Energy poverty, temperature and climate change

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Abstract

We examine the effect of temperature shocks on the proclivity to be in energy poverty and combine our estimates with simulated weather data to predict the effect of global warming on the incidence of energy poverty over the rest of the century. To do so, we match representative household panel data for Australia with weather data at a geographically localized level. We find that each additional 'cold day' (average temperature below 15ºC) increases the incidence of energy poverty by 0.01%-0.03%, compared to if the day had been in the comfortable temperature range (20-24ºC). We find that global warming can be expected to result in modest decreases in the extent of energy poverty in the short-medium and long-run. Most studies have emphasized the economic and social costs of climate change. Our findings are important in pointing to a specific outcome for which climate change may be beneficial for a large country with a relatively mild climate.

Keywords: temperature, climate change, energy poverty

* This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the authors and should not be attributed to either DSS or the Melbourne Institute.

1. Introduction

The effect of temperature increases, due to climate change, are expected to have negative effects on a range of outcomes. For example, global warming, as a consequence of climate change, is expected to result in higher crime rates (Ranson, 2014), more natural disasters (Benevolenza & DeRigne, 2019), poorer health outcomes (Woodward et al., 2014) and increased prevalence of violent conflict (Scheffran et al., 2012). One outcome that has received little attention is the effect of global warming on the incidence of energy poverty. While a number of definitions of energy poverty exist, in their review of energy poverty indicators, Siksnelyte-Butkiene et al. (2021, p. 1) suggest: "All energy poverty definitions can be summarized into two main categories – (i) very high share of income spent on energy needs, and (ii) inability to consume modern energy for various reasons". The first category is typically employed in studies for developed countries, while the latter is a common use of energy poverty in studies for developing countries. In a developed country context Lowans et al. (2021, p. 1) state: "The term 'energy poverty' commonly refers to the inability of a home or small business to afford an adequate supply of heat, electricity, or energy services". Thus, while inability to afford energy focuses attention on the combination of low incomes and high energy prices, energy inefficiency also contributes to households being in energy poverty, especially given that low-income households tend to live in less energy efficient homes and use appliances that consume more energy and are more costly to run (Farrell & Fry, 2021).

The effect of temperature increases on the incidence of energy poverty can be expected to depend on the climate. In cold climates, in which energy poverty is typically associated with the inability to adequately heat one's home, one might expect temperature increases to unambiguously lower the incidence of energy poverty holding other factors constant. However, in warm climate countries, in which energy poverty is primarily due to the cost of cooling, rising temperatures might exacerbate energy poverty. This is because in countries, or regions, with hot climates, spikes in energy consumption, contributing to energy poverty, are mainly due to extremely hot days (Auffhammer & Aroonruengsawat, 2011; Chai et al., 2021; Deschênes & Greenstone, 2011). Moreover, low-income households are often not on the best energy plan to minimize the cost associated with energy spikes on hot days (Uddin et al., 2021). The effect of temperature increases, due to climate change, on the incidence of energy poverty in countries such as Australia, which is where our study is situated, which have very large landmasses with considerable regional differences in climate, is somewhat ambiguous and may depend on the extent to which energy poverty is due to the cost of heating or cooling.

We examine the effect of temperature shocks on the incidence of energy poverty in Australia. To do so, we employ 16 waves of the Household Income Labour Dynamics Australia (HILDA) survey, which we match with data on temperature at the postcode level.[1] We find that each additional 'cold day' (average temperature below 15^{o}C) increases the incidence of energy poverty by 0.01%-0.03%, compared to if the day had been in the comfortable temperature range (20-24^{o}C). Combining this result with simulated weather data from the NASA Earth

[1] The postcode is a small geographical area in Australia. In urban areas, a postcode broadly corresponds to a town or suburb. In rural or regional areas, postcodes are larger in area terms, but because population density is lower, still have relatively few people. There are approximately 3,000 postcodes in Australia; the average area is 2,911 square kilometres with each postcode having an average population of 9,075 people.

Exchange (NEX) Global Daily Downscaled Projections (GDDP) and the CMIP6 Project, we also quantify the effects of global warming on the prevalence of energy poverty over the rest of the twenty-first century. We show that global warming change can be expected to result in modest decreases in the incidence of energy poverty in the short, medium and long-run.

The only other study to examine how temperature shocks affect the incidence of energy poverty is Feeny et al. (2021) who find that in Vietnam temperature shocks lead to an increase in energy poverty. We differ from Feeny et al. (2021) in that in addition to examining how temperature shocks influence the extent of energy poverty, we also quantify the short, medium and long-term effects of global warming on energy poverty. Feeny et al. (2021) emphasise that their results are important when considering the effect of climate change on the incidence of energy poverty. For instance, they note that "understanding the varied impacts of higher temperatures is crucial to forming a measured view of the implications of climate change" (Feeny et al., 2021, p. 11). However, they do not use their results to simulate the long-term effects of global warming on the prevalence of climate change. We also differ from Feeny et al. (2021) in that while they find that temperature shocks increase the prevalence of energy poverty, we find that they lower the likelihood of being in energy poverty. This has important implications for the long-term effects of global warming on the extent of energy poverty. Feeny et al. (2021, p. 11) conclude "given the link between climate change and temperature shocks, the international community should strengthen its commitment to reduce carbon emissions in order to curb future temperature increases". While their results imply that global warming would increase the proclivity to be in energy poverty, we find that projected temperature increases due to global warming lowers the incidence of energy poverty. That our findings differ from Feeny et al. (2021) likely reflects that Vietnam, which is geographically closer to the equator, has a warmer climate than Australia, so more energy is used for cooling than in Australia. Low-income households in Vietnam are also more susceptible to the effect of temperature shocks on agricultural productivity which affects energy poverty through an income channel.

Our study also intersects with a broader literature on energy poverty and climate change. This literature asks the question whether taking steps to reduce energy poverty will contribute to climate change. These studies generally find that policies to reduce energy poverty will lead to greater carbon emissions by increasing energy consumption; thus, exacerbating climate change (see, e.g., Chakravarty & Tavoni, 2013). These effects are likely compounded by the high costs to low-income households of switching to renewable sources of energy, such as solar (Farrell & Fry, 2021). This literature tends to conclude that the best way to solve the trade-off between energy poverty alleviation and global warming is through improving energy efficiency (Ürge-Vorsatz & Tirado Herrero, 2012). We ask the opposite question: what are the implications of climate change for energy poverty? Our findings suggest that there need not be a trade-off, but rather that global warming can be complementary to reducing energy poverty.

2. Data

To examine the effect of temperature shocks on energy poverty, we use data from two mains sources. The first source is individual- and household-level data from HILDA. The HILDA survey is a nationally representative longitudinal study that provides information on family, household formation and socioeconomic indicators of Australians. The annual survey, which is described in more detail in Watson and Wooden (2012), commenced in 2001. We use Restricted Release 20 of the survey, which includes annual data covering the years 2001 to

2020. Our analysis is, however, restricted to waves 5 to 20 given that information on energy expenditure, used to measure energy poverty, is only available in these waves. The Restricted Release of HILDA provides information on the postcode in which respondents live. The use of the Restricted Release allows us to merge the HILDA survey data with ERA5 satellite reanalysis data, which is taken from our second data source, ECMWF. ERA5 combines information from ground stations, satellites, weather balloons and other inputs with a climate model to provides hourly estimates of several climate-related variables at a grid spacing of around 31 km globally with data available since 1979 (Dell et al., 2014). We use air temperature, measured as annual averages, and map the grid spacings in ERA5 to postcodes.

To examine the impact of future climate change on energy poverty, we obtain climate change prediction data from the NASA Earth Exchange (NEX) Global Daily Downscaled Projections (GDDP) and the CMIP6 Project. The NEX-GDDP-CMIP6 data provides average temperature projections for the short term (2020 to 2040), the medium term (2041–2060) and the long term (2061–2099) using nine global climate models (GCMs).[2]

2.1. Temperature shocks

We define temperature shocks at time t for postcode (p) as the difference between observed temperature at t and the long-run mean for each postcode p, divided by the long-run standard deviation for the postcode (see, e.g., Graff Zivin et al., 2020; Hirvonen, 2016; Letta et al., 2018). This measure of temperature shock represents the deviation in actual temperature from the historical mean for postcode p in time t, standardised by the standard deviation, and, thus, reflects both cold and hot temperature shocks. Our main measure of temperature shocks entails dividing the daily average temperature into one of five temperature bins: bin 1 is temperature below 15°C; bin 2 is temperature between 15°C and 19°C; bin 3 is temperature between 20°C and 24°C; bin 4 is temperature between 25°C and 29°C; and bin 5 is temperature above 29°C. The choice of temperature bin as the reference category depends on the country or regional climate (Karlsson & Ziebarth, 2018; White, 2017; Yu et al., 2019), with the most comfortable temperature range in a country or region typically employed as the reference bin (Yu et al., 2019). Given that Australia's climate is generally mild, we employ bin 3 (temperatures between 20°C and 24°C) as the reference category. In robustness checks, we consider the sensitivity of our results to alternative bin classifications, as well as different reference categories.

We also examine the robustness of our results to alternative measures of temperature shocks based on temperature deviations. We consider hot and cold temperature shocks separately where we define temperature shocks in terms of extreme heat (i.e., hot shocks) as temperature greater than one standard deviation above the mean and extreme cold (i.e., cold shocks) as temperature less than negative one standard deviation below the mean.

2.2. Energy poverty

We use measures of energy poverty that reflect both objective and subjective dimensions of energy poverty (Awaworyi Churchill & Smyth, 2021; Awaworyi Churchill et al., 2020; Llorca et al., 2020; Munyanyi et al., 2021; Prakash & Munyanyi, 2021). Our subjective indicator of energy poverty is designed to reflect the level of material deprivation that is perceived by

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[2] The nine GCMs are MRI-ESM2-0, MIROC6, MIROC-ES2L, IPSL-CM6A-LR, BCC-CSM2-MR, CNRM-ESM2-1, CNRM-CM6-1, GFDL-ESM4, CanESM5. Details are available at: https://www.worldclim.org/data/cmip6/cmip6climate.html

households that are unable to heat their homes (Awaworyi Churchill & Smyth, 2020; Awaworyi Churchill et al., 2020; Prakash & Munyanyi, 2021). We use a question in HILDA which asks respondents: "did any of the following happen to you because of a shortage of money?" The subjective indicator of energy poverty is a dummy variable equal to one if the respondent selects "was unable to heat home" in response to the question. In checks, we consider an alternative measure of subject energy poverty based on the question in HILDA, which asks respondents if they "could not pay electricity, gas or telephone bills on time" because of shortage of money. We use an energy poverty indicator that is a dummy variable equal to one if the respondent agrees that they could not pay their bills on time. This is a relatively noisy measure of energy poverty given that in addition to electricity and gas, it also captures telephone bills. However, we include it as an additional indicator of subjective energy poverty given that it has been used in the literature (see, e.g., Farrell & Fry, 2021).

To measure objective energy poverty, we employ the "low income-high cost" (LIHC) measure (Hills, 2012), which reflects households' low-income status and the high energy costs that they face. With the LIHC measure, a household is in energy poverty if their "energy costs are above the median level and were they to spend that amount they would be left with a residual income below the official poverty line" (Hills, 2012, p. 9). The objective indicator of energy poverty is equal to one if a household's condition is consistent with the LIHC criteria defined above. We use the LIHC indicator in preference to the expenditure-income indicator in our main analysis, given that the latter "is likely to either understate or overstate energy poverty rates depending on household income and/or energy rationing practices" (Awaworyi Churchill & Smyth, 2021, p. 4).[3] In robustness checks, we the 5%, 10% and 15% threshold indicators based on this ratio. The use of different cut-offs has the advantage that it avoids relying on a single threshold. We find that the results are robust to alternative measures of energy poverty.

3. Empirical Strategy

We estimate the following empirical specification:

$$EP_{ipt} = \gamma_0 + \sum_{j=1}^{5} \beta_j T_{pjt} + \delta_p R_{pt} + \varphi_i + \mu_s + \delta_t + \varepsilon_{it} \tag{1}$$

where EP_{it} is the energy poverty status of household i living in postcode p in year t, where EP is either the LIHC or 'unable to heat' indicators. T_{pjt} is the measure of temperature shock for postcode p in the period (t) and captures the number of days that fall into each of the five average temperature bins with bin 3 excluded as the reference category. R_{pt} is an indicator measuring rainfall for postcode p in period (t). Household fixed effects (φ_i), state fixed effects (μ_r) and time fixed effects (δ_t) are also included to absorb the effects of unobservable household, time-invariant state or time characteristics, and ε_{it} denotes the error term.

We cluster standard errors at the postcode level. By controlling for household and year fixed effects, the impact of temperature shocks is identified from location-specific deviations in temperature, while controlling for annual shocks common to all postcodes. In various sensitivity checks, we also control for a wider range of fixed effects including location-by-year fixed effects and time trends among others. Dell et al. (2014) caution against controlling for

[3] For a more general discussion of the limitations of the threshold measure see (Awaworyi Churchill et al., 2020; Boardman, 1991; Herrero, 2017; Hills, 2012; Thomson et al., 2017).

household demographic characteristics which might be influenced by temperature shocks. Thus, to avoid “over controlling”, in our main analysis we specify our model without household covariates. However, in robustness checks, for completeness we include demographic controls and our main conclusions remain qualitatively unchanged.

4. Results

4.1. Impact of temperature shocks on energy poverty

Table 1 reports the impact of temperature on energy poverty. Columns (1) and (2) present results for effects on LIHC using OLS and the panel fixed effect method, respectively, while Columns (3) and (4) run similar models focussed on the effects of temperature on the subjective indicator of energy poverty. For both the LIHC and ‘unable to heat’ measures, with the preferred panel fixed effect specification that controls for household fixed effects, the number of days when daily average temperatures are below 15^{o}C has a positive effect on energy poverty, relative to the number of days in the 20-24^{o}C range. Specifically, having one additional day with an average temperature below 15^{o}C increases the probability of being in energy poverty by 0.03% based on the LIHC measure and 0.01% based on the ‘unable to heat’ measure, compared to if the day had been in the 20-24^{o}C temperature range.

For other temperature bins, the results are mixed across measures, although there is some evidence of non-linear effects. For the LIHC measure, the number of days in the 25-29^{o}C range has a positive effect on energy poverty, while for the ‘unable to heat’ measure, the number of days between 15-19^{o}C category has a positive effect on energy poverty, relative to the reference category with panel fixed effects. The other temperature bins are insignificant. The results for ‘unable to heat’ for the 25-29^{o}C and days above 29^{o}C bins are to be expected, given that subjective ability to heat the home is unlikely to be an issue on warmer days. A limitation of the HILDA dataset is that it does not ask whether households were ‘unable to cool’.

The main results in Table 1 are based on temperature shocks measured using temperature bins, which is the most widely used approach in the literature (see, e.g., Agarwal et al., 2021; Graff Zivin et al., 2020; Taraz, 2018; Zhang et al., 2018). In Table 2, we use an alternative measure of temperature shocks, where we define temperature shocks for each postcode at a given time as the difference between observed temperature and the long-run average for each postcode divided by the long-run standard deviation for the postcode (see, e.g., Graff Zivin et al., 2020; Hirvonen, 2016; Letta et al., 2018). This measure of temperature shock represents the deviation in actual temperature from the historical mean for a postcode, standardised by the standard deviation. We also use indicators of temperature shocks that isolate the effects of extreme hot weather shocks from extreme cold shocks. We measure hot shocks as temperature deviation greater than one standard deviation above the mean and cold shocks as temperature deviation less than one standard deviation below the mean. We find that our results are consistent. Specifically, in Panel A, temperature deviations are associated with a decline in energy poverty, implying that hot shocks are likely to be driving the results. This is reinforced by the findings in Panels B and C, where hot temperature shocks are associated with a decline in energy poverty, while cold shocks are associated with an increase in energy poverty.

4.2.Climate change projections and energy poverty

We simulate changes in future levels of energy poverty due to climate change. To do this, we combine the estimate from Panel A of Table 2 with data on simulated weather conditions at the postcode level for 2021 to 2099. We focus on RCP4.5 and RCP8.5, which are two extreme emission pathways that represent opposite ends of the climate spectrum depending on the uptake of renewable energy.[4] Given that estimates of the economic effects of climate change are sensitive to the specific choice of GCM (Burke et al., 2015), we use future projections from eight of the nine GCMs at 2.5-minutes spatial resolution to ensure that our results are robust.[5]

Following Burke et al. (2009), we generate monthly average temperature projections. First, for 2001 to 2020, we use daily average temperature to construct monthly average temperature and probability distribution functions. We then calculate projected changes in monthly average temperatures as the difference between the projected and the historical average temperatures. Finally, we assume that the distribution of the projected average temperatures closely mirror that of historical temperature and, thus, construct the distribution of average temperature in the short, medium and long terms for the RCP4.5 and RCP8.5 emission pathways.

Table 3 provides a summary of the projected changes for temperature and LIHC for each of the eight GCMs for the RCP4.5 and RCP8.5 emission pathways in the short, medium and long terms, while Table 4 does the same for the projected changes for temperature for the subjective 'unable to heat" indicator. Under the RCP4.5 and RCP8.5 pathways, the average change in temperature peaks at 1.448 and 1.807 standard deviations, respectively, in the long-term.

In Table 3, using the maximum temperature projection across CGMs for the RCP4.5 pathway, average temperature increases are associated with, at most, a 0.024, 0.025 and 0.027 standard deviation decrease in energy poverty in each of the short, medium and long terms, respectively. For the RCP8.5 pathway, average temperature increases are associated with, at most, a 0.024, 0.028 and 0.033 standard deviation decrease in energy poverty based on the LIHC indicator in the short, medium and long terms, respectively. Thus, without any countervailing strategies to address climate change between 2021 and 2099, in the form of investment in renewable energy, there would be an additional 0.006 standard deviation decrease in energy poverty as a result of climate change, compared with the 'best case' RCP4.5 scenario.[6]

In Table 4, for the RCP4.5 pathway, average temperature increases are associated with, at most, a 0.010, 0.011 and 0.011 standard deviation decrease in energy poverty in the short, medium and long terms, respectively. For the RCP8.5 pathway, average temperature increases are associated with, at most, a 0.009, 0.012 and 0.014 standard deviation decrease in energy poverty in the short, medium and long terms, respectively. Thus, without any countervailing strategies to address climate change, there would be an additional 0.003 standard deviation

[4] RCP is the Representative Concentration Pathway, which captures future trends in climate change under alternative scenarios of human activities. RCP8.5 tracks emissions consistent with current trends (business as usual scenario in which greenhouse gas emissions go unchecked), while RCP4.5 considers a scenario with increased reliance on renewable energy and less reliance on coal-fired power.

[5] GFDL-ESM4 is excluded because future projections are not available for this under the RCP8.5 pathway.

[6] Under RCP4.5, in which the government actively promotes renewables, we can expect at most a 0.027 standard deviation decrease in energy poverty and under RCP8.5, in which the government does nothing, we can expect at most a 0.033 standard deviation decrease in energy poverty. The difference in outcomes under the two pathways is a 0.006 standard deviation decrease in energy poverty.

decrease in energy poverty based on the subjective 'unable to heat' indicator as a result of climate change compared with the 'best case' RCP4.5 scenario.

4.3.Robustness checks

We examine the sensitivity of our results to three alternative indicators of energy poverty based on the ratio of energy expenditure to income. While our preference is to use the LIHC indicator to capture objective energy poverty given its benefits over the threshold indicators, we also employ the threshold indicators for completeness. Threshold indicators, especially the 10 per cent threshold, which is based on the energy expenditure-income ratio is one of the most widely used indicators of energy poverty (Awaworyi Churchill & Smyth, 2020, 2021; Boardman, 1991; Healy & Clinch, 2004; Thomson et al., 2017). We consider 5%, 10% and 15% as thresholds, which we choose to overcome the sensitivity of our results to the use of a single threshold. The results, which are reported in Table 5, remain robust to these alternative measures. Specifically, having one additional day with an average temperature below 15^{o}C increases the probability of being in energy poverty by 0.01% to 0.06%, compared to if the day had been in the 20-24^{o}C temperature range, depending on threshold. Our results are also robust to the alternative indicator of subjective energy poverty which reflects respondents' inability to pay their electricity, gas and telephone bills on time as a result of money shortage. One additional day with an average temperature below 15^{o}C increases the probability of being unable to pay the electricity, gas or telephone bills on time as a result of money shortage by 0.06%, compared to if the day had been in the 20-24^{o}C temperature range

Next, we examine if our results are robust to the use of different temperature bins and reference temperature groups. Our main results are based on five temperature bins. In Panels A and B of Figure 1, we measure temperature shocks using seven and nine temperature bins, respectively, with different reference categories. In each case, our results are consistent with the findings that lower temperatures, relative to more normal temperature ranges, are associated with higher energy poverty. Consistently, across Panels A and B, we find that an additional day with an average temperature below 10^{o}C increases the probability of being in energy poverty.

In the main results, the most comfortable temperature range is used as the reference range. For a country with an overall mild climate, such as Australia, this averages around 20-24^{o}C (Graff Zivin et al., 2018). However, Australia's climate varies significantly, and in warmer regions, particularly in the northern states, the most comfortable temperature range is likely to be different from that in the colder states in the south of the country. In further checks, we employ a higher temperature bin (25-29^{o}C) as the reference in warmer postcodes and a lower temperature bin (16-18^{o}C) as a reference category in the colder postcodes.[7] The results, reported in Figures 2 and 3, are consistent with the conclusion that one additional day with a relatively lower average temperature increases the probability of being in energy poverty.

Past temperatures are likely to influence current economic outcomes, such as energy poverty, and may be correlated with current temperature. To address this potential source of bias, we consider alternative models in which we include one-year and two-year lagged temperature bins. In Table 6, we find that our results remain robust. We also find that the one- and two-year lags are statistically significant with the effects of temperature waning over time.

[7] Following Awaworyi Churchill et al. (2020), we consider postcodes and temperatures with actual temperatures above and below the mean as 'warm' and 'cold', respectively.

Different socioeconomic conditions, as well as differences in temperature across states, means that the observed effects of temperature shocks could be stronger in some states than others. To ensure that our results are not being driven by the effects of a single state, we drop each state one-by-one in alternating models. The results, which are presented in Figure 4, show that our results in each case are close to baseline and are not driven by any specific state.

Next, we control for additional fixed effects that take into account the month in which the HILDA interview took place as well as control for state-specific time trends[8]. The results, which are presented in Table 7, suggest that our results remain robust.

As a final check on our main results, we examine if omitted variables are biasing our estimates. In Table 1, we do not control for the characteristics of the respondent, which are potentially endogenous, to avoid over controlling (Dell et al., 2014). In a first check, consistent with the energy poverty literature, we control for characteristics of the household reference person. Our controls for characteristics of the household reference person include age, marital status, number of dependants, education, and health status. The results, which are presented in Table A2, show that the effects of temperature shocks are similar to those in Table 1. Specifically, having one additional day with an average temperature below 15°C increases the probability of being in energy poverty based on the LIHC and subjective indicators by 0.03% and 0.01%, respectively, compared to if the day had been in the 20-24°C temperature range.

As a second check on omitted variables bias, we conduct the Oster (2019) bounds analysis which allows for partial identification of the impact of temperature shocks on energy poverty and constructs consistent bounds on the 'true' coefficients that would have been estimated assuming that information on all unobserved and observed covariates were known. In doing this, we examine the sensitivity of the estimates in Table 1 to the inclusion of observed covariates as shown in Table A2, and establish coefficient stability (Altonji et al., 2005).

Table 8 reports results from the bounds analysis. Panels A and B report results for LIHC and the subjective indicator, respectively. Columns 1 and 3 report estimates of the effect of temperature shocks on energy poverty from the uncontrolled and controlled models, respectively. Column 3 shows the identified set of upper and lower bounds of the estimated coefficients, while Column 4 shows whether this set exclude zero. The upper and lower bounds show that the identified set excludes zero, implying that the estimates from the controlled regressions are robust to omitted variable bias. In Column 5, the ratio of the impact of unobserved covariates relative to observed covariates which shows the effect for unobserved variables to bias our estimates is reported. We find that for LIHC this value is 14.22 and for the subjective indicator, 2.244. These values imply that the effects of any omitted variables have to be more than 2.3 to 14.2 times larger than the effects of the included covariates, which seems unlikely. This suggests that our results are robust to omitted variable bias.

5. Conclusion

We have examined the effect of temperature shocks on the incidence of energy poverty and used the results to project the effect of global warming on the prevalence of energy poverty in the short, medium and long terms. We find that each additional 'cold day' increases the

[8] HILDA interviews typically take place between the months of July to November, with most interviews occurring in August, September and October.

incidence of energy poverty and that global warming, associated with climate change can be expected to have modest effects on decreasing the extent of energy poverty.

Most of the literature has emphasised the negative effects of climate change for myriad outcomes. Conceptually, though, the effects of global warming on the prevalence of energy poverty are uncertain. Our results are consistent with there being at least modest initial benefits of climate change for energy poverty reductions over the rest of the century. However, in the very long-run, it is certainly possible that these benefits may dissipate and become costs as temperature continues to rise beyond the projections to the turn of the century. In this respect, our results are consistent with studies of the economic effects of climate change reviewed in Tol (2009, p. 34) that “point to initial benefits of a modest increase in temperature followed by losses as temperatures increase further”. A caveat on our findings is that the benefits are likely greater, and more long-lasting, for countries with colder climates than Australia, with the opposite being the case for countries with hotter climates where higher temperatures will more quickly exacerbate the costs of cooling. Initial differences in climate are likely to be important in explaining the differences in our results and those reported in Feeny et al. (2021), which suggest that higher temperatures are associated with an increase in energy poverty in Vietnam.

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Table 1: Temperature shocks and energy poverty – Main results

	LIHC		Unable to heat	
	OLS	Panel	OLS	Panel
	(1)	(2)	(3)	(4)
Temperature (Reference: # days temperature between 20-24^{o}C)				
# days below 15^{o}C	0.0004***	0.0003***	0.0000	0.0001**
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
# days between 15-19^{o}C	0.0001	0.0001	-0.0000	0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0000)
# days between 25-29^{o}C	0.0004***	0.0002***	-0.0001	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0000)
# days above 29^{o}C	0.0005**	0.0001	-0.0001	-0.0002
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Controlling for rainfall	Yes	Yes	Yes	Yes
Household FE	No	Yes	No	Yes
State and Time FE	Yes	Yes	Yes	Yes
Observations	122,523	122,523	123,630	123,630

Notes: Clustered standard errors at postcode level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 2: Results using temperature deviation

	LIHC	Unable to heat
	(1)	(2)
Panel A: Temperature deviation		
Temperature deviations	-0.0185***	-0.0078**
	(0.0050)	(0.0034)
Panel B: Hot temperature (deviation > 1)		
Hot temperature	-0.0068***	0.0017
	(0.0023)	(0.0017)
Panel C: Cold temperature (deviation < -1)		
Cold temperature	0.0094***	0.0051***
	(0.0026)	(0.0019)
Controlling for rainfall	Yes	Yes
Household FE	Yes	Yes
State and Time FE	Yes	Yes
Observations	122,466	123,606

Notes: Clustered standard errors at postcode level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 3: Simulated effect of temperature on incidence of ‘LIHC energy poverty 2021-2099

	Representative Concentration Pathway (RCP) 4.5					
	Short-term (2021-2040)		Medium-term (2041-2060)		Long-term (2061-2099)	
GCM Models	∆Temperature	∆LIHC	∆Temperature	∆ LIHC	∆Temperature	∆ LIHC
BNU_ESM	1.246	-0.023	1.297	-0.024	1.400	-0.026
CCSM4	1.266	-0.023	1.314	-0.024	1.384	-0.026
CNRM_CM5	1.180	-0.022	1.245	-0.023	1.326	-0.025
CanESM2	1.261	-0.023	1.356	-0.025	1.448	-0.027
IPSL_CM5A_MR	1.279	-0.024	1.361	-0.025	1.472	-0.027
MIROC_ESM	1.286	-0.024	1.313	-0.024	1.441	-0.027
MIROC_ESM_CHEM	1.257	-0.023	1.327	-0.025	1.447	-0.027
MRI_CGCM3	1.142	-0.021	1.181	-0.022	1.269	-0.023
	Representative Concentration Pathway (RCP) 8.5					
	Short-term (2021-2040)		Medium-term (2041-2060)		Long-term (2061-2099)	
GCM Models	∆Temperature	∆ LIHC	∆Temperature	∆ LIHC	∆Temperature	∆ LIHC
BNU_ESM	1.246	-0.023	1.297	-0.024	1.400	-0.026
CCSM4	1.264	-0.023	1.396	-0.026	1.620	-0.030
CNRM_CM5	1.189	-0.022	1.352	-0.025	1.554	-0.029
CanESM2	1.318	-0.024	1.503	-0.028	1.793	-0.033
IPSL_CM5A_MR	1.296	-0.024	1.454	-0.027	1.807	-0.033
MIROC_ESM	1.260	-0.023	1.346	-0.025	1.643	-0.030
MIROC_ESM_CHEM	1.233	-0.023	1.351	-0.025	1.668	-0.031
MRI_CGCM3	1.161	-0.021	1.275	-0.024	1.489	-0.028

Notes: Change in temperature and energy poverty is measured in standard deviation. Data on simulated weather conditions at the postcode level are from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). The projection is estimated using the coefficient of -0.0185 reported in Column (1) of Table 2 (Panel A).

Table 4: Simulated effect of temperature on incidence of being 'Unable to Heat' 2021-2099

	Representative Concentration Pathway (RCP) 4.5					
	Short-term (2021-2040)		Medium-term (2041-2060)		Long-term (2061-2099)	
GCM Models	∆Temperature	∆UTH	∆Temperature	∆ UTH	∆Temperature	∆ UTH
BNU_ESM	1.246	-0.010	1.297	-0.010	1.400	-0.011
CCSM4	1.266	-0.010	1.314	-0.010	1.384	-0.011
CNRM_CM5	1.180	-0.009	1.245	-0.010	1.326	-0.010
CanESM2	1.261	-0.010	1.356	-0.011	1.448	-0.011
IPSL_CM5A_MR	1.279	-0.010	1.361	-0.011	1.472	-0.011
MIROC_ESM	1.286	-0.010	1.313	-0.010	1.441	-0.011
MIROC_ESM_CHEM	1.257	-0.010	1.327	-0.010	1.447	-0.011
MRI_CGCM3	1.142	-0.009	1.181	-0.009	1.269	-0.010
	Representative Concentration Pathway (RCP) 8.5					
	Short-term (2021-2040)		Medium-term (2041-2060)		Long-term (2061-2099)	
GCM Models	∆Temperature	∆ UTH	∆Temperature	∆ UTH	∆Temperature	∆ UTH
BNU_ESM	1.246	-0.010	1.297	-0.010	1.400	-0.011
CCSM4	1.264	-0.010	1.396	-0.011	1.620	-0.013
CNRM_CM5	1.189	-0.009	1.352	-0.011	1.554	-0.012
CanESM2	1.318	-0.010	1.503	-0.012	1.793	-0.014
IPSL_CM5A_MR	1.296	-0.010	1.454	-0.011	1.807	-0.014
MIROC_ESM	1.260	-0.010	1.346	-0.010	1.643	-0.013
MIROC_ESM_CHEM	1.233	-0.010	1.351	-0.011	1.668	-0.013
MRI_CGCM3	1.161	-0.009	1.275	-0.010	1.489	-0.012

Notes: Change in temperature and energy poverty is measured in standard deviation. Data on simulated weather conditions at the postcode level are from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). UTH stands for unable to heat. The projection is estimated using the coefficient of -0.0078 reported in Column (2) of Table 2 (Panel A).

Table 5: Alternative measures of energy poverty

Dependent variable	Energy poverty - 5% threshold	Energy poverty - 10% threshold	Energy poverty - 15% threshold	Could not pay electricity, gas or telephone bills on time
	(1)	(2)	(3)	(4)
Temperature (Reference: # days temperature between 20-24^{o}C)				
# days below 15^{o}C	0.0006***	0.0001***	0.0001***	0.0006***
	(0.0001)	(0.0000)	(0.0000)	(0.0001)
Controlling for rainfall	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes
State and Time FE	Yes	Yes	Yes	Yes
Observations	125,754	125,754	125,754	124,146

Notes: Clustered standard errors at postcode level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6: Lagged effects of temperature shocks

	LIHC		Unable to heat	
	(1)	(2)	(3)	(4)
Temperature (Reference: # days temperature between 20-24^{o}C)				
# days below 15^{o}C – Lag 1	0.0003***		0.0001**	
	(0.0001)		(0.0000)	
# days below 15^{o}C – Lag 2		0.0002***		0.0001*
		(0.0001)		(0.0000)
Controlling for rainfall	Yes	Yes	Yes	Yes
Household FE	No	Yes	No	Yes
State and Time FE	Yes	Yes	Yes	Yes
Observations	122,523	122,523	117,047	110,814

Notes: Clustered standard errors at postcode level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7: Controlling for different fixed effects

	LIHC	Unable to heat
	(1)	(2)
Panel A: Controlling for month of interview		
# days below 15ºC	0.0003***	0.0001**
	(0.0001)	(0.0000)
Panel B: Controlling for state-specific time trend		
# days below 15ºC	0.0003***	0.0001**
	(0.0001)	(0.0000)
Controlling for rainfall	Yes	Yes
Household FE	Yes	Yes
State and Time FE	Yes	Yes

Notes: Clustered standard errors at postcode level in parentheses; *** p<0.01, ** p<0.05, * p<0.1

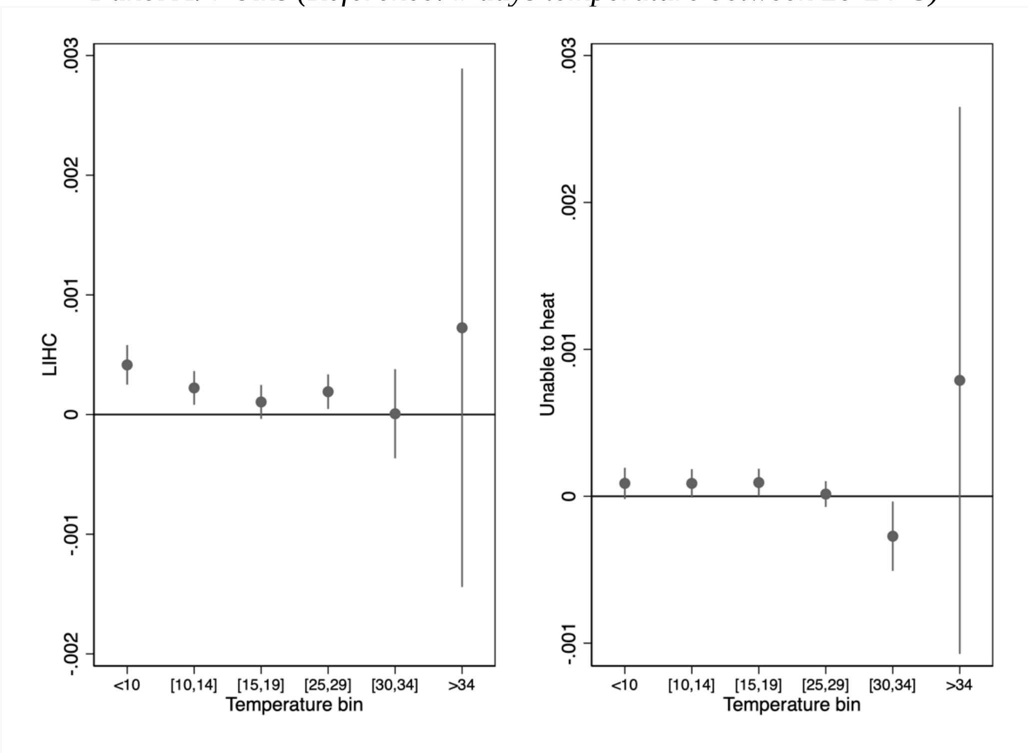
Table 8: Parameter stability and robustness to omitted variable bias

	(1)	(2)	(3)	(4)	(5)
Treatment variable	Coefficient on temperature without any controls	Coefficient on temperature including covariates	Upper and lower bound of estimated coefficients	Exclude zero?	Effect for unobserved variables to bias estimates
Panel A: Outcome is LIHC					
# days below 15^{o}C	0.00030***	0.00031***	[0.00030, 0.00031]	Yes	14.220
Observations	126,143	126,143			
Panel B: Outcome is Unable to heat					
# days below 15^{o}C	0.00004*	0.00009**	[0.00004, 0.00009]	Yes	2.244
Observations	128,139	128,139			

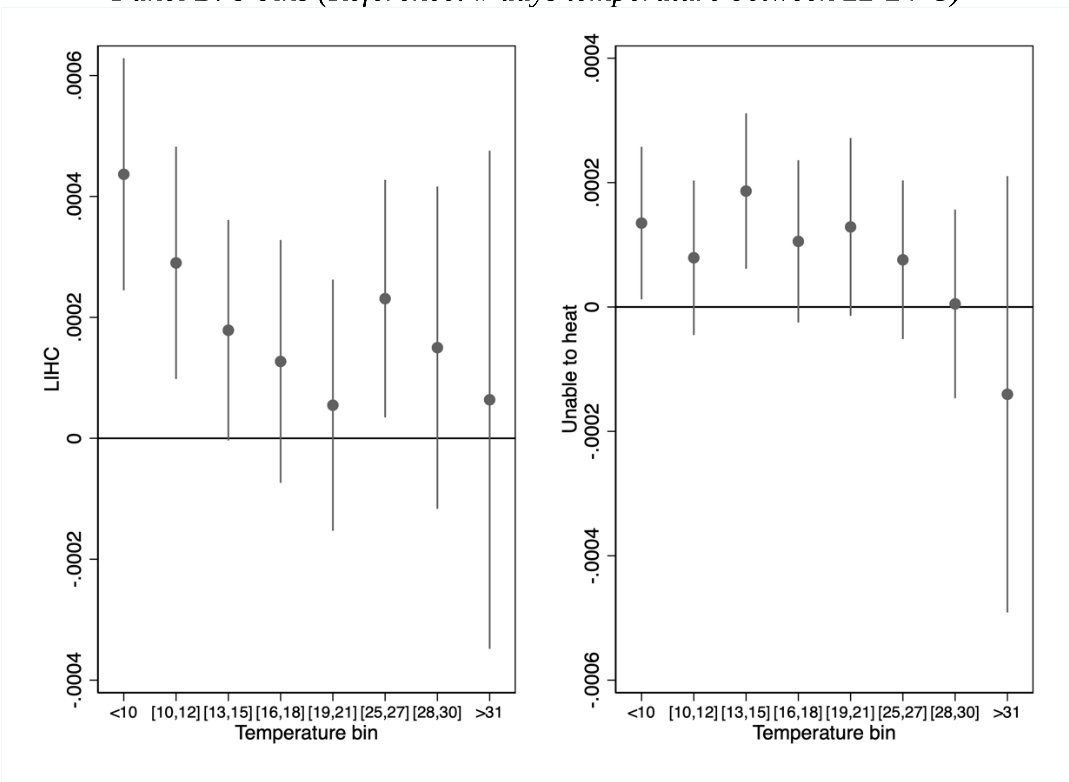
Notes: Standard errors are clustered at the postcode level; *** p<0.01, ** p<0.05, * p<0.1

Figure 1: Different bins of temperature

Panel A: 7 bins (Reference: # days temperature between 20-24^{o}C)

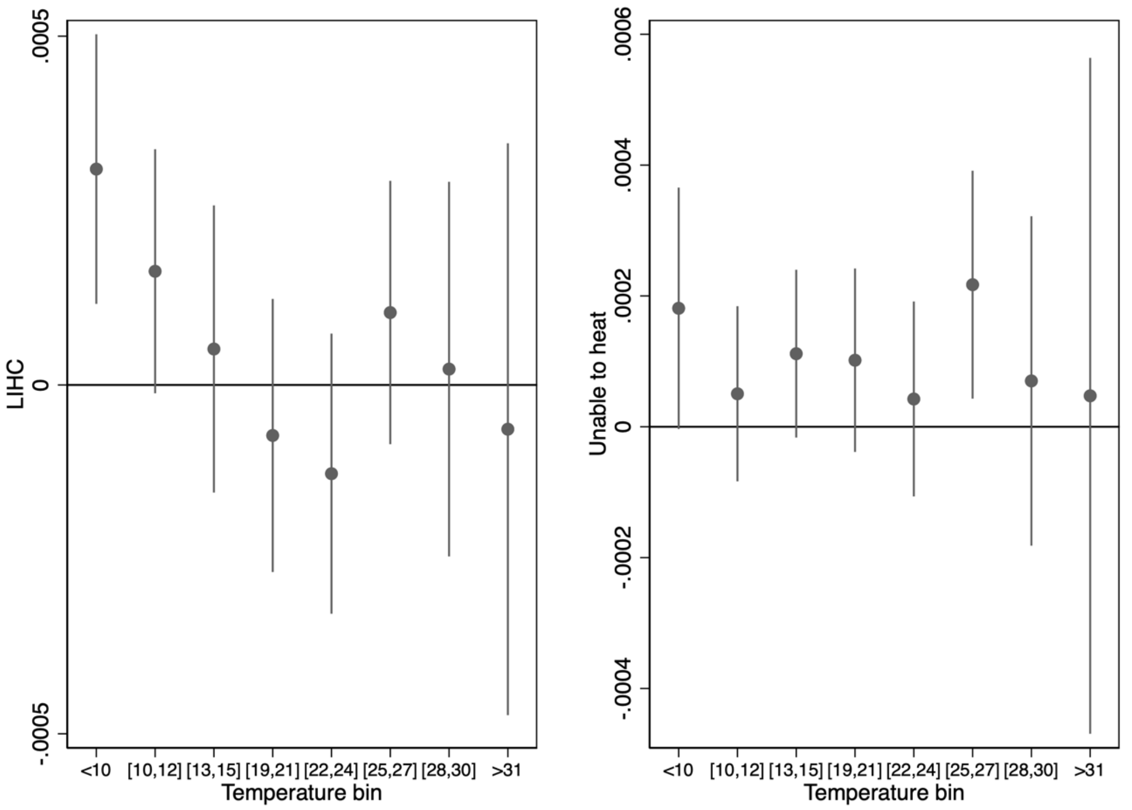


Panel B: 9 bins (Reference: # days temperature between 22-24^{o}C)



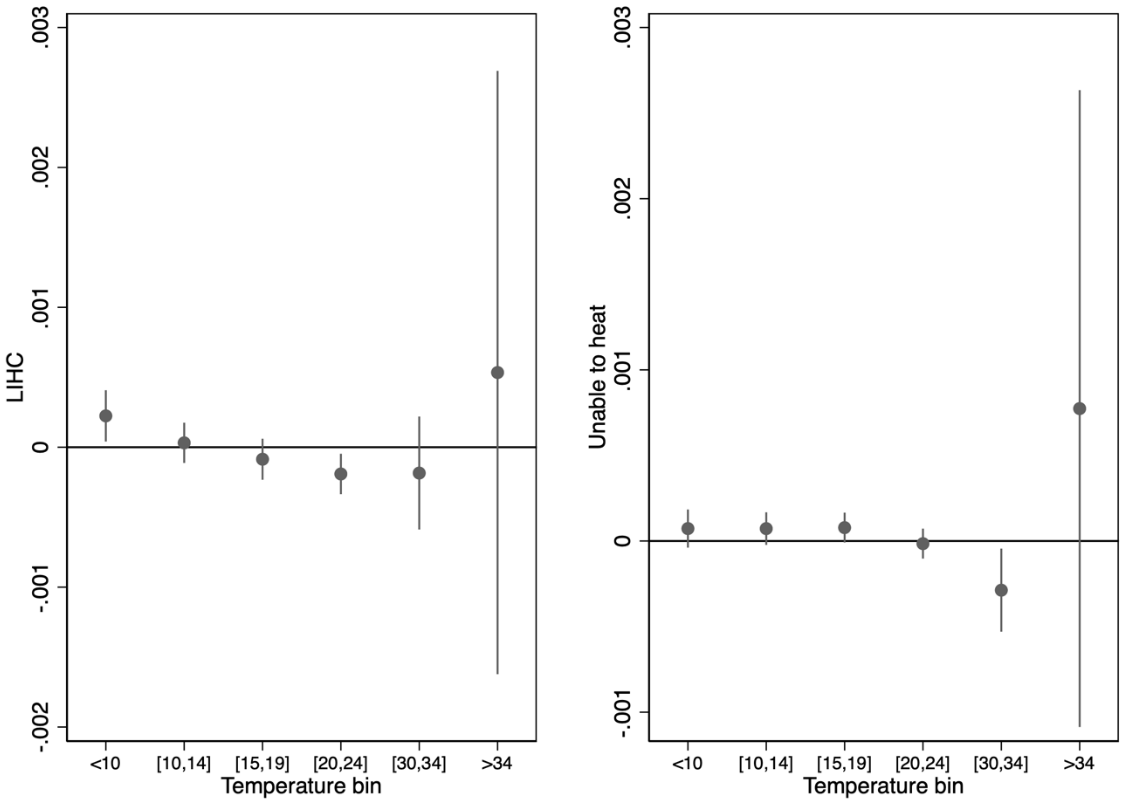
Notes: The figure shows estimates and their 95% confidence intervals of separate regressions using different temperature bins. All regressions include rainfall, state, and time fixed-effects.

Figure 2: Reference category of temperature between 16-18^{o}C (cold postcodes)



Notes: The figure shows estimates and their 95% confidence intervals of separate regressions using alternative source of temperature. All regressions include rainfall, state, and time fixed-effects. The reference category is temperature between 16-18^{o}C.

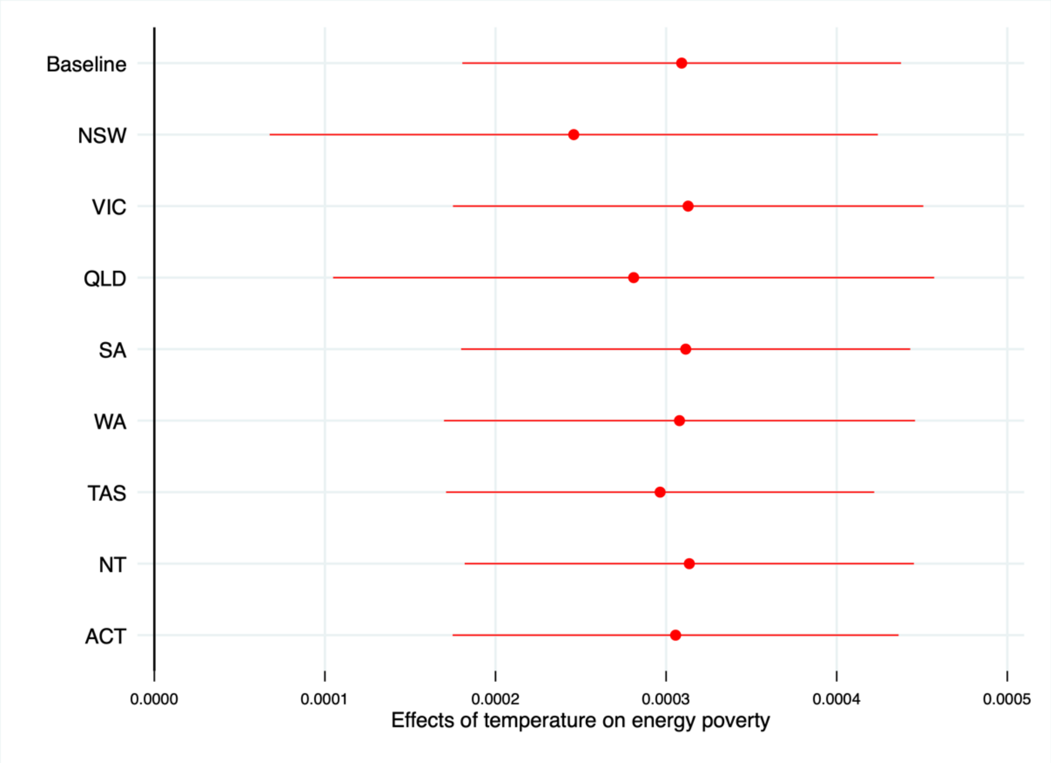
Figure 3: Reference category of temperature between 25-29^{o}C in warm postcodes



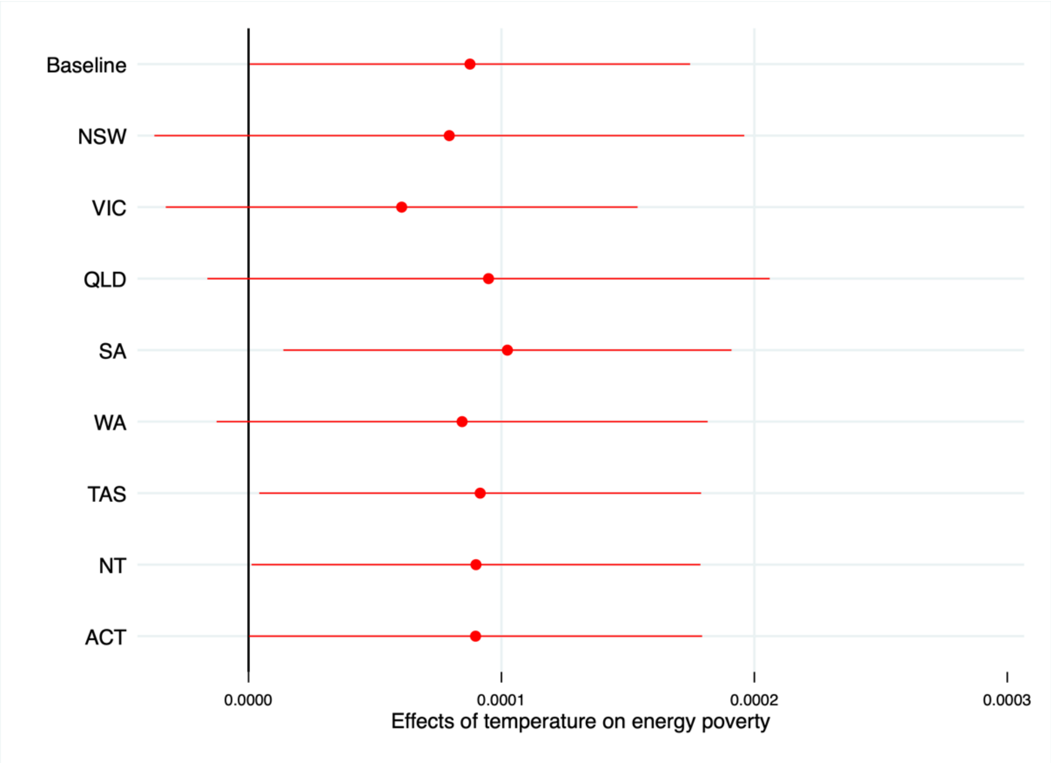
Notes: The figure shows estimates and their 95% confidence intervals of separate regressions using alternative source of temperature. All regressions include rainfall, state, and time fixed-effects. The reference category is temperature between 25-29^{o}C.

Figure 4: Robustness to dropping states one by one

Panel A: LIHC



Panel B: Unable to heat



Notes: Reported are treatment effect estimates and their 95% confidence intervals; Each estimate comes from a panel fixed-effects regression of energy poverty on temperature shocks and other control variables; The state indicated is the excluded state; Standard errors are clustered at the postcode level.

Table A1: Variable descriptions and summary statistics

Variables	Description	Mean	St. Dev
Energy poverty			
LIHC	=1 if household has energy costs are above the median level and a residual income after energy expenditure is below the poverty line	0.077	0.266
Unable to heat	=1 if household was unable to heat their home because of money shortage	0.037	0.189
Temperature shocks			
# days below 15^{o}C	Number of days temperature below 15^{o}C	143.226	74.367
# days between 15-19^{o}C	Number of days temperature between 15^{o}C and 19^{o}C	108.312	29.398
# days between 20-24^{o}C	Number of days temperature between 20^{o}C and 24^{o}C	85.656	48.708
# days between 25-29^{o}C	Number of days temperature between 25^{o}C and 29^{o}C	26.028	33.848
# days above 29^{o}C	Number of days temperature above 29^{o}C	1.989	6.685
Rainfall			
Rainfall	Average yearly rainfall	0.002	0.0005
Other variables			
Year 11 and below	Equals 1 if highest educational attainment is Year 11 or lower [reference group]	0.282	0.450
Year 12	Equals 1 if highest educational qualification is completing high school (i.e., Year 12)	0.126	0.332
Diploma / Certificate	Equals 1 if highest educational qualification is a diploma or Level III or IV certificate	0.335	0.472
Degree	Equals 1 if highest educational qualification is bachelor's degree or higher-level qualification	0.256	0.437
Single	Equals 1 if not married or living with someone in a relationship [reference group]	0.424	0.494
Cohabiting	Equals 1 if not married, and living with someone in a relationship	0.444	0.497
Married	Equals 1 if married	0.131	0.338
Income	Disposable income (in log)	10.814	0.988
Age	Age of household head	48.933	17.893
Long-term health condition	Equals 1 if has health condition or disability that restricts everyday activity	0.300	0.458
Number of dependents	Number of dependents	0.498	0.943

Notes: Monetary units are adjusted for inflation.

Table A2: Temperature shocks and energy poverty – Controlling for individual/household characteristics

	LIHC		Unable to heat	
	OLS	Panel	OLS	Panel
	(1)	(2)	(3)	(4)
Temperature (Reference: # days temperature between 20-24^{o}C)				
# days below 15^{o}C	0.0003***	0.0003***	-0.0000	0.0001**
	(0.0001)	(0.0001)	(0.0000)	(0.0000)
# days between 15-19^{o}C	0.0001	0.0001	0.0000	0.0001**
	(0.0001)	(0.0001)	(0.0001)	(0.0000)
# days between 25-29^{o}C	0.0003***	0.0002***	-0.0001*	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0000)
# days above 29^{o}C	0.0004**	0.0001	-0.0002	-0.0002
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Education level (Reference: Year 11 and below)				
Year 12	-0.0011	-0.0110	-0.0149***	-0.0220*
	(0.0050)	(0.0141)	(0.0036)	(0.0129)
Vocational	-0.0026	-0.0257**	0.0008	-0.0102
	(0.0039)	(0.0119)	(0.0028)	(0.0108)
Bachelor and higher	-0.0073*	-0.0067	-0.0128***	-0.0147
	(0.0039)	(0.0146)	(0.0027)	(0.0127)
Marital status (Reference: Single)				
Married	0.0040	-0.0084*	-0.0335***	-0.0236***
	(0.0035)	(0.0049)	(0.0023)	(0.0028)
Cohabiting	-0.0096***	-0.0140***	-0.0244***	-0.0189***
	(0.0027)	(0.0040)	(0.0028)	(0.0031)
Other controls				
Household income (log)	-0.0809***	-0.0709***	-0.0180***	-0.0047***
	(0.0024)	(0.0028)	(0.0013)	(0.0012)
Age	0.0010***	0.0059	-0.0007***	-0.0036
	(0.0001)	(0.0040)	(0.0001)	(0.0027)
Long-term health condition	0.0179***	0.0032	0.0398***	0.0082***
	(0.0029)	(0.0028)	(0.0023)	(0.0018)
Number of dependents	0.0003	-0.0001	0.0075***	-0.0012
	(0.0009)	(0.0013)	(0.0010)	(0.0010)
Rainfall	-0.8126	4.1534	-4.7172**	-3.1268
	(3.2134)	(2.7886)	(2.3769)	(1.9569)
Household FE	No	Yes	No	Yes
State and Time FE	Yes	Yes	Yes	Yes
Observations	122,466	122,466	123,606	123,606
R-squared	0.106	0.385	0.037	0.428

Notes: Clustered standard errors at postcode level in parentheses; *** p<0.01, ** p<0.05, * p<0.1