 2017b; KIUC 2008-2016; KIUC, 2017). About 70% is located on Oahu (Hawaiian Electric Companies, 2017a).

This study analyzes demographic factors related to residential PV system adoption in Hawaii. It provides an econometric analysis, augmented by maps, to better understand the demographic characteristics of households adopting PV systems. Understanding drivers of past uptake is important to gaining insight into future trends, particularly as Hawaii continues towards its 2045 RPS goal of 100%.

2. Data and Methods

We focus our analysis on Oahu and Maui counties due to public availability of building permit data for PV installations.¹ Our analysis covers the years 2008 through 2016.² Data for this study comes from five sources: 1) City and County of Honolulu (2017), 2) Maui Department of Public Works (2017), 3) U.S. Census (2010), 4) American Community Survey (2015) and 5) Solar Radiation of Hawaii Project (Giambelluca et al., 2014). The data are used for the purposes of estimating the relationship between residential PV adoption and census tract-level demographic factors. Our selection of demographic variables comes from a review of available data within the Census and ACS as well as of other studies that test the spatial variation of PV adoption. In particular, we draw upon two studies of the social dimensions of PV adoption. Bollinger and Gillingham (2012) and Graziano and Gillingham

¹ We submitted a data request to Kauai County but the data we received was not spatially attributable. After beginning work, we eventually found data for Hawaii County but it had only the date of when the permit was issued and not completed. For consistency, because there were backlogs in PV installations as well as potential error in assuming a house actually installs PV without a permit completion, we omit Hawaii County.

² While Maui data is available back to 2005, we restrict our analysis to the beginning of the Oahu data in 2008. The first observation in 2008 for Maui occurs in February. Using monthly data, this amounts to 107 time periods.

(2015) assess the diffusion of PV technology in California and Connecticut, respectively. They find that factors like income, gender, age and owner-occupancy matter in influencing PV adoption.³ In addition, DBEDT (2017) identifies owner-occupied houses, single family houses, median income and married-couple family households as data related to PV ownership.⁴ For this study, data used from the Census includes tract-level median age, the percentage of owner-occupied units, and the number of occupied units. Data from the ACS include median household income, percentage of single family units, and percentage of owner-occupied units with a mortgage.⁵

Accounting for differences in solar resources, we expect that tracts with higher median income and a greater share of single-family owner-occupied units will have a higher concentration of households with PV. Apartment owners likely do not have sufficient rooftop space or ease of decision-making afforded by single family ownership. Commonly referred to as a “principal-agent” problem, renters lack autonomy over decision-making regarding capital investments and landowners often face a disconnect between cost and benefits of capital investments into rental assets (Graziano and Gillingham, 2015).

2.1 Data

The PV permit data was first filtered for residential building permits only, including checking for occupancy type. To bring the residential permit data into the GIS for analysis, we created a parcel point shapefile that shows a central point for each tax map key (TMK) from existing data provided by the State of Hawaii, Office of Planning (State of Hawaii, 2017). The residential building permit data that identifies the installation of solar PV⁶ was then appended to this shapefile to allow spatial visualization using ArcMap. Multiple permit records for the installation of PV exist for many of the parcels so the data was sorted oldest to newest by the date the work was completed (Oahu) or the

³ In both of these studies the primary focus is on identifying whether there is a neighborhood-based peer effect in the adoption of solar PV. This is different in scope from our study. However, their analysis of other factors that affect household PV adoption is relevant. Bollinger and Gillingham (2012) find that factors such as population, income, gender, age, ethnicity, education, and home value can affect PV adoption. They also find that factors like commute time and owning a hybrid matter. They fail, however, to show how these variables are correlated and thus we omit ethnicity (likely highly correlated to income) and travel-related variables. Graziano and Gillingham (2015) additionally find that renter-occupancy and “solarize” programs matter. We did initially run regressions using ACS data on education levels, but found it is highly correlated with income and, when income is excluded, this leads to large omitted variable bias.

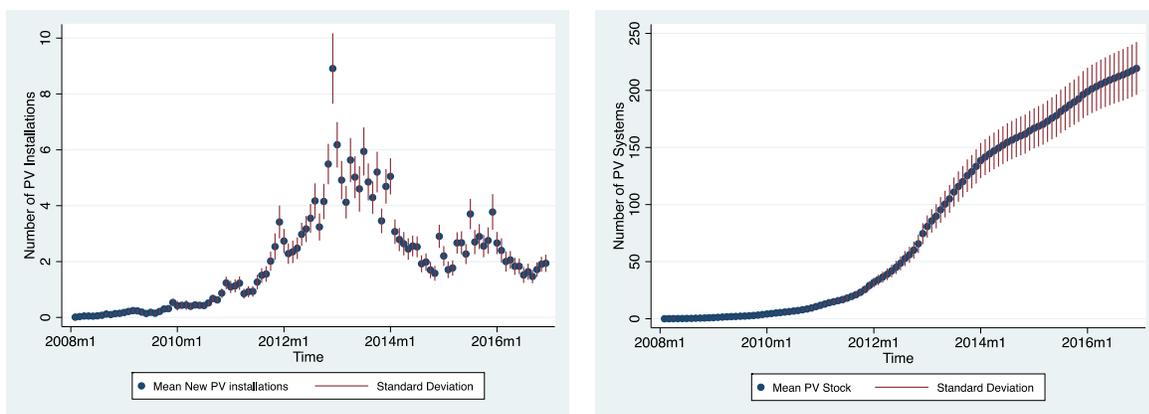
⁴ DBEDT (2017) provides a presentation of the PV permit data for Oahu and, though these data are plotted in comparison to PV adoption at the tract level, there is no statistical analysis. We exclude married-couple household because there is little explanation as to why this might be an important marker of PV uptake.

⁵ Note, ACS data at the tract-level (also zipcode) is only available as 5 year estimates. This, along with the 2010 Census data, restricts these variables to a single tract value throughout our sample period. While prior researchers have used consecutive multiyear estimates to create a time series, each multiyear file does not represent a single year so we take a more cautious approach relative to Bollinger and Gillingham (2012).

⁶ Building permit data also includes the estimated value of work, but we cannot use it in our analysis since PV is often coupled with other building work in a single permit - for instance, in the case of new construction.

date of the final inspection (Maui) before appending the permit records to the shapefile.⁷ This ensured only the first permit record would be matched to each parcel.⁸ Though there were initially a total of 64,642 observations of PV permits across Maui and Oahu Counties between 2008 and 2016 for residential occupancy types,⁹ this filtering process reduced the total to 50,615.¹⁰ Once the permit data was connected to the shapefile, census tract information was appended. The solar resources dataset was processed by taking an average of solar radiation at 1pm within a census tract, after excluding conservation and agriculturally zoned lands. This data was then joined to the PV and demographic datasets. Figure 3 below illustrates the average number of new PV installations per tract each month and the average number of homes with PV per tract.

Figure 3. Average New PV Installations per Month (left) and Average Number of Homes with PV (right) Per Tract for both Oahu and Maui, 2008 – 2016



Source: CCH, 2017; Maui Department of Public Works, 2017.

PV adoption boomed in 2012 and 2013. Interestingly, 42% of new capacity additions in 2012 were installed in the fourth quarter (Hawaiian Electric Companies, 2012ab). This was likely due to the November 2012 announcement that there would be substantial changes to the implementation of the state tax credit, effective the following calendar year (DOT, 2012). The administrative rules were changed such that “systems” were more clearly defined, effectively lowering the overall amount that a household could receive in state subsidies. In Figure 3 (left), the average number of PV installations per tract in December 2012 was 9, an approximate 50% increase from the quarters before or after.

⁷ Note, the completed/final inspection date denotes when the county determines the PV system is up to code and the permit application is subsequently closed. It does not however necessarily indicate that the system is operational (i.e. connected to the grid). On Oahu, prior to interconnection backlog in 2013 - 2014, the City and County of Honolulu’s Department of Planning and Permitting (DPP) did not coordinate the issuing of permits with approval from the utility. We acknowledge that the completed/final inspection date for observations during this time period on Oahu may not reflect the operational date. For the purposes of the analysis, this is not a critical distinction as we are interested in who installs PV and when.

⁸ We are interested in when homes first had PV. Properties may have filed multiple PV permits in instances where capacity was added or inverters were replaced.

⁹ A total of 51,957 on Oahu and 12,685 Maui.

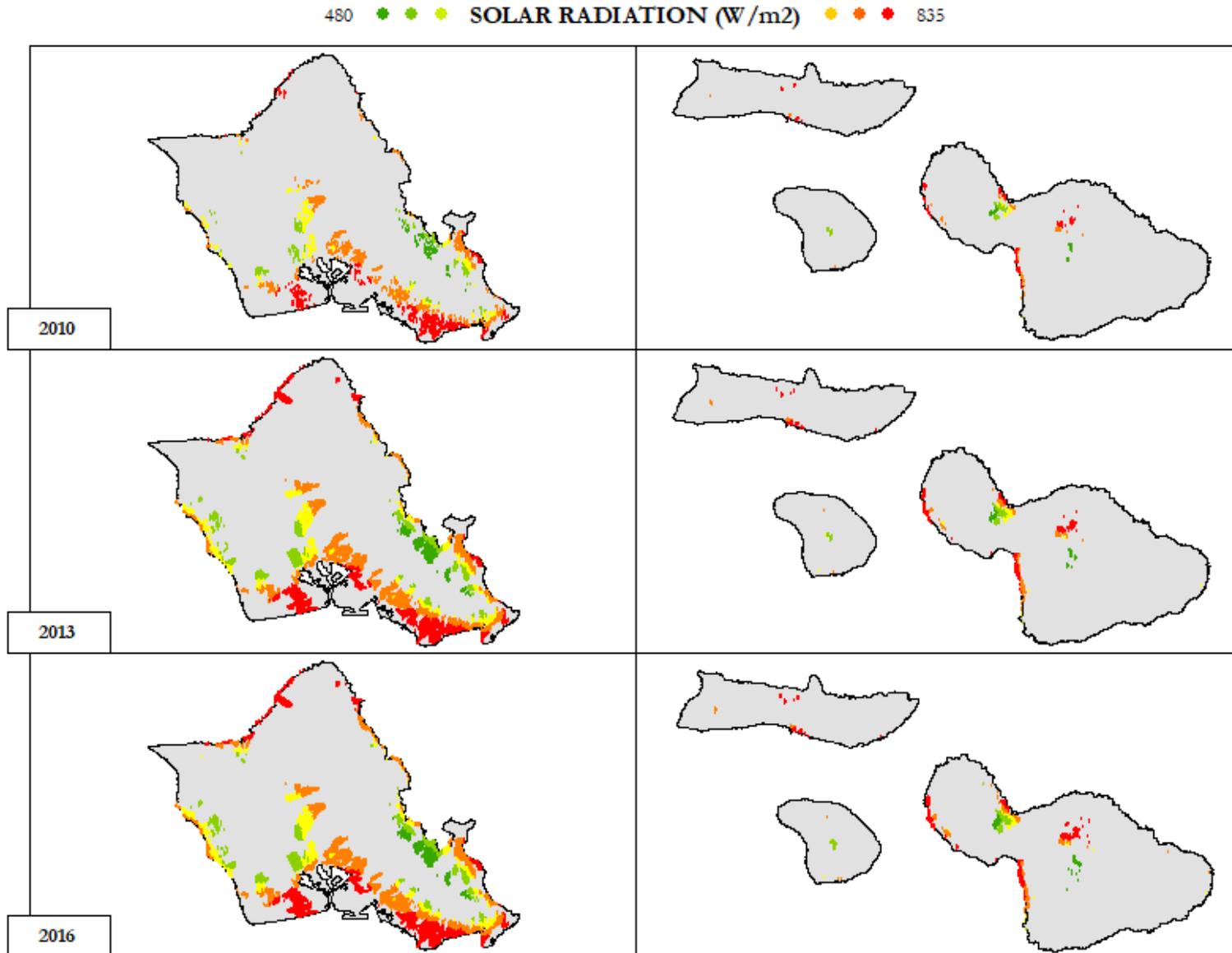
¹⁰ A total of 43,102 on Oahu and 7,513 on Maui.

For the first three quarters of 2013, PV installations remained fairly high, with the average number of monthly PV installs ranging from 4 to 6. The slight decline in new PV installs in the last quarter of 2013 was likely a result of Hawaiian Electric Companies changing the metric used to determine whether a system could connect to the grid. This created an interconnection queue that persisted until mid-2015 (Hawaiian Electric Companies, 2015).¹¹ Despite the close of NEM in October 2015 (Public Utilities Commission, 2015), customers opted for PV systems that could export to excess electricity to the grid at a relatively lower rate. This “grid-supply” program reached capacity a year later in September 2016 and permits for the remainder of 2016 reflected non-exportable PV systems (Shallenberger, 2016). In terms of the cumulative number of PV systems (Figure 3, right), by the end of 2016, there were on average about 220 homes with PV per tract.

To get a better sense of the spatial distribution of PV uptake, Figures 4 below maps PV system uptake on Oahu and Maui counties between 2008 and 2016. A “dot” for each PV system installed are shown in 2010, 2013 and 2016. Each PV installation point is colored to represent solar radiation at that location, using the estimated annual average of solar resources at 1pm each day, as provided within the Solar Radiation of Hawaii dataset. Within the scale that we use, the lowest observation is 480 watts per square meter and the high is 835. Hawaii has incredibly strong solar resources – meaning that even a place with average resources is really quite high. It would be more important to consider tree canopy over household rooftops – though this outside of the study scope.

¹¹ As explained in footnote 7, the permit completion/inspection date does not necessarily indicate the operational date. Due to the lack of coordination between the issuing of permits and interconnection approval prior to 2014 (DBEDT, 2014), there may be some systems that have a completed permit, but were not connected to the grid. Therefore, there may be a lag between when the system was completed (i.e. passed inspection) and when the system is operational.

Figure 4. PV systems installed on Oahu and Maui Counties between 2008-2016



On Oahu, the majority of early PV adoption occurred in Honolulu and on the windward side of the island, though there has been adoption across the island, including on the west and north ends, during the entire duration. Maui County has seen PV installations on all three islands (Maui, Lanai and Molokai), though the majority are on Maui Island. There installations have primarily been within Kahului, Paia, Kihei, Wailuku, Lahaina and Kaanapali.

2.2 Econometric Approach

We use the variation in PV installations between census tracts to estimate the effect of demographics on PV adoption.¹² We define the dependent variable, PV adoption, as the share of households with PV in a tract. This is computed by dividing the number of households with PV in a tract by the number of occupied units in that tract (U.S. Census, 2010). Using ordinary least squares (OLS), our base specification is shown in Equation 1:

Equation 1.

$$PV_{ct} = \alpha + \beta_1 income_c + \beta_2 owneroccupied_c + \beta_3 homemortgage_c + \beta_4 singlefamily_c + \beta_5 medianage_c + \beta_6 solarradiation_c + \sigma_t + \mu_{ct}$$

where PV_{ct} is the share of households with PV in tract c at time t (end of month-year); $income_c$ is the median income (in \$10,000s) in tract c between 2011 - 2015;¹³ $owneroccupied_c$ is the percentage of owner-occupied units in tract c in 2010; $homemortgage_c$ is the percentage of owner-occupied units with a mortgage in tract c between 2011 - 2015; $singlefamily_c$ is the percentage of single-family units in tract c between 2011 - 2015; $medianage_c$ is the median age in tract c in 2010; $solarradiation_c$ represents the average amount of sunlight in tract c after excluding conservation and agriculturally zoned lands; σ_t are month-year indicators to pick up overarching time trends that may affect PV adoption; and μ_{ct} is the error term (robust standard errors). In an ideal specification, the demographic data would similarly vary over time t . However, due to limitations in the Census and ACS data, this is not possible. The model makes the strong assumption that demographic characteristics within tracts have not changed over the study period (see footnote 5).

Though we start with these five demographic variables, many are highly correlated. The correlation coefficient of income with owner-occupancy is 0.75, between income and single-family is 0.65, and between owner-occupancy and single-family is 0.63. The way that mortgage data is reported is only as owner-occupied units, which also poses an issue in its relationship to the owner-occupied variable.¹⁴

¹² Regressions are restricted to 233 residential tracts with recorded values for variables of interest in the Census and ACS data.

¹³ The 2010 U.S. Census data does not report median household income, along with single-family units, and home mortgage, at the tract level. We instead use the 2015 ACS 5-year estimates which cover years 2011-2015.

¹⁴ This has a correlation coefficient of 0.37. This means that the higher the rate of owner-occupancy within a tract is somewhat correlated to a higher rate of having a home mortgage.

We therefore specify a series of regressions that systematically exclude highly correlated variables as well as the prevalence of mortgages. In addition, since the available data does not include a statistic on single-family owner-occupied units, we instead model the two separate measures. Due to the binary nature of the PV data, meaning that we can only discern which homes have PV,¹⁵ we do not include average household size as an independent variable. This would be appropriate if we knew the system size or actual value associated with each PV system.

Table 1 below details the summary statistics for the full sample including both Oahu and Maui. Tables that break out Oahu and Maui separately are provided in Appendix A.

Table 1. Summary Statistics for Oahu and Maui

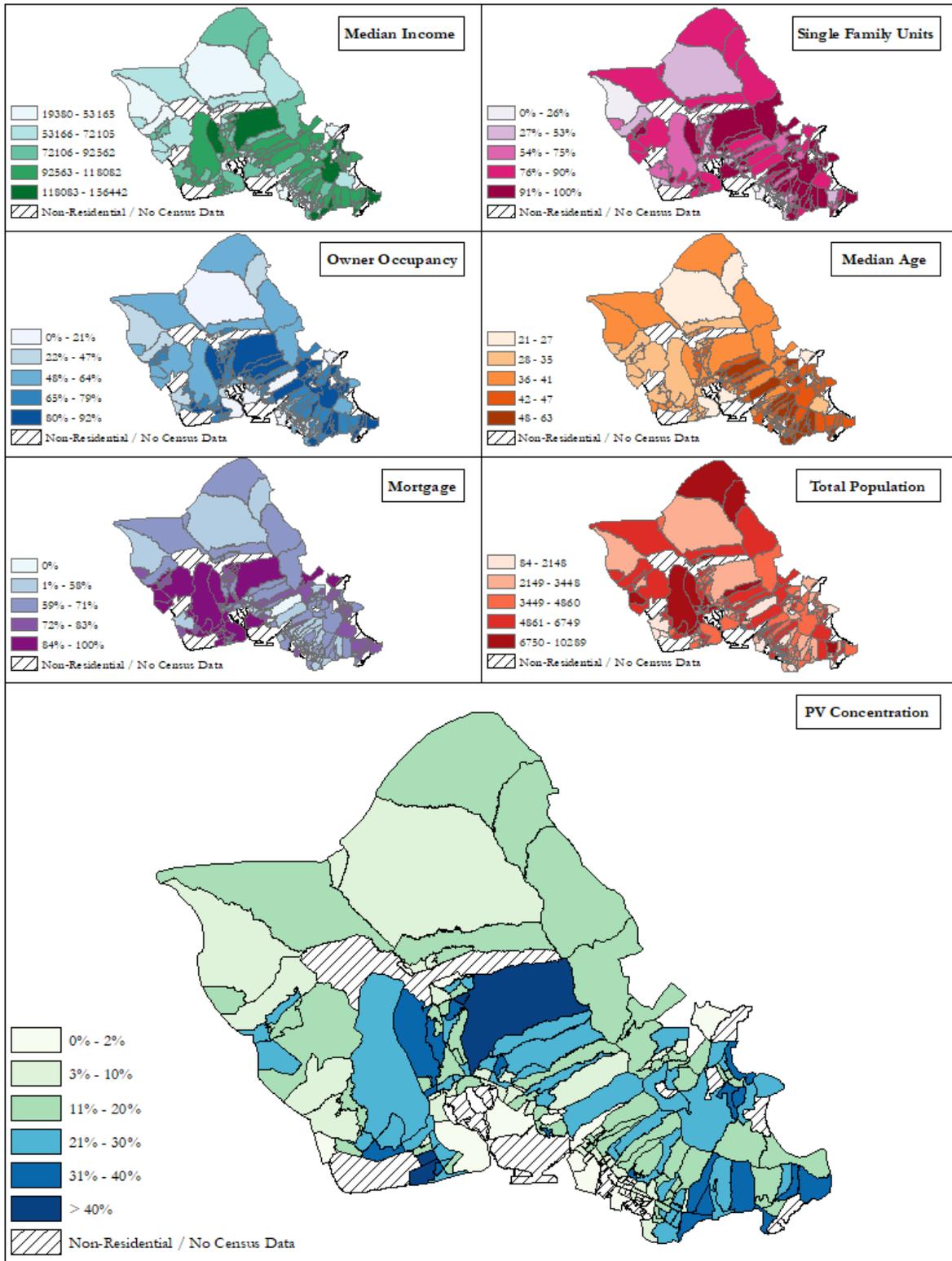
Variable	Description	Mean	Std. Dev.	Min	Max
PV concentration (%)	Share of occupied units with PV in month-year t in Census tract c (applies number of occupied units in 2010 to all observations)	0.06	0.08	0.00	0.59
Income (in \$10,000)	Median household income (in 10,000s) in Census tract c (2011-2015 estimate)	8.09	2.55	1.94	15.64
Owner-occupied (%)	Percent of owner-occupied units in Census tract c in 2010	0.59	0.22	0.00	0.92
Home mortgage (%)	Percent of owner-occupied units with a mortgage in Census tract c (2011-2015 rolling average)	0.66	0.16	0.00	1.00
Single-family (%)	Percent of single family units in Census tract c (2011-2015 estimate)	0.65	0.31	0.00	1.00
Median age (years)	Median age in Census tract c in 2010	40.12	6.76	20.90	62.60
Solar radiation (kW/m ²)	Average solar radiation weighted by block-group population (per 1,000) in Census tract c	0.67	0.05	0.51	0.83

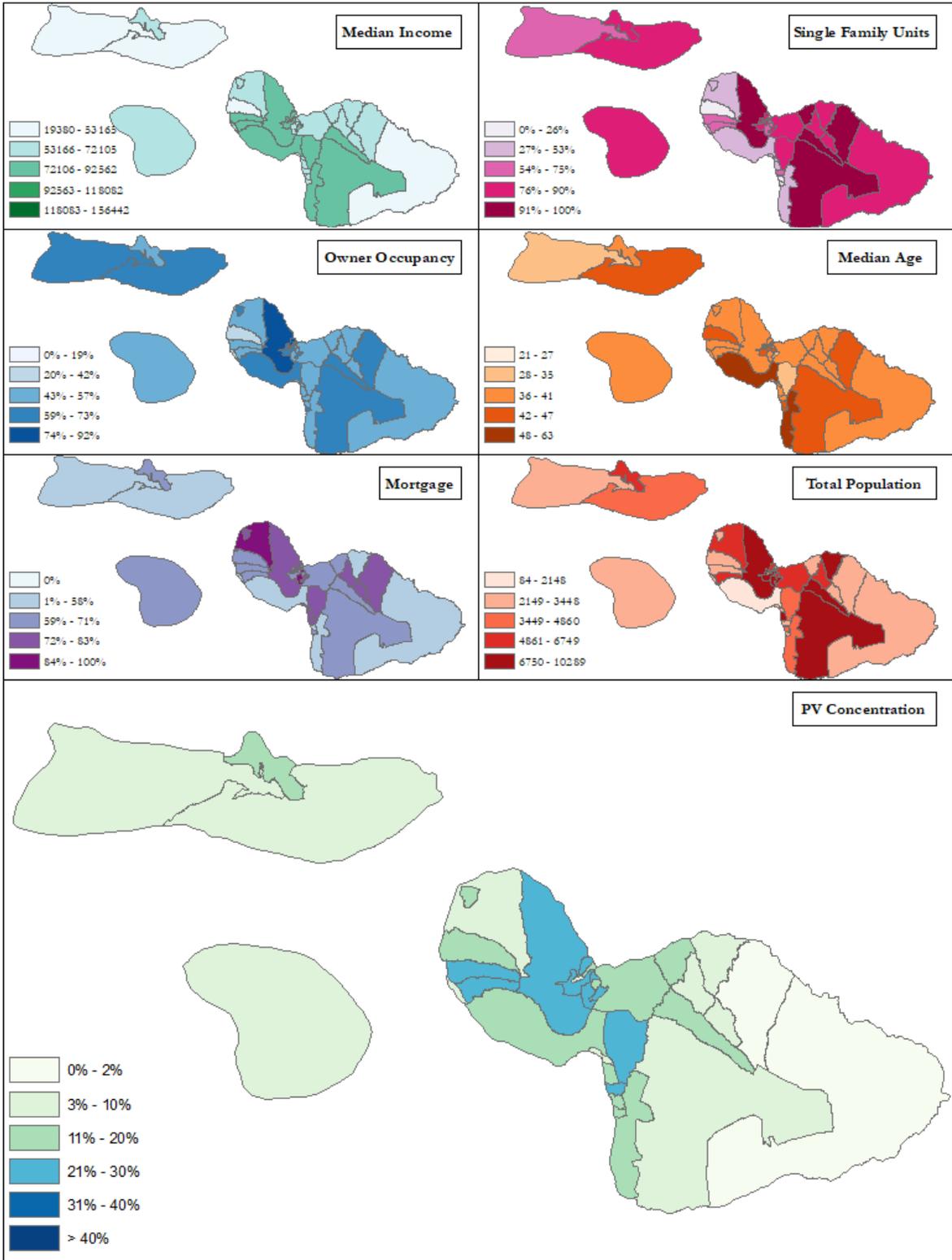
There is a total of 24,931 observations in the dataset and the first observation begins February 2008 (107 months multiplied by 233 census tracts with full demographic data, a total of 199 on Oahu and 34 on Maui). The average tract has 6% of residences with PV, though the upward outlier has almost 60%. Within the summary demographic data, the mean household income is \$81,000 and the average tract median age is 40 years. The average tract has 59% owner-occupied residences and, amongst

¹⁵ Though we know the monetary value of the permit that includes PV installation, we are unable to translate this into system size because other household construction is often included within the permit value. See footnote 6.

those, 66% have a mortgage. The average tract has 65% of its residences as single-family homes. Solar radiation, measured in kilowatts per square meter (kW/m^2), has relatively little variation across tracts. Figure 5 below graphically summarizes the demographic variables in relation to PV uptake. Though population is not used explicitly within the regression analysis, because our measure of PV concentration normalizes for population, it is shown in Figure 5 for context.

Figure 5. Oahu and Maui Demographic Data and PV Adoption by Tract





3. Results

We find all five demographic variables and solar resources to be statistically significant factors in explaining the variation in adoption of residential solar PV between census tracts. Table 2 reports selected regression results. The specifications begin by including all identified demographic variables¹⁶ and systematically drops variables that are likely resulting in multi-collinearity. Since “home mortgage” is really a sub-set of “owner-occupancy,” specification (2) drops “home mortgage.” Because of the high correlation coefficient between “owner-occupancy” and “single-family,” specification (3) additionally excludes “owner-occupancy.” Specification (4) restores “owner-occupancy” and “home mortgage” but excludes “single-family.” As overall robustness checks, specification (5) excludes “solar radiation” and specification (6) only includes “income” and “solar radiation.”

Table 2. Regression Results, Oahu and Maui
Dependent Variable: PV Concentration by Census Tract
Number of Observations: 24,931

	(1)	(2)	(3)	(4)	(5)	(6)
Income (\$10,000)	0.006*** [0.000]	0.006*** [0.000]	0.010*** [0.000]	0.007*** [0.000]	0.006*** [0.000]	0.014*** [0.000]
Owner-occupied (%)	0.100*** [0.003]	0.098*** [0.003]		0.121*** [0.003]	0.093*** [0.003]	
Home mortgage (%)	-0.003 [0.003]			-0.017*** [0.002]	-0.001 [0.003]	
Single-family (%)	0.027*** [0.001]	0.028*** [0.001]	0.046*** [0.001]		0.027*** [0.001]	
Median age (years)	-0.000*** [0.000]	-0.000*** [0.000]	0.000*** [0.000]	-0.001*** [0.000]	-0.000*** [0.000]	
Solar radiation (kW/m ²)	0.067*** [0.006]	0.067*** [0.006]	0.010* [0.006]	0.068*** [0.006]		-0.005 [0.006]
Adjusted R-squared	0.68	0.68	0.65	0.67	0.67	0.64

*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively. Robust standard errors are in brackets.

The demographic factors and solar radiation explain 64-68% of variation in PV adoption between census tracts. Specification (6) accounts for only differences in income and solar radiation between tracts and shows that an increase of \$10,000 in the median household income corresponds to a 1.4% increase in PV concentration within the tract. The estimate for adjusted R-squared is still relatively high, however, likely because much of the explanation for PV adoption is captured by the time trend (due to declining PV system costs relative to electricity prices). This will be further explored in

¹⁶ We have already omitted several demographic variables with extremely high correlations. In particular, educational attainment was initially considered but its high correlation to income is problematic within the results.

subsequent versions of this paper.¹⁷ It is also in this specification that the estimation of solar radiation is found to not be statistically significant. In all other specifications, (1) through (5), we find that solar radiation is positive and statistically significant. Specification (6) likely suffers from omitted variable bias, however, and it is likely that the estimated coefficients on specifications (1) through (4) are more accurate. This means that a \$10,000 increase in median household income is associated with a 0.6-1.0% increase in PV concentration. On the other hand, specification (1) includes several variables that are highly correlated, including with income. This specification suffers from multi-collinearity. Regardless of specification, income is found to be highly statistically significant.

The rate of owner-occupancy is found to be statistically significant at the 1% level throughout all specifications in which it is included. We find that a 1% increase in the rate of owner-occupancy within the tract is associated with a 9-12% increase in PV concentration. Though we view our findings regarding having a home mortgage with caution, because it is measured as owner-occupants with a home mortgage, we do find that it is small and negative throughout the specifications, though only statistically significant in (4).

Similar to owner-occupancy, we find that the rate of single-family homes within a tract is positive and statistically significant at the 1% level across specifications in which it is included. A 1% increase in single-family homes is associated with a 2-4% increase in PV concentration.

We find that the effect of median age is incredibly small. In all specifications other than (3) it is negative. When owner-occupancy and home mortgage are excluded, this is found to be extremely small and positive. This is likely explained because median age is most correlated with the rate of owner-occupancy (correlation coefficient of 0.43).

We run several different sensitivity tests. The first includes a county fixed effect. This would pick up time-varying differences between the two counties; for example, different electricity rates or other macroeconomic conditions that would affect PV uptake. The results did not meaningfully change from what is presented in Table 2. We also used a different dependent variable, where PV is measured as new PV systems installed in a tract in that month. Though the coefficients are now interpreted with respect to only new installations, versus cumulatively, the significance around household income, owner-occupancy and single-family homes remain similar. In addition, we run regressions for Oahu alone and provide these results in Appendix B. The results for Oahu alone are largely similar to those of the full sample. While we did run regressions for Maui alone, the small number of tracts, 34, make these results problematic.

¹⁷ To do this, we need to get better data on PV installation costs, as well as estimate ongoing relative cost-savings in electricity due to net energy metering or other grid or self-supply pricing policies which changed over this period.

4. Conclusions

This study estimates the effect of demographic variables on the adoption of residential solar PV systems on Oahu and Maui counties from 2008 to 2016, accounting for the variation in solar resources. We leverage the differences in demographic characteristics by tract to statistically estimate the relationship to varying levels of PV adoption by tract using monthly permit data on PV systems installed. We find that median income, the rate of owner-occupancy, the rate of home mortgages, the rate of single-family dwellings, and median age of the population are all statistically meaningful in explaining variation in PV uptake between tracts. In particular, the variables for income, owner-occupancy and single-family homes are positive and statistically significant across all relevant specifications. We find that a \$10,000 increase in a tract's median income is associated with an increase in the share of households with PV of 0.6-1.0%. Our estimated coefficients for owner-occupancy find that a 1% increase is associated with an increase in the share of households with PV of 9-12%. Though somewhat hard to compare, this is probably the largest impact on PV uptake within our set of variables. Single-family homes also matter, where the estimated coefficient shows that a 1% increase in the rate of single-family homes is associated with an increase in the share of households with PV of 2-4%.

The implications of these findings for policy largely rest in the consideration of distributive impacts of solar PV adoption due to historical preferential rate treatment under, for example, net energy metering (NEM), as well as the likely proliferation of distributed battery systems. The question of how to bring about the benefits of renewable energies to a broader set of residents, meaning lower income and non-owner-occupants, requires a more detailed analysis of rate-setting procedures and rate design. Borenstein (2015) argues that in an era of distributed energy technologies, any rate design that deviates from cost-based pricing will result in arbitrage of the price differences and what he calls "inefficient bypass" of utility services. The question of the magnitude of this issue, however, is yet unknown. Given that a substantial number of residential customers benefit from NEM and, by our analysis are likely to be higher income and owner-occupants, the question remains what benefits can accrue to individual households from further adoption of distributed energy resources. The current solution set to bringing in renters and underserved communities is community-based renewable energy programs. How these programs will broaden access to distributed energy resources and/or contribute to any cross-subsidization within rates, relative to utility-scale renewable energy projects, is an area of future research.

References

American Community Survey (2015a). Median Household Income in the Past 12 Months (in 2015 inflation-adjusted dollars). 2011 – 2015 American Community Survey 5-Year Estimates. B19013.

American Community Survey (2015b). Selected Housing Characteristics. 2011 – 2015 American Community Survey 5-Year Estimates. DP04.

Bollinger, B. and Gillingham, K (2012). Peer Effects in the Diffusion of Solar Photovoltaic Panels. *Marketing Science* 31(6), 900-912.

Borenstein, S. (2015). The Decline of Sloppy Electricity Rate Making. Available at: <https://energyathaas.wordpress.com/2015/08/24/the-decline-of-sloppy-electricity-rate-making/>

City and County of Honolulu (CCH). (2017). Building Permits. Accessed 15 February 2017. Available at: <https://data.honolulu.gov/Business/Building-Permits-January-1-2005-thru-December-31-2/ibbr-77pq/data#column-menu>

Coffman, M., Wee, S., Bonham, C., and Salim, G. (2016). A Policy Analysis on Hawaii's Solar Tax Incentive. *Renewable Energy* 85, 1036-1043.

Department of Business, Economic Development, and Tourism (DBEDT). (2014). Residential Photovoltaic Systems. Available at: <http://energy.hawaii.gov/wp-content/uploads/2011/12/City-and-County-of-Honolulu-Residential-Photovoltaic.pdf>

Department of Business, Economic Development, and Tourism (DBEDT). (2017). Solar PV Installations in Honolulu, an analysis based on building permit data, 2017 update. Available at: http://files.hawaii.gov/dbedt/economic/data_reports/Solar_PV_Installation_In_Honolulu_Sep2017.pdf

Department of Taxation (DOT). (2012). Temporary Administrative Rules Relating to the Renewable Energy Technologies Income Tax Credit (RETTTC). State of Hawaii. Available at: <http://files.hawaii.gov/tax/legal/tir/tir12-01.pdf>

Giambelluca, T.W., X. Shuai, M.L. Barnes, R.J. Alliss, R.J. Longman, T. Miura, Q. Chen, A.G. Frazier, R.G. Mudd, L. Cuo, and A.D. Businger. (2014). Evapotranspiration of Hawai'i. Final report submitted to the U.S. Army Corps of Engineers—Honolulu District, and the Commission on Water Resource Management, State of Hawai'i. Data available at: <http://solar.geography.hawaii.edu/>

Graziano, M., and Gillingham, K. (2015). Spatial patterns of solar photovoltaic system adoption: the influence of neighbors and the built environment. *Journal of Economic Geography* 15, 815-839.

Hawaiian Electric Companies (2012a). Quarterly Installed PV Data. Cumulative Installed PV-As of December 31, 2012. Available at: https://www.hawaiianelectric.com/Documents/clean_energy_hawaii/going_solar/pv_summary_4_Q_2012.pdf

Hawaiian Electric Companies. (2012b). Quarterly Installed PV Data. Cumulative Installed PV-As of September 30, 2012. Available at: https://www.hawaiianelectric.com/Documents/clean_energy_hawaii/going_solar/pv_summary_3_Q_2012.pdf

Hawaiian Electric Companies. (2015). Hawaiian Electric Companies continue to move ahead with rooftop PV. News Release. 25 February 2015. Available at: <https://www.hawaiianelectric.com/hawaiian-electric-companies-continue-to-move-ahead-with-rooftop-pv>

Hawaiian Electric Companies. (2017a) Quarterly Installed PV Data. Cumulative Installed PV - As of Dec 31, 2016. Available at: https://www.hawaiianelectric.com/Documents/clean_energy_hawaii/going_solar/pv_summary_4_Q_2016.pdf

Hawaiian Electric Companies. (2017b). 2016 Renewable Portfolio Standard Status Report. Docket No. 2007-0008. Available at: <https://puc.hawaii.gov/wp-content/uploads/2013/07/RPS-HECO-2016.pdf>

Kauai Island Electric Utility (KIUC). (2008 – 2016). Net Energy Metering (NEM) Annual Reports (Docket 2006-0084). Available at: <http://puc.hawaii.gov/reports/energy-reports/net-energy-metering-nem-annual-reports-electric-docket-2006-0084/>

Kauai Island Electric Utility (KIUC). (2017). Renewable Portfolio Standards (RPS) Status Report. Docket No. 2007-0008. Available at: <https://puc.hawaii.gov/wp-content/uploads/2013/07/RPS-KIUC-2016.pdf>

Maui Department of Public Works. (2017). Electrical Permit Extract. County of Maui. Accessed 15 February 2017. Available at: <http://www.co.maui.hi.us/1032/Download-Public-Information>

Public Utilities Commission. (2015). (PUC). (2015). Docket No. 2014-0192. Instituting a Proceeding to Mitigate Distributed Energy Resource Policies. Decision and Order No. 33258. Filed 12 October 2015. State of Hawaii.

Shallenberger, K. (2016). Growing pains: Hawaii solar sector howls as grid-supply incentives hit caps. 13 September 2016. Available at: <http://www.utilitydive.com/news/growing-pains-hawaii-solar-sector-howls-as-grid-supply-incentives-hit-caps/426149/>

State of Hawaii (2017). Hawaii Statewide GIS Program. Parcels – Hawaii Statewide. Available at: <http://geoportal.hawaii.gov/datasets/parcels-hawaii-statewide?geometry=-168.188%2C18.763%2C-148.885%2C22.363>

Trabish, H. (2016). 17% of Hawaiian Electric customers now have rooftop solar. 1 February 2016. Available at: <http://www.utilitydive.com/news/17-of-hawaiian-electric-customers-now-have-rooftop-solar/413014/>

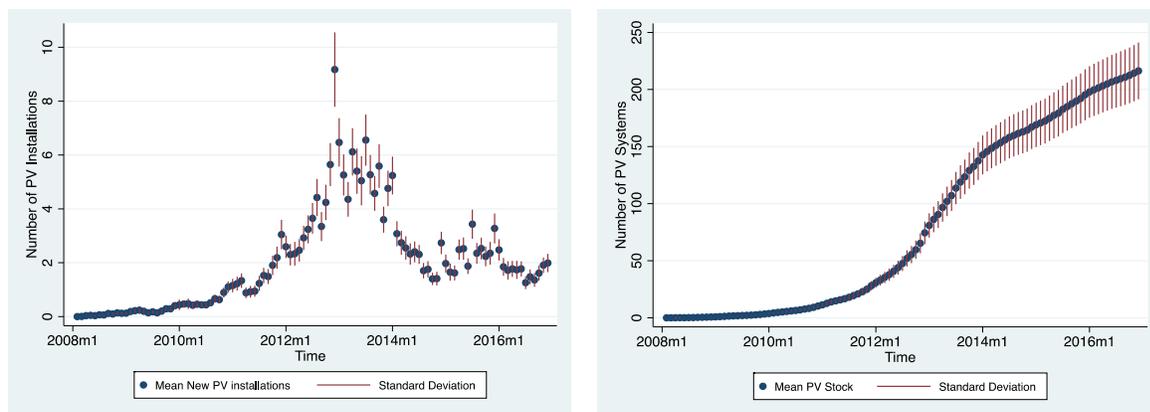
U.S. Census Bureau. (2010). Profile of General Population and Housing Characteristics: 2010. 2010 Demographic Profile Data. DP-1.

U.S. Energy Information Administration (EIA). (2017). EIA-923 Monthly Generation and Fuel Consumption Time Series File, 2016 Final Revision. Available at: <https://www.eia.gov/electricity/data/eia923/>

Appendix A. Detailed Summary Statistics

Figure A.1 and Table A.1. shows temporal PV installation and summary data for Oahu. The average number of new PV installations in a tract each month is shown on the left and the cumulative number of homes with PV by tract are shown on the right.

Figure A.1. Average New PV Installations per Month (left) and Average Number of Homes with PV (right) Per Tract for Oahu 2008 – 2016



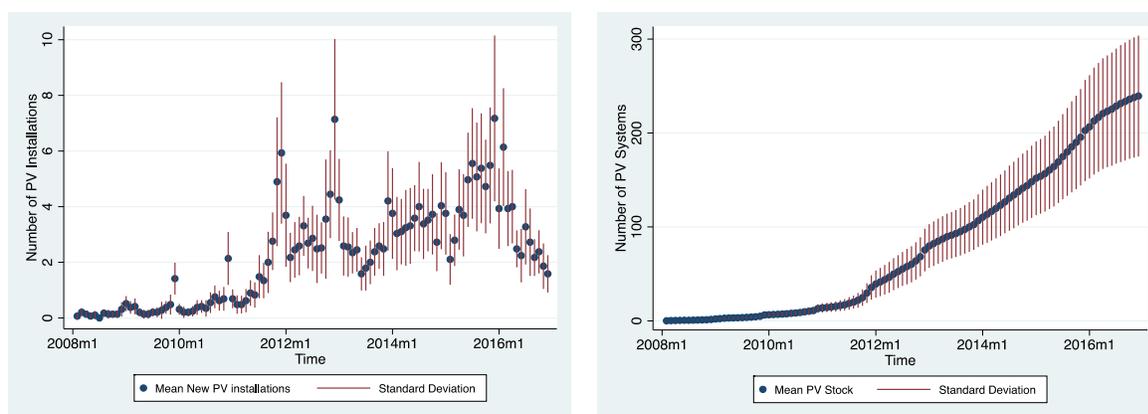
Source: CCH, 2017.

Table A.1. Summary Statistics for Oahu

Variable	Description	Mean	Std. Dev.	Min	Max
PV concentration (%)	Share of occupied units with PV in month-year t in Census tract c (applies number of occupied units in 2010 to all observations)	0.06	0.09	0.00	0.59
Income (in \$10,000)	Median household income (in 10,000s) in Census tract c (2011-2015 estimate)	8.36	2.60	1.94	15.64
Owner-occupied (%)	Percent of owner-occupied units in Census tract c in 2010	0.59	0.23	0.00	0.92
Home mortgage (%)	Percent of owner-occupied units with a mortgage in Census tract c (2011-2015 estimate)	0.66	0.17	0.00	1.00
Single-family (%)	Percent of single family units in Census tract c (2011-2015 estimate)	0.65	0.32	0.00	1.00
Median age (years)	Median age in Census tract c in 2010	40.11	7.09	20.90	62.60
Solar radiation (kW/m ²)	Average solar radiation weighted by block-group population (per 1,000) in Census tract c	0.67	0.05	0.51	0.77

Because Oahu has many more tracts than Maui, with a total of 21,293 observations, the mean summary statistics for Oahu are quite similar to that of the pooled sample. Stronger differences arise in looking at Maui alone, in Figure A.2 and Table A.2 below.

Figure A.2. Average New PV Installations per Month (left) and Average Number of Homes with PV (right) Per Tract for Maui 2008 – 2016



Source: Maui Department of Public Works, 2017.

Table A.2. Summary Statistics for Maui

Variable	Description	Mean	Std. Dev.	Min	Max
PV concentration (%)	Share of occupied units with PV in month-year t in Census tract c (applies number of occupied units in 2010 to all observations)	0.05	0.06	0.00	0.28
Income (in \$10,000)	Median household income (in 10,000s) in Census tract c (2011-2015 estimate)	6.56	1.42	3.95	9.26
Owner-occupied (%)	Percent of owner-occupied units in Census tract c in 2010	0.55	0.10	0.28	0.80
Home mortgage (%)	Percent of owner-occupied units with a mortgage in Census tract c (2011-2015 estimate)	0.66	0.11	0.39	0.85
Single-family (%)	Percent of single family units in Census tract c (2011-2015 estimate)	0.65	0.25	0.17	0.97
Median age (years)	Median age in Census tract c in 2010	40.16	4.30	33.30	53.00
Solar radiation (kW/m ²)	Average solar radiation weighted by block-group population (per 1,000) in Census tract c	0.70	0.07	0.53	0.83

The figures show that Oahu and Maui have had distinct patterns of PV adoption. Whereas Oahu had a greater spike in adoption in the 2012-2013 time period, followed by a decline in the rate of adoption, Maui's was more steady through 2016. In addition, Maui has greater variation in rates of PV adoptions across tracts.

Maui's dataset consists of a total of 3,638 observations. The average tract has 5% of residences with PV and a maximum of 28%. This is somewhat lower than Oahu at 6%. In addition, Maui's average tract has an annual median household income approximately \$17,900 lower than Oahu. Maui's average tract has a similar median age, at 40 years, as well as the rate of single-family residences (65%). The rate of owner-occupancy is slightly lower than Oahu, by 4%. There are overall slightly better solar resources on Maui, though there is also slightly more variation. This should be taken with caution because all resources are relatively high at the urban-zoned tract level.

Appendix B. Regression Results for Oahu

Table B.1. Regression Results, Oahu Only

Dependent Variable: PV Concentration by Census Tract

Number of Observations: 21,293

	(1)	(2)	(3)	(4)	(5)	(6)
Income (\$10,000)	0.004*** [0.000]	0.004*** [0.000]	0.009*** [0.000]	0.007*** [0.000]	0.005*** [0.000]	0.014*** [0.000]
Owner-occupied (%)	0.110*** [0.003]	0.107*** [0.003]		0.136*** [0.003]	0.096*** [0.003]	
Home mortgage (%)	-0.006** [0.003]			-0.027*** [0.003]	-0.004 [0.003]	
Single-family (%)	0.039*** [0.002]	0.040*** [0.001]	0.057*** [0.001]		0.038*** [0.002]	
Median age (years)	-0.000*** [0.000]	-0.000*** [0.000]	0.000*** [0.000]	-0.001*** [0.000]	-0.000*** [0.000]	
Solar radiation (kW/m ²)	0.115*** [0.007]	0.114*** [0.007]	0.021*** [0.007]	0.109*** [0.007]		-0.014** [0.007]
Adjusted R-squared	0.69	0.69	0.66	0.68	0.68	0.64

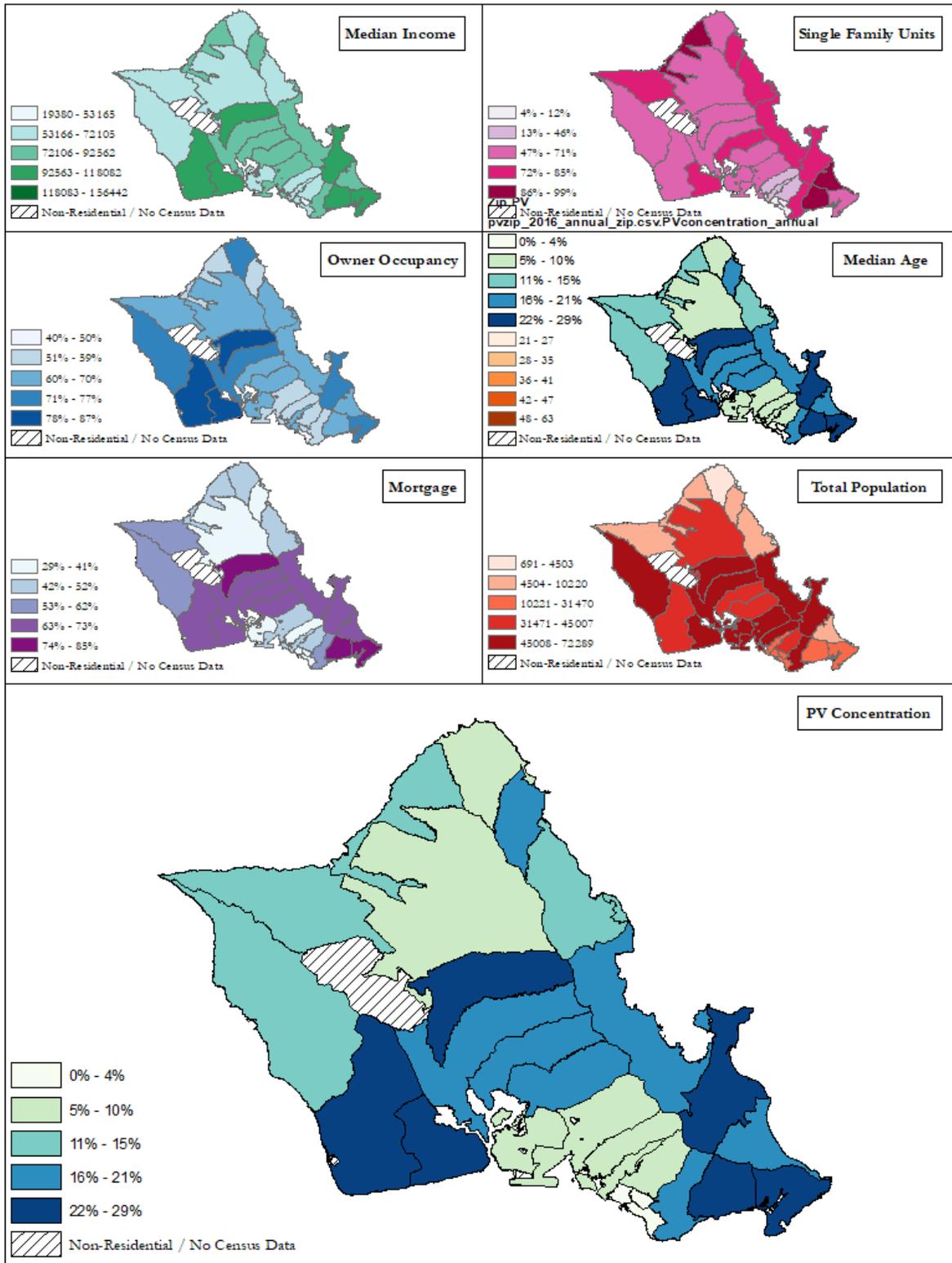
*, **, and *** indicate statistical significance at the 10%, 5%, and 1% level respectively. Robust standard errors are in brackets.

The results for Oahu alone are largely similar to those of the full sample.

Appendix C. Maps at the Zipcode Level

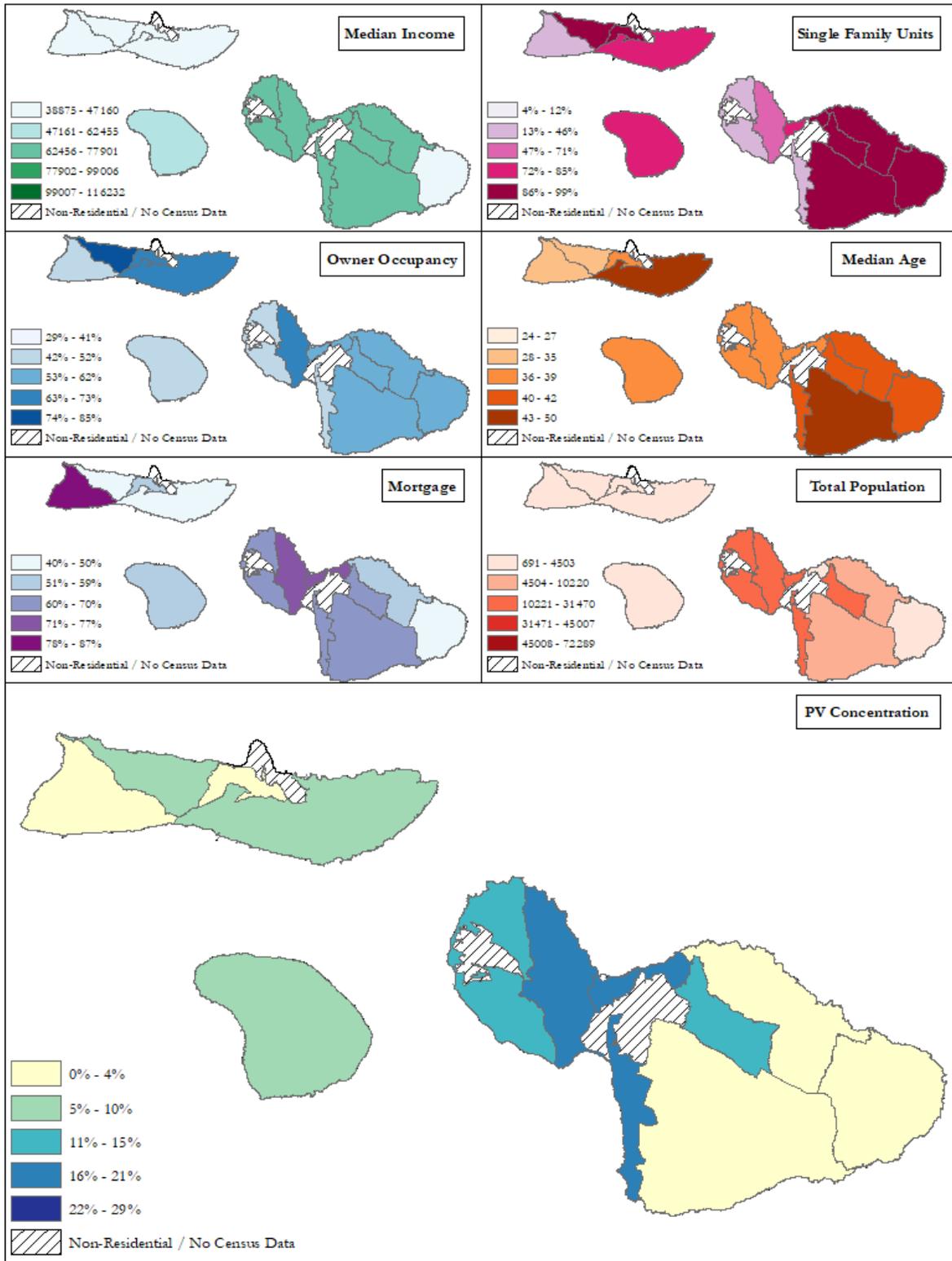
In general, there is greater familiarity with zipcode level data and visually we find this helpful because people can situate themselves within their own zipcodes. As such, Figures C.1 and C.2 below show demographic and PV concentration data at the zipcode level for Oahu and Maui County. Figures C.3 and C.4 zoom into median income and owner-occupancy, showing maps for Oahu and Maui County.

Figure C.1 Demographic and Solar PV Data at the Zipcode Level for Oahu



On Oahu, the zipcodes with the highest rates of PV uptake (21-29% of houses) are Hawaii Kai (96825), Kuliouou-Kalani Iki (96821), Kailua (96734), Ewa Beach (96706), Makakilo-Kapolei (96707) and Mililani (96789). These zipcodes all have a median household income above \$79,000 annually, and Hawaii Kai and Kuliouou-Kalani Iki are above \$100,000 annually. All zipcodes with high rates of PV adoption also have rates of owner-occupancy near or above the state average. Hawaii Kai, Kuliouou-Kalani Iki and Mililani have rates of owner occupancy that are substantially higher than the state average, at 74-85% of households living in homes they own. Ewa Beach, Makakilo-Kapolei and Mililani all have higher than average rates of having a home mortgage, between 78-87%. There is wider variation within these zipcodes regarding the rate of single family units and median age. For example, whereas Hawaii Kai and Ewa Beach have a rate of single family units between 47-71%, Kailua, Kuliouou-Kalani Iki and Kapolei's are between 72-85%.

Figure C.2 Demographic and Solar PV Data at the Zipcode Level for Maui



On Maui, the zipcodes with the highest rates of PV uptake (21-29%) are Kahului (96732) and Paia (96779). The zipcodes with the next highest levels of uptake (16-20%) include Lahaina-Kaanapali (96761), Wailuku (96793), and Kihei (96753). Both Kahului and Paia have rates of owner-occupancy slightly below (or at) the state average, between 53-62%. Only Wailuku has a rate of owner-occupancy higher than the state average. In addition, Kahului, Paia and Wailuku have the highest on-island rates of having a home mortgage between 71-77%. Median income by tract has less variation on Maui than Oahu, with all zipcodes with high PV concentration between \$63-\$78,000 annually. There is similarly less variation in the rates of single family units, as most zipcodes are between 86-99%. Wailuku and Lahaina-Kaanapali have proportionately more multi-family units, and these are also larger population centers. The median age of zipcodes with high PV concentration is between 35 and 39.

Figure C.3 Median Income and Total PV Systems for Oahu and Maui Counties

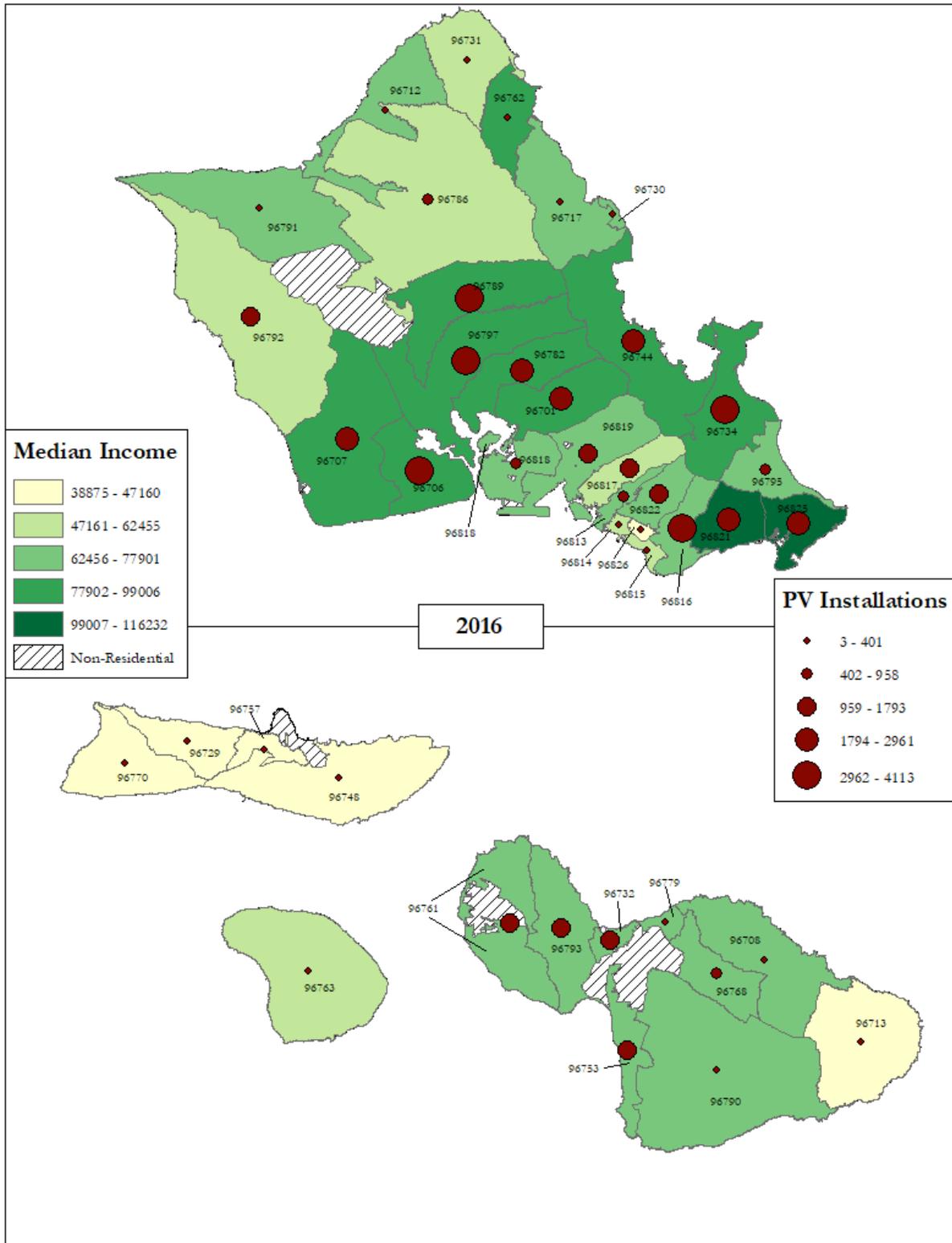


Figure C.4 Owner-Occupancy and Total PV Systems for Oahu and Maui Counties

