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Fuel poverty policy: Go big or go home insulation

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ABSTRACT

Using the Residential Energy Consumption Survey (RECS) data for 2005 and 2015, we quantify key factors contributing to fuel poverty dimensions in the United States. Our results suggest some differences in explanations for two key fuel-poverty dimensions of unaffordability and inadequacy. Explanatory variables with positive associations with the unaffordability aspect include binary variables for renting and vulnerability signalled by prior receipt of energy assistance. Education and dwelling insulation are negatively associated with unaffordability aspects of fuel poverty. Solar panels might also be beneficial in this context. Insulation and prior receipt of energy assistance have consistent associations across both the unaffordability and inadequacy aspects of fuel poverty. We find no evidence of an association of renting or education with the inadequacy aspect of fuel poverty, in contrast to the case for the unaffordability aspect. Our results suggest that a policy providing small-scale assistance is not likely to substantially improve fuel poverty outcomes. However, a greater focus on home insulation and other big investments such as solar panels could be a more effective and transformative policy alternative.

1. Introduction

1.1. The research question

Fuel poverty has been discussed for several decades (Bradshaw and Hutton, 1983), however it remains a persistent problem, affecting over 20% of households in the United States (US Energy Information Administration, 2018a). The inability of a household to afford basic energy needs can harm subjective wellbeing, cause consumption reductions for non-energy essentials such as food, have adverse health outcomes, and limit future prospects for children (Awaworyi Churchill et al., 2020; Baker et al., 2018; Hernández and Siegel, 2019). Fuel poverty is responsible for more deaths than car crashes in Vermont (Teller-Elsberg et al., 2016).

Despite its importance, fuel poverty remains understudied in the US (Mohr, 2018). More broadly, there are not many studies of energy assistance efforts toward reducing deprivation across dimensions of fuel poverty (Carley and Konisky, 2020). The influence of some potential causes of fuel poverty, such as behavior and investments like solar panels, have not been investigated extensively. There is also potential for more engagement of energy justice and fuel poverty analysis with fundamental economic concepts (Jenkins et al., 2016).

To inform understanding of the ongoing issue of fuel poverty in the United States, we attempt to comprehensively analyze multiple dimensions of fuel poverty to assess whether different factors are associated with different dimensions of fuel poverty. We use multiple measures within each of two main categories for unaffordability and inadequacy. We also aim to be comprehensive in including potentially important explanatory variables, such as solar panel systems and behavioral factors that have received little prior attention.

1.2. Definitions of fuel poverty

There is no consensus in the literature on the definition of fuel poverty, possibly due to its complexity. This has encouraged multiple ways of conceptualizing and measuring the issue, involving either combined measures or consideration of multiple separate indicators (Baker et al., 2018; Best and Burke, 2019; Meyer et al., 2018; Ntaintasis et al., 2019). Fuel poverty, succinctly described as the inability to afford adequate warmth (Bradshaw and Hutton, 1983), can be broadened to refer to the inability to afford adequate energy. While definitions of fuel poverty and related concepts have varied over the years, unaffordability and inadequacy are two key components (Bradshaw and Hutton, 1983; Boardman, 1991; Sovacool and Dworkin, 2015).

Fuel poverty can also be considered in a fundamental economic framework of utility maximization subject to a budget constraint. Inadequate energy detracts from subjective utility, while high energy expenditure relative to income contributes to unaffordability through the

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budget constraint. Factors affecting each type of fuel poverty could differ.

Both subjective and objective indicators have been used to quantify fuel poverty. The primary indicators on the EU Energy Poverty Observatory (2020) include two objective measures based on energy expenditure along with a subjective measure (inability to keep homes adequately warm). Objective measures such as the ratio of energy expenditure to income, popularized by Boardman (1991), can be classified in the budget-constraint category, as can measures based on disconnection notice receipt, or forgoing necessity spending due to budget pressure from energy bills. Arrears on energy bills are a further measure of fuel poverty used in academic literature (Aristondo and Onaindia, 2018) that focuses on unaffordability. Subjective measures are particularly suitable to assess impacts on subjective utility. For example, households feeling that their homes are at unhealthy temperatures aligns with the core aspect of inadequacy which is missed by measures that focus on actual energy expenditure.

1.3. Possible causes of fuel poverty

Previous studies have identified many contributing causes to fuel poverty. There are factors relating to costs, including housing costs and fuel costs (Burlinson et al., 2018). Locational factors, such as climate conditions, are also likely to affect susceptibility to fuel poverty. Robinson et al. (2018) found that there is higher fuel poverty in urban locations compared to rural locations in England. More broadly, Middlemiss and Gillard (2015) note the importance of fuel costs, income, social relations, dwelling characteristics, health issues, and tenancy relations. A detailed discussion of the possible drivers of fuel poverty is also explained in the study by Mahoney et al. (2020).

Of the many potential contributors to fuel poverty, home characteristics and housing tenure could be important. A number of previous studies have found that insulation can substantially reduce fuel poverty (Legendre and Ricci, 2015; Sovacool, 2015; Mohr, 2018). For tenure, Legendre and Ricci (2015) found that renters experience fuel poverty more often than homeowners in France. There are multiple potential explanations for this effect, beyond just socioeconomic differences. Renters may face property rights constraints as they may not have the right to modify their residences. Landlords may not have an incentive to invest in energy-efficient upgrades, such as insulation, if there are market failures where rental prices do not reflect home energy efficiency accurately.

Behavioral differences across households could also be important contributors to fuel-poverty outcomes. Householders can benefit from energy-efficiency upgrades through improved energy outcomes for the same expenditure, reduced spending for the same energy outcomes, or enjoy some combination of the two benefits. Other behavior that may be unrelated to energy efficiency, such as the duration of lighting use, would also affect energy bills and possibly fuel-poverty aspects.

1.4. Fuel poverty in the US

For the US context, national policies to address fuel poverty administered at the state level include the Low-Income Home Energy Assistance Program (LIHEAP) and the Department of Energy Weatherization Assistance Program (WAP). LIHEAP provides energy assistance for households meeting the primary eligibility condition of being a low-income household. There are three main categories of this assistance: bill-paying assistance, responding to an energy crisis, and for weatherization or fixing broken equipment related to energy. The breakdown of how funding is used varies across the states, but most of the funding is for bill-paying assistance. The category of weatherization and home repairs is usually up to 15% of funds and is for low-cost improvements (HHS, 2020). The WAP also targets low-income households but focuses more on energy efficiency improvements such as insulation and installation of efficient appliances.

Previous studies related to US fuel poverty have identified some possible causes but note mixed success for past policies. Mohr (2018) focused on explaining fuel poverty of homeowners in the east of the US using the 2009 Residential Energy Consumption Survey, finding that insulation is an important determinant. Hernández and Phillips (2015) used interviews to confirm that energy efficiency measures helped to improve thermal comfort, enhanced health, and reduced energy costs among low-income residents in New York City. Fowlie et al. (2018) found that a Michigan weatherization program had costs exceeding benefits of energy savings over 2011–2014 and did not have a detectable effect on home temperatures.

2. Data

We use survey data from the 2005 and 2015 Residential Energy Consumption Survey (RECS) that was conducted by the US Energy Information Administration (2018b). These surveys used nationally representative samples of 4382 households in 2005 and 5686 households in 2015. The survey collection technique in the RECS in 2015 involved a combination of self-administered reporting and computer-assisted personal interviews.

We focus on the more recent data for 2015 and use the included probability weights that can be used to weight each household in the survey according to how many other households in the US population that it represents. We exclude households who are not paying their utility bills since they are not subject to the marginal price of electricity.[1] Consequently, we exclude approximately 4% of households that were not responsible for paying electricity bills as they are covered by rent or condo payments. The results of a robustness check are also similar when using the full sample (as available through the code in the Supplementary section: Supplementary material 2).

For comparison purposes, we also analyze the 2005 survey which allows us to assess if there are persistent relationships that are maintained in the 2015 survey. The 2005 survey is also useful as it has additional fuel poverty variables.

3. Methods and variables

3.1. Model and dependent variables

We start with a logit model to explain multiple fuel poverty dimensions. This logit model is defined in Eq. (1). Our logit results in Section 4 report marginal effects.

$$\ln\left[p^j/\left(1-p^j\right)\right] = \theta^j + R_h\alpha^j + \boldsymbol{L'_h\beta^j} + \boldsymbol{S'_h\gamma^j} + \boldsymbol{V'_h\mu^j} + \boldsymbol{P'_h\xi^j} + \boldsymbol{E'_h\lambda^j} + \boldsymbol{\varepsilon_h^j} \tag{1}$$

We use a range of dependent variables to measure multiple aspects of fuel poverty. For the logit model, the dependent variable is the log of the odds of a fuel poverty outcome where the odds are the probability (p) of each of the j fuel poverty outcomes, divided by the complement probability. There is an ex-ante probability of households in the random sample experiencing the fuel poverty outcomes. These fuel poverty outcomes in the 2015 survey include binary outcomes for when a household: (a) has received a disconnection notice, (b) has had an unhealthy home temperature, and (c) has forgone basic necessities due to home energy bills.

The binary outcome for unhealthy home temperatures is based on self-assessment for the following question from the RECS survey: "In the last year, how many months did your household keep your home at a temperature that you felt was unsafe or unhealthy?" The four choices for respondents were never, 1 or 2 months, some months, and almost every month. For our analysis, we set a value of 0 for households

[1] We thank a referee of this paper for mentioning this issue.

that give a response of never, and 1 otherwise.[2] The Supplementary material section includes code with ordered logit models, however, these results produce similar interpretations, so we retain our more parsimonious model.

Other dependent variables are based on similarly structured questions. The disconnection notice variable is based on the question: "In the last year, how many months did your household receive a disconnection notice, shut off notice, or non-delivery notice for an energy bill?" A further variable is for households who self-report "reducing or forgoing basic necessities due to (their) home energy bill" (US Energy Information Administration, 2018b).

Subjective and self-reported measures of fuel poverty can play a valuable role in the policy development process (Waddams Price et al., 2012). They have been widely assessed in high-income countries outside of the US, such as Spain (Aristondo and Onaindia, 2018), Australia (Best and Burke, 2019), Belgium (Meyer et al., 2018), Greece (Ntaintasis et al., 2019) and across other European countries (Thomson et al., 2017). Subjective measures align well with the subjective nature of the utility concept in economics and can complement other measures that relate more directly to budget constraints, such as the ratio of energy expenditure to income.

3.2. Explanatory variables

The independent variables in eq. (1) include a binary variable for renter status, *R,* which equals one for renters. A location vector ***L*** includes 11 climate zones and 3 metropolitan categories. The vector for socioeconomic variables, ***S***, includes many variables such as income and education. A vector of behavioral variables, ***V***, includes measures such as the frequency of use of energy appliances. A vector of policy variables, ***P***, includes a binary variable identifying households that have received energy assistance in any of the previous four years. This assistance is of a small-scale nature and includes help paying bills and fixing broken equipment. Finally, we also include home energy efficiency characteristics, ***E***, that are likely to affect fuel poverty outcomes. The complete variable list is in Appendix Table A.1 which is in Supplementary material 1.

For the socioeconomic category, higher income is likely to be associated with lower fuel poverty. Most directly, higher income would ease pressure through budget constraints, but may also lead to higher energy consumption and less fuel poverty through a subjective-utility channel, assuming energy is a normal good. Education is likely associated with enhanced budgeting ability and therefore less fuel poverty in the budget-constraint category. Renting exposes households to the fundamental issue of property rights constraints. This likely implies that renters will have lower-efficiency appliances that lead to higher expenditure for given energy outcomes and more fuel poverty through budget constraints. However, there are generally no property rights constraints for switching appliances on or off, so renters might not experience more fuel poverty related to subjective utility.

The association of fuel poverty with behavior and appliances could vary. Greater use of appliances that control temperature could reduce impacts on subjective utility, while greater use of appliances that are unrelated to temperature control may have no major association with the subjective-utility dimension of fuel poverty. Greater use of any type of appliance could worsen the unaffordability aspect of fuel poverty as it would raise expenditure. Using more efficient appliances or having insulation should lower all dimensions of fuel poverty by reducing bills for given energy outcomes and/or improving energy outcomes for given expenditure. Higher prices may raise fuel poverty, directly through impacts on budget constraints. Including separate variables on quantities and price instead of only aggregate effects through expenditure is advantageous for more detailed understanding, beyond the generalized link between high energy expenditure and fuel poverty.

Policy assistance can generally be designed toward lowering all fuel poverty dimensions, although policy variables that capture eligibility for energy assistance based on low income may pick up offsetting signal effects. That is, prior receipt of policy assistance for schemes with restricted eligibility would signal that these households have experienced fuel poverty in the past and may therefore be vulnerable to experiencing further fuel poverty. A variable for prior energy assistance could therefore proxy for other unobserved variables associated with financial difficulties.

Key hypotheses to be tested therefore include:

- Renting contributes substantially to the unaffordability aspect, as evident in disconnection notices, but not inadequacy, as evident in unhealthy home temperatures
- Education is related to unaffordability but not inadequacy
- Inadequate insulation contributes to both aspects of fuel poverty

3.3. Key relationships

An association between socioeconomic status and fuel poverty is evident in Fig. 1 which graphs the percentage of households that either reduced or went without necessities due to their home energy bill in 2015, split by income category. This figure shows that there were positive proportions of households reducing necessity consumption due to their home energy bill across all income ranges. These proportions were highest for the lowest category of income below $20,000. Households in higher income categories were progressively less likely to experience fuel poverty. This figure also suggests that renting could influence fuel poverty, as the proportions were higher for renters than non-renters for every income category.

Fig. 2 indicates that as education increases, the proportion of households receiving disconnection notices falls. Regardless of the level of education, renters are more likely to receive disconnection notices. One broader challenge is separating effects of income and education. This challenge is discussed further in Subsection 3.4 and investigated in more detail in the results in Section 4.

Fig. 3 suggests that there could also be a negative relationship between education and the proportion of households reporting an unhealthy temperature for at least one month. We analyze this issue in detail in Section 4 where we consider if this might be due to socioeconomic factors that are correlated with education.

Potential benefits of insulation are evident in Fig. 4 which shows that the proportion of households experiencing various fuel poverty dimensions is much higher for homes without (self-reported) adequate insulation.[3] For example, the probability of forgoing necessities is around 18 percentage points higher for homes without adequate insulation. We complement this unconditional association with calculation of conditional associations in Section 4.

3.4. Econometric challenges

There is potential reverse causation arising from fuel poverty outcomes to some explanatory variables in the behavior, policy, and efficiency groups. As an example, experience of fuel poverty could motivate households to use their televisions less or restrict the use of lighting. Homes experiencing fuel poverty may also be more likely to receive policy support in the form of home energy assistance. Also, fuel poverty may motivate installation of energy-efficient appliances in some cases.

[2] Indoor temperature can be a difficult variable to analyze as it can be affected by behavior. This motivates us to include an extensive vector of behavioral variables. An alternative way to incorporate temperatures is to use actual self-reported temperatures in homes, following Mohr (2018).

[3] While self-reported measures of insulation are common in household energy surveys, there is potential for measurement error.

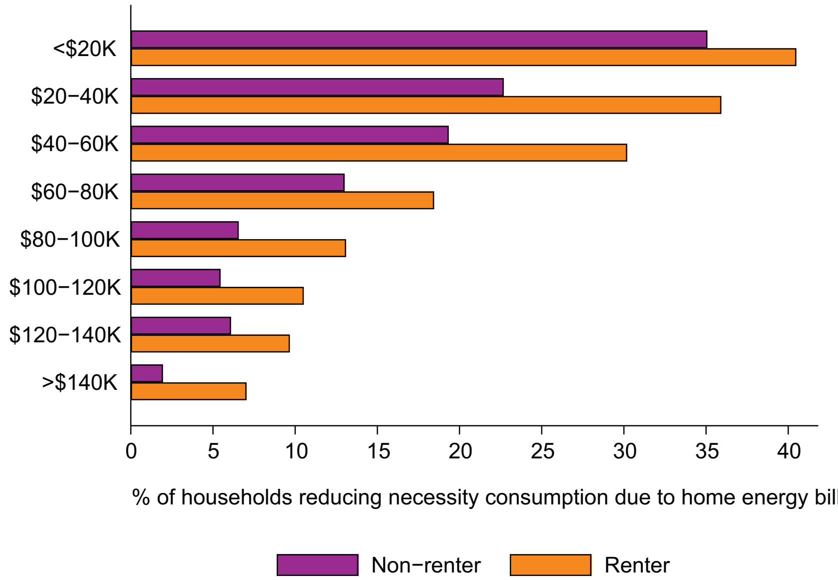

Fig. 1. Percentage of households that reduced or went without necessities due to their home energy bill in 2015, by income category. Renters and non-renters are shown separately. Source: based on US Energy Information Administration (2018b) data.

We address potential reverse causation in several ways. Many of the energy quantity and efficiency variables relate to appliance uptake in previous years; it is only the small number of appliances purchased in the current year that pose an econometric problem of fuel poverty potentially affecting appliance uptake. We produce similar results when restricting the sample to households that have not made major energy upgrades in the past two years (results are available through the code in the Supplementary material). We also progressively add variables, so that we can see associations both with and without variables that could pose reverse causation concerns. For instance, we show results just with location and socioeconomic controls and find that coefficients for these variables do not change substantially when including other variables associated with behavior or energy efficiency. Also, the energy assistance variable that we use is temporally prior to the fuel-poverty dependent variables. In other words, the energy assistance variable relates to the time period 2011–2014, which precedes the variables for the experience of fuel poverty.

We adopt two approaches to address the potential issue of omitted variable bias related to a wealth variable. Our first approach entails controlling for several variables related to wealth (see Appendix Table A.1) including other socioeconomic variables such as household income, education, and the age of respondents. The number and size of appliances are other variables that would be positively correlated with wealth as more wealthy households can more easily afford large appliances in greater quantities. The number and size of housing characteristics would also be positively correlated with wealth. These correlations would not be as high for renters who are restricted from modifying their residence, but it is still likely that renters with higher wealth

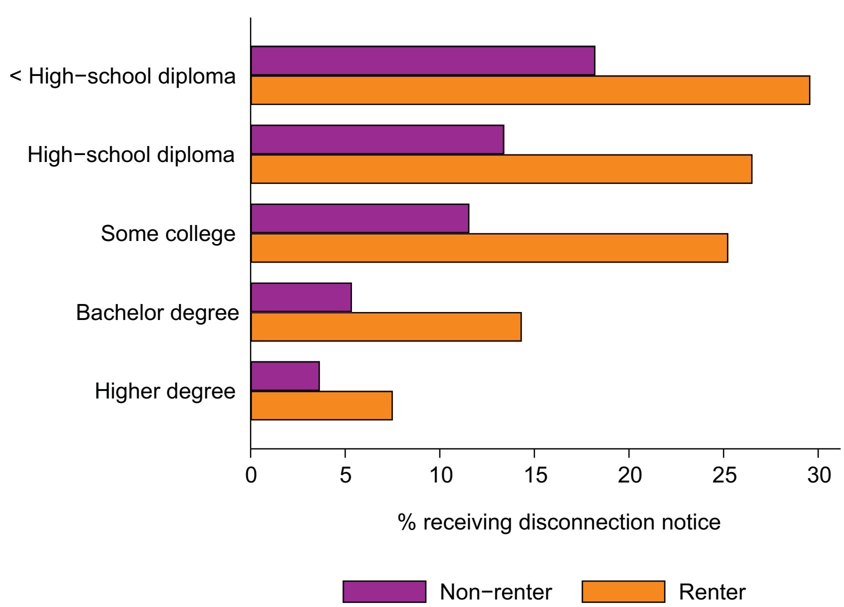

Fig. 2. Percentage of households that received a disconnection notice, by education category and housing tenure. Education is the highest level achieved by the respondent who answers on behalf of the household. Source: based on US Energy Information Administration (2018b) data.

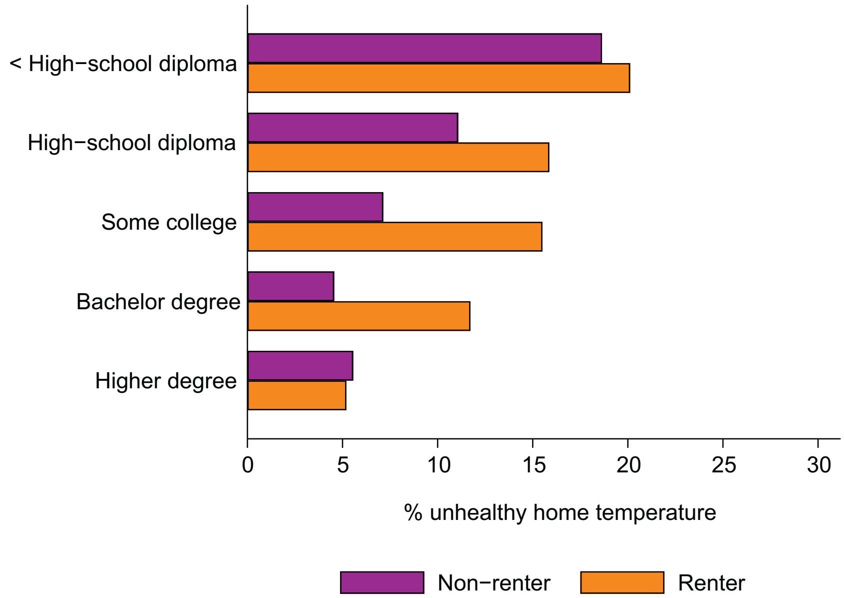

Fig. 3. Percentage of households with a home at an unhealthy temperature in at least one month, by education category. Education is the highest level achieved by the household respondent. Renters and non-renters are shown separately. Source: based on US Energy Information Administration (2018b) data.

would choose residences with better housing characteristics. A housing-type variable is also related to wealth, as a mobile-home binary variable could be an implicit low-wealth indicator.

In the second approach accounting for unavailable wealth controls, we produce a table of results for a subsample of households that likely have low wealth, when explaining the receipt of disconnection notices. This subsample includes households if:

- Gross household income is less than $20,000 for the last year; or
- Education of the respondent is less than high-school-diploma level; or
- Housing-unit type is mobile home; or
- Home temperature has been at an unhealthy level; or
- Basic necessities have been forgone due to the home energy bill; or
- Households could not afford to fix, replace, or use heating or cooling equipment; or
- Medical attention was needed because the home was too cold or hot; or
- Home energy assistance was received in the previous four years.

Multicollinearity could be an issue if there are high correlations between explanatory variables. For example, income and education are generally positively correlated, such as the correlation of 0.5 in the RECS. We still include both as explanatory variables as the correlation is not close to one. Other energy studies have also followed this approach, such as the study by De Groote et al. (2016) that explains solar panel uptake. More generally, the code available through Supplementary material 2 includes variance inflation factors of below 10 for the variables in the regressions in Section 4, suggesting that multicollinearity is not a major issue.

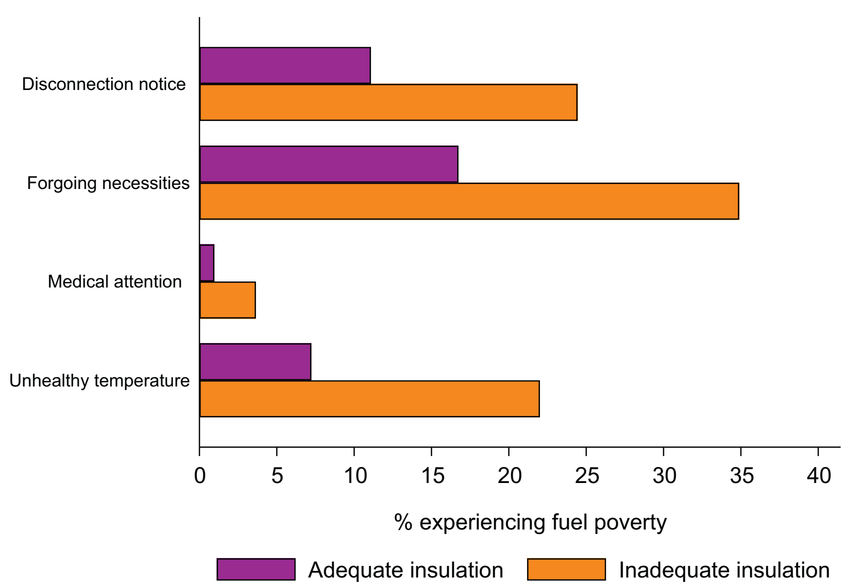

Fig. 4. Percentage of households experiencing various fuel poverty dimensions, by insulation status. The fuel poverty dimensions are binary variables equal to one when: disconnection notices are received; basic necessities are forgone due to the home energy bill; medical attention was needed because the home was too cold or hot; home temperatures have been unhealthy. Source: based on US Energy Information Administration (2018b) data.

Table 1
Marginal effects (logit). Dependent variable: received disconnection notice, 2015.

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Renter	0.139***	0.110***	0.104***	0.101***	0.089***
	(0.007)	(0.017)	(0.015)	(0.015)	(0.016)
High-school diploma		−0.028	−0.030	−0.026	−0.024
		(0.025)	(0.026)	(0.024)	(0.025)
Some college		−0.014	−0.018	−0.017	−0.013
		(0.030)	(0.031)	(0.029)	(0.029)
Bachelor degree		−0.051*	−0.052	−0.048	−0.047
		(0.031)	(0.032)	(0.030)	(0.029)
Higher degree		−0.090***	−0.091***	−0.087***	−0.085***
		(0.031)	(0.033)	(0.031)	(0.030)
Number of lights on for 4+ hours a day			0.003***	0.003***	0.003***
			(0.000)	(0.000)	(0.000)
Received energy assistance previously				0.092***	0.087***
				(0.022)	(0.021)
Adequate insulation					−0.047***
					(0.011)
Solar panels					−0.079
					(0.087)
Additional Controls:					
Location	Yes	Yes	Yes	Yes	Yes
Socioeconomic/appliance quantity	No	Yes	Yes	Yes	Yes
Behavioral factors	No	No	Yes	Yes	Yes
Policy	No	No	No	Yes	Yes
Energy efficiency/type of appliance	No	No	No	No	Yes
Pseudo R^2 (logit)	0.051	0.194	0.210	0.217	0.228

Notes. ***, **, * show statistical significance at 1, 5 and 10% level respectively. There are 5444 observations in each regression/column. Standard errors are shown in brackets below the coefficients and are clustered by region (climate zone). The full list of additional controls in each category is included in Appendix Table A.1. Coefficients for controls are shown in Appendix Table A.2.

Another econometric challenge is measurement error. For example, survey respondents may not know if the appliances are classified as efficient under the US Government Energy Star program. This may not cause considerable concern in cases where Energy Star labels remain on appliances, as 90% of households in the US recognize the Energy Star symbol (United States Environmental Protection Agency, 2018).[4]

3.5. Other methods

Regression analysis using an ordinary least squares model is also included in Section 4. This is appropriate for analyzing a continuous dependent variable of the ratio of energy expenditure to income. The numerator of this variable uses the continuous variable for energy expenditure, which is mostly for electricity on average but also includes natural gas, propane, and kerosene. The denominator is the mid-point of the income ranges supplied in the RECS. We code income as \$150,000 for the highest category of \$140,000 or more.

We also use entropy balancing to calculate average treatment effects of adequate insulation. Entropy balancing is a novel data processing technique proposed by Hainmueller (2012) for use in observational studies with a binary treatment. It is a matching technique which involves weighting the control group data to align with the covariate moments in the treatment group (Hainmueller, 2012; Hainmueller and Xu, 2013). In particular, entropy balancing can weight the sample so that the mean, variance, and skewness of the control group are similar to the treatment group for each of the explanatory variables. This approach deals with drawbacks of some matching approaches where covariates may not be balanced across treatment and control groups, such as propensity score matching, by directly building in covariate balance to the weighting function (Hainmueller and Xu, 2013). In addition to propensity score matching, entropy balancing has been shown to outperform several other techniques including difference in means, Mahalanobis distance matching and genetic matching, in terms of both bias and mean square error (Hainmueller, 2012). In the present analysis we weight the sample using entropy balancing to get similar measures for each group. The resulting treatment effects are then the mean of the binary dependent variable for the group with adequate insulation less the mean for the group without adequate insulation.

4. Results

Renter status has a positive association with household receipt of disconnection notices in Table 1. Being a renter is associated with a higher probability of disconnection notice receipt by around nine percentage points. This result controls for other variables such as housing structure (mobile home, single-family detached, single-family attached, apartment in a building with 2 to 4 units, or apartment in a building with 5 or more units) and the square footage of each dwelling. A robustness check in the online code also shows a positive and significant renter coefficient for a dependent variable with four numerical values to measure the frequency of disconnection notice receipt.

There is a negative association for households with a respondent educated beyond an undergraduate degree relative to the base case of not completing high school. There are also negative coefficients for education at the bachelor level, but only the coefficient in column (2) is statistically significant. An interaction term between renting and education levels available through the online code in the Supplementary material section shows that renting is no longer a significant contributor to disconnection notice receipt for households with a respondent with education beyond bachelor level.

Having more lights on for at least four hours a day is an example of a behavioral factor that may contribute to a higher probability of disconnection notice receipt. There is a positive and significant association for the number of lights on for more than four hours over a day. To account for the possibility of lights being left on for more than four hours to be correlated with employment, our models control for the employment status of the household respondent and for the number of weekdays

[4] Regression results are similar for the robustness checks with a categorical variable for appliance efficiency that separately identifies households who state that they don't know about the efficiency status of appliances. This is useful to account for households not remembering the efficiency rating of their appliance. We thank a reviewer for raising this issue. In contrast, the variables in the main results assign a value of one if households answer affirmatively to efficiency questions and zero otherwise.

Table 2
Marginal effects (logit), received disconnection notice, 'low-wealth' subsample.

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Renter	0.118***	0.156***	0.147***	0.145***	0.125***
	(0.022)	(0.035)	(0.031)	(0.033)	(0.035)
High-school diploma		0.004	0.001	0.001	−0.001
		(0.041)	(0.039)	(0.038)	(0.039)
Some college		0.032	0.024	0.021	0.025
		(0.051)	(0.048)	(0.047)	(0.046)
Bachelor degree		−0.039	−0.051	−0.049	−0.052
		(0.062)	(0.060)	(0.057)	(0.051)
Higher degree		−0.090**	−0.100**	−0.102***	−0.098**
		(0.045)	(0.045)	(0.039)	(0.041)
Number of lights on 4+ hours a day			0.007***	0.008***	0.008***
			(0.001)	(0.001)	(0.001)
Received energy assistance previously				0.090**	0.082**
				(0.044)	(0.038)
Adequate insulation					−0.076***
					(0.022)
Solar panels					−0.112
					(0.096)
Additional Controls:					
Location	Yes	Yes	Yes	Yes	Yes
Socioeconomic/appliance quantity	No	Yes	Yes	Yes	Yes
Behavioral factors	No	No	Yes	Yes	Yes
Policy	No	No	No	Yes	Yes
Energy efficiency/type of appliance	No	No	No	No	Yes
Pseudo R^2 (logit)	0.020	0.136	0.155	0.160	0.175

Notes. ***, **, * show statistical significance at 1, 5 and 10% level respectively. There are 2120 observations in each regression/column. Standard errors are shown in brackets below the coefficients and are clustered by region (climate zone). The full list of additional controls is given in Appendix Table A.1.

that someone is at home, as evident in Table A.2 through Supplementary material 1 (which shows control variables for Table 1).

Another key factor associated with fuel poverty in Table 1 is the home energy assistance variable, with a positive and significant coefficient at the 1% level. For households that received home energy assistance from 2011 to 2014, the probability of receiving a disconnection notice in 2015 was approximately nine percentage points higher, all else equal. This suggests that there is persistence in fuel poverty, as those who have required and received energy assistance in the past continue to experience difficulty in paying energy bills.

The probability of receiving disconnection notices was approximately five percentage points higher for households without inadequate insulation, compared to households with adequate insulation, all else equal. People who feel cold from perceived inadequate insulation may be more likely to subsequently spend more on electricity and then face greater trouble paying electricity bills. The marginal association for solar panels is larger in absolute value terms than for insulation, based on the point estimates, but the solar coefficient is statistically insignificant.

There are several other variables with significant coefficients in explaining the receipt of disconnection notices, as evident in Appendix Table A.2. The average variance inflation factor is 2 and nearly all the values are below 5,[5] suggesting that multicollinearity is not a major issue when interpreting these coefficients. The coefficients for income in explaining disconnection notices mostly become more negative as income increases, confirming that higher income lowers the odds of disconnection notices.[6] In particular, having income above $80,000 is associated with lower likelihood of disconnection notice receipt. Most of the binary variables for the house age are insignificant at the 10% level of significance in Table A.2.

Having some appliance types, such as having bigger televisions, shows significant associations with disconnection-notice probability. Having televisions on for four or more hours on a weekday is also positively associated with receiving a disconnection notice, all else equal. This coefficient for television, along with the coefficient for the number of lights that are on for four or more hours, are statistically significant, including when controlling for employment. We also produce results interacting television watching with employment categories showing positive coefficients for television watching across employment categories (see the code in the Supplementary section).

The online code in the Supplementary section includes a range of robustness checks. As suggested by a reviewer of this paper, analysis of fuel poverty in the context of a large country like the US should have a regional focus. Accordingly, we undertake robustness analysis in separately focusing on each region and find similar key results for each region (Northeast, Midwest, South, and West). Thus, our analysis suggests there are similar outcomes across cold and warmer parts of the US. This aligns with analysis of the east of the US by Mohr (2018).[7] A further robustness check drops the variable for subsidized home energy audits, showing very similar results.

There are similar results for the 'low-wealth' subsample in Table 2, compared to the corresponding results for the full sample, indicating robustness of results for a key subsample. There are positive associations from renting, the number of lights on for four or more hours a day, and prior receipt of energy assistance. There are negative associations for insulation and for educational degrees beyond bachelor level relative to the base category of households with a respondent who did not finish high school.

Table 3 presents results for another fuel poverty dimension: unhealthy temperature in the home. There are some common associations across fuel poverty dimensions, evident in the similar relationships

5 Variance inflation factors range from 1 (indicating no correlation) upwards. As a general rule of thumb for interpreting variance inflation factors, values ranging between 1 and 5 indicate low to moderate correlation and greater than 5 indicate moderate to high correlation.

6 Including expenditure divided by income as an explanatory variable instead of only income does not have a substantial effect on the results, as shown in a robustness check available through the Supplementary material section. Thus, our approach of separately controlling for quantities and price related to energy can be viewed as a detailed alternative to controlling for energy expenditure.

7 Key results are maintained in additional robustness checks that include fuel poverty dimensions as explanatory variables. Key results are also similar when either excluding households that are experiencing other dimensions of fuel poverty or when only including households that are experiencing other fuel-poverty dimensions.

Table 3
Marginal effects (logit), dependent variable: unhealthy temperature in home, 2015.

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Renter	0.078***	0.030**	0.026**	0.027**	0.009
	(0.015)	(0.015)	(0.012)	(0.011)	(0.011)
High-school diploma		−0.020	−0.020	−0.017	−0.016
		(0.030)	(0.031)	(0.030)	(0.027)
Some college		−0.015	−0.016	−0.017	−0.013
		(0.019)	(0.021)	(0.019)	(0.017)
Bachelor degree		−0.018	−0.019	−0.020	−0.020
		(0.032)	(0.035)	(0.034)	(0.032)
Higher degree		−0.025	−0.026	−0.026	−0.028
		(0.028)	(0.027)	(0.026)	(0.027)
Number of lights left on for 4 + hours			−0.000	0.000	0.000
			(0.001)	(0.001)	(0.001)
Received energy assistance previously				0.088***	0.076***
				(0.014)	(0.015)
Adequate insulation					−0.071***
					(0.014)
Additional Controls:					
Location	Yes	Yes	Yes	Yes	Yes
Socioeconomic/appliance quantity	No	Yes	Yes	Yes	Yes
Behavioral factors	No	No	Yes	Yes	Yes
Policy	No	No	No	Yes	Yes
Energy efficiency/type of appliance	No	No	No	No	Yes
Pseudo R^2 (logit)	0.028	0.107	0.118	0.131	0.160

Notes. ***, **, * show statistical significance at 1, 5 and 10% level respectively. There are 5444 observations in each regression/column. Standard errors are shown in brackets below the coefficients and are clustered by region (climate zone). The full list of additional controls is given in Appendix Table A.1.

between Table 1 and Table 3, but also some differences. Two similarities are the positive coefficient for the receipt of previous home energy assistance (2011–2014) and the negative coefficient for adequate insulation. The differences include the non-significance of coefficients for renting, education, and the behavioral variable for the number of lights that are on for four or more hours a day. The renting coefficient is significant in column (1) of Table 3 but diminishes in size and significance as control variables are added. The insignificant coefficient for education in explaining unhealthy home temperatures contrasts with the appearance of a possible relationship in Fig. 3 which showed the unconditional association.

Table 4 presents results to explain reduced or forgone consumption of necessities due to home energy bills. This is an important variable to assess as it shows how fuel poverty can flow over into other dimensions of poverty. There are similarities in the coefficients observed in Table 4 compared to Table 1 that explains disconnection notices. This includes the positive associations from renting, greater appliance use (such as lighting), and prior receipt of energy assistance. There are negative associations with education and insulation. The similarity in results is due to the common element of the difficulty in paying energy bills that is captured by both disconnection notice receipts and reducing consumption of other necessities.

The dependent variable in Table 5 is the budget share relating to fuel (ratio of energy expenditure to income). There is a positive coefficient for renting in each column, significant at the 1% level, and also for prior receipt of energy assistance. There are also negative coefficients for education levels, relative to the excluded category of not finishing high school. These results are generally similar to those in Table 1. This is consistent with the idea that disconnection-notice receipt and the ratio of energy expenditure to income are both related to the unaffordability or budget-constraint aspect of fuel poverty. In contrast to Table 1, the coefficient for the number of lights that are on for four or more hours is not statistically significant in Table 5. But there are positive and significant coefficients for other behavioral variables, such as having the main television on for four or more hours on a weekday (see the online code in the Supplementary section). The insulation coefficient is not significant but there is a significant coefficient for solar panels at the 5% level in explaining the ratio of energy expenditure to income. This is similar to the finding for Australia where solar panels are also found to reduce an unaffordability dimension of fuel poverty (Best and Burke, 2019).

Table 6 shows entropy balanced treatment effects to enhance the strength of causal interpretations of associations with fuel poverty outcomes. There is an average treatment effect of having adequate insulation on disconnection notice receipt and on forgone consumption of other necessities (both reflecting budget constraints and difficulty

Table 4
Marginal effects (logit), reduced necessity consumption due to home energy bill.

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Renter	0.170***	0.086***	0.077***	0.075***	0.059**
	(0.007)	(0.027)	(0.026)	(0.027)	(0.025)
High-school diploma		−0.054	−0.056	−0.051	−0.050
		(0.046)	(0.045)	(0.043)	(0.040)
Some college		−0.036	−0.040	−0.037	−0.035
		(0.043)	(0.044)	(0.044)	(0.041)
Bachelor degree		−0.091*	−0.092*	−0.091*	−0.095**
		(0.049)	(0.051)	(0.049)	(0.047)
Higher degree		−0.118***	−0.117***	−0.114***	−0.117***
		(0.038)	(0.037)	(0.037)	(0.034)
Number of lights left on for 4+ hours			0.002***	0.002***	0.002***
			(0.001)	(0.001)	(0.001)
Received energy assistance previously				0.087**	0.072**
				(0.034)	(0.033)
Adequate insulation					−0.078***
					(0.015)
Additional Controls:					
Location	Yes	Yes	Yes	Yes	Yes
Socioeconomic/appliance quantity	No	Yes	Yes	Yes	Yes
Behavioral	No	No	Yes	Yes	Yes
Policy	No	No	No	Yes	Yes
Energy efficiency/type of appliance	No	No	No	No	Yes
Pseudo R^2 (logit)	0.050	0.197	0.207	0.215	0.230

Notes. ***, **, * show statistical significance at 1, 5 and 10% level respectively. There are 5444 observations in each regression/column. Standard errors are shown in brackets below the coefficients and are clustered by region (climate zone). The full list of additional controls is given in Appendix Table A.1.

Table 5
OLS results. Dependent variable: energy expenditure divided by income, 2015.

Explanatory variables	(1)	(2)	(3)	(4)	(5)
Renter	0.013***	0.014***	0.014***	0.013***	0.012***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
High-school diploma		−0.009	−0.009	−0.008	−0.008
		(0.006)	(0.006)	(0.007)	(0.007)
Some college		−0.026***	−0.026***	−0.026***	−0.024***
		(0.006)	(0.006)	(0.006)	(0.007)
Bachelor degree		−0.038***	−0.038***	−0.036***	−0.035***
		(0.006)	(0.006)	(0.006)	(0.006)
Higher degree		−0.036***	−0.035***	−0.034***	−0.033***
		(0.006)	(0.006)	(0.006)	(0.006)
Number of lights left on for 4+ hours			0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)
Received energy assistance previously				0.025***	0.025***
				(0.005)	(0.005)
Adequate insulation					−0.001
					(0.001)
Solar panels					−0.009**
					(0.003)
Additional Controls:					
Location	Yes	Yes	Yes	Yes	Yes
Socioeconomic/appliance quantity	No	Yes	Yes	Yes	Yes
Behavioral factors	No	No	Yes	Yes	Yes
Policy	No	No	No	Yes	Yes
Energy efficiency/type of appliance	No	No	No	No	Yes
R^2	0.045	0.264	0.265	0.273	0.280

Notes. ***, **, * show statistical significance at 1, 5 and 10% level respectively. There are 5444 observations in each regression/column. Standard errors are shown in brackets below the coefficients and are clustered by region (climate zone). The full list of additional controls is given in Appendix Table A.1.

Table 6
Insulation treatment effect using entropy balanced weights, 2015.

Dependent variable	Adequate insulation treatment effect
Disconnection notice receipt	−0.064***
	(0.017)
Unhealthy home temperature	−0.070***
	(0.016)
Forgone consumption of other necessities	−0.058***
	(0.017)
Medical attention due to home temperature	−0.016**
	(0.007)

Notes. ***, **, * show statistical significance at 1, 5 and 10% level respectively. There are 5444 observations in each case. Standard errors are shown in brackets below the coefficients. The entropy balancing is based on the full set of covariates as in Appendix Table A.1. The treatment effects are the mean of the binary dependent variable for the group with adequate insulation less the mean for the group without adequate insulation, after weighting the sample using entropy balancing.

experienced by households in paying electricity bills) of six percentage points, significant at the 1% level. In other words, the probability of receiving disconnection notices or forgoing consumption of other necessities is six percentage points higher for households without adequate insulation. The corresponding average treatment effect on unhealthy home temperatures is seven percentage points, again significant at the 1% level. The average treatment effect of adequate insulation on requiring medical attention due to the home being too hot or too cold was two percentage points, significant at the 5% level.

Table 7 uses data from the 2005 version of the RECS and gives a consistent story on key relationships.[8] There is a persistent problem of renters being more likely to experience some dimensions of fuel poverty, as evident in the positive and significant coefficients for the renter binary variable in explaining the first five fuel poverty dimensions in Table 7 that relate closely to budget constraints and unaffordability. There are no significant renter coefficients for the fuel poverty dimensions related to temperature control, consistent with the results for 2015 in Table 3 when all controls are included.[9] Having adequate

Table 7
Marginal effects (logit), based on various binary dependent variables, 2005.

Dependent variable	Renting	Adequate Insulation
Budget-constraint aspects (unaffordability)		
Unable to pay energy bill	0.065***	−0.083***
	(0.014)	(0.011)
Reduce basic household expenses	0.061***	−0.082***
	(0.015)	(0.011)
Need to borrow to pay energy bill	0.043***	−0.041***
	(0.011)	(0.009)
Skip or pay less than whole energy bill	0.043***	−0.051***
	(0.012)	(0.009)
Ever been threatened with energy cut off	0.044***	−0.049***
	(0.011)	(0.008)
Subjective-utility aspects (inadequacy)		
Close off part of home to save energy	−0.001	−0.042***
	(0.010)	(0.007)
Keep temperature at an unsafe/unhealthy level	−0.011	−0.033***
	(0.008)	(0.006)
Leave home because it was too hot or too cold	0.012	−0.031***
	(0.008)	(0.006)
Use your kitchen stove or oven to provide heat	0.010	−0.056***
	(0.008)	(0.006)

Notes. ***, **, * show statistical significance at 1, 5 and 10% level respectively. There are 4382 observations in each regression/row. Standard errors are shown in brackets below the coefficients. Other controls not shown include income split into four groups (the first three ranges specified in Appendix Table A.2 and then $60,000+), age of respondent, number of rooms, and house type (mobile home / detached house / attached house / apartment building with 2–4 dwellings / apartment building with 5+ dwellings).

[8] Tables 6-7 can be interpreted as robustness checks, as the dependent variables are from the same two main categories as Tables 1-5 (either fuel poverty dimensions that relate more to unaffordability, or those that relate more to inadequacy).

[9] Table 7 uses a smaller number of socioeconomic controls, as specified in the notes to Table 7. These controls include important variables, based on the results in Appendix Table A.2. The full list of variables in Appendix Table A.2 is not available for the 2005 survey, and some available variables have different definitions in 2005 and 2015 surveys.

insulation reduced fuel poverty likelihood for every dimension for the 2005 results in Table 7. Home energy improvements, such as having adequate insulation, therefore appear to provide a robust solution to alleviate fuel poverty across multiple dimensions.

5. Conclusion and policy implications

Our analysis seeks to identify fundamental factors that have common associations with multiple fuel poverty indicators, while also understanding the reasons for any differences across dimensions. Our results reveal common associations of explanatory variables with measures for fuel poverty within the same main category. For the unaffordability aspect that is closely related to budget constraints, explanatory variables have similar associations with energy expenditure divided by income, and a binary measure for disconnection notice receipt. In showing similar associations for what might at first seem to be different dimensions of fuel poverty, we can contribute to a conceptual unification of seemingly disparate aspects. In contrast, there are some possible differences between causes of the unaffordability and inadequacy aspects of fuel poverty.

Homes with inadequate insulation are more likely to experience both main types of fuel poverty. These households tend to suffer from lower subjective utility as they are more likely to feel they are unable to attain healthy temperatures. There may also be increased expenditure on energy to compensate for inadequate insulation, evident in receipt of disconnection notices being more likely when householders self-report inadequate insulation. We find similar results using multiple econometric approaches including calculation of average treatment effects using entropy balanced weights.

Our results give some initial evidence of solar panels reducing the ratio of energy expenditure to income, but low solar uptake by 2015 was an obstacle for more precise conclusions. The initial US evidence matches evidence from Australia, which suggests that solar panel installation can make a big difference to the ‘budget constraint’ aspect of fuel poverty (Best and Burke, 2019). Solar panels have greater potential for reducing fuel poverty if combined with battery storage.

Better insulation and solar panels both have potential to reduce fuel poverty across climate zones. Mohr (2018) found that adequate insulation reduced fuel poverty in the warmer South Atlantic states of the US, where insulation standards differ substantially, but an absence of a detectable association for colder regions of the north-east of the US, where insulation standards are more similar. While solar panels can be more effective in more sunny areas, these areas do not always have higher uptake (Kwan, 2012).

For renters, associations with fuel poverty differ across dimensions. Renters appear to experience greater difficulty paying energy bills, as evident in being more likely to receive disconnection notices, even when controlling for other variables. Policy to address difficulty paying bills could be more targeted than the current operation of LIHEAP by focusing on households with multiple characteristics, such as low-income renters with lower education and low energy efficiency in their homes (Bird and Hernández, 2012). In contrast, unhealthy home temperatures are not particular to renters, but can be understood as a broader socioeconomic issue.

Policy toward renters could be modified going forward. Historically, renters have tended to be at a substantial disadvantage, due to split incentive problems including where landlords do not have an incentive to install efficient appliances when renters pay energy bills. Moreover, weatherization programs that improve housing insulation or subsidies for solar panels tend to be restricted to homeowners. There is potential for this practice to be modified in the future. A current example is support for solar panels for rental properties in the Australian state of Victoria (Solar Victoria, 2020).

Prior assistance does not seem to reduce fuel poverty in a major way in our results. A negative association of prior energy assistance and fuel poverty is not detected in our analysis as the association between the prior energy assistance variable and each of the dependent variables is positive and statistically significant. This indicates that the increased vulnerability signalled by prior receipt of energy assistance has a dominant impact resulting in a positive and significant coefficient in each case.

Future policy could consider more substantial assistance for vulnerable households and a range of financing methods. More substantial assistance (aimed at longer term needs) can complement current assistance (targeting short-term needs) that has an important role in addressing urgent needs related to a lack of affordable energy and broken appliances. Public budgets may constrain larger interventions, although home energy improvements can be capitalized into home values (Thorsnes and Bishop, 2013; Qiu et al., 2017). This would allow governments to recover a portion of policy expenditures through property taxes, although property taxes do not exist in all countries and there may be adverse effects on disadvantaged groups. Carley and Konisky (2020) suggest further research into public-private partnerships that could contribute when public funds are scarce.

Future research can attempt comprehensive quantification of the co-benefits of policy support for home-energy improvements. In addition to possible associations with fuel poverty, home-improvements such as greater solar uptake can reduce expenditure on centralised electricity generation, reduce air pollution, and reduce climate risks in a relatively cost-effective manner. For example, the subsidy cost for a small-scale solar scheme in Australia has likely been similar to the social cost of carbon (Best et al., 2019). Future studies could attempt to aggregate benefits of policy interventions, to complement focus on single co-benefits. This could further promote the justification for policy assistance for big home improvements such as insulation or solar panels.

Credit author statement

Rohan Best: Conceptualization, Formal analysis, Methodology, Writing - original draft, Writing - review & editing.

Kompal Sinha: Conceptualization, Methodology, Writing - original draft, Writing - review & editing.

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Appendix A. Supplementary data

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References

Aristondo, O., Onaindia, E., 2018. Inequality of energy poverty between groups in Spain. Energy 153, 431–442. https://doi.org/10.1016/j.energy.2018.04.029.

Awaworyi Churchill, S., Smyth, R., Farrell, L., 2020. Fuel poverty and subjective wellbeing. Energy Econ. 86, 104650. https://doi.org/10.1016/j.eneco.2019.104650.

Baker, K.J., Mould, R., Restrick, S., 2018. Rethink fuel poverty as a complex problem. Nat. Energy 3, 1–3. https://doi.org/10.1038/s41560-018-0204-2.

Best, R., Burke, P.J., 2019. Factors contributing to energy-related financial stress in Australia. Econ. Rec. 95, 462–479. https://doi.org/10.1111/1475-4932.12504.

Best, R., Burke, P.J., Nishitateno, S., 2019. Evaluating the effectiveness of Australia's small-scale renewable energy scheme for rooftop solar. Energy Econ. 104475. https://doi.org/10.1016/j.eneco.2019.104475.

Bird, S., Hernández, D., 2012. Policy options for the split incentive: increasing energy efficiency for low-income renters. Energy Policy 48, 506–514. https://doi.org/10.1016/j.enpol.2012.05.053.

Boardman, B., 1991. Fuel Poverty: From Cold Homes to Affordable Warmth. Belhaven Press.

Bradshaw, J., Hutton, S., 1983. Social policy options and fuel poverty. J. Econ. Psychol. 3, 249–266. https://doi.org/10.1016/0167-4870(83)90005-3.

Burlinson, A., Giulietti, M., Battisti, G., 2018. The elephant in the energy room: establishing the nexus between housing poverty and fuel poverty. Energy Econ. 72, 135–144. https://doi.org/10.1016/j.eneco.2018.03.036.

Carley, S., Konisky, D.M., 2020. The justice and equity implications of the clean energy transition. Nat. Energy. https://doi.org/10.1038/s41560-020-0641-6.
De Groote, O., Pepermans, G., Verboven, F., 2016. Heterogeneity in the adoption of photovoltaic systems in Flanders. Energy Econ. 59, 45–57. https://doi.org/10.1016/j.eneco.2016.07.008.
EU Energy Poverty Observatory, 2020. Indicators and Data. https://www.energypoverty.eu/indicators-data (accessed August 15, 2020).
Fowlie, M., Greenstone, M., Wolfram, C., 2018. Do energy efficiency investments deliver? Evidence from the weatherization assitance program. Q. J. Econ. 1–48. https://doi.org/10.1093/qje/qjy005.Advance.
Hainmueller, J., 2012. Entropy balancing for causal effects: a multivariate reweighting method to produce balanced samples in observational studies. Polit. Anal. 20, 25–46. https://doi.org/10.1093/pan/mpr025.
Hainmueller, J., Xu, Y., 2013. Ebalance: a stata package for entropy balancing. J. Stat. Softw. 54, 1–18. https://doi.org/10.18637/jss.v054.i07.
Hernández, D., Phillips, D., 2015. Benefit or burden? Perceptions of energy efficiency efforts among low-income housing residents in New York City. Energy Res. Soc. Sci. 8, 52–59. https://doi.org/10.1016/j.erss.2015.04.010.
Hernández, D., Siegel, E., 2019. Energy insecurity and its ill health effects: a community perspective on the energy-health nexus in New York City. Energy Res. Soc. Sci. 47, 78–83. https://doi.org/10.1016/j.erss.2018.08.011.
HHS, 2020. US Department of Health and Human Services. LIHEAP funds by program component. https://liheapch.acf.hhs.gov/tables/components.htm. (Accessed 18 August 2020).
Jenkins, K., McCauley, D., Heffron, R., Stephan, H., Rehner, R., 2016. Energy justice: a conceptual review. Energy Res. Soc. Sci. 11, 174–182. https://doi.org/10.1016/j.erss.2015.10.004.
Kwan, C.L., 2012. Influence of local environmental, social, economic and political variables on the spatial distribution of residential solar PV arrays across the United States. Energy Policy 47, 332–344. https://doi.org/10.1016/j.enpol.2012.04.074.
Legendre, B., Ricci, O., 2015. Measuring fuel poverty in France: which households are the most fuel vulnerable? Energy Econ. 49, 620–628. https://doi.org/10.1016/j.eneco.2015.01.022.
Mahoney, K., Gouveia, J.P., Palma, P., 2020. (Dis)United Kingdom? Potential for a common approach to energy poverty assessment. Energy Res. Soc. Sci. 70, 101671. https://doi.org/10.1016/j.erss.2020.101671.
Meyer, S., Laurence, H., Bart, D., Lucie, M., Kevin, M., 2018. Capturing the multifaceted nature of energy poverty: lessons from Belgium. Energy Res. Soc. Sci. 40, 273–283. https://doi.org/10.1016/j.erss.2018.01.017.
Middlemiss, L., Gillard, R., 2015. Fuel poverty from the bottom-up: characterising household energy vulnerability through the lived experience of the fuel poor. Energy Res. Soc. Sci. 6, 146–154. https://doi.org/10.1016/j.erss.2015.02.001.
Mohr, T.M., 2018. Fuel poverty in the US: evidence using the 2009 residential energy consumption survey. Energy Econ. 74, 360–369. https://doi.org/10.1016/j.eneco.2018.06.007.
Ntaintasis, E., Mirasgedis, S., Tourkolias, C., 2019. Comparing different methodological approaches for measuring energy poverty: evidence from a survey in the region of Attika, Greece. Energy Policy 125, 160–169. https://doi.org/10.1016/j.enpol.2018.10.048.
Qiu, Y., Wang, Y.D., Wang, J., 2017. Soak up the sun: impact of solar energy systems on residential home values in Arizona. Energy Econ. 66, 328–336. https://doi.org/10.1016/j.eneco.2017.07.001.
Robinson, C., Bouzarovski, S., Lindley, S., 2018. 'Getting the measure of fuel poverty': the geography of fuel poverty indicators in England. Energy Res. Soc. Sci. 36, 79–93. https://doi.org/10.1016/j.erss.2017.09.035.
Solar Victoria, 2020. Solar Rebates for Rental Properties. https://www.solar.vic.gov.au/solar-rental-properties (accessed August 16, 2020).
Sovacool, B.K., 2015. Fuel poverty, affordability, and energy justice in England: policy insights from the warm front program. Energy 93, 361–371. https://doi.org/10.1016/j.energy.2015.09.016.
Sovacool, B.K., Dworkin, M.H., 2015. Energy justice: conceptual insights and practical applications. Appl. Energy 142, 435–444. https://doi.org/10.1016/j.apenergy.2015.01.002.
Teller-Elsberg, J., Sovacool, B., Smith, T., Laine, E., 2016. Fuel poverty, excess winter deaths, and energy costs in Vermont: burdensome for whom? Energy Policy 90, 81–91. https://doi.org/10.1016/j.enpol.2015.12.009.
Thomson, H., Bouzarovski, S., Snell, C., 2017. Rethinking the measurement of energy poverty in Europe: a critical analysis of indicators and data. Indoor Built Environ. 26, 879–901. https://doi.org/10.1177/1420326X17699260.
Thorsnes, P., Bishop, T., 2013. The value of basic building code insulation. Energy Econ. 37, 68–81. https://doi.org/10.1016/j.eneco.2013.02.001.
United States Environmental Protection Agency, 2018. About Energy Star - 2017.
US Energy Information Administration, 2018a. Comparing the 2015 RECS with Previous RECS and Other Studies. https://www.eia.gov/consumption/residential/reports/2015/comparison/.
US Energy Information Administration, 2018b. Residential Energy Consumption Survey: 2015 RECS Survey Data. https://www.eia.gov/consumption/residential/.
Waddams Price, C., Brazier, K., Wang, W., 2012. Objective and subjective measures of fuel poverty. Energy Policy 49, 33–39. https://doi.org/10.1016/j.enpol.2011.11.095.