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Getting warmer: fuel poverty, objective and subjective health and well-being

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Abstract

This paper uses data from U*nderstanding Society: the UK Household Longitudinal Study* to explore the association between fuel poverty and a set of well-being outcomes: life-satisfaction, self-reported health measures and more objectively measured biomarker data. Over and above the conventional income–fuel cost indicators, we also use more proximal heating deprivation indicators. We create and draw upon a set of composite indicators that concomitantly capture (the lack of) affordability and thermal comfort. Depending on which fuel deprivation indicator is used, we find heterogeneous associations between fuel poverty and our well-being outcomes. Employing combined fuel deprivation indicators, which takes into account the income–fuel cost balance and more proximal perceptions of heating adequacy, reveals the presence of more pronounced associations with life satisfaction and fibrinogen, one of our biological health measures. The presence of these strong associations would have been less pronounced or masked when using separately each of the components of our composite fuel deprivation indicators as well as in the case of self-reported generic measures of physical health. Lifestyle and chronic health conditions plays a limited role in attenuating our results, while material deprivation partially, but not fully, attenuates our associations between fuel deprivation and well-being. These results remain robust when bounding analysis is employed to test the potential confounding role of unobservables. Our analysis suggests that composite fuel deprivation indicators may be useful energy policy instruments for uncovering the underlining mechanism via which fuel poverty may get "under the skin".

Keywords: Fuel poverty, biomarkers, health, well-being
JEL codes: I12, I31, I32, Q4

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1. Introduction

The health risks of households living in fuel poverty has been highlighted as a priority in the energy policy agenda in several OECD countries (OECD, 2018). Boardman (1991) has pioneered the fuel poverty debate, arguing for its recognition as a distinct form of poverty which, compared to income-related poverty, may not be necessarily solely mitigated by redistributing income but also via thermal efficiency and, more generally, by policies to enhance adequate warmth in homes. The United Kingdom's Government responds a decade later with an Act of Parliament and formal recognition of fuel poverty as a major issue of public well-being (HM Government, 2001), and the introduction of the Fuel Poverty Strategy (Department of Trade and Industry, 2001); the latter recognises the potential damage fuel poverty could exert on health and quality of life, particularly to the vulnerable households who naturally rely more on heating (e.g., those with children or people with long-term illnesses or disabilities). However, whilst fuel poverty has been of international interest, with existing studies from Australia (Awaworyi Churchill et al., 2020), China (Wang et al., 2015), France (Legendre and Ricci, 2015), India (Sadath and Acharya, 2017) and Great Britain (Burlinson et al., 2018), as well as complementary research on energy insecurity in low- and middle-income countries (Boateng et al., 2020), the link between indicators of fuel poverty and more objective measures (biomarkers) of health has been relatively overlooked.

Fuel poverty, i.e., the inability of a household to attain an adequate level of energy services, particularly warmth (Boardman, 1991), is likely to become more acute as energy expenditure is expected to rise expressed as a proportion of declining household income (Scottish Government, 2020). This represents the first of two key channels through which fuel poverty may affect health, particularly mental health. A seminal quasi-experimental study of a government-led energy efficiency initiative in the UK (namely, the Warm Front Scheme) established that the "financial security" channel is the most important route between fuel poverty and mental health, at least in the short-run, even more so than the "thermal comfort" pathway (Green and Gilbertson, 2008; Gilbertson et al., 2012).

Climate change driving evermore severe winter seasons may sharpen the nexus between fuel poverty, thermal comfort, and ill health, including cardiovascular health risk, inflammation and mental health impairment (Public Health England, 2014). For example, England and Wales has experienced close to 50,000 excess winter deaths in

2017/2018, the highest since the 1970s (ONS, 2020). With the growing concern of the impact of low temperatures on vulnerable households, Public Health England follows the World Health Organisation (WHO) by recommending a minimum home temperature threshold for bedrooms (18°C) and living rooms (21°C) in order to minimise the risk to health (Public Health England, 2014). Improving housing thermal environment may reduce excess cardiovascular mortality risks during winter (Saeki et al., 2014; Shiue, 2016). According to the Marmot Review Team (2011) around 22% of excess winter deaths in England can be attributed to the coldest 25% of households. Evidence from biomedical observational studies shows that cold in/outdoor conditions are associated with increased levels of inflammatory biomarkers (fibrinogen) and with thrombosis, hypertension and cardiovascular mortality risks (Woodhouse et al., 1994; Gallerani et al., 2004). Such relationships are also confirmed in laboratory settings, with existing studies finding that exposure to cold temperatures is associated with increased blood pressure, inflammation and cardiovascular mortality risks regardless of age or gender (Collins et al., 1985; Inoue et al., 1992; Fares, 2013).

In light of these health risks, the measurement of fuel poverty is of particular importance for policy makers. The United Kingdom's Government has adopted the Low-Income-High-Cost indicator (LIHC), which records households as fuel poor if their required fuel costs are above the national median and, upon deducting such costs, their residual household income falls below the income poverty line (60% of the median national income) (Hills, 2012). This indicator was introduced in order to overcome key shortcomings often associated with its predecessor, the 10% indicator (FP10), which deems households to be fuel poor if they spend more than this proportion of their household income on energy.[1] Specifically, arguments against the FP10 indicator relate to the fact that high income households are not necessarily excluded and the indicator was considered too sensitive to rapid swings in energy prices (Hills, 2012). However, the FP10 indicator is still the most commonly used indicator in many European Union countries (OECD, 2018) as well as employed by some of the UK nations. This reflects the limited agreement or common, gold standard definition of fuel poverty to be employed (Deller et al., 2019).

Despite their widespread use by policy makers in the UK, both the LIHC and the FP10 indicators are indirect measures of the individuals' lived experiences as they are mainly

[1] FP10 was originally based on twice the national median proportion of income spent on energy (Boardman, 1991).

based on the income-fuel cost balance and overcome individual subjective *perceptions* of their ability to keep their house warm. It should be mentioned here that indicators based on the income-fuel cost balance (such as LIHC and FP10) and those on subjective reports on the ability to keep their accommodation warm, although related, should be viewed as distinct indicators; the latter are much more proximal to individual perceived ability (financial, mainly, but may be also relevant to thermal efficiency of their house and beyond) to keep their homes warm and to lesser extent to broader indebtedness/budget problems. Typically, people with similar income levels may make different judgements about adequacy of their income to cover different life expenses (including fuel costs) potentially due to different expectations or social comparisons; existing studies have shown that these distinguishable concepts may have different effects on individuals' health (Arber et al., 2014; Davillas and Benzeval, 2016). In support of these arguments, in the context of fuel deprivation in particular, Waddams Price et al. (2012) employ more direct measures of heating adequacy, which are based on whether people *feel* unable to afford their energy services to keep their home warm. Moreover, longitudinal pan-European studies have explored similar fuel deprivation indicators, unveiling a higher prevalence of fuel poverty in southern European and in newer member states (Healy and Clinch, 2002; Deller, 2018).

In this paper we aim to explore the relationship between fuel deprivation, using several alternative indicators to capture both thermal comfort and financial security channels, and a set of health and well-being outcomes. For the needs of this study, nationally representative data from *Understanding Society: the UK Household Longitudinal Study* (UKHLS) are employed. There is no plethora of studies on whether indicators of fuel poverty are associated with health outcomes. Indeed, the economics of happiness literature has burgeoned since Easterlin (1974)'s seminal research on economic growth[2], and has garnered considerable support for the use of subjective (self-reported) measures of well-being (health) in the exploration of economic problems (Horn et al., 2017). However, a challenge in the relevant literature is that the majority of the existing studies rely solely on subjective well-being or life satisfaction outcomes and self-reported health measures (e.g. Gilbertson et al., 2006; Lacroix and Chaton, 2015; Welsch and Biermann, 2017; Llorca et al., 2020; Awaworyi Churchill et al., 2020; Kahouli, 2020; Awaworyi Churchill et al., 2021). Self-reported health and wellbeing measures are subject to

[2] See Clark (2018) for a review of the extant literature.

measurement error (Baker et al., 2004; Greene et al., 2015; Black et al., 2017). For example, it has been shown that within-household peer effects and minor differences in the survey design can substantially influence econometric results on subjective (job) satisfaction outcomes (Conti and Pudney, 2011). Moreover, the self-reported health indicators do not necessarily identify pre-symptom and pre-diagnosis stages. Exploring the role of fuel poverty in physiological processes that occur before a health condition manifests or has reached the stage of diagnosis may be of importance for better understanding how fuel poverty may get "under the skin". To the best of our knowledge, this is the first paper that combines a set of well-being measures as well as subjective and more objectively measured health measures with several fuel deprivation indicators to explore their association within the context of the same study.

Our study complements Kahouli (2020) and Awaworyi Churchill et al. (2021) who utilise panel and instrumental variable (IV) estimation (i.e. regional energy prices) to identify the relationship between fuel poverty indicators and self-reported measures of health. The authors establish a statistically significant and negative relationship between a set of fuel poverty indicators and self-reported health. These studies rely on general measures of health, including the conventional self-assessed health and the composite SF-36 general health score. However, it remains unclear the extent to which fuel poverty indicators are related to physiological and biological processes. Hence, in comparison, the present paper not only draws upon blood-based biomarkers as measures of infection and inflammation related to physical health conditions, but also the physical (PCS-12) and the mental (MCS-12) component sub-scores based on the 12-item Short-Form Health Survey (SF-12) in order to paint a richer and more detailed picture than general health scores. Due to the cross-sectional nature of our biomarker data and the lack of key survey questions to match retail energy prices by payment method (in order to generate the between- *and* within-regional variation that exists in the GB energy system), the present paper cannot rely on panel or IV approaches (discussed in Section 4). Nonetheless, we employ a wider array of confounding factors than the preceding studies (i.e., lifestyle factors, self-reported diagnosed conditions) and Oster's (2019) bounding approach to assess whether our preferred specifications are robust to omitted variable bias. Oster's (2019) bounding approach is particularly suitable when an instrument cannot be relied upon (Clark et al., 2021).

Perhaps more closely related to our study, in terms of the dependent variable of interest, Crossley and Zilio (2017) explored, using regression discontinuity design, the role of targeted and unconditional cash-transfers (Winter Fuel Payments; WFP), which aim to cover additional heating costs, on health (Crossley and Zilio, 2017). The authors find a robust link between fibrinogen and the WFP. However, given that eligibility to the WFP does not depend on individual's income (or any proxy of wealth), these analyses do not seek to unearth whether there is a direct relationship between fuel poverty *per se* and individual's well-being and health. Moreover, the external validity of the study could be hampered as the initiative targets households with a particular composition structure (i.e., older household members).

Our paper contributes to the literature in two main ways. Firstly, complementary to self-reported health and well-being measures, we employ blood-based biomarkers that reflect general chronic or systemic inflammation (Jain et al., 2011; Emerging Risk Factors Collaboration, 2010): C-reactive protein (CRP) and fibrinogen. Self-reported life satisfaction and general health measures are commonly used measures in the economics literature. We believe however that complementing this analysis using more objectively measured health indicators (biomarkers) has its virtues. Our set of biomarkers allow us to focus on inflammation; elevated levels of inflammation suggest infection processes as inflammation is one of the body's defence mechanisms from infection from outside invaders, such as bacteria and viruses. As such, our set of inflammatory biomarkers are more proximal outcomes in the process through which fuel poverty may affect individual's health outcomes.

Secondly, in addition to fuel poverty indicators that are based on the income-fuel cost balance (LIHC and FP10), we also employ more direct deprivation indictors capturing respondents' perceptions of whether they are able to keep their house warm. Importantly we take advantage of the fuel deprivation indicator (as our data's questionnaire frames the variable independent of affordability in Wave 2) by combining it with the fuel poverty indicators (proxies for affordability) in order to give important insights on the association of fuel poverty with health and well-being measures — such associations are masked when solely relying on conventional income-energy costs fuel poverty indicators (Waddams Price et al., 2012). In this vein, we further complement the existing literature by introducing a set of fuel deprivation indicators by combining our income adequacy indicators (LIHC and FP10) with direct indicators of reported inability to keep their house warm (IHEAT); these indicators may address concerns on whether heating inadequacy arises due to low income (Waddams Price et al., 2012). This is a novel opportunity to explore whether combining subjective feelings about keeping the home warm (i.e., capturing the “thermal comfort” channel) and objective measures of affordability (i.e., capturing the “financial security” channel) reveals the impact of fuel poverty on health, mental and/or physical, and well-being.[3]

We found heterogeneous associations between fuel deprivation and our set of well-being outcomes, depending on which fuel deprivation indicator is used. Our composite fuel deprivation indicators, which specifically takes into account the income-fuel costs balance and more proximal perceptions of heating adequacy, show the presence of more pronounced relationship with life satisfaction and fibrinogen, one of our biological health measures. Of particular interest, these associations would have been less pronounced or masked when using separately each of the components of our composite fuel deprivation indicators as well as in the case of self-reported generic measures of physical health. Lifestyle and chronic health conditions plays limited role in attenuating our results, while material deprivation partially, but not fully, attenuates our results. Our conclusions remained robust when Oster (2019)’s bounding analysis is employed to test the potential confounding role of unobservables. Overall, this paper reveals novel insights on the value of composite fuel poverty indicators, which combine affordability (objectively capturing the “financial security” channel) and heating deprivation (subjectively capturing the “thermal comfort” channel), to uncover the mechanisms through which fuel poverty may get “under the skin”.

[3] It is important to note that our approach differs from composite indices currently employed in the literature. For example, Awaworyi Churchill et al. (2020) create a composite index using LIHC, FP10 and a subjective indicator of fuel poverty. The question underpinning their subjective indicator already captures affordability and the thermal component of fuel poverty. Moreover, their composite indicator is set equal to 1 if a household is defined as fuel poor by at least one objective and/or subjective indicator. Instead, here, we combine LIHC/FP10 and IHEAT in order to create measures that defines fuel poverty based on both (objective) affordability *and* (subjective) heating deprivation, thereby requiring each of these two components to hold.

2. Data

The data came from *Understanding Society*: the UK Household Longitudinal Study (UKHLS) – a longitudinal, nationally representative study in the UK. For the needs of our analysis, we use the General Population Sample (GPS), a random sample of the general UK population. As part of UKHLS Wave 2 (1/2010-3/2012), a set of blood-based biomarkers were collected by qualified nurses following the main UKHLS Wave 2 data collection. The nurse visits conducted for the GPS, with the respondents being eligible if they are aged 16 or over, live in England, Wales or Scotland and are not pregnant. Collection of the blood samples were further restricted to those respondents who had no clotting or bleeding disorders and no history of fits.[4] This results in a potential sample of 9,803 individuals who consent to the blood collection and at least one blood-based biomarker is available. Our self-reported health and well-being outcomes, the fuel deprivation indicators and all other covariates included in our models are extracted from the main UKHLS Wave 2. Excluding observations with missing values on all variables used in our analysis further reduces our working sample to 6,854 respondents.

All analyses were weighted using probability sample weights to ensure that our sample is representative to the population of Great Britain (GB). These sample weights are calculated by adjusting the published UKHLS sample weights to account for successful blood sample collection, as well as for item nonresponse for all variables used in our analysis, using backward stepwise logistic regressions on observed predictors from the UKHLS main Wave 2 survey.

2.1 Outcome variables

Life satisfaction

Our life satisfaction measure (*LIFESAT*) categorises respondents on a seven-category scale, ranging from completely dissatisfied (value of 1) to completely satisfied (value of 7) (Table 1). Whilst inherently subjective, self-reported well-being measures have been used extensively in the economics literature. For example, Clark et al. (2018) argue that life satisfaction is an overarching (reflects upon the life of a person), clear (easy to interpret

[4] Participants gave informed written consent for their blood to be taken. The UKHLS has been approved by the University of Essex Ethics Committee and the nurse data collection by the National Research Ethics Service (10/H0604/2).

across participants and by researchers), and democratic (allows individuals to freely assess the determinants of their own lives without persuasion) measure.

Self-reported measures of physical and mental health functioning

To explore the link between fuel poverty and mental and physical health, we employ measures based on the 12-item Short-Form Health Survey (SF-12). The SF-12 is a self-reported generic measure of health-related quality of life, based on a questionnaire of 12 health-related questions that cover various health dimensions. For this study we use both the physical (PCS-12) and the mental (MCS-12) component sub-scores that are created using validating algorithms on aggregating responses to the SF-12 questionnaire (Ware et al., 1995). By definition, these scores have values between zero and 100 and are standardized to have a mean of 50 and a standard deviation of 10; higher values indicate better physical or mental health (Ziebarth, 2010). Both the PCS-12 and MCS-12 measures are log-transformed to account for the skewness of their distribution. Table 1 presents summary statistics of the raw PCS-12 and MCS-12 scores (before being log-transformed).

Although the PCS-12 and MCS-12 are self-reported, they are considered as comprehensive health indicators. As such, they are often referred as quasi-objective health measures to differentiate from the more objectively measured nurse-collected and blood-based biomarkers (Ziebarth, 2010).

Biomarkers

Two blood-based biomarkers of inflammation are used in this study: fibrinogen and CRP. Fibrinogen (g/l) is a glycoprotein that aids the body to stop bleeding by promoting blood clotting, but it is also considered as an inflammatory biomarker (Jain et al., 2011). Elevated fibrinogen levels have been strongly linked to higher risk of ischaemic heart diseases, such as myocardial infarction, stroke and coronary heart diseases, and to increased mortality risks (Acevedo et al., 2002; Danesh et al., 2005).

C-reactive protein, measured in milligrams per litre of blood (mg/l), is an inflammatory biomarker that rises as part of the immune response to infection. Rising CRP levels are associated with a higher risk of coronary heart disease, stroke and cardiovascular mortality (Emerging Risk Factors Collaboration, 2010). CRP and fibrinogen are log-transformed to account for the skewness of their distribution; Table 1 presents summary statistics for the raw biomarker data, before being log-transformed.

Table 1. Definition and summary statistics for the outcome and fuel deprivation measures.

Variable name	Definition	Mean	Std. Dev.
Outcome measures			
LIFESAT	Satisfaction with life overall:1 if completely dissatisfied, 2 if mostly dissatisfied, 3 if somewhat dissatisfied, 4 if neither satisfied nor dissatisfied, 5 if somewhat satisfied, 6 if mostly satisfied, 7 if completely satisfied	5.262	1.457
PCS-12	SF-12 physical component summary score	49.690	11.141
MCS-12	SF-12 mental component summary score	50.063	9.647
Fibrinogen	Fibrinogen (g/l)	2.756	0.596
CRP	C-reactive protein (mg/l)	3.190	7.227
Fuel poverty and fuel deprivation indicators			
LIHC	1 if low-income, high energy expenditure; 0 otherwise	0.101	0.301
FP10	1 if proportion of income spent on energy exceeds 10%; 0 otherwise	0.207	0.405
IHEAT	1 if unable to keep the house adequately warm in winter; 0 otherwise	0.067	0.250
Composite			
IHEAT -LIHC	1 if IHEAT=1 and LIHC=1; 0 otherwise	0.018	0.133
IHEAT-10	1 if IHEAT=1 and FP10=1; 0 otherwise	0.027	0.161

2.2 Indicators of fuel poverty

Indicators based on income – fuel cost balance

We construct two indicators of fuel poverty based on the income-fuel cost relationship: the LIHC (Hills, 2012) and FP10 (Boardman, 1991) indicators. Whilst such indicators are more proximal measures of fuel poverty compared to alterative indicators used in the literature (Awaworyi Churchill et al., 2020) – for example, energy prices and presence of condensation, damp or leaks in the home (Deller, 2018) – we consider them as more indirect compared to those based on subjective reports on individual's reported ability of keeping homes warm (which will be described below).

The *LIHC* indicator takes a value of 1 if: a) the individual's household spends more than the national median on energy and, b) upon deducting energy expenditure, their residual household net income falls below the income poverty threshold (i.e. 60% of the median national income); the *LIHC* indicator is coded as zero otherwise. For the needs of constructing the *LIHC* indicator, income is equivalised using the OECD equivalence scale and energy expenditure is adjusted using Hills (2012) fuel cost equivalisation factors.

Our 10 percent fuel poverty indicator (*FP10*) takes the value of one if respondent's household spends more than 10 per cent of the household income on energy, and zero otherwise. Fuel poverty prevalence is 10% when the LIHC indicator is used, compared to 21% under our FP10 indicator (Table 1).

Direct indicators of heating deprivation

We also use a more proximal indicator of whether individuals are able to keep their home warm. This question is part of the household questionnaire at UKHLS wave 2 and is generally asked for the person who owns or rents the accommodation (or the elder of the two if jointly owned or rented). Specifically, our *IHEAT* indicator takes the value of one for those individuals who either (as household representative) report an inability to keep their accommodation warm during winter (for any possible reason) or they are a member of a household whose household representative reports this is the case, and zero otherwise. Table 1 shows that about 7 per cent of our sample reported that they are unable to keep their accommodation warm (Table 1), which is consistent with the European Union-15 average (Deller, 2018).

Composite indicators

Whilst the indicator above may better identify unmet heating needs, they nonetheless overlook the income-related budget constraints captured by the income-fuel cost indicators (and vice versa). Given the absence of a gold standard, we constructed a set of composite fuel deprivation indicators, which identifies whether a household is able to keep their home warm (*IHEAT)* and *simultaneously* classified as fuel poor based on the conventional income-energy costs indicators (*LIHC* or *FP10*). This is in the spirit of existing research (Waddams Price et al., 2012), which highlights the need for identifying whether heating inadequacy is directly related to low income, a characteristic that is not directly captured by *IHEAT* alone.

Specifically, we create two composite fuel deprivation indicators. The *IHEAT-LIHC* indicator takes the value of one if the respondent reports that they are unable to keep their accommodation warm during winter (based on the *IHEAT* indicator) and are identified as fuel poor using the *LIHC* indicator; the *IHEAT-LIHC* indicator takes the value of zero otherwise. Similarly, our *IHEAT-FP10* indicator takes the value of one if the respondent reports inadequate heating problems during winter (based on the *IHEAT* indicator) and is simultaneously identified as fuel poor based on the *FP10* definition, and zero otherwise.

These composite fuel deprivation indicators result in a much lower proportion of individuals falling within this definition (about 1.8% and 2.7%, depending on the composite indicator used, see Table 1). Table 2 shows that the income-fuel cost indicators (LIHC and FP10) are distinct measures to the self-reported heating adequacy (IHEAT), although correlated. For example, about 16 percent of those classified as fuel poor based on the LIHC indicator also report heat adequacy problems (110/692=0.159); moreover, about 5.7 percent of those who are not identified as fuel poor (LIHC) experience heating adequacy problems (349/6,162=0.057). Similar results are observed for the FP10-IHEAT cross-tabulations. These results further confirm the need of considering our composite fuel deprivation indicators to capture not only potential income inadequacy in terms of the affordability of energy costs but also individuals' perceived lived experiences of heating adequacy at home. Indeed, simultaneously capturing both dimensions (thermal comfort and affordability) is of importance, especially when taking in account the poorest individuals who spend relatively more on energy in the home by trading-off necessities, such as food, particularly in response to cold weather (Beatty et al., 2014).

Table 2: Cross-tabulations (frequencies) of alternative indicators of fuel deprivation

	IHEAT = No	IHEAT = Yes	Total
LIHC = No	5,812	349	6,162
LIHC = Yes	582	110	692
Total	6,395	459	6,854
Correlation coefficient = 0.123			
FP10 = No	5,161	277	5,438
FP10 = Yes	1235	181	1,416
Total	6,395	459	6,854
Correlation coefficient =0.124			

2.3 Covariates

The explanatory covariates used in our analysis are demographic and socioeconomic characteristics that have been shown to be associated with health and well-being measures as well as with individual's ability to afford energy bills (e.g., Fuchs, 2004; Awaworyi Churchill et al., 2020). These variables are collected as part of the UKHLS Wave 2 main survey.

The following variables are included in our base case model specification (Specification 1). Gender and a squared polynomial of age are used to account for the non-linear relationship with our health and well-being outcomes. We also account for migration status (NON-UK vs UK-BORN). Marital status is captured using a four-category variable (*MARRIED, SEPARATED, WIDOW, SINGLE*). We also include the number of children leaving in the household (*CHILDREN*) and an indicator of whether the respondent undertakes carer responsibilities for disabled or elderly household members (*CARER vs NONCARER*). Employment status is captured using a six-category variable: *EMPLOYED, UNEMPLOYED, RETIRED, STUDENT, DISABLE, OTHER*. We also account for two socioeconomic status measures: educational qualification (*NO/BASIC-QUAL, A-LEVEL/DEGREE*) and house tenure (*RENT vs HOMEOWN*). Regional indicators (nine government office regions for England and indicators for Scotland and Wales) are also included to account for regional variation.

To explore the role of the potential underlying mechanisms on explaining the association of energy deprivation with our well-being measures as well as the sensitivity of our findings we include a set of additional covariates sequentially. The first set of covariates account for lifestyle variables: a three-category smoking variable ascertaining whether or not they have smoked or currently smoke (*NEVER-SMOKER, EXSMOKER, SMOKER*); an indicator of whether the respondent eats at least the recommended five potions of fruit and vegetables per day (*FIVEADAY vs NOFIVEADAY*); and a self-reported physical activity score that ranges from 0 (if they do no sports at all) to 10 (if very active) (*ACTIVE*). Lifestyle is an important determinant of individuals' health and well-being outcomes (Contoyannis and Jones, 2004; Humphreys et al., 2014).

A set of self-reported diagnosed chronic health conditions are also accounted for. This set includes dichotomous variables for ever diagnosed with respiratory diseases (*RESPIRATORY vs NORESPIRATORY),* arthritis (*ARTHRITIS* vs *NOATHRITIS*), endocrine (*ENDOCRINE* vs *NOENDOCRINE)*, cardiovascular-related diseases (*CVD* vs *NOCVD)* and other health conditions (*OTHERCONDITION* vs *NO-OTHERCONDITION).* Fuel poverty and well-being are both correlated with chronic conditions and, thus, accounting for the latter may help us to understand their potentially confounding role (Marmot Review Team, 2011; Vázquez et al., 2015).

Finally, we also control for a dichotomous variable that takes the value of one for those household that reports material deprivation in three or more necessary goods or services (*DEPRIVATION* vs *NODEPRIVATION*). Deprivation is an important determinant of health (Fuchs, 2004), and correlated with people's ability to afford energy bills. Accounting for material deprivation allows us to explore whether material deprivation is an important driving force of the observed fuel deprivation-wellbeing association. A full description and summary statistics of all covariates are available in Table A1 (appendix).

3. Empirical methodology

Ordered logit models are estimated to explore the association between fuel deprivation and life satisfaction. For the case of our continuous health models (PCS-12, MCS-12, fibrinogen or CRP), we employ log-linear regression models of our log-transformed outcomes on our set of predictor variables estimated using ordinary least squares (OLS).

A general model specification can be written as:

$$y_i^* = \alpha + \mathrm{FUELPOV}_i\beta + \mathrm{X}_i\delta + \varepsilon_i \tag{1}$$

where, y_i^* stands for the outcome variable for each individual (i), $FUELPOV_i$ represents the fuel deprivation indicator of interest, X_i is the set of our covariates; β and δ are the regression coefficients to be estimated. For the continuous outcome variables, y_i^* coincides with the observed (log transformed) health measure. Regarding the ordered logit models for life satisfaction, y_i^* represents the relevant latent variable.

Separate models are estimated for each well-being and health outcome of interest to explore their association with our alternative fuel deprivation indicators. We initially estimate these models (eq. 1) using a base case set of covariates (Specification 1). To assess whether these base case results are driven by other confounders that are associated with both fuel deprivation and our well-being outcomes we estimated three additional model specifications. Specifically, we enhance Specification 1 by adding lifestyle indicators (Specification 2). In subsequent analysis, Specification 2 is further augmented by a set of self-reported diagnosed conditions (Specification 3), while our full model specification further accounts for individuals' material deprivation (Specification 4). All specifications control for regional fixed effects (at the Government Office Region level) as well as year and month of interview fixed effects to account for potential seasonality as the UKHLS wave 2 interviews are spread during the 2010-2012 time period.

4. Results

4.1 Income-fuel cost indicators and direct indicators of heating deprivation

Table 3 presents the results from the ordered logit model of life satisfaction on our set of fuel deprivation indicators (*LIHC, FP10* and *IHEAT*). The table shows the coefficients for each fuel deprivation indicator and the relevant average partial effects (APE) for each of the categories of the ordered life satisfaction outcome. Results from each model specification are presented separately, with our base model specification (Specification 1) augmented with lifestyle factors (Specification 2). Specification 3 further adjusts specification 2 for self-reported diagnosed chronic conditions and, finally, Specification 4 adds material deprivation measures to Specification 3.

Turning to Specification 1, Table 3 shows the presence of a strong negative association between life satisfaction and our set of energy deprivation indicators; all our fuel deprivation indicators are negatively associated with higher life satisfaction levels (i.e., higher life satisfaction values since life satisfaction is coded from completely dissatisfied [1] to completely satisfied [7]). The APEs present the magnitude of the association between each of the seven life satisfaction categories and fuel deprivation measures, while their sign has a clear qualitative interpretation, with a positive (negative) sign implying a positive (negative) association with each satisfaction outcome. For example, the APEs calculated based on Specification 1 show that the LIHC fuel poor are about 1.1 percentage points more likely to report complete dissatisfaction with their life that the non-fuel poor; these APE seem to follow an increasing trend up to the somewhat satisfied category and, then, negative APE are observed indicating that the fuel poor are less likely to report mostly (by 7.7 percentage points) or complete (by 4.3 percentage points) life satisfaction versus the non-fuel pour counterparts.

The observed negative fuel deprivation-life satisfaction gradient remains robust and highly significant, although reducing in magnitude, after sequentially accounting for our set of lifestyle, chronic conditions and material deprivation (Specification 2, 3 and 4). Specifically, for the case of all fuel deprivation indicators, limited differences in the observed gradients are evident between our base case specifications (Specification 1) and those specifications that adjust for lifestyle variables (Specification 2) and, subsequently, further account for chronic conditions (Specification 3). Much lower, but still systematic, APEs are estimated for our full model specifications (Specification 4), suggesting that material deprivation is an important confounder in the association between fuel deprivation and life satisfaction.[5] For example, the fuel poor individuals based on the FP10 indicator are about 4.2 percentage points less likely to report complete satisfaction with their life as opposed to non-fuel poor in the case of base case model (Specification 1); after accounting for our full set of covariates (Specification 4), the corresponding APE reduces by more than 30%, indicating that the FP10 fuel poor individuals are about 2.9 percentage points less likely to report complete satisfaction with their life.

It should be noted here that the APEs are larger in magnitude for the inadequate heating (*IHEAT*) indicator of fuel deprivation compared to both fuel deprivation indicators measured based on the income-energy cost balance (*LIHC* and *FP10*). For example, in the case of APEs from our full model specifications (Specification 4), those with inadequate heating are about 4.7 percentage points less likely to report complete life satisfaction; this is larger than the corresponding values for those individuals classified as fuel deprived based on the *LIHC* and the *FP10* indicators (about 2.9 percentage points). This heterogeneity in the associations with life satisfaction highlights the importance of considering alternative fuel deprivation indicators.

[5] Material deprivation remains the most important cofounder, followed by lifestyle choices and chronic conditions, regardless of their sequential order.

Table 3. Ordered logit regressions of life satisfaction on measures of fuel deprivation: low-income-high-costs; 10% expenditure-income; and inadequate heating

Fuel deprivation measure	Coeff. (std.err.)	Average Partial Effects (std.err.)						
		Completely dissatisfied	Mostly dissatisfied	Somewhat dissatisfied	Neither dissatisfied Nor satisfied	Somewhat satisfied	Mostly satisfied	Completely satisfied
Panel A. Low-income-high-costs indicator (LIHC)								
Specification 1†	-0.488***	0.011***	0.019***	0.033***	0.030***	0.028***	-0.077***	-0.043***
	(0.111)	(0.003)	(0.005)	(0.008)	(0.007)	(0.005)	(0.019)	(0.008)
Specification 2‡	-0.455***	0.010***	0.017***	0.030***	0.028***	0.028***	-0.072***	-0.040***
	(0.111)	(0.003)	(0.005)	(0.008)	(0.007)	(0.005)	(0.020)	(0.008)
Specification 3#	-0.438***	0.009***	0.016***	0.029***	0.027***	0.027***	-0.070***	-0.038***
	(0.111)	(0.003)	(0.005)	(0.008)	(0.007)	(0.006)	(0.020)	(0.008)
Specification 4##	-0.324***	0.006**	0.011***	0.021***	0.021***	0.022***	-0.051***	-0.028***
	(0.110)	(0.002)	(0.004)	(0.008)	(0.007)	(0.006)	(0.019)	(0.009)
Panel B. 10% expenditure-income indicator (FP10)								
Specification 1	-0.452***	0.009***	0.016***	0.029***	0.028***	0.028***	-0.069***	-0.042***
	(0.078)	(0.002)	(0.003)	(0.006)	(0.005)	(0.004)	(0.013)	(0.006)
Specification 2	-0.421***	0.008***	0.015***	0.027***	0.026***	0.027***	-0.065***	-0.038***
	(0.079)	(0.002)	(0.003)	(0.006)	(0.005)	(0.005)	(0.013)	(0.006)
Specification 3	-0.416***	0.008***	0.014***	0.026***	0.026***	0.027***	-0.064***	-0.037***
	(0.078)	(0.002)	(0.003)	(0.005)	(0.005)	(0.005)	(0.013)	(0.006)
Specification 4	-0.315***	0.006***	0.010***	0.020***	0.020***	0.022***	-0.049***	-0.029***
	(0.079)	(0.002)	(0.003)	(0.005)	(0.005)	(0.005)	(0.013)	(0.007)
Panel C. Inadequate heating (IHEAT)								
Specification 1	-0.881***	0.023***	0.039***	0.064***	0.053***	0.038***	-0.149***	-0.067***
	(0.118)	(0.005)	(0.007)	(0.010)	(0.007)	(0.003)	(0.022)	(0.007)
Specification 2	-0.858***	0.021***	0.037***	0.062***	0.052***	0.039***	-0.147***	-0.064***
	(0.121)	(0.005)	(0.007)	(0.010)	(0.007)	(0.003)	(0.023)	(0.007)
Specification 3	-0.828***	0.020***	0.035***	0.060***	0.051***	0.039***	-0.142***	-0.062***
	(0.122)	(0.004)	(0.007)	(0.010)	(0.007)	(0.003)	(0.023)	(0.007)
Specification 4	-0.592***	0.012***	0.022***	0.040***	0.038***	0.034***	-0.099***	-0.047***
	(0.127)	(0.004)	(0.006)	(0.010)	(0.008)	(0.005)	(0.023)	(0.008)

† Specification 1: base model specification.
‡ Specification 2: base model specification further adjusted for lifestyle (smoking, healthy eating, physically active).
# Specification 3: specification 2 further adjusted for a set of self-reported, diagnosed health conditions.
Specification 4: specification 3 further adjusted for material deprivation.
*p<0.1, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

Table 4 presents the corresponding results for our self-reported measures of physical (*PCS-12*) and mental health (*MCS-12*). We find limited evidence of systematic associations of our fuel deprivation indicators that are based on income-energy costs balances (*LIHC* and *FP10*) with physical health functioning scores. On the other hand, these indicators appear more so associated with lower levels of mental health, specifically *FP10* not least because *LIHC* is completely attenuated upon controlling for material deprivation. By contrast, our more proximal measure of respondent's inability to keep their house warm (*IHEAT*) is negatively and systematically associated with better mental and physical health functioning (higher *PCS-12* and *MCS-12* scores). These associations remain statistically significant (at least at the 5% level), despite being reduced in magnitude after accounting for our full set of covariates, material deprivation (as well as chronic conditions in the case of physical health) seems to exert the most important role on partially attenuating these associations.

Table 4. OLS regressions of PCS-12 and MCS-12 on measures of fuel deprivation

Panel A. PCS-12				
Fuel deprivation measure	**Specification 1†**	**Specification 2‡**	**Specification 3⌗**	**Specification 4⌗⌗**
LIHC indicator	-0.010	-0.003	-0.001	0.003
	(0.014)	(0.014)	(0.013)	(0.013)
FP10 indicator	-0.008	-0.001	-0.002	0.002
	(0.009)	(0.009)	(0.009)	(0.009)
IHEAT indicator	-0.066***	-0.061***	-0.045***	-0.039**
	(0.018)	(0.018)	(0.017)	(0.017)
Panel B. MCS-12				
Fuel deprivation measure	**Specification 1†**	**Specification 2‡**	**Specification 3⌗**	**Specification 4⌗⌗**
LIHC indicator	-0.039**	-0.034**	-0.034**	-0.024
	(0.016)	(0.016)	(0.016)	(0.016)
FP10 indicator	-0.037***	-0.033***	-0.033***	-0.023**
	(0.011)	(0.011)	(0.011)	(0.011)
IHEAT indicator	-0.081***	-0.077***	-0.075***	-0.053**
	(0.023)	(0.023)	(0.023)	(0.024)

†Specification 1: base model specification.
‡Specification 2: base model specification further adjusted for lifestyle (smoking, healthy eating, physically active).
⌗Specification 3: specification 2 further adjusted for a set of self-reported, diagnosed health conditions.
⌗⌗Specification 4: specification 3 further adjusted for material deprivation.
*p<0.1, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

Turning to CRP and fibrinogen models (Table 5), we find no systematic associations with all our fuel deprivation indicators considered here (LIHC, FP10 and IHEAT). The observed positive association between heating inadequacy (IHEAT) and fibrinogen in our base case model specification is completely attenuated in the case of less parsimonious specifications (Specifications 2-4).

Table 5. OLS regressions of fibrinogen and C-reactive on measures of fuel deprivation

		Panel A. Fibrinogen		
Fuel deprivation measure	**Specification 1†**	**Specification 2‡**	**Specification 3ǂ**	**Specification 4ǂǂ**
LIHC indicator	0.006	0.002	0.001	-0.001
	(0.010)	(0.010)	(0.010)	(0.011)
FP10 indicator	0.001	-0.002	-0.002	-0.005
	(0.008)	(0.008)	(0.008)	(0.008)
IHEAT indicator	0.024**	0.019	0.017	0.012
	(0.012)	(0.012)	(0.012)	(0.012)
		Panel B. CRP		
Fuel deprivation measure	**Specification 1†**	**Specification 2‡**	**Specification 3ǂ**	**Specification 4ǂǂ**
LIHC indicator	0.001	-0.023	-0.027	-0.038
	(0.057)	(0.057)	(0.057)	(0.057)
FP10 indicator	0.019	-0.004	-0.002	-0.012
	(0.043)	(0.043)	(0.043)	(0.043)
IHEAT indicator	0.014	-0.006	-0.027	-0.053
	(0.074)	(0.072)	(0.072)	(0.073)

†Specification 1: base model specification
‡Specification 2: base model specification further adjusted for lifestyle (smoking, healthy eating, physically active)
ǂSpecification 3: specification 2 further adjusted for a set of self-reported, diagnosed health conditions.
ǂǂSpecification 4: specification 3 further adjusted for material deprivation.
*p< 0.1, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

Composite measures of fuel deprivation

We also employ a set of composite indicators, which identify whether a household is able to keep their home warm (*IHEAT*) and *simultaneously* classified as fuel poor based on the conventional income-energy costs indicators (*LIHC* or *FP10*). These composite indicators address concerns on whether heating inadequacy is directly related to low income, a characteristic that is not directly captured by *IHEAT* alone and vice versa.

Tables 6 presents our results for life satisfaction models. Our base case model specifications (Specification 1) show that there is a highly statistically significant and negative association of our composite fuel deprivation indicators with higher levels of life satisfaction. These associations remain mostly unaffected following adjustments for lifestyle and chronic conditions (limited differences in the APE between Specifications 1, 2 and 3), suggesting that they only exert a limited confounding role in the association between life satisfaction and our composite energy deprivation measures. However, as when our energy deprivation measures are explored separately rather than as a composite measure (Table 3), material deprivation exerts a much more important role on partially attenuating the association between the composite fuel deprivation measures and life satisfaction. Focusing on the full model specification (Specification 4; Table 6), it should be noted that the APE for both our composite fuel deprivation measures are larger in magnitude compared to the corresponding APE when these fuel deprivation measures are explored separately (Table 3). These results highlight the presence of a sharper fuel deprivation-life satisfaction gradient, which would have been masked when each of the components of our composite fuel deprivation measures are explored separately.

Table 6. Ordered logit regressions of life satisfaction on combined measures of fuel deprivation.

Fuel deprivation measure	Coeff. (std.err.)	Average Partial Effects (std.err.)						
		Completely dissatisfied	Mostly dissatisfied	Somewhat dissatisfied	Neither dissatisfied Nor satisfied	Somewhat satisfied	Mostly satisfied	Completely satisfied
Panel A. Inadequate heating and low-income-high-costs (IHEAT-LIHC)								
Specification 1†	-1.131***	0.036***	0.057***	0.087***	0.063***	0.031***	-0.197***	-0.077***
	(0.236)	(0.012)	(0.017)	(0.021)	(0.010)	(0.007)	(0.043)	(0.010)
Specification 2‡	-1.099***	0.033***	0.054***	0.084***	0.063***	0.033***	-0.193***	-0.073***
	(0.237)	(0.012)	(0.017)	(0.021)	(0.010)	(0.006)	(0.043)	(0.010)
Specification 3#	-1.081***	0.031***	0.052***	0.083***	0.063***	0.034***	-0.191***	-0.072***
	(0.239)	(0.011)	(0.017)	(0.021)	(0.011)	(0.006)	(0.044)	(0.010)
Specification 4##	-0.800***	0.019**	0.033**	0.058***	0.050***	0.036***	-0.140***	-0.057***
	(0.245)	(0.008)	(0.014)	(0.021)	(0.014)	(0.003)	(0.047)	(0.013)
Panel B. Inadequate heating and 10% expenditure-income indicator (IHEAT-FP10)								
Specification 1	-1.274***	0.042***	0.067***	0.100***	0.069***	0.027***	-0.223***	-0.082***
	(0.180)	(0.010)	(0.014)	(0.016)	(0.007)	(0.007)	(0.032)	(0.007)
Specification 2	-1.267***	0.040***	0.065***	0.099***	0.070***	0.029***	-0.224***	-0.080***
	(0.181)	(0.010)	(0.014)	(0.016)	(0.007)	(0.007)	(0.032)	(0.007)
Specification 3	-1.236***	0.038***	0.063***	0.096***	0.070***	0.031***	-0.219***	-0.078***
	(0.184)	(0.010)	(0.014)	(0.017)	(0.007)	(0.007)	(0.033)	(0.007)
Specification 4	-0.957***	0.024***	0.042***	0.072***	0.059***	0.038***	-0.169***	-0.065***
	(0.189)	(0.008)	(0.012)	(0.017)	(0.010)	(0.003)	(0.036)	(0.009)

† Specification 1: base model specification.
‡ Specification 2: base model specification further adjusted for lifestyle (smoking, healthy eating, physically active).
# Specification 3: specification 2 further adjusted for a set of self-reported, diagnosed health conditions.
Specification 4: specification 3 further adjusted for material deprivation.
*p<0.1, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

Table 7 shows limited evidence of the presence of a robust association between our composite fuel deprivation indicators and physical health functioning. Turning to mental health functioning, there is a negative association of both our composite fuel deprivation indicators and better mental health functioning, which remains statistically significant for the IHEAT-FP10 indicator (at least at the 5% level) after accounting for lifestyle and self-reported, diagnosed health conditions. However, material deprivation fully attenuates this association upon controlling for our full set of covariates.

Table 7. OLS regressions of PCS-12 and MCS-12 on combined measures of fuel deprivation

	Panel A. PCS-12			
Fuel deprivation measure	**(1†)**	**(2‡)**	**(3♯)**	**(4♯♯)**
IHEAT-LIHC indicator	-0.058	-0.050	-0.048	-0.041
	(0.044)	(0.042)	(0.041)	(0.041)
IHEAT-FP10 indicator	-0.059*	-0.055*	-0.042	-0.035
	(0.033)	(0.031)	(0.030)	(0.030)
	Panel B. MCS-12			
Fuel deprivation measure	**(1†)**	**(2‡)**	**(3♯)**	**(4♯♯)**
IHEAT-LIHC indicator	-0.136**	-0.129*	-0.128*	-0.104
	(0.069)	(0.069)	(0.070)	(0.071)
IHEAT-FP10 indicator	-0.111**	-0.107**	-0.104**	-0.080
	(0.048)	(0.048)	(0.049)	(0.050)

†Specification 1: base model specification.
‡Specification 2: base model specification further adjusted for lifestyle (smoking, healthy eating, physically active).
♯Specification 3: specification 2 further adjusted for a set of self-reported, diagnosed health conditions.
♯♯Specification 4: specification 3 further adjusted for material deprivation.
*p<0.1, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

Finally, unlike the results from when the fuel deprivation indicators are used separately (Table 5), we find evidence of a systematic positive association between higher fibrinogen (indicating higher inflammation) and our composite fuel deprivation indicators (Table 8); these associations are more pronounced in case of the *IHEAT-FP10* fuel deprivation indicator, with the relevant coefficient remaining statistically significant (at least at the 5% level), although reducing in magnitude, when adjusting for our full set of covariates. Identifying the presence of systematic associations between inflammation and our composite fuel deprivation indicator, that is masked when each component of our fuel deprivation indicator is explored separately, highlights the importance of considering composite energy deprivation indicators in order to better understand how fuel deprivation may get "under the skin".

Table 8. OLS regressions of fibrinogen and C-reactive on combined measures of fuel deprivation

	Panel A. Fibrinogen			
Fuel deprivation measure	**Specification 1†**	**Specification 2‡**	**Specification 3♯**	**Specification 4♯♯**
IHEAT-LIHC indicator	0.049**	0.041*	0.040*	0.034
	(0.024)	(0.024)	(0.024)	(0.024)
IHEAT-FP10 indicator	0.055***	0.050***	0.049***	0.044**
	(0.019)	(0.019)	(0.019)	(0.019)
	Panel B. CRP			
Fuel deprivation measure	**Specification 1†**	**Specification 2‡**	**Specification 3♯**	**Specification 4♯♯**
IHEAT-LIHC indicator	-0.127	-0.160	-0.164	-0.192
	(0.147)	(0.143)	(0.143)	(0.144)
IHEAT-FP10 indicator	-0.079	-0.095	-0.111	-0.141
	(0.117)	(0.114)	(0.115)	(0.116)

†Specification 1: base model specification
‡Specification 2: base model specification further adjusted for lifestyle (smoking, healthy eating, physically active)
♯Specification 3: specification 2 further adjusted for a set of self-reported, diagnosed health conditions.
♯♯Specification 4: specification 3 further adjusted for material deprivation.
*p<0.1, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

Bounding the estimates: potential selection on unobservables

Our models include a wide array of relevant controls, however, concerns about potential endogeneity due to unobserved heterogeneity are likely to remain as one cannot rule out omitted variable bias. For example, cognitive ability may be an unobserved variable that is both correlated with fuel poverty and people's health and, thus, our results may be biased due to omitting to control for this. Another example could be that our findings may be biased due to the lack of precise records of the combination of ambient temperatures and levels of humidity within the home – variables that are typically not collected as part of multipurpose social science surveys. [6]

To investigate the extent to which our results are robust to omitted variable bias we employ Oster's (2019) bounding approach. Oster's approach builds on the work by Altonji et al. (2005), who collectively argue that observing coefficient stability across models may be insufficient to make the (commonly held) claim that estimates are robust to potential sources of endogeneity. Instead, Oster (2019) argues that not only movements in the coefficients are important, but also the concomitant change in the coefficient of determination (R^2) needs to be considered. This argument arises not least because the

[6]Although UKHLS collects ambient temperature data during the nurse visit, these data only represent a single point in time and do not provide an accurate representation of living conditions. Our results are robust to the inclusion of ambient temperatures measured during the nurse visit as well as regional, monthly average temperatures. Like Churchill et al. (2021), who control for regional effects and average temperatures, the latter exerts negligible influence on the results. For brevity and because these temperature data capture a snapshot of time rather than permanent in-house conditions, our results including temperature controls are available upon request.

observed variables in models may, in some cases, explain little of the variation in the outcome. Oster's bounding approach exploits the movement in the coefficient of interest and the R^2 estimated in the controlled and uncontrolled models (i.e., those with and without controls respectively), in order to investigate the potential influence of omitted variables bias in the model estimates.

Oster (2019) argued that unobserved covariates are typically relatively less important than those included in models, and, thus, the relative degree of selection on observables and unobservables is between zero and one ($0 < \delta < 1$), as one may expect if extensive controls are employed based on relevant literature. Following existing studies (Oster, 2019; Clark et al., 2021; Pan et al., 2021), we apply the more conservative assumption of δ=1, suggesting that the relative degree of selection on observed and unobserved variables is set equal to 1.

In addition, Oster (2019) utilises experimental publications in top journals to ascertain a limit for the R^2. Clearly the theoretical maximum is unity, however due to measurement error, the maximum R^2_{MAX} in practice is likely to be less than one. Oster (2019) applied the bounding method and, upon assessing the survival rate of findings published using the experimental data, proposes that the maximum can be assumed to take the value of $\min\left\{1,\ 1.3\hat{R}^2\right\}$, where $\hat{R}^2$ is estimated using the controlled model specification (i.e., our full model specification; specification 4).

The experimental findings considered by Oster (2019) are judged to survive if the estimated bounds do not contain zero. In the presence of upward bias, assuming the population coefficient $\beta>0$, the bound is $\left[\beta^*(\min\left\{1,\ 1.3\hat{R}^2\right\}, \delta = 1), \hat{\beta}\right]$ where β^* provides the lower bound to the controlled regression estimate $\hat{\beta}$ (Specification 4). Conversely, an upper bound $\left[\hat{\beta}, \beta^*(\min\left\{1,\ 1.3\hat{R}^2\right\}, \delta = 1)\right]$ is estimated if there is downward bias.[7] Specifically, β^* is defined as:

$$\beta^* = \hat{\beta} - \delta(\dot{\beta} - \hat{\beta})\frac{R^2_{MAX} - \hat{R}^2}{\hat{R}^2 - \dot{R}^2} \tag{2}$$

[7] The bounds are reversed if $\beta<0$.

where, $\dot{\beta}$ and $\dot{R}^2$ are estimated using the uncontrolled version of Equation 1 (i.e., bivariate regressions of health on fuel deprivation). If the bounds contain zero, then our baseline estimates can be considered non-robust to the potential role of unobservables.

Table 9 presents the bounded OLS estimates for all our health and wellbeing outcomes Column 1 contains the fuel deprivation coefficients estimated using our full model (specification 4), i.e. setting δ=0; by definition, these estimates coincide with those presented in Tables 4, 5, 7 and 8 for our full model specification for the case of PCS-12, MCS-12, Fibrinogen and CRP, while new OLS estimates (rather than our ordered logit regressions in Tables 3 and 6) are presented for our full model specification for our life satisfaction outcome (as the Oster's approach is employed to OLS models). Column 2 presents the upper (or lower) bound, and both the upper and lower bounds are collected in Column 3.

Table 9 shows that where systematic associations were observed between our fuel deprivation indicators and our wellbeing and health outcomes, the corresponding identified bounds do not contain zero. This may indicate that our baseline full model specification estimates, where systematic associations between fuel poverty indicators and our wellbeing and health outcomes are observed, are robust to the potential confounding influence of unobservables. Overall, these results indicate that our conclusions based on our full model specification (specification 4) are robust.

Table 9. Bounding (OLS) regressions for measures of health and well-being on indicators of fuel deprivation⧺

	(1)	(2)	(3)
Panel A. Life satisfaction			
	$\hat{\beta}(\delta=0)$	$\beta^{*}(\min\left\{1,\ 1.3\hat{R}^{2}\right\}, \delta=1)$	Bound
LIHC indicator	-0.282***	-0.168	[-0.282, -0.168]
FP10 indicator	-0.245***	-0.146	[-0.245, -0.146]
IHEAT indicator	-0.46***	-0.222	[-0.460, -0.222]
IHEAT-LIHC indicator	-0.743***	-0.505	[-0.743, -0.505]
IHEAT-FP10 indicator	-0.636***	-0.39	[-0.636, -0.39]
Panel B. PCS-12			
Fuel deprivation measure	$\hat{\beta}(\delta=0)$	$\beta^{*}(\min\left\{1,\ 1.3\hat{R}^{2}\right\}, \delta=1)$	Bound
LIHC indicator	0.003	0.028	[0.028, 0.003]
FP10 indicator	0.002	0.028	[0.028, 0.002]
IHEAT indicator	-0.039**	-0.011	[-0.039, -0.011]
IHEAT-LIHC indicator	-0.041	-0.02	[-0.041, -0.020]
IHEAT-FP10 indicator	-0.035	-0.01	[-0.035, -0.010]
Panel C. MCS-12			
Fuel deprivation measure	$\hat{\beta}(\delta=0)$	$\beta^{*}(\min\left\{1,\ 1.3\hat{R}^{2}\right\}, \delta=1)$	Bound
LIHC indicator	-0.024	-0.005	[-0.024, -0.005]
FP10 indicator	-0.023**	-0.007	[-0.024, -0.007]
IHEAT indicator	-0.053**	-0.018	[-0.053, -0.018]
IHEAT-LIHC indicator	-0.104	-0.065	[-0.104, -0.065]
IHEAT-FP10 indicator	-0.080	-0.043	[-0.080, -0.043]
Panel D. Fibrinogen			
Fuel deprivation measure	$\hat{\beta}(\delta=0)$	$\beta^{*}(\min\left\{1,\ 1.3\hat{R}^{2}\right\}, \delta=1)$	Bound
LIHC indicator	-0.001	-0.012	[-0.012, -0.001]
FP10 indicator	-0.005	-0.016	[-0.016, -0.005]
IHEAT indicator	0.012	0.002	[0.012, 0.002]
IHEAT-LIHC indicator	0.034	0.024	[0.034, 0.024]
IHEAT-FP10 indicator	0.044**	0.032	[0.044, 0.032]
Panel E. CRP			
Fuel deprivation measure	$\hat{\beta}(\delta=0)$	$\beta^{*}(\min\left\{1,\ 1.3\hat{R}^{2}\right\}, \delta=1)$	Bound
LIHC indicator	-0.038	-0.092	[-0.092, -0.038]
FP10 indicator	-0.012	-0.064	[-0.064, -0.012]
IHEAT indicator	-0.053	-0.120	[-0.12, -0.053]
IHEAT-LIHC indicator	-0.192	-0.259	[-0.259, -0.192]
IHEAT-FP10 indicator	-0.141	-0.215	[-0.215, -0.141]

⧺Specification 4: base model specification further adjusted for lifestyle (smoking, healthy eating, physically active), self-reported, diagnosed health conditions, current and material deprivation.
$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

5. Conclusion

Fuel poverty is widely acknowledged as a distinct form of income poverty with far-reaching implications for health and well-being. The inability of households to attain an adequate standard of energy services can be detrimental to health, particularly cardiovascular disease, inflammation and lower levels of mental health. The debate surrounding how to measure fuel poverty is contested between indicators based on income-fuel cost balance and, more proximal measures, derived from the subjective perceptions of one's ability to keep one's home warm (Deller et al., 2021). Emerging alongside this literature, there is a growing consensus surrounding the effect of fuel poverty on subjective well-being outcomes, while there is limited evidence on the potential role of fuel poverty on more objective measures of health. This paper contributes to the literature by exploring both objective and subjective measures of well-being along with a large set of different indicators of fuel deprivation; beyond the conventional income-fuel cost balance indicators of fuel poverty we also employ direct indictors capturing respondents' perceptions of whether they are able to keep their home warm as well as composite measures capturing whether heating inadequacy is relevant to low income-high energy costs.

In line with existing literature, we find a robust negative association between higher life satisfaction and all our measures of fuel deprivation (Awaworyi Churchill et al., 2020). However, we find significant heterogeneity in the magnitude of these association across the different energy deprivation measures employed. Our results show the presence of more pronounced associations in the case of our composite fuel deprivation indicators as opposed to when each of the conventional income-fuel cost balance measures or the one based on self-reported inadequate heating are employed separately.

Turning to our self-reported generic measures of physical and mental health functioning (MCS-12 and PCS-12), we find that —in general— there are more pronounced associations between fuel deprivation and mental rather than physical health functioning. However, utilisation of more objectively measured biomarker data on inflammation shows a different pattern. Specifically, we find the presence of a systematic association between our composite fuel deprivation indicator and higher fibrinogen, suggesting higher levels of inflammation; these associations are masked when conventional income-fuel cost balance or heating inadequacy measures are used separately. Identifying the presence of the systematic associations between inflammation and our composite energy deprivation indicator, which is masked when its components are explored separately, highlights the importance of considering composite fuel deprivation indicators and biological measures of health to better understand how fuel deprivation may get “under the skin”.

Of particular importance, we find that the systematic associations between our fuel deprivation indicators and well-being measures are mainly unaffected following adjustments for lifestyle and chronic conditions, suggesting that these factors have a limited role on the pathway through which fuel deprivation affects well-being. However, accounting for material deprivation seems to play a more important role but only partially alleviates the associations under investigation, which remained meaningful in magnitude and statistically significant after augmenting our models with material deprivation measures.

Sensitivity analysis using the Oster’s (2019) bounding approach shows that our main findings are robust to the potential role of confounding influence of unobservables. It should be explicitly mentioned however that in this study we are not able to address endogeneity from omitted variables bias via instrumental variables approach. Specifically, the leading instrumental variable utilised in the relevant literature, regional energy prices, cannot be robustly employed here (see e.g. Awaworyi Churchill et al., 2020; Kahouli, 2020; Awaworyi Churchill and Smyth, 2021; Munyanyi et al., 2021). In the context of GB, variation in retail energy prices not only exists between-region (Ofgem, 2015), but also within-region (Davies et al., 2014), and reflects the cost differences of incumbent companies (i.e. suppliers, distributed network operators and transmission network operators). Studies have shown that most of the dispersion in GB is attributed to within-region differences in retail pricing strategies and payment methods (Otero and Waddams Price, 2001; Davies et al., 2014; Deller et al., 2018). Given that fuel payment method data are not available in UKHLS for the period covered in our paper, and fixed cost and unit prices has only been collected by the Department for Business, Energy and Industrial Strategy (BEIS) since 2010, we cannot allocate prices by payment method or utilise prices from preceding periods in order to increase the strength and exogeneity of any potential instrumental analysis here. Finally, lack on longitudinal data on biomarkers as well as critical differences in the wording on the heating adequacy questions in later UKHLS waves does not allow us to explore any longitudinal analysis.

Overall, and despite these shortcomings, our results show that using composite indicators of fuel deprivation, capturing whether the perceived heating inadequacy at home is due to low income compared to energy costs, does matter in order to better understand their underlying effects on people's health and well-being measures. Moreover, upon combining perceptions-based with expenditure-based indicators (specifically the 10% threshold), a route between fuel poverty and biological health is revealed. This finding is crucial since the evaluation of targeted interventions and policies to mitigate the adverse effects of fuel deprivation in the population are typically benchmarked against the conventional income-fuel cost measures (BEIS, 2017; Deloitte, 2020).

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