Australian National University

Crawford School of Public Policy

Centre for Climate & Energy Policy

Solar PV and energy poverty in Australia's residential sector

CCEP Working Paper 2203
May 2022

Mara Hammerle
Crawford School of Public Policy, Australian National University

Paul J. Burke
Crawford School of Public Policy, Australian National University

Abstract

Expanding access to solar photovoltaics (PV) may help to reduce the incidence of energy poverty. Yet little is known about the strength and magnitude of this relationship. This paper uses cross-sectional survey data from the Australian Bureau of Statistics to conduct a retrospective analysis of the effects of having rooftop solar PV for Australian households. As the main identification challenges are the potential for omitted variables and reverse causality, we present results for regressions controlling for potential confounders and also use an instrumental variable approach. The study finds that having solar PV is associated with a large decrease in the likelihood of experiencing energy poverty based on objective indicators that compare household incomes and energy bills. Having solar PV is also associated with a reduction in self-reported difficulty in paying bills on time, although this effect is less robust across estimations. The findings could inform future policies for promoting residential solar PV through an improved understanding of likely impacts.

Keywords:
energy expenditures; energy justice; energy poverty; households; solar PV.

JEL Classification:
D10, I32, I30, Q40

Acknowledgements:
We acknowledge the helpful feedback from two anonymous reviewers, Lee White, and Rohan Best as well as comments from presentations at the Australian National University and the 1st IAEE Online Conference 2021. This work was supported by an Australian Government Research Training Program (RTP) Scholarship and funding from the Australian-German Energy Transition Hub. Funding sources had no other involvement in the study.

Suggested Citation:
Hammerle, M. and Burke, PJ. (2022), Solar PV and energy poverty in Australia's residential sector, CCEP Working Paper 2203, May 2022. Crawford School of Public Policy, The Australian National University.

Address for Correspondence:
Mara Hammerle
PhD Candidate,
Crawford School of Public Policy,
Australian National University,
Email: mara.hammerle@anu.edu.au.

Solar PV and energy poverty in Australia's residential sector

Mara Hammerle* Paul J. Burke

Australian National University

May 2022

Abstract

Expanding access to solar photovoltaics (PV) may help to reduce the incidence of energy poverty. Yet little is known about the strength and magnitude of this relationship. This paper uses cross-sectional survey data from the Australian Bureau of Statistics to conduct a retrospective analysis of the effects of having rooftop solar PV for Australian households. As the main identification challenges are the potential for omitted variables and reverse causality, we present results for regressions controlling for potential confounders and also use an instrumental variable approach. The study finds that having solar PV is associated with a large decrease in the likelihood of experiencing energy poverty based on objective indicators that compare household incomes and energy bills. Having solar PV is also associated with a reduction in self-reported difficulty in paying bills on time, although this effect is less robust across estimations. The findings could inform future policies for promoting residential solar PV through an improved understanding of likely impacts.

Key words: energy expenditures; energy justice; energy poverty; households; solar PV.
JEL classifications: D10, I32, I30, Q40

Corresponding author. Crawford School of Public Policy, Australian National University, ACT, 2601, Australia. Email: mara.hammerle@anu.edu.au.

1 Introduction

Policymakers around the world are increasingly focusing on addressing energy poverty given its links to outcomes such as physical and mental health risks (Howden-Chapman et al., 2012; Liddell and Morris, 2010). Energy-poor households are more likely to face social isolation, use health services more frequently, and have higher rates of depression and asthma (Thomson and Snell, 2013). Broadly, a household is said to experience energy poverty when it is unable to maintain a minimum level of domestic energy services to meet biological and social requirements (Bouzarovski and Petrova, 2015). While the term "fuel poverty" is similar, this paper uses the term "energy poverty" because it is more common outside Western Europe and is a broader term, encompassing other energy forms besides fuels.

While energy poverty is a particularly important challenge in developing countries (Nussbaumer, Bazilian and Modi, 2012), some residents in developed countries such as Australia are also energy poor in some key dimensions. Efforts to address energy poverty in developed countries often concentrate on improving the energy efficiency of dwellings, for example by installing more energy-efficient heating equipment or insulation (Sovacool, 2015). Higher levels of energy efficiency decrease the marginal cost of energy services. This can help to place downward pressure on energy bills and also enable higher consumption of energy services such as heating and cooling (Best and Burke, 2019; Hammerle and Burke, 2022; Sovacool, 2015).

Similarly, rooftop solar PV may have an important effect in reducing energy poverty. Solar households are able to reduce their purchases of electricity from the grid and boost their overall electricity consumption (Best and Sinha, 2021; Rodríguez et al., 2018; Judson and Zirakbash, 2022; Scheier and Kittner, 2022). Some households also receive feed-in tariffs for their solar exports. The opportunity provided by residential solar PV is particularly relevant in sunny countries, such as Australia. However, differences remain in the uptake of different household groups, driven by barriers such as landlord-tenant information asymmetries, credit constraints, and imperfect information (Best, Burke, and Nishitateno, 2021). Households with high levels of wealth, who are homeowners, and who live in either semi- or fully-detached houses are among those with the highest rates of rooftop solar access (Best, Burke, and Nishitateno, 2019; Zander, 2020). Solar PV is often less accessible to less well-off households.

In response, governments around Australia have introduced policies to support specific groups of households to access solar PV. However, little is known about the extent to which the technology is associated with reductions in energy poverty. Past studies have typically treated solar PV as one of many determinants of energy poverty and have not conducted a comprehensive assessment of impacts (Best and Burke, 2019; Best and Sinha, 2021). Relevant research would enable policymakers who aim to address energy poverty to better understand their options.

Existing literature typically finds no consistently significant impact of binary measures of having solar PV on subjective indicators of energy poverty (Best and Burke, 2019; Best and Sinha, 2021). Subjective indicators are based on asking respondents to personally assess their own situations. A natural next step is to further consider objective indicators of energy poverty, which often compare energy expenditures against household incomes. Additionally, using the size of a household's solar PV system in kilowatts rather than binary measures of access will enable a more detailed understanding of any impacts, including potentially diminishing marginal returns.

This paper conducts a retrospective analysis of the impacts of solar PV on energy expenditures and energy poverty in Australia. The main research question is: are Australian households with solar PV less likely to experience energy poverty? To answer this question we use cross-sectional household-level survey data from the combined Australian Bureau of Statistics (ABS) 2015-16 Household Expenditure Survey and Survey of Income and Housing. Our study focuses on rooftop solar PV and does not consider solar thermal technologies.

To the best of our knowledge, this is the first study to seek to assess the impacts of solar PV on energy poverty using household survey data and rigorous econometric methods.

Three indicators of energy poverty are used: two objective and one subjective. Additionally, the study uses two measures of household access to solar PV: the size of a household's solar PV system and the expected daily solar PV output from the system. We present results of regressions that control for a range of potential confounders and also use an instrumental variable (IV) approach. Specifically, we instrument a household's solar PV capacity with the average capacity of similar households in a household's state or territory who do not live in their same local area. A measure of household net wealth is controlled for in all estimations.

The next section provides background on the adoption of solar PV in Australia and the determinants of energy poverty. We then present the methods, followed by the results. The paper concludes by exploring possible implications of the results for policies that expand access to residential solar PV in Australia.

2 Background

2.1 Solar PV in Australia

Australia is one of the global forerunners in the uptake of rooftop solar PV. In June 2021, around 30 percent of suitable Australian dwellings used the technology (Australian Photovoltaic Institute, 2021b).[1] Solar PV has also become a key source of electricity for some off-grid communities in regional and remote areas, including Indigenous communities. A 2016 survey of Northern Territory homelands and outstations found that 40 percent had a solar PV system, the majority of which were diesel hybrids (Martire, 2020).

Various government incentive programs have been set up to help promote the uptake of solar PV in Australia. The federal government's Small-Scale Renewable Energy Scheme (SRES) provides an upfront subsidy that is higher for postcodes with greater solar exposure (Australian Government, 2022). More recently, a policy in the state of Victoria provides

[1] This figure uses data from the Australian Bureau of Statistics on the number of freestanding and semi-detached dwellings in each postcode.

financial support to install solar PV to households who have a combined gross household income of less than A$180,000 per year (Solar Victoria, 2021), while the Australian Capital Territory has implemented a policy to support low-income households to install solar panels on their rooftops (ACT Government, 2019).[2] There have also been programs to increase solar PV uptake in remote Indigenous communities. For example, the federal government's Remote Australia Strategies Program funded the program "Bushlight" to install stand-alone systems between 2002 and 2013 (Martire, 2020).

Among other factors, the theoretical relationship between solar PV and energy poverty depends on the type of metering used for solar systems. In Australia, there are two types of metering that have been used for systems connected to electricity grids. With net metering, only excess electricity that a household does not use themselves is fed onto the electricity grid. Households also only purchase residual electricity from the grid. In contrast, gross meters are set up so that all electricity produced by the system is exported to the grid. Households with gross meters receive larger feed-in tariff revenues but pay to consume more electricity from the grid than households on net meters, all else equal.

The impact of rooftop solar PV and energy poverty also depends on who pays for the system. The purchase of a solar PV system brings energy costs forward in time, as the purchaser incurs a large upfront capital cost. For vulnerable households, paying for solar panels may consequently even exacerbate energy poverty in the short term. If the system were instead paid for by an external agency, such as the government (and funded by taxes on high-income earners, for example), the benefits for vulnerable households would be expected to be larger.

The dataset does not enable us to identify how a household's solar PV system was financed. However, depending on the location of the household, the SRES subsidy covered approximately 35 to 48 percent of the average 3 kW solar PV system cost of A$5,347 in 2015

[2] A$1 is approximately equal to US$0.70, so A$180,000 is around US$126,000.

(Solar Choice, 2015).[3] The installation of a system leads to the generation of small-scale technology certificates, which form the basis of the subsidy. Large purchasers of wholesale electricity, including electricity retailers, are legally required to buy these certificates and can pass the costs onto customers.

2.2 Solutions to energy poverty

Research on the causes of energy poverty in developed countries often refers to three factors: (1) low incomes; (2) high energy prices; and (3) insufficient energy efficiency (Boardman, 2013; Churchill and Smyth, 2020). Low levels of income or wealth do not fully explain the prevalence of energy poverty by themselves (Hills, 2011). High energy prices are particularly problematic for households with low incomes and/or high energy needs, resulting from factors such as climate and whether dwellings are energy efficient (Bouzarovski and Herrero, 2017; Churchill and Smyth, 2020). Households can face different prices within and across regions for reasons including that they use different combinations of energy types including electricity and natural gas and are customers of different energy retailers. Other important factors for energy poverty include access to energy grids and levels of energy needs, for example whether household members rely on electrical medical equipment. In Australia, 2 percent of the population lives in remote or regional areas that are off-grid and thus need to rely on distributed energy solutions (ARENA, 2021).

Low energy efficiency due to factors such as inadequate insulation is often highly influential in whether a household experiences energy poverty in developed countries (Best and Burke, 2019; Best and Sinha, 2021; Mohr, 2018; Sovacool, 2015; Walker and Day, 2012). Other energy efficiency measures – such as double glazing of windows – may also help to reduce the likelihood that households are energy poor (Legendre and Ricci, 2015). However, some households may remain in energy poverty even after large improvements to the energy

[3]This calculation is a multiplication of the size of the system, the period of time during which SRES certificates can be created, a variable certificate price of A$35 (close to the maximum of A$40), and a subsidy factor that varies across postcodes (Australian Government, 2022).

efficiency of their dwellings if for example they have low incomes or difficulties accessing affordable energy (Walker et al., 2014).

Helping vulnerable households to install solar PV is increasingly viewed as an important way to reduce energy poverty. In communities around the world, solar PV plays a crucial role in improving livelihoods and supporting economic growth and social development (Pagliaro and Meneguzzo, 2020). For households who live in remote communities without access to established power grids, the use of solar PV systems can support basic electrification cheaply, reliably, and quickly, while being more environmentally sustainable than other solutions such as diesel generators (Stojanovski, Thurber and Wolak, 2017; Urmee and Md, 2016). In developing countries, the use of solar PV systems can reduce the use of kerosene, increase the tendency to charge mobile phones at home, and help to transition households to using modern electric lights as their main source of lighting (Stojanovski et al., 2017).

The magnitude of the impact of installing solar PV on a household's propensity to experience energy poverty is not yet clear. While a study by Obeng et al. (2008) found that 80 percent of non-electrified households in Ghana are energy poor compared with only 10 percent of solar households, whether there were causal effects of having solar panels is not known. To understand how installing solar PV can reduce energy poverty, studies have conducted simulations of the solar potential in disadvantaged areas of Scotland (Andreadis et al., 2013) and Spain (Rodríguez et al., 2018). Others have relied on qualitative analyses based on focus groups and interviews to understand the barriers and enablers of extending decentralised solar PV to vulnerable households in India (Yadav et al., 2019) and experiences with solar PV among South Korean social housing residents (Lee and Shepley, 2020). Pitt and Nolden (2020) identified business models to extend access to solar PV to disadvantaged households. In general, studies stress the importance of solar PV in addressing inequities but do not accurately quantify impacts.

3 Data

This paper uses detailed microdata from the 2015-16 Household Expenditure Survey (HES) and Survey of Income and Housing (SIH) of the Australian Bureau of Statistics (Australian Bureau of Statistics, 2017). The HES and SIH are cross-sectional household surveys and ask respondents questions on their household and personal characteristics, housing attributes, income, and net wealth. In the HES, respondents also complete questions about household expenditures and financial stress. Since 2003-2004, the SIH has been conducted every two years, and the HES every six years. In every sixth year, some households are asked to complete questions for the SIH only. Others answer questions for the HES after they complete the SIH, meaning that the same response ID connects their answers. We use the responses from this second group of households.

The surveys collect information from the usual residents of private dwellings in urban and rural areas of Australia. Usual residents are those who view the dwelling as their own or main home. The population from which a sample is drawn represents about 97 percent of Australian residents, as very remote areas are excluded. Some energy poor households are thus excluded from the analysis, especially given that energy poverty is more severe in remote areas. The dwellings of the households are selected from the private dwelling framework of the ABS Population Survey Master Sample. With the aim of ensuring that income and expenditure patterns are representative across the year, the ABS selects dwellings over a twelve-month enumeration period. Each household is surveyed once at some stage over this time period.

In 2015-2016, 15,294 households were contacted and in the scope of both surveys. 66 percent of these households were included in the final dataset, with 99 percent of those who were not included either not responding or responding inadequately (Australian Bureau of Statistics, 2017). In total, 10,046 households completed both surveys, with households selected based on a stratified multistage cluster design.

The sample used in this paper includes both households who do not have solar PV and solar households who provided information on the size of their solar PV system (measured in kilowatts). To understand whether households have solar PV, the SIH asks: "Thinking about solar energy, does this [dwelling] have solar panels to generate electricity?" The sample size is 9,900 households, of whom 84 percent did not have solar PV. Around 150 households were excluded as they reported having solar PV but did not report the size of their system. A full list of variables and descriptive statistics is provided in Table A.1. of the Appendix.

There are two reasons for using data from both the HES and SIH. First, the analysis requires information on both energy expenditures and solar PV. The HES collects information about household energy expenditures (excluding gasoline and diesel expenditures for transport), while the SIH enables examination of whether households have solar PV. Second, these surveys are the most recent national Australian datasets to combine these variables for the same households.

Two datasets from the Australian Government's Bureau of Meteorology are also used. The first is monthly data on solar exposure over July 2015–June 2016 (Bureau of Meteorology, 2020), measured as the total amount of solar energy per day in megajoules per square meter that falls on a horizontal surface. The second is annual data on the numbers of heating and cooling degree days, otherwise called HDDs and CDDs, during 1 July 2015–30 June 2016. The Bureau of Meteorology calculates HDDs and CDDs based on deviations from the "average" daily temperature, with this average proxied by the sum of the maximum and minimum daily temperatures for a day divided by two. As recommended by the World Health Organization (Ormandy and Ezratty, 2012), we use a base of 24 degrees Celsius for CDDs and 18 degrees Celsius for HDDs. For example if the average daily temperature in a region is 30 degrees, the cooling equivalent is 6 degrees (6 CDDs).

We use Geographical Information Systems (GIS) to match the weather variables to households. GIS zonal statistics are used to estimate solar exposure at the postal area level.[4] Each

[4]The ABS releases data at the postal area level rather than the postcode level. Postcodes do not exist for some areas and postcode boundaries can be defined differently by different agencies.

postal area is assigned the average value for solar exposure of the 100m^2 areas contained within their boundaries. For the CDDs and HDDs variables, we assign the values measured at the closest weather station to each household in a postal area.

4 Methods

Let E_h represent the energy expenditure of household h or alternatively if household h experiences energy poverty. The energy expenditure variable is continuous, whereas the energy poverty indicators are binary variables. E_h can be modelled as the following general function:

$$E_h = \beta_0 + \beta_1 S_h + X_h \beta + \varepsilon_h \tag{1}$$

Where S_h equals the number of kilowatts of a household's solar PV system; X_h is a vector of covariates that may cause E_h to vary; and ε_h is a random error term. For the main regressions, we use ordinary least squares for the energy expenditure outcome variable and logit models for the (binary) energy poverty indicator variables. To check for diminishing returns to solar PV, a squared solar PV system size variable is also included in some subsequent regressions.

We used Stata MP v. 16.1 in the secure ABS environment DataLab to estimate the models. Linear IV two-stage least squares (2SLS) was used for the IV regressions. We ran the command "margins, dydx(*)" to obtain the average marginal effects of variables in the logit model. Stata estimates marginal effects for each survey respondent by using the values of their individual characteristics, and then takes the average of those effects. We did not include the additional "at means" option given that the averages of the categorical explanatory variables are not meaningful values. The average marginal effect for a binary variable is the expected difference in the outcome variable when the value of the binary variable changes from 0 to 1.

4.1 Outcome variables

4.1.1 Weekly energy expenditures

HES survey respondents were asked to indicate the dollar amount of their most recent payment for various types of residential energy and the period of time that the payment covered. The energy types are electricity, mains gas, LPG gas, oil for heating, and firewood. The ABS then converts the payment to an average weekly energy expenditures measure. For solar households, the Australian Bureau of Statistics deducts the value of feed-in tariffs (FiTs) from gross electricity expenditures to get net expenditures (which can be negative). FiTs are per-kWh payments to compensate households for exporting solar electricity to the grid.

Energy expenditures vary substantially over a year and across the country, for reasons including differences in energy prices as well as in needs for cooling and heating. Although the ABS sampled households across the 2015-16 Australian financial year, most were surveyed in the fourth quarter of 2015 and the smallest share was surveyed in the first quarter of 2016. This implies that energy expenditure patterns may be over-represented for some parts of the year. We partially correct for seasonality by including quarter-by-state binary variables that interact the household's state or territory with the quarter of the year during which each household was surveyed. The inclusion of these variables also helps to control for variation in policies for solar PV, which is primarily at the state level.

4.1.2 Energy poverty indicators

This study analyses two objective indicators and one subjective indicator of energy poverty. There are two main reasons for doing so. First, both types of indicator have limitations. The objective energy poverty indicators are based on work in the United Kingdom and potentially have less applicability in regions with different climates and energy requirements (Castaño-Rosa et al., 2019). Subjective indicators may better reflect the lived experiences of households

(Meyer et al., 2018), but are prone to social desirability bias as people may respond to survey questions in a way that avoids the perceived stigma associated with admitting to being energy poor (Chard and Walker, 2016; Middlemiss and Gillard, 2015). Second, objective and subjective energy poverty indicators do not always identify the same households as being energy poor (Middlemiss and Gillard, 2015; Price et al., 2012). The lack of a unique energy poverty line has led to the development of many relevant metrics (Culver, 2017).[5]

The objective energy poverty indicators couple information from the HES on energy expenditures with information from the SIH on income. The SIH asks about the dollar values of different types of receipts received by members of the household, such as employee income, profits and losses from own unincorporated businesses, and government pensions and allowances. Questions are also asked about the length of time that the payment covered. Subsequently, the ABS converts income to a per-week average measure. The variable does not however include feed-in tariff payments. As noted, these are instead deducted out of energy expenditures.

Our first energy poverty indicator is the "Low Income High Costs" (LIHC) indicator developed by Hills (2012). For this, two conditions are used to classify households as energy poor. First, households must have "required" energy costs above the median level. Hills (2012) measured "required" energy costs based on modelling of a household's energy requirements given their household characteristics and the characteristics of their dwellings and geographical areas. As the ABS datasets do not provide sufficient information to do this, we follow the common approach of using actual energy expenditures. Second, there is a requirement that energy-poor households have a residual equivalised income after energy expenditures that is below the official poverty line. Residual income is defined as disposable income net of housing costs. Disposable income is all current receipts received by members of the household minus income tax and levies to fund the healthcare system.

[5] Provided in Table B.1. of the Appendix, the correlations between the objective and subjective indicators do not exceed 0.16.

According to Hills (2012), energy-poor households are those for whom the following two conditions hold:

$$\left(\frac{energy\, expenditures}{LIHC\, factor}\right)_h > median\left(\frac{energy\, expenditures}{LIHC\, factor}\right)_{\forall\, h \in H} \tag{2}$$

and

$$\begin{aligned} &\left(\frac{disposable\, income - housing\, costs}{OECD\, factor}\right)_h - \left(\frac{energy\, expenditures}{LIHC\, factor}\right)_h \\ &< 60\, percent\, of\, median\left(\frac{disposable\, income - housing\, costs}{OECD\, factor}\right)_{\forall\, h \in H} \end{aligned} \tag{3}$$

There are two types of equivalising factors in the above equations. The "LIHC factor" in equations (2) and (3) is based on the work of Hills (2012). Due to differences in the degrees of economies of scale, Hills (2012) argues that the same equivalising factors should not be used to compare incomes and energy consumption between households. The factors for energy expenditure should arguably exhibit less variation, as people living in the same household can benefit from the same energy service – for example by sharing a heated room (Hills, 2012). The "OECD factor" in equation (3) refers to the modified OECD equivalence scale and is used to equivalise household incomes. The scale was designed to enable comparisons of households of different sizes and with members of different ages. For this scale, the first adult in each household is assigned a value of 1.0, each subsequent adult receives 0.5, and each dependent child (under 15 years of age) receives 0.3. Table B.2. of the Appendix compares the LIHC factors with the modified OECD equivalence scale.

As a second energy poverty indicator we use the widely-applied "Ten Percent Rule" (TPR), which classes a household as experiencing energy poverty if it must pay more than ten percent of its income to acquire a necessary level of energy services (Boardman, 1991). Our application of the TPR adjusts (actual) energy expenditures and disposable incomes using the LIHC factors and OECD factors, respectively. Households are counted as energy poor if the below condition applies:

$$\left(\frac{energy\ expenditures / LIHC\ factor}{disposable\ income / OECD factor} \right)_h > 10\, percent \tag{4}$$

We also count households who have disposable (net) incomes less than or equal to AUS$0 and positive energy expenditures as being energy poor according to the TPR.

The subjective indicator that we use refers to whether a household faces financial difficulties preventing them from paying utility bills on time. The HES asked respondents "Over the past year, have any of the following happened to you/your household because of a shortage of money?" We focus on the option "Could not pay electricity, gas or telephone bills on time." The responses are coded as either "yes" or "no". Although telephone bills are not an energy expenditure, energy costs tend to be a greater concern for many Australian households as some low-cost mobile phone plans are available. The indicator is relevant for this study as one of the key reasons for households to install solar PV is to reduce their energy bills. The HES did not ask a similar question focused only on energy bills.

While our study applies some of the most commonly used indicators to measure energy poverty, the concept is multifaceted and our indicators do not capture all aspects. For example, research in developing countries often focuses on whether households have access to basic energy services such as cooking and lighting, based on Sen's capability approach (Nussbaumer et al., 2013; Pelz, Pachauri, and Groh, 2018). Recent work in Australia has also highlighted that disconnection rates from the electricity grid are an important dimension of energy insecurity (Longden et al., 2022).

Most Australian households do not experience energy poverty, consistent with high living standards on average. As per the ABS surveys. around 12.5 percent and 13.1 percent of all households experienced energy poverty based on the LIHC and TPR indicators in 2015-16, respectively. Figure 1 indicates that households with solar PV are among those less likely to experience energy poverty. However the effects of solar PV on energy poverty are likely to be smaller than the unconditional associations in Figure 1 given other relevant differences between solar and non-solar households such as income and wealth levels.

[Insert Figure 1: Households experiencing energy poverty, by solar PV status]

4.2 Treatment variables

For the main analysis, the treatment variable is the size of a household's solar PV system in kilowatts. Figure 2 shows a histogram of the solar PV system sizes for households with solar PV. The figure uses bins of 2 kW to align with ABS privacy requirements for sample size. In 2015, the Australian residential sector consumed 59,273 GWh of electricity (International Energy Agency, 2022). After dividing by the number of households in Australia in 2015-16, the average household consumed about 6,600 kWh of electricity per annum. This compares to an average capacity for the solar households in Figure 2 of 3.21 kW and a standard deviation of 1.46 kW. Using the minimum and maximum values of average daily production of solar PV systems listed in Table B.3 of the Appendix, this translates into approximately 4,000–6,000 kWh of solar generation per solar household per year, depending on location.

[Insert Figure 2: Histogram of solar PV capacities for solar households in estimation sample]

As a second treatment variable we use the daily expected solar PV output from a system. This is calculated by multiplying the capacity of each solar household's system with the average output per kW per day in the closest city in Table B.3 of the Appendix. The latter is based on the simple average of values reported in 2012 and 2020 by the Clean Energy Council (2012; 2020). The values are based on real-world rather than lab conditions. We use GIS to match the postal areas of each household with the closest city. The unit of the expected output is kWh per day (system size in kW multiplied by an output factor in kWh per kW per day). The average value of the variable for the households with solar in the study is 13.56 kWh per day. Although tools exist to estimate expected output at a more disaggregated geographical level, full accuracy would rely on detailed features of each solar

PV system such as the degree of rooftop shading and the quality of the system's components. The ABS dataset does not provide information on these features.

The dataset also does not contain information on when households' panels were installed. One issue is that some panels may have been installed in the immediate lead-up to the surveys. Consequently, insufficient time may have elapsed for these solar panels to affect the energy expenditures and energy poverty statuses of the households. However, only around 1.5 percent of Australian households installed solar PV panels in 2015-16, so this issue is not relevant for many households. [6]

4.3 Control variables

Solar and non-solar households likely differ in key ways. Omitted variable bias is a threat if there are unobserved characteristics in the error term that are correlated with both a household's solar PV system size (and whether it has solar PV more generally) and the outcome variable. The regressions therefore include several control variables related both to a household's socioeconomic characteristics and the features of their dwelling. Descriptive statistics for these variables are provided in Appendix A. Importantly, the models control for household net wealth. Households with higher net wealth tend to have larger solar PV systems and to be less likely to experience energy poverty on average, all else constant (Best and Burke, 2019; Best, Burke, and Nishitateno, 2019).[7]

Socioeconomic characteristics include variables for the number of people in a household, the inverse hyperbolic sine (IHS) of household net wealth, the IHS of household disposable

[6] In Australia, there were around 8,963,300 households in 2015-16 (Australian Bureau of Statistics, 2019). In 2015, there were 141,500 new small-scale solar PV panel installations while in 2016 there were 132,697 (Clean Energy Regulator, 2022).

[7] The variance inflation factors are below the threshold of 10 for all variables. The correlation between the IHS of household net wealth and the IHS of household disposable income is also only 0.18. The low level of correlation is related to many older Australians having high levels of housing wealth including in the family home, which is a non-income generating asset if no rooms are rented out, whereas income levels tend to be lower for older ages (Tapper and Fenna, 2019). Thus, multi-collinearity is unlikely to be an issue for the estimated results of this study.

income, and the age of the survey respondent.[8] Binary variables include whether the household's main income source is government pensions and allowances, the employment status of the household respondent, and whether the respondent is female. Household composition variables, such as whether a survey respondent lives by themselves or with a partner or children, are also accounted for. There are also separate binary variables for whether at least one member of a household: is 65 years of age or older, has a disability and/or long-term illness, has a university-level education, and/or was born in Australia.

Net wealth is given by total assets minus total liabilities. The calculation is based on international guidelines for measuring statistics at the household level (Australian Bureau of Statistics, 2017), with survey respondents being asked for the values of various categories of assets and liabilities. Ownership of solar panels is considered indirectly in the net wealth measure via the value of the home. Any loans incurred to pay for the solar panels are part of the household's liabilities. We take the IHS of the household net wealth and disposable income variables to reduce the skewness of the distributions and retain zero and negative values.

Dwelling characteristics include the number of bedrooms in a dwelling, the type of housing tenure, and the type of dwelling. The types of housing tenure are whether the dwelling is rented, owned with a mortgage, owned without a mortgage, or occupied via some other means (measured using binary variables). In Australia, households who rent their homes typically pay for their own energy expenditures (rather than the landlord). Dwelling characteristics also include the average monthly solar exposure for the year and yearly numbers of CDDs and HDDs for the dwelling's postal area, plus binary variables for whether the location is regional or remote.

[8] The IHS is given by: $\widetilde{x} = ln\left(x + \sqrt{x^2 + 1}\right)$.

4.4 Instrumental variable approach

There may be differences between households with and without solar PV that are difficult to observe and measure. These include differences in values concerning the environment, in access to financial and technical knowledge about solar PV, or in demand for energy autonomy (Alipour et al., 2020). If these variables are also correlated with the outcome variables, the estimated impacts of solar PV on energy expenditures and energy poverty may be biased. Another potential estimation issue is reverse causality given that a major driver for uptake of solar panels has been concern about high electricity costs.

We thus pursue an IV strategy, instrumenting a household's solar PV capacity with the average solar PV capacity of households with similar characteristics who live in the same state or territory but outside the household's statistical area level 3 (SA3). The instrument exploits the fact that energy prices and policies for solar PV differ across state and territory boundaries, so similar households in different regions within a state face similar incentives to install. The instrument varies by household, so is not collinear with the quarter-by-state dummies.

To construct the instrument, we group households into one of 24 categories based on their household net wealth (in quartiles), type of dwelling (fully detached, semi-detached, or other), and housing tenure (homeowner, or other). For example, one category includes households who are in the top wealth quartile and own their fully-detached home, while another includes those in the bottom wealth quartile, who do not own their home, and live in a semi-detached building. The value of the instrument for each household is the average solar PV system size for households who are in the same category and live in the same state but not the same SA3.

This IV approach seeks to remove the impact of omitted variable bias and reverse causality within each local area. There are some possible issues with satisfying the exclusion restriction, as omitted variables may exist that are correlated with the solar uptake of similar households. The results are robust to using a regional aggregation other than SA3s.

SA3s provides a good balance between the size of the region and the number of households that were unable to be matched with similar households outside their local area. There are 358 SA3s in Australia, with populations generally between 30,000 and 130,000 people (Australian Bureau of Statistics, 2016).

5 Results

5.1 Main results

We commence by presenting OLS and logit regressions to examine the impact of solar PV capacity on energy poverty. Table 1 provides the results. They indicate that a one-kilowatt increase in the size of a household's solar PV system is associated with a reduction in weekly energy expenditures of around A$3.73 on average, holding the control variables constant. It is also associated with a lower likelihood that a household will experience objective measures of energy poverty, by around 1.7 percentage points per kilowatt for the LIHC indicator and 1.8 percentage points per kilowatt for the TPR indicator on average. These impacts are large given the underlying probability of experiencing energy poverty is quite low in the sample. No significant effect is found for the subjective energy poverty indicator.

[Insert Table 1: OLS and logit regressions for impact of solar PV capacity on energy poverty]

The IV results are presented in Table 2. The first-stage results suggest that the instrument is positively correlated with a household's solar PV system size. The instrument satisfies the weak IV test of Montiel Olea and Pflueger (2013) for all dependent variables.[9] As an additional test of weak instruments, we compare the minimum eigenvalue statistic of the instrument with the Stock and Yogo values for the size of a nominal 5 percent Wald test. The minimum eigenvalue statistic was first proposed by Cragg and Donald (1993) for a

[9]The effective F-statistic is larger than the threshold critical value with τ (the fraction of the worst-case bias benchmark) = 5 percent and α (the level of statistical significance) = 1 percent in all cases.

test of under-identification. It is larger than the 10 percent size threshold for all dependent variables. Compared to the OLS and logit results in Table 1, the IV results typically have the same sign and statistical significance. The effect of solar PV on the "unable to pay bills on time" indicator becomes statistically significant, indicating a 3.5 percentage point decrease per kilowatt on average, all else equal.

[Insert Table 2: Instrumental variable results for impact of solar PV capacity on energy poverty]

5.2 Effects for low-wealth households

Table 3 explores whether the observed reductions in energy expenditures and energy poverty hold specifically for low-wealth households. To do so, we re-ran the regressions in Table 1 including an interaction between the system size variable and a binary variable equal to one if the household is in the lowest quartile of net wealth and zero otherwise. We also replaced the IHS net wealth variable with the binary low-wealth variable as a control. We used OLS and logit for these regressions due to difficulties in finding a plausible instrument for the interaction of the household net wealth variable with the size of a household's solar PV system.

For the energy expenditures variable as well as the objective indicators, no statistically significant difference due to household net wealth is found. However Table 3 provides evidence that low-wealth households with solar PV are more likely than low-wealth households without solar PV to report being energy poor based on the "unable to pay bills on time" indicator. Specifically, having solar PV increases the likelihood that a low-wealth household faces difficulties in paying their bills on-time by 3 percentage points per kilowatt (the sum of the two coefficients). This is an interesting finding given the reduction in weekly energy expenditures for these households observable in the first column.[10] One explanation may be

[10] The null hypothesis of a two-sided t-test of $b_{system\ size} + b_{system\ size*low\ wealth} = 0$ for the "weekly energy expenditures" regression is rejected, with a p-value of 0.00.

that some low-wealth households have insufficient funds to pay their bills after purchasing a solar system.

[Insert Table 3: OLS and logit regressions for heterogeneity analysis by low-wealth status]

5.3 Potential non-linearities

Table 4 explores non-linearities in the impacts of solar PV system size by including a squared term for a household's solar PV capacity. To avoid the need to include two instrumental variables, we again estimate the quadratic specifications using OLS and logit models. The results suggest that there are diminishing returns to solar PV capacity. Based on the "weekly energy expenditures" regression, the turning point is at a capacity of 5.37 kW.[11] As relatively few households had systems larger than this in 2015-16, the relationship between solar PV capacity and energy expenditures thus slopes downwards at a decreasing rate over the relevant in-sample range of kilowatt values.

[Insert Table 4: OLS and logit regressions for impact of solar PV capacity on energy poverty, testing for non-linearities]

5.4 Solar output

As an alternative treatment variable, we consider the estimated daily solar PV output of each household's system. Given the solar variable appears only once on the right-hand side, we estimate using IV. We apply a slight variation to our IV approach: rather than using the average capacity of similar households as the instrument, we now use the average daily per-household system output of similar households.

Table 5 provides the results. The instrument is positively correlated with the system size variable and satisfies the weak instruments test of Montiel Olea and Pflueger for all dependent variables. The minimum eigenvalue statistic is larger than the 10 percent size threshold for all dependent variables. The estimated coefficients are similar in sign to the

[11] $(-(-6.672)/(2(0.621) = 5.37$

results in Tables 1 and 2. A kWh per day increase in the output of a household's solar PV system predicts a reduction in weekly energy expenditures of about 77 cents on average and reductions in all energy poverty indicators. The results are also quite similar if using OLS and logit models, although the coefficient for the "unable to pay bills on time" indicator is only statistically significant when using the IV approach.

[Insert Table 5: Instrumental variable results for impact of estimated solar PV output on energy poverty]

5.5 Additional estimations and results

Appendix C provides the full results for Tables 1–5, including the coefficients for the other explanatory variables. The estimated coefficients for the controls are similar across specifications and align with expectations. For example, higher disposable incomes are associated with households spending more on energy bills but reduced likelihoods of energy poverty on average. Higher household net wealth predicts higher energy expenditures and a lower likelihood of reporting being unable to pay bills on-time, on average. However the impact of household net wealth on the objective measures of energy poverty is not consistently significant.

Other factors such as the respondent having completed tertiary education and living in an apartment predict reductions in the likelihood of experiencing energy poverty on average. For the former, higher levels of education may be associated with better understanding of how to reduce energy bills, while for the latter, apartments typically need less energy for heating and cooling if they are well-insulated from external elements by connecting apartments. Conversely, having more household members or members with long-term medical conditions is associated with higher energy expenditures and a higher propensity of energy poverty on average.

Appendix D presents other robustness checks, altering the specifications used in Table 1. We use OLS and logit regressions as a baseline approach. In Table D.1, the sample is split by whether households own their home (panel A) or rent (panel B).[12] During this year, only around 4 percent of households with rooftop solar were renters. While some Australian renters have solar PV, the share is considerably lower than for homeowners in part because property investors feel they are not always able to benefit as much from having solar PV as they would if they lived in the property (Best, 2022). The share was higher for households with low net wealth: 63 percent of the households in the lowest net wealth quartile who had solar PV rented their homes.

The results in Table D.1 for homeowners are similar to the main results in Tables 1 in sign, magnitude, and statistical significance. The results in panel B for renters are also similar for the weekly energy expenditures and objective energy poverty indicator variables although not always statistically significant. They are also less precisely estimated, as indicated by the larger standard errors.

Table D.2 excludes households in New South Wales, the Australian Capital Territory, and the Northern Territory, as early adopters in these regions tend to have gross meters (Poruschi et al., 2018). Other states and territories, and recent versions of feed-in tariffs in NSW, the ACT, and the NT, rely on net metering. Households on early feed-in tariff arrangements with gross meters in NSW and the ACT receive relatively large per-kWh feed-in tariff payments, potentially resulting in larger reductions in their net energy expenditures. The point estimates in Table D.2 are similar to those in Table 1, both in magnitude and statistical significance. This similarity may relate to low numbers of households with gross meters in the sample.

Table D.3 highlights results for alternative energy poverty indicators. In the main estimations, the poverty line for the LIHC indicator was calculated at 60 percent of equivalised residual income, consistent with Hills (2012). As a robustness check, we instead use a poverty line equal to 50 percent of median equivalised residual median income. There is also controversy about the setting of the threshold for the Ten Percent Rule given that it is an arbitrary

[12] Based on a t-test of equality of means, renters were more likely to experience energy poverty in 2015-16.

cut-off. We follow Churchill and Smyth (2020) and use two other cut-offs: 5 percent and 15 percent. The 5 percent cut-off counts more households as energy poor, whereas the 15 percent cut-off counts fewer households as energy poor. The results are similar to those in Table 1 in sign and statistical significance.

6 Conclusion and policy implications

This paper provides a quantitative assessment of the impact of having solar PV on the likelihood of energy poverty among Australian households. Efforts to reduce energy poverty in colder-climate countries such as the United Kingdom have largely concentrated on initiatives aimed at improving energy efficiency in heating and installing insulation. The results in this paper suggest that government policies that boost access to solar PV are likely to be important in reducing the likelihood that households experience energy poverty in countries such as Australia, all else equal. The benefits increase at a diminishing rate with system size.

Having solar PV is associated with lower likelihoods of experiencing energy poverty based on both the objective and subjective indicators used in this study, although the results for the subjective indicator are not always statistically significant. Using the LIHC and TPR indicators, there is a reduction in the likelihood that a household will experience energy poverty by around 1.5–2.5 percentage points per kilowatt on average. These effects are quite large considering the low underlying probabilities of energy poverty in Australia and reveal just how transformative solar PV can be. The estimated impacts of solar PV on households being unable to pay their bills on time are less robust across specifications.

For households in the lowest quartile of net wealth, an interesting finding is that having solar PV is associated with a lower likelihood of experiencing the objective measures of energy poverty but a greater likelihood of being unable to pay bills on time, all else equal. However the relevant sub-sample is quite small; only 4 percent of households in the lowest net wealth quartile of the sample had solar PV in 2015-16. Future research could examine the impacts of solar PV on energy poverty as more low-wealth households gain access to the technology.

The estimates also suggest that having solar panels has a sizeable effect in reducing energy expenditures. The solar households in the dataset have an average system size of around 3.21 kilowatts. Non-solar households have average weekly energy expenditures of A$40.56. Based on the average system size, a A$2.06 per kilowatt reduction in average weekly energy bills amounts to around A$6.63, or 16 percent of the average weekly energy expenditures of non-solar households.[13] Per year, the average solar household thus benefits from an approximately A$344.55 reduction in energy bills.[14] This is smaller than the finding by the Australian Competition and Consumer Commission (ACCC) that solar households spent approximately A$538 less on net electricity bills (inclusive of feed-in tariffs) than non-solar households on average over 2016-17 (Australian Competition & Consumer Commission, 2018), or about A$530 when converted to 2015-16 dollars. The method used in the current paper is based on household-level survey data and examines energy use rather than electricity consumption. Our results incorporate any rebound effects in electricity use or in use of other types of residential energy such as natural gas.

A limitation of the study is our lack of instrumental variables for the regressions with interaction terms and quadratics in Tables 3–4. Consequently, endogeneity issues may remain in these specifications. Future work could explore ways to instrument these regressions or test the robustness of the results to the use of other econometric specifications. Results in the simpler specification in Table 1 remain relatively similar in an IV estimation (see Table 2).

The overall findings suggest that solar PV adoption by households in Australia is associated with reduced energy expenditures and a lower probability of experiencing energy poverty. However governments looking to extend access to vulnerable households through targeted subsidies also need to consider trade-offs with other spending objectives and also

[13]Based on Table 5, $-6.672(4.21-3.21)+0.621(4.21^2-3.21^2)=-2.06$.

[14]The calculated yearly reduction in energy bills is A$413.59 using the IV estimate.

how subsidies are funded. Future research could assess whether the benefits of specific government policies that subsidise solar PV for energy-poor households outweigh the costs and also the distributional implications of these policies. Future work might also examine the poverty reduction benefits from installing insulation in countries that regularly experience hot temperatures such as Australia. Comparative cost-benefit analyses of investments in solar PV and in insulation would also be useful.

Acknowledgements

We acknowledge the helpful feedback from two anonymous reviewers, Lee White, and Rohan Best as well as comments from presentations at the Australian National University and the 1st IAEE Online Conference 2021. This work was supported by an Australian Government Research Training Program (RTP) Scholarship and funding from the Australian-German Energy Transition Hub. Funding sources had no other involvement in the study.

Data availability

Datasets related to this article are confidential. To apply to access them, please visit: https://www.abs.gov.au/ausstats/abs@.nsf/mf/1406.0.55.007 The website is a user guide of the DataLab by the Australian Bureau of Statistics.

References

ACT Government (2019). *Solar for Low Income Program.* https://www.climatechoices.act.gov.au/policy-programs/solar-for-low-income-program.

Alipour, M., Salim, H., Stewart, R. A., and Sahin, O. (2020). Predictors, taxonomy of predictors, and correlations of predictors with the decision behaviour of residential solar photovoltaics adoption: A review. *Renewable and Sustainable Energy Reviews*, 123:109749.

Andreadis, G., Roaf, S., and Mallick, T. (2013). Tackling fuel poverty with building-integrated solar technologies: the case of the city of Dundee in Scotland. *Energy and buildings*, 59:310–320.

Australian Bureau of Statistics (2016). *Australian Statistical Geography Standard (ASGS): Volume 1 - Main Structure and Greater Capital City Statistical Areas, July 2016*. https://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/1270.0.55.001~July%202016~Main%20Features~Statistical%20Area%20Level%203%20(SA3)~10015.

Australian Bureau of Statistics (2017). *6503.0 - Household Expenditure Survey and Survey of Income and Housing, User Guide, Australia, 2015-16*. https://www.abs.gov.au/ausstats/abs@.nsf/Lookup/6503.0main+features12015-16.

Australian Bureau of Statistics (2019). *Housing occupancy and costs, Australia, 1994–95 to 2017–18*. https://www.abs.gov.au/statistics/people/housing/housing-occupancy-and-costs/2017-18.

Australian Competition and Consumer Commission (2018). Restoring electricity affordability & Australia's competitive advantage. Technical report, Australian Competition and Consumer Commission.

Australian Government (2022). *Renewable Energy (Electricity) Regulations 2001.* https://www.legislation.gov.au/Details/F2017C00269.

Australian Photovoltaic Institute (2021). *Mapping Australian Photovoltaic installations.* https://pv-map.apvi.org.au/historical.

Australian Renewable Energy Agency (2021). *Off grid.* https://arena.gov.au/renewable-energy/off-grid/.

Best, R. (2022). Household wealth of tenants promotes their solar panel access. *Economic Modelling*, 106:105704.

Best, R. and Burke, P. (2019). Factors contributing to energy-related financial stress in Australia. *Economic Record*, 95:462–479.

Best, R., Burke, P., and Nishitateno, S. (2019). Understanding the determinants of rooftop solar installation: Evidence from household surveys in Australia. *Australian Journal of Agricultural and Resource Economics*, 63:922–939.

Best, R., Burke, P., and Nishitateno, S. (2021). Factors affecting renters' electricity use: More than split incentives. *The Energy Journal*, 42(1).

Best, R. and Sinha, K. (2021). Fuel poverty policy: Go big or go home insulation. *Energy Economics*, 97:105195.

Boardman, B. (1991). *Fuel poverty: From cold homes to affordable warmth.* Belhaven Press.

Boardman, B. (2013). *Fixing fuel poverty: Challenges and solutions.* Routledge.

Bouzarovski, S. and Petrova, S. (2015). A global perspective on domestic energy deprivation: Overcoming the energy poverty–fuel poverty binary. *Energy Research & Social Science*, 10:31–40.

Bouzarovski, S. and Tirado Herrero, S. (2017). Geographies of injustice: the socio-spatial determinants of energy poverty in Poland, the Czech Republic and Hungary. *Post-Communist Economies*, 29(1):27–50.

Bureau of Meteorology (2020). *Gridded monthly solar exposure metadata.* http://www.bom.gov.au/climate/austmaps/metadata-monthly-solar-exposure.shtml.

Castaño-Rosa, R., Solís-Guzmán, J., Rubio-Bellido, C., and Marrero, M. (2019). Towards a multiple-indicator approach to energy poverty in the European Union: A review. *Energy and Buildings*, 193:36–48.

Chard, R. and Walker, G. (2016). Living with fuel poverty in older age: Coping strategies and their problematic implications. *Energy Research & Social Science*, 18:62–70.

Churchill, S. A. and Russell, S. (2020). Ethnic diversity, energy poverty and the mediating role of trust: Evidence from household panel data for Australia. *Energy Economics*, 86:104663.

Clean Energy Council (2012). Consumer guide to buying household solar panels (photovoltaic panels). Technical report, Clean Energy Council.

Clean Energy Council (2020). Guide to installing solar PV for business and industry. Technical report, Clean Energy Council.

Clean Energy Regulator (2022). *Postcode data for small-scale installations.* http://www.cleanenergyregulator.gov.au/RET/Forms-and-resources/Postcode-data-for-small-scale-installations.

Cragg, J. G. and Donald, S. G. (1993). Testing identifiability and specification in instrumental variable models. *Econometric Theory*, 9(2):222–240.

Culver, L. (2017). Energy poverty: What you measure matters. Technical report, The Stanford Natural Gas Initiative.

Hammerle, M. and Burke, P. J. (2022). From natural gas to electric appliances: Energy use and emissions implications in Australian homes. *Energy Economics*, 110:106050.

Hills, J. (2012). Getting the measure of fuel poverty: Final report of the fuel poverty review. Technical Report 72, Centre for Analysis of Social Exclusion, London School of Economics and Political Science, London, UK.

Howden-Chapman, P., Viggers, H., Chapman, R., O'Sullivan, K., Barnard, L. T., and Lloyd, B. (2012). Tackling cold housing and fuel poverty in New Zealand: A review of policies, research, and health impacts. *Energy Policy*, 49:134–142.

International Energy Agency (2015). *Electricity, Australia, 2015*. https://www.iea.org/data-and-statistics/data-tables?country=AUSTRALI&energy=Electricity&year=2015.

Judson, E. and Zirakbash, F. (2022). Investigating the potential of solar energy for low-income communities in Australia to reduce hardship, debt and inequality. *Energy Research & Social Science*, 84:102386.

Lee, J. and Shepley, M. M. (2020). Benefits of solar photovoltaic systems for low-income families in social housing of Korea: Renewable energy applications as solutions to energy poverty. *Journal of Building Engineering*, 28:101016.

Legendre, B. and Ricci, O. (2015). Measuring fuel poverty in France: Which households are the most fuel vulnerable? *Energy Economics*, 49:620–628.

Liddell, C. and Morris, C. (2010). Fuel poverty and human health: A review of recent evidence. *Energy Policy*, 38(6):2987–2997.

Longden, T., Quilty, S., Riley, B., White, L. V., Klerck, M., Davis, V. N., and Frank Jupurrurla, N. (2022). Energy insecurity during temperature extremes in remote australia. *Nature Energy*, 7:43–54.

Martire, J. L. (2020). Powering Indigenous communities with renewables. *Renew: Technology for a Sustainable Future*, 151:17–20.

Meyer, S., Laurence, H., Bart, D., Middlemiss, L., and Maréchal, K. (2018). Capturing the multifaceted nature of energy poverty: Lessons from Belgium. *Energy Research & Social Science*, 40:273–283.

Middlemiss, L. and Gillard, R. (2015). Fuel poverty from the bottom-up: Characterising household energy vulnerability through the lived experience of the fuel poor. *Energy Research & Social Science*, 6:146–154.

Mohr, T. M. (2018). Fuel poverty in the US: Evidence using the 2009 Residential Energy Consumption Survey. *Energy Economics*, 74:360–369.

Nussbaumer, P., Bazilian, M., and Modi, V. (2012). Measuring energy poverty: Focusing on what matters. *Renewable and Sustainable Energy Reviews*, 16(1):231–243.

Nussbaumer, P., Nerini, F. F., Onyeji, I., and Howells, M. (2013). Global insights based on the multidimensional energy poverty index (mepi). *Sustainability*, 5(5):2060–2076.

Obeng, G. Y., Evers, H.-D., Akuffo, F. O., Braimah, I., and Brew-Hammond, A. (2008). Solar photovoltaic electrification and rural energy-poverty in Ghana. *Energy for Sustainable Development*, 12(1):43–54.

Olea, J. L. M. and Pflueger, C. (2013). A robust test for weak instruments. *Journal of Business & Economic Statistics*, 31(3):358–369.

Ormandy, D. and Ezratty, V. (2012). Health and thermal comfort: From WHO guidance to housing strategies. *Energy Policy*, 49:116–121.

Pagliaro, M. and Meneguzzo, F. (2020). Distributed generation from renewable energy sources: ending energy poverty across the world. *Energy Technology*, 8(7):2000126.

Pelz, S., Pachauri, S., and Groh, S. (2018). A critical review of modern approaches for multidimensional energy poverty measurement. *Wiley Interdisciplinary Reviews: Energy and Environment*, 7(6):e304.

Pitt, J. and Nolden, C. (2020). Post-subsidy solar PV business models to tackle fuel poverty in multi-occupancy social housing. *Energies*, 13(18):4852.

Poruschi, L., Ambrey, C. L., and Smart, J. C. (2018). Revisiting feed-in tariffs in Australia: A review. *Renewable and Sustainable Energy Reviews*, 82:260–270.

Price, C. W., Brazier, K., and Wang, W. (2012). Objective and subjective measures of fuel poverty. *Energy Policy*, 49:33–39.

Rodríguez, L. R., Ramos, J. S., Delgado, M. G., Félix, J. L. M., and Domínguez, S. A. (2018). Mitigating energy poverty: Potential contributions of combining PV and building thermal mass storage in low-income households. *Energy Conversion and Management*, 173:65–80.

Scheier, E. and Kittner, N. (2022). A measurement strategy to address disparities across household energy burdens. *Nature Communications*, 13(1):1–11.

Solar Choice (2015). *Residential Solar PV Price Index – March 2015*. https://www.solarchoice.net.au/blog/residential-solar-system-prices-2kw-3kw-4kw-5kw-10kw-march-2015/.

Solar Victoria (2021). *Solar panel (PV) rebate*. http://www.solar.vic.gov.au/solar-panel-rebate.

Sovacool, B. K. (2015). Fuel poverty, affordability, and energy justice in England: Policy insights from the Warm Front Program. *Energy*, 93:361–371.

Stojanovski, O., Thurber, M., and Wolak, F. (2017). Rural energy access through solar home systems: Use patterns and opportunities for improvement. *Energy for Sustainable Development*, 37:33–50.

Tapper, A. and Fenna, A. (2019). The relationship between income, wealth and age in Australia. *Australian Economic Review*, 52(4):393–405.

Thomson, H. and Snell, C. (2013). Quantifying the prevalence of fuel poverty across the European Union. *Energy Policy*, 52:563–572.

Urmee, T. and Md, A. (2016). Social, cultural and political dimensions of off-grid renewable energy programs in developing countries. *Renewable Energy*, 93:159–167.

Walker, G. and Day, R. (2012). Fuel poverty as injustice: Integrating distribution, recognition and procedure in the struggle for affordable warmth. *Energy Policy*, 49:69–75.

Walker, R., Liddell, C., McKenzie, P., Morris, C., and Lagdon, S. (2014). Fuel poverty in Northern Ireland: Humanizing the plight of vulnerable households. *Energy Research & Social Science*, 4:89–99.

Yadav, P., Malakar, Y., and Davies, P. J. (2019). Multi-scalar energy transitions in rural households: Distributed photovoltaics as a circuit breaker to the energy poverty cycle in India. *Energy Research & Social Science*, 48:1–12.

Zander, K. K. (2020). Unrealised opportunities for residential solar panels in Australia. *Energy Policy*, 142:111508.

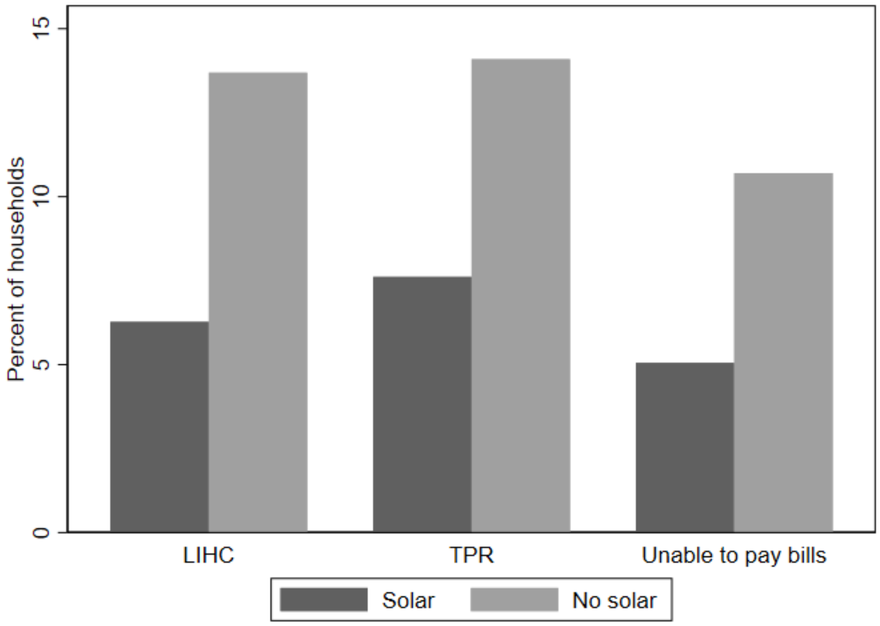

Figure 1: Households experiencing energy poverty, by solar PV status

Source: 2015-16 Household Expenditure Survey and Survey of Income and Housing. Data are for our estimation sample.

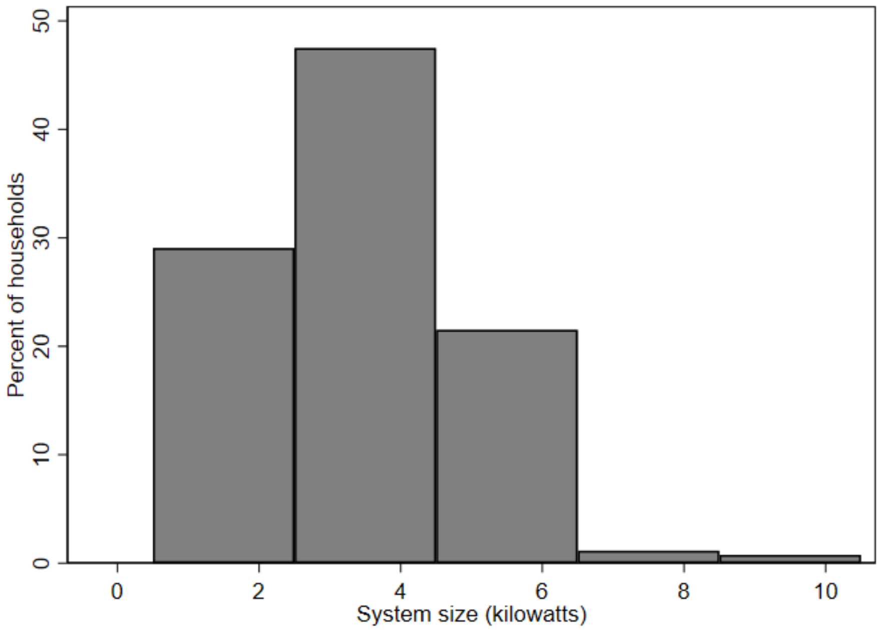

Figure 2: Histogram of solar PV capacities for solar households in estimation sample

Source: 2015-16 Household Expenditure Survey and Survey of Income and Housing.

Table 1: OLS and logit regressions for impact of solar PV capacity

	Weekly energy expenditures ($)	Low Income High Costs (binary)	Ten-Percent -Rule (binary)	Unable to pay bills on time (binary)
System size (kW)	-3.727***	-0.017***	-0.018***	-0.003
	(0.224)	(0.004)	(0.003)	(0.003)
R^2	0.284	0.245	0.371	0.206
Obs	9,900	9,900	9,870	9,900

Notes: Regressions control for all covariates in section 4.3. The "weekly expenditures" regression uses OLS. The binary regressions use logit models, with average marginal effects presented. Standard errors are in brackets. Robust standard errors for the OLS model; Delta-method standard errors for the logit models. Pseudo R^2 for logit models. Some observations are omitted due to multicollinearity issues. Estimated coefficients for other covariates are shown in Table C.1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Instrumental variable results for impact of solar PV capacity

	Weekly energy expenditures ($)	Low Income High Costs (binary)	Ten-Percent -Rule (binary)	Unable to pay bills on time (binary)
System size (kW)	-2.471**	-0.024*	-0.016	-0.035***
	(1.159)	(0.013)	(0.013)	(0.011)
First-stage coeff.	0.726***	0.726***	0.726***	0.726***
	(0.055)	(0.055)	(0.055)	(0.055)
Effective F-statistic	172.555	172.555	172.555	172.555
Minimum eigenvalue statistic	283.465	283.465	283.465	283.465
Stock & Yogo critical value	16.38	16.38	16.38	16.38
Obs	9,874	9,874	9,874	9,874

Notes: Instrument is average solar PV capacity of similar households. 2SLS is used. Robust standard errors are in brackets. Regressions control for all covariates in section 4.3. The effective F-statistic is from the Montiel Olea and Pflueger test of weak instruments. The Stock and Yogo critical values are for 2SLS size of nominal 5 percent Wald tests at the 10 percent threshold level. Minimum eigenvalue statistics and Stock and Yogo critical values are from regressions without robust standard errors. Estimated coefficients for other covariates are shown in Table C.2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: OLS and logit regressions for heterogeneity analysis by low-wealth status

	Weekly energy expenditures ($)	Low Income High Costs (binary)	Ten-Percent -Rule (binary)	Unable to pay bills on time (binary)
System size (kW)	-3.755***	-0.017***	-0.018***	-0.004**
	(0.230)	(0.004)	(0.003)	(0.002)
System size (kW) *	0.685	-0.007	0.000	0.034**
low-wealth (binary)	(0.814)	(0.014)	(0.010)	(0.016)
R^2	0.280	0.244	0.371	0.143
Obs	9,900	9,898	9,871	9,900

Notes: Regressions control for all covariates in section 4.3. The "weekly expenditures" regression uses OLS. The binary regressions use logit models, with average marginal effects presented. Standard errors are in brackets. Robust standard errors for the OLS model; Delta-method standard errors for the logit models. Pseudo R^2 for logit models. Some observations are omitted due to multicollinearity issues. Estimated coefficients for other covariates are shown in Table C.3. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: OLS and logit regressions for impact of solar PV capacity, testing for non-linearities

	Weekly energy expenditures (\$)	Low Income High Costs (binary)	Ten-Percent -Rule (binary)	Unable to pay bills on time (binary)
System size (kW)	-6.672***	-0.037***	-0.033***	-0.009
	(0.553)	(0.007)	(0.006)	(0.006)
System size (kW) squared	0.621***	0.004***	0.003***	0.001
	(0.105)	(0.001)	(0.001)	(0.001)
Turning point (kW)	5.372	4.625	5.500	4.500
R^2	0.284	0.246	0.372	0.207
Obs	9,900	9,900	9,870	9,900

Notes: Regressions control for all covariates in section 4.3. The "weekly expenditures" regression uses OLS. The binary regressions use logit models, with average marginal effects presented. Standard errors are in brackets. Robust standard errors for the OLS model; Delta-method standard errors for the logit models. Pseudo R^2 for logit models. Some observations are omitted due to multicollinearity issues. Estimated coefficients for other covariates are shown in Table C.4. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Instrumental variable results for impact of estimated solar PV output

	Weekly energy expenditures (\$)	Low Income High Costs (binary)	Ten-Percent -Rule (binary)	Unable to pay bills on time (binary)
System output	-0.771***	-0.006*	-0.005*	-0.008***
(kWh per day)	(0.261)	(0.003)	(0.003)	(0.003)
First-stage coeff.	0.736***	0.736***	0.736***	0.736***
	(0.055)	(0.055)	(0.055)	(0.055)
Effective F-statistic	181.529	181.529	181.529	181.529
Minimum eigenvalue statistic	322.982	322.982	322.982	322.982
Stock & Yogo critical value	16.38	16.38	16.38	16.38
Obs	9,874	9,874	9,874	9,874

Notes: Instrument is average solar PV capacity of similar households. 2SLS is used. Robust standard errors are in brackets. Regressions control for all covariates in section 4.3. The effective F-statistic is from the Montiel Olea and Pflueger test of weak instruments. The Stock and Yogo critical values are for 2SLS size of nominal 5 percent Wald tests at the 10 percent threshold level. Minimum eigenvalue statistics and Stock and Yogo critical values are from regressions without robust standard errors. Estimated coefficients for other covariates are shown in Table C.5. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Supporting information

Appendix A

Table A.1: Descriptive statistics

	Variable name	Solar		Non-solar	
		Mean	S.D.	Mean	S.D.
Variables of interest					
Capacity of solar system (kW)	System size	3.21	1.46	0.00	0.00
Expected output (kWh per day)	System output	13.56	6.37	0.00	0.00
Respondent characteristics					
Age	AGER	58.15	14.45	53.55	17.62
Female	FEMALE	0.39		0.45	
Employed[a]	EMPLOYED	0.57		0.58	
Unemployed[a]	UNEMPLOYED	0.01		0.03	
Household characteristics					
Number of people	PERSONSH	2.53	1.24	2.31	0.01
IHS of disposable income (weekly, in A$)	IHSINCOME	7.82	1.06	7.68	0.96
IHS of net wealth (in A$)	IHSWEALTH	14.23	1.32	13.06	3.08
Couple with children household[b]	COUPLECHILD	0.24		0.21	
Single parent household[b]	LONEPARENT	0.04		0.07	
Multiple family household[b]	MULTIPLEFAM	0.01		0.01	
Lone person household[b]	LONEPERSON	0.15		0.31	
Other household type[b]	OTHERFAM	0.13		0.12	
>1 person aged 65 or older	OLDER	0.44		0.33	
>1 person born in Australia	BORNAUS	0.78		0.67	
>1 person with long-term health condition	DISABILITY	0.52		0.47	
>1 person with university-level education	EDUCHIGH	0.37		0.28	
Main income source is government transfers	GOVERNMENT	0.29		0.34	
Dwelling characteristics					
Number of bedrooms	NUMBED	3.48	0.79	2.99	0.94
Housing tenure = homeowner with mortgage[c]	OWNERM	0.44		0.33	
Housing tenure = renter[c]	RENTER	0.04		0.34	
Housing tenure = other[c]	TENOTHER	0.01		0.02	
Dwelling = semi-detached[d]	DWELSSEMI	0.00		0.00	
Dwelling = apartment/flat[d]	DWELSFLAT	0.04		0.13	
Dwelling = other type[d]	DWELSOTHER	0.01		0.12	
Location characteristics					
Household lives in remote/very remote area[e]	REMOTE	0.02		0.02	
Household lives in regional area[e]	REGIONAL	0.29		0.25	
Av. solar exposure per year in postal area	AVSOLAR	16.98	1.68	16.49	1.82
Av. number CDDs per year in postal area	AVCDDS	0.01	0.15	0.04	0.26
Av. number HDDs per year in postal area	AVHDDS	5.73	4.18	6.13	3.84
Obs		1,563		8,337	

Notes: Covariates also include survey quarter-by-state binary variables. Variables with means and standard deviations are continuous variables; variables with means only are binary. Reference categories are: [a] not in the labour force, [b] couple only, [c] homeowner no mortgage (owns home outright), [d] fully-separated house, [e] household lives in a major city.

Appendix B

Table B.1: Correlations between energy poverty indicators in the sample

	Low Income High Costs	Ten-Percent -Rule	Unable to pay bills on time
Low Income High Costs	1.00		
Ten Percent Rule	0.61	1.00	
Unable to pay bills on time	0.16	0.14	1.00

Table B.2: LIHC adjustment factors versus modified OECD equivalence scale

Household type	LIHC factor	OECD factor
Couple with dependent children (2 adults, 2 children)	1.15	2.30
Couple without dependent children (2 adults)	1.00	1.50
Lone parent (1 adult, 2 children)	0.94	1.60
Single person (1 adult)	0.82	1.00
Other multi-person household (4 adults)	1.07	2.50

Notes: Examples of household types in brackets. These examples are used to calculate the OECD factors. The LIHC factors are the same for any expression of that household type.

Table B.3: Average daily production of solar PV systems, in kilowatt hours

City	Daily output from 1kW system size (kWh)
Sydney	3.95
Melbourne	3.65
Canberra	4.25
Cairns	4.50
Brisbane	4.35
Perth	4.55
Adelaide	4.20
Hobart	3.45
Darwin	4.80
Alice Springs	5.15

Notes: Averages of production from Clean Energy Council (2012) and (2020).

Appendix C

Table C.1: OLS and logit regressions for impact of solar PV capacity

	Weekly energy expenditures ($)		Low Income High Costs (binary)		Ten-Percent -Rule (binary)		Unable to pay bills on time (binary)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
System size	-3.727***	0.224	-0.017***	0.004	-0.018***	0.003	-0.003	0.003
AGER	0.143***	0.025	-0.000	0.000	0.001*	0.000	-0.001***	0.000
FEMALE	-0.891*	0.496	0.012*	0.006	0.005	0.006	0.010	0.006
EMPLOYED	1.635**	0.828	-0.003	0.012	0.005	0.010	0.017*	0.010
UNEMPLOYED	3.566*	1.961	0.011	0.016	0.025*	0.014	0.028**	0.013
PERSONSH	4.493***	0.522	0.040***	0.005	0.064***	0.005	0.012***	0.004
IHSINCOME	1.309***	0.413	-0.111***	0.014	-0.245***	0.008	-0.011***	0.003
IHSWEALTH	0.378***	0.097	0.001	0.001	0.001	0.001	-0.004***	0.001
COUPLECHILD	1.262	1.278	0.001	0.014	0.003	0.014	0.014	0.012
LONEPARENT	-0.523	1.150	0.016	0.013	0.038***	0.012	0.062***	0.011
MULTIPLEFAM	0.084	3.500	-0.049	0.034	0.033	0.028	0.010	0.029
LONEPERSON	-4.252***	0.820	-0.004	0.010	-0.057***	0.009	0.025**	0.010
OTHERFAM	-0.895	0.860	-0.026**	0.012	0.009	0.011	0.025**	0.011
OLDER	-3.312***	0.859	-0.008	0.012	-0.015	0.011	-0.076***	0.012
BORNAUS	2.551***	0.534	-0.011	0.007	0.004	0.007	0.020***	0.008
DISABILITY	1.301**	0.546	0.024***	0.007	0.016**	0.006	0.050***	0.006
EDUCHIGH	-1.357**	0.568	-0.027***	0.008	-0.019***	0.007	-0.053***	0.007
GOVERNMENT	-3.684***	0.760	0.082***	0.011	-0.015*	0.009	0.054***	0.010
NUMBED	4.746***	0.374	0.026***	0.004	0.030***	0.004	-0.006	0.004
OWNERM	3.812***	0.751	0.030***	0.010	0.010	0.009	0.093***	0.011
RENTER	2.490***	0.780	0.068***	0.010	0.011	0.009	0.122***	0.011
TENOTHER	-0.119	1.932	0.020	0.022	0.062***	0.017	0.083***	0.021
DWELSSEMI	-1.860**	0.762	-0.016	0.010	-0.017*	0.010	-0.027***	0.009
DWELSFLAT	-2.575***	0.819	-0.054***	0.014	-0.042***	0.014	-0.034***	0.011
DWELSOTHER	1.328	7.126	-0.036	0.065	-0.020	0.058	-0.020	0.052
REMOTE	-4.253	2.959	-0.019	0.036	0.034	0.027	0.039**	0.020
REGIONAL	-2.284***	0.771	0.015*	0.009	0.003	0.008	0.007	0.008
AVSOLAR	1.629***	0.463	0.009	0.005	0.011**	0.005	-0.003	0.004
AVCDDS	-1.618	1.867	-0.006	0.023	-0.023	0.022	-0.022	0.024
AVHDDS	0.412***	0.142	0.002	0.002	0.004***	0.001	0.000	0.002
R^2	0.284		0.245		0.371		0.206	
Obs	9,900		9,900		9,870		9,900	

Notes: Variable names and reference categories are as in Table A.1. Regressions also include quarter-by-state controls. The "weekly expenditures" regression uses OLS. The binary regressions use logit models, with average marginal effects presented. Standard errors are in brackets. Robust standard errors for the OLS model; Delta-method standard errors for the logit models. Pseudo R^2 for logit models. Some observations are omitted due to multicollinearity issues. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.2: Instrumental variable results for impact of solar PV capacity

	Weekly energy expenditures ($)		Low Income High Costs (binary)		Ten-Percent -Rule (binary)		Unable to pay bills on time (binary)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
System size	-2.471**	1.159	-0.024*	0.013	-0.016	0.013	-0.035***	0.011
AGER	0.131***	0.025	-0.001***	0.000	-0.001	0.000	-0.001***	0.000
FEMALE	-0.795	0.508	0.014**	0.007	0.008	0.007	0.009	0.006
EMPLOYED	1.385*	0.841	-0.037***	0.012	-0.035***	0.012	-0.019*	0.010
UNEMPLOYED	3.509*	1.986	0.064**	0.032	0.147***	0.032	0.072**	0.031
PERSONSH	4.428***	0.520	0.054***	0.006	0.072***	0.007	0.022***	0.006
IHSINCOME	1.403***	0.416	-0.101***	0.008	-0.146***	0.011	-0.012***	0.004
IHSWEALTH	0.368***	0.101	0.003*	0.002	0.003*	0.001	-0.007***	0.002
COUPLECHILD	1.156	1.290	-0.047***	0.014	-0.063***	0.014	-0.015	0.015
LONEPARENT	-0.694	1.159	0.028	0.018	0.049***	0.018	0.124***	0.019
MULTIPLEFAM	0.033	3.491	-0.099***	0.036	-0.053	0.042	-0.031	0.034
LONEPERSON	-3.959***	0.871	0.007	0.011	-0.012	0.011	0.015	0.010
OTHERFAM	-0.924	0.872	-0.044***	0.010	-0.038***	0.010	0.001	0.011
OLDER	-3.486***	0.872	-0.034***	0.012	-0.047***	0.011	-0.065***	0.010
BORNAUS	2.371***	0.541	-0.013*	0.008	-0.005	0.008	0.023***	0.006
DISABILITY	1.445***	0.553	0.023***	0.007	0.014**	0.007	0.054***	0.007
EDUCHIGH	-1.250**	0.579	-0.016**	0.007	-0.018**	0.007	-0.047***	0.006
GOVERNMENT	-3.827***	0.775	0.097***	0.011	0.025**	0.011	0.044***	0.009
NUMBED	4.383***	0.415	0.028***	0.005	0.028***	0.005	0.002	0.004
OWNERM	3.676***	0.764	0.026***	0.009	-0.008	0.009	0.047***	0.007
RENTER	2.539***	0.912	0.066***	0.012	-0.004	0.012	0.083***	0.011
TENOTHER	0.525	2.033	0.013	0.022	0.079***	0.026	0.017	0.020
DWELSSEMI	-1.420*	0.780	-0.019*	0.011	-0.018*	0.010	-0.034***	0.010
DWELSFLAT	-3.116***	0.827	-0.047***	0.012	-0.019*	0.011	-0.044***	0.013
DWELSOTHER	1.017	7.267	-0.014	0.057	-0.014	0.046	-0.013	0.055
REMOTE	0.379	2.770	-0.008	0.024	0.056**	0.027	0.023	0.024
REGIONAL	-2.021***	0.675	0.003	0.008	0.001	0.008	0.010	0.008
AVSOLAR	0.140	0.221	0.002	0.003	0.001	0.003	0.002	0.002
AVCDDS	4.436***	1.224	0.011	0.013	0.024**	0.012	-0.045***	0.012
AVHDDS	0.956***	0.078	0.006***	0.001	0.007***	0.001	0.001	0.001
First-stage coeff.	0.726***	0.055	0.726***	0.055	0.726***	0.055	0.726***	0.055
Effective F-statistic	172.555		172.555		172.555		172.555	
Minimum eigenvalue statistic	283.465		283.465		283.465		283.465	
Stock & Yogo critical value	16.38		16.38		16.38		16.38	
Obs	9,874		9,874		9,874		9,874	

Notes: Variable names and reference categories are as in Table A.1. Regressions also include quarter-by-state controls. Instrument is average solar PV capacity of similar households. 2SLS is used. Robust standard errors are in brackets. The effective F-statistic is from the Montiel Olea and Pflueger test of weak instruments. The Stock and Yogo critical values are for 2SLS size of nominal 5 percent Wald tests at the 10 percent threshold level. Minimum eigenvalue statistics and Stock and Yogo critical values are from regressions without robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.3: OLS and logit regressions for heterogeneity analysis by low-wealth status

	Weekly energy expenditures ($)		Low Income High Costs (binary)		Ten-Percent -Rule (binary)		Unable to pay bills on time (binary)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
System size	-3.755***	0.230	-0.017***	0.004	-0.018***	0.003	-0.004**	0.002
System size * low-wealth	0.685	0.814	-0.007	0.014	0.000	0.010	0.034**	0.016
AGER	0.154***	0.025	0.000	0.000	0.001**	0.000	-0.001***	0.000
FEMALE	-0.856*	0.496	0.012*	0.006	0.005	0.006	0.010	0.006
EMPLOYED	1.645**	0.832	-0.002	0.012	0.004	0.010	-0.017*	0.010
UNEMPLOYED	3.514*	1.958	0.011	0.016	0.025*	0.014	0.071**	0.030
PERSONSH	4.463***	0.522	0.040***	0.005	0.064***	0.005	0.021***	0.007
IHSINCOME	1.374***	0.414	-0.111***	0.014	-0.245***	0.008	-0.010**	0.004
low-wealth	-1.229	0.885	0.011	0.012	-0.009	0.011	0.075***	0.013
COUPLECHILD	1.387	1.277	0.002	0.014	0.003	0.014	-0.012	0.015
LONEPARENT	-0.538	1.147	0.015	0.013	0.038***	0.012	0.124***	0.019
MULTIPLEFAM	0.193	3.499	-0.049	0.034	0.033	0.028	-0.030	0.034
LONEPERSON	-4.329***	0.819	-0.005	0.010	-0.057***	0.009	0.021**	0.009
OTHERFAM	-0.909	0.862	-0.027**	0.012	0.009	0.011	0.003	0.011
OLDER	-3.328***	0.861	-0.008	0.012	-0.015	0.011	-0.069***	0.010
BORNAUS	2.551***	0.534	-0.011	0.007	0.004	0.007	0.026***	0.006
DISABILITY	1.287**	0.545	0.023***	0.007	0.016***	0.006	0.053***	0.007
EDUCHIGH	-1.359**	0.569	-0.027***	0.008	-0.019***	0.007	-0.045***	0.006
GOVERNMENT	-3.972***	0.759	0.081***	0.011	-0.015*	0.009	0.046***	0.009
NUMBED	4.775***	0.375	0.027***	0.004	0.030***	0.004	-0.002	0.004
OWNERM	3.706***	0.758	0.028***	0.010	0.010	0.009	0.043***	0.007
RENTER	2.311**	1.015	0.058***	0.013	0.016	0.012	0.066***	0.011
TENOTHER	-0.327	2.005	0.013	0.023	0.066***	0.018	0.004	0.019
DWELSSEMI	-1.919**	0.759	-0.017*	0.010	-0.018*	0.010	-0.028***	0.010
DWELSFLAT	-2.754***	0.815	-0.055***	0.014	-0.042***	0.014	-0.039***	0.013
DWELSOTHER	1.299	7.116	-0.036	0.064	-0.020	0.059	-0.030	0.054
REMOTE	-4.281	2.947	-0.019	0.035	0.033	0.027	0.051**	0.025
REGIONAL	-2.291***	0.771	0.015*	0.009	0.003	0.008	0.006	0.009
AVSOLAR	1.631***	0.463	0.009	0.005	0.011**	0.005	-0.002	0.005
AVCDDS	-1.676	1.858	-0.006	0.023	-0.023	0.022	-0.003	0.014
AVHDDS	0.411***	0.142	0.002	0.002	0.004***	0.001	0.000	0.002
R^2	0.280		0.244		0.371		0.143	
Obs	9,900		9,898		9,871		9,900	

Notes: Variable names and reference categories are as in Table A.1. Regressions also include quarter-by-state controls. The "weekly expenditures" regression uses OLS. The binary regressions use logit models, with average marginal effects presented. Standard errors are in brackets. Robust standard errors for the OLS model; Delta-method standard errors for the logit models. Pseudo R^2 for logit models. Some observations are omitted due to multicollinearity issues. low-wealth equals one if household is in the lowest quartile of household net wealth, and zero otherwise. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.4: OLS and logit regressions for impact of solar PV capacity, testing for non-linearities

	Weekly energy expenditures ($)		Low Income High Costs (binary)		Ten-Percent -Rule (binary)		Unable to pay bills on time (binary)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
System size	-6.672***	0.553	-0.037***	0.007	-0.033***	0.006	-0.009	0.006
System size squared	0.621***	0.105	0.004***	0.001	0.003***	0.001	0.001	0.001
AGER	0.142***	0.025	0.000	0.000	0.001**	0.000	-0.001***	0.000
FEMALE	-0.816*	0.496	0.012*	0.006	0.005	0.006	0.010*	0.006
EMPLOYED	1.436*	0.826	-0.004	0.012	0.004	0.010	0.017*	0.010
UNEMPLOYED	3.555*	1.958	0.011	0.016	0.025*	0.014	0.028**	0.013
PERSONSH	4.428***	0.520	0.040***	0.005	0.063***	0.005	0.012***	0.004
IHSINCOME	1.375***	0.413	-0.111***	0.014	-0.245***	0.008	-0.011***	0.002
IHSWEALTH	0.375***	0.097	0.001	0.001	0.001	0.001	-0.004***	0.001
COUPLECHILD	1.301	1.274	0.000	0.014	0.002	0.014	0.014	0.012
LONEPARENT	-0.567	1.149	0.015	0.013	0.037***	0.012	0.062***	0.011
MULTIPLEFAM	0.313	3.488	-0.049	0.034	0.034	0.028	0.011	0.029
LONEPERSON	-4.468***	0.822	-0.005	0.010	-0.058***	0.009	0.024**	0.010
OTHERFAM	-0.983	0.859	-0.027**	0.012	0.008	0.011	0.025**	0.011
OLDER	-3.308***	0.855	-0.008	0.011	-0.015	0.011	-0.076***	0.012
BORNAUS	2.502***	0.533	-0.012	0.007	0.004	0.007	0.020***	0.008
DISABILITY	1.335**	0.545	0.024***	0.007	0.016***	0.006	0.050***	0.006
EDUCHIGH	-1.358**	0.566	-0.027***	0.008	-0.019***	0.007	-0.053***	0.007
GOVERNMENT	-3.746***	0.759	0.082***	0.011	-0.015*	0.009	0.054***	0.010
NUMBED	4.684***	0.374	0.026***	0.004	0.030***	0.004	-0.006	0.004
OWNERM	3.747***	0.748	0.029***	0.010	0.009	0.009	0.093***	0.011
RENTER	2.197***	0.782	0.066***	0.010	0.010	0.009	0.121***	0.011
TENOTHER	-0.216	1.927	0.020	0.022	0.061***	0.017	0.083***	0.021
DWELSSEMI	-2.080***	0.769	-0.017*	0.010	-0.018*	0.010	-0.027***	0.009
DWELSFLAT	-2.846***	0.820	-0.054***	0.014	-0.042***	0.014	-0.034***	0.011
DWELSOTHER	1.108	7.130	-0.037	0.065	-0.021	0.059	-0.020	0.052
REMOTE	-4.075	2.958	-0.019	0.036	0.034	0.027	0.039**	0.020
REGIONAL	-2.388***	0.766	0.014	0.009	0.002	0.008	0.007	0.008
AVSOLAR	1.608***	0.463	0.009	0.005	0.011**	0.005	-0.003	0.004
AVCDDS	-1.644	1.862	-0.006	0.023	-0.023	0.022	-0.022	0.024
AVHDDS	0.395***	0.143	0.002	0.002	0.004***	0.001	0.000	0.002
R^2	0.284		0.246		0.372		0.207	
Obs	9,900		9,900		9,870		9,900	

Notes: Variable names and reference categories are as in Table A.1. Regressions also include quarter-by-state controls. The "weekly expenditures" regression uses OLS. The binary regressions use logit models, with average marginal effects presented. Standard errors are in brackets. Robust standard errors for the OLS model; Delta-method standard errors for the logit models. Pseudo R^2 for logit models. Some observations are omitted due to multicollinearity issues. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C.5: Instrumental variable results for impact of estimated solar PV output

	Weekly energy expenditures ($)		Low Income High Costs (binary)		Ten-Percent -Rule (binary)		Unable to pay bills on time (binary)	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
System size	-0.771***	0.261	-0.006*	0.003	-0.005*	0.003	-0.008***	0.003
AGER	0.132***	0.025	-0.001***	0.000	-0.001	0.000	-0.001***	0.000
FEMALE	-0.826*	0.507	0.014**	0.007	0.008	0.007	0.010	0.006
EMPLOYED	1.395*	0.838	-0.037***	0.012	-0.035***	0.012	-0.020**	0.010
UNEMPLOYED	3.542*	1.988	0.064**	0.032	0.147***	0.032	0.071**	0.031
PERSONSH	4.431***	0.519	0.054***	0.006	0.073***	0.007	0.022***	0.006
IHSINCOME	1.378***	0.415	-0.101***	0.008	-0.146***	0.011	-0.011***	0.004
IHSWEALTH	0.370***	0.101	0.003*	0.002	0.003*	0.001	-0.007***	0.002
COUPLECHILD	1.080	1.287	-0.047***	0.014	-0.064***	0.014	-0.016	0.015
LONEPARENT	-0.797	1.158	0.028	0.018	0.048***	0.018	0.124***	0.019
MULTIPLEFAM	-0.099	3.500	-0.100***	0.036	-0.054	0.042	-0.032	0.034
LONEPERSON	-4.134***	0.865	0.007	0.011	-0.012	0.011	0.016	0.010
OTHERFAM	-0.972	0.869	-0.045***	0.010	-0.038***	0.010	0.001	0.011
OLDER	-3.436***	0.868	-0.035***	0.012	-0.047***	0.011	-0.065***	0.010
BORNAUS	2.367***	0.539	-0.013*	0.008	-0.005	0.008	0.023***	0.006
DISABILITY	1.441***	0.551	0.023***	0.007	0.014**	0.007	0.054***	0.007
EDUCHIGH	-1.251**	0.578	-0.016**	0.007	-0.018**	0.007	-0.048***	0.006
GOVERNMENT	-3.867***	0.773	0.097***	0.011	0.025**	0.011	0.044***	0.009
NUMBED	4.471***	0.410	0.028***	0.005	0.029***	0.005	0.002	0.004
OWNERM	3.722***	0.762	0.026***	0.009	-0.008	0.009	0.046***	0.007
RENTER	2.232**	0.899	0.067***	0.012	-0.005	0.011	0.084***	0.011
TENOTHER	0.290	2.025	0.013	0.022	0.078***	0.026	0.017	0.020
DWELSSEMI	-1.528**	0.780	-0.019*	0.011	-0.018*	0.010	-0.034***	0.010
DWELSFLAT	-3.156***	0.825	-0.047***	0.012	-0.020*	0.011	-0.044***	0.013
DWELSOTHER	1.360	7.244	-0.013	0.057	-0.012	0.046	-0.012	0.055
REMOTE	0.296	2.761	-0.008	0.024	0.055**	0.027	0.023	0.025
REGIONAL	-1.883***	0.667	0.003	0.008	0.002	0.008	0.010	0.008
AVSOLAR	0.273	0.228	0.003	0.003	0.001	0.003	0.003	0.003
AVCDDS	4.056***	1.221	0.010	0.013	0.022*	0.012	-0.045***	0.012
AVHDDS	0.949***	0.077	0.006***	0.001	0.007***	0.001	0.001	0.001
First-stage coeff.	0.736***	0.055	0.736***	0.055	0.736***	0.055	0.736***	0.055
Effective F-statistic	181.529		181.529		181.529		181.529	
Minimum eigenvalue statistic	322.982		322.982		322.982		322.982	
Stock & Yogo critical value	16.38		16.38		16.38		16.38	
Obs	9,874		9,874		9,874		9,874	

Notes: Variable names and reference categories are as in Table A.1. Regressions also include quarter-by-state controls. Instrument is average solar PV capacity of similar households. 2SLS is used. Robust standard errors are in brackets. The effective F-statistic is from the Montiel Olea and Pflueger test of weak instruments. The Stock and Yogo critical values are for 2SLS size of nominal 5 percent Wald tests at the 10 percent threshold level. Minimum eigenvalue statistics and Stock and Yogo critical values are from regressions without robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix D

Table D.1: OLS and logit regressions for impact of solar PV capacity, by home-ownership

	Weekly energy expenditures ($)	Low Income High Costs (binary)	Ten-Percent -Rule (binary)	Unable to pay bills on time (binary)
Panel A: Homeowners				
System size (kW)	-3.770***	-0.012***	-0.015***	-0.002
	(0.241)	(0.003)	(0.003)	(0.002)
R^2	0.284	0.275	0.376	0.145
Obs	6,740	6,732	6,719	6,649
Panel B: Renters				
System size (kW)	-2.286**	-0.034*	-0.013	0.012
	(1.003)	(0.018)	(0.013)	(0.011)
R^2	0.290	0.232	0.382	0.155
Obs	2,940	2,894	2,915	2,940

Notes: Regressions control for all covariates in section 4.3. The "weekly expenditures" regression uses OLS. The binary regressions use logit models, with average marginal effects presented. Standard errors are in brackets. Robust standard errors for the OLS model; Delta-method standard errors for the logit models. Pseudo R^2 for logit models. Some observations are omitted due to multicollinearity issues. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.2: OLS and logit regressions for impact of solar PV capacity, NSW ACT, and NT excluded

	Weekly energy expenditures ($)	Low Income High Costs (binary)	Ten-Percent -Rule (binary)	Unable to pay bills on time (binary)
System size (kW)	-3.746***	-0.018***	-0.020***	-0.004
	(0.251)	(0.004)	(0.004)	(0.003)
R^2	0.280	0.254	0.355	0.204
Obs	7,068	7,060	7,051	7,068

Notes: Regressions control for all covariates in section 4.3. The "weekly expenditures" regression uses OLS. The binary regressions use logit models, with average marginal effects presented. Standard errors are in brackets. Robust standard errors for the OLS model; Delta-method standard errors for the logit models. Pseudo R^2 for logit models. Some observations are omitted due to multicollinearity issues. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table D.3: OLS and logit regressions for alternative objective energy poverty indicators

	LIHC, alt poverty line (binary)	Five Percent Rule (binary)	Fifteen Percent Rule (binary)
System size (kW)	-0.011***	-0.049***	-0.006***
	(0.003)	(0.004)	(0.002)
Pseudo R^2	0.264	0.304	0.442
Obs	9,900	9,872	9,873

Notes: Regressions control for all covariates in section 4.3. The regressions use logit models, with average marginal effects presented. Delta-method standard errors are in brackets. Some observations are omitted due to multicollinearity issues. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.