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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 *Understanding Society: the UK Household Longitudinal Study* to explore the association between fuel poverty and a set of wellbeing 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 wellbeing 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 play a limited role in attenuating our results, while material deprivation partially, but not fully, attenuates our associations between fuel deprivation and wellbeing. These results remain robust when bounding analysis, IV and panel data models are employed to test the potential role of various sources of endogeneity biases. 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 wellbeing (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 is 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 and access to electricity and clean energy in low- and middle-income countries (Boateng et al., 2020; Acheampong et al., 2021), 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 surrounding the impact of low temperatures on vulnerable households, Public Health England has followed 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 about the most common or gold standard definition of fuel poverty to be employed (Deller et al., 2018).

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

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 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 wellbeing 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. A challenge in the relevant literature is that the majority of the existing studies rely solely on subjective wellbeing or life satisfaction outcomes and self-reported health measures in adults and children (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; Zhang et al., 2021). Indeed, the economics of happiness literature has burgeoned since Easterlin (1974)'s seminal research on economic growth[2], and has garnered considerable support

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

for the use of subjective (self-reported) measures of wellbeing (health) in the exploration of economic problems (Horn et al., 2017). However, self-reported health and wellbeing measures are subject to 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 wellbeing 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), Baudu et al. (2020), Awaworyi Churchill and Smyth (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.

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 wellbeing 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 several key ways. Firstly, complementary to self-reported health and wellbeing 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 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 wellbeing 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 wellbeing.[3]

We employed several analyses to explore the robustness of our findings to potential sources of endogeneity. Although we employ a wider array of confounding factors than the preceding studies (i.e., lifestyle factors, self-reported diagnosed conditions), omitted variables bias may be still a potential source of bias in our analysis. We use Oster's (2019) bounding approach to assess whether our preferred specifications are robust to omitted variable bias. Moreover, building and expanding on the existing literature in the context of the association between energy deprivation and health (Awaworyi Churchill et al., 2020; Kahouli, 2020; Awaworyi Churchill and Smyth, 2021), we use the between- and within-region variation in energy prices as instrumental variables (IV) to provide more convincing evidence towards causal interpretations. We employ a wide set of IV analyses including traditional two-stage least square models and the Lewbel (2012) approach, which combines external and internal instruments generated using heteroskedasticity in the data as a way to address weak instruments concerns. Finally, although the biomarker outcomes are only available as cross-sectional data (as well as longitudinal availability of some of our explanatory variables), fixed effects panel data models, conditional on the longitudinally available wellbeing and health outcomes, are estimated to further test the robustness of our results upon eliminating time-invariant unobserved heterogeneity.

We find heterogeneous associations between fuel deprivation and our set of wellbeing outcomes, depending on which fuel deprivation indicator is used. Our composite fuel deprivation indicators, which specifically take 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

[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.

material deprivation partially, but not fully, attenuates our results. Our conclusions remain robust when bounding analysis, IV and panel data models are estimated to test potential endogeneity biases. 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".

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 main 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 wellbeing 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 (for our main analysis).

All analyses were weighted using probability sample weights to ensure that our sample is representative of 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.

[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).

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 wellbeing 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 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	0.016	0.126
IHEAT-10	1 if IHEAT=1 and FP10=1; 0 otherwise	0.027	0.161

Note: Summary statistics are calculated on our main analysis sample (UKHLS wave 2).

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 1.6% 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	5,813	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	1,235	181	1,416
Total	6,396	458	6,854
Correlation coefficient =0.124			

Note: Cross-sectional tabulations are based on our main analysis sample (UKHLS wave 2).

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 wellbeing 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 survey and are used for our main analysis.

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 wellbeing outcomes. We also account for migration status (*NON-UK-IRISH* vs *UK-IRISH*). 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, DISABILITY, 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 wellbeing 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 wellbeing 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 wellbeing 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:

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

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 wellbeing 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 wellbeing 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)[5]. All specifications control for regional fixed effects (at the Government Office Region level). Year and month of interview fixed effects are also included in our model specifications; this allows us to account for seasonal variations in weather and their potential confounding role in our analysis.

3.1 Bounding approach

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] The direction of the omitted variables bias to our

[5] Sequential addition of covariates allows us to explore the potential mechanisms (confounders) that may explain part of the observed association between our wellbeing measures and fuel deprivation. It should be noted however that formal mediation analysis is beyond the scope of our paper.

[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

models relies on the direction of the association between the omitted variables, the explanatory variables and the outcome; thus, the bounding approach allows us to empirically estimate the lower and higher bounds of the energy deprivation coefficients after accounting for the potential role of omitted variables.

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 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) argues 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 $\delta=1$, 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) applies 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

temperatures. Like Awaworyi Churchill and Smyth (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.

$\min\left\{1, 1.3\widehat{R}^2\right\}$, where $\widehat{R}^2$ 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 $\left[\beta^*(\min\left\{1, 1.3\widehat{R}^2\right\}, \delta = 1), \hat{\beta}\right]$ where β^* provides the lower bound to the controlled regression estimate $\hat{\beta}$ (Specification 4). Conversely, an upper bound $\left[\hat{\beta}, \beta^*(\min\left\{1, 1.3\widehat{R}^2\right\}, \delta = 1)\right]$ is estimated if there is downward bias.[7] Specifically, β^* is defined as:

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

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.

3.2 Instrumental variable estimations

As a further attempt to address endogeneity, we employ IV models. For example, we aim to attenuate reverse causality which could bias the estimates if wellbeing or health directly influences whether or not an individual is fuel poor. Indeed, evidence suggests that healthier individuals have greater labour market participation and earnings potential (García-Gómez et al., 2010; Jones et al., 2020), which would reduce energy expenditure as a proportion of income (Deller et al., 2021). Moreover, individuals with lower levels of wellbeing and/or with long-term health conditions (e.g. diabetes, asthma) are often encouraged by healthcare professionals to keep warm (cool) in winter (summer) (NHS, 2021), thereby increasing energy expenditure shares. Another potential concern is measurement error. Despite the potential errors in life satisfaction, Krueger and Schkade (2008) have deemed such measures sufficiently reliable for use as a dependent variable. Moreover, as long as the errors in self-reported wellbeing and health outcomes are random, the correlations with independent variables will be biased towards zero (Kreuger and Schkade, 2008); based on this source of endogeneity, simple regression models, compared to the IV models, are likely to provide a lower bound.

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

Our instruments rely on the variation in regional retail energy prices. Regional energy prices are the leading IVs implemented in the relevant literature – building on the studies by Awaworyi Churchill et al. (2020), Kahouli (2020) and Awaworyi Churchill and Smyth (2021). Energy prices are reasonable contenders for instruments, given their potential to satisfy the relevance condition (i.e., correlated with the expenditure share component of the potentially endogenous variable of interest, fuel poverty here) and the exclusion restrictions condition (i.e., energy prices are only indirectly related to wellbeing and health outcomes, through the role of the former on household energy bills and the expenditure component of our energy poverty measures) – for a relevant discussion see, e.g., Kahouli (2020) and Awaworyi Churchill and Smyth (2021).[8]

More specifically, we take advantage of GB's nonlinear energy pricing structure, akin to Burlinson et al. (2021), which varies not only between-region (Ofgem, 2015), but also within-region (Davies et al., 2014), thus reflecting 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). However, unlike Burlinson et al. (2021), fuel payment method data are not available in UKHLS for the period covered in the main analysis of this paper, and when biomarker data are available (Wave 2). Hence, we use a proxy by assigning the payment method declared in Wave 3 – this is reasonable since around 40-60% of energy consumers in 2011 are considered 'sticky' (Ofgem, 2011). Gas and electricity unit prices (£/kWh) and standing charges (£/year) – the latter is independent of consumption and recoups the cost of supplying the meter – are collected annually for each GB region by the Department of Business, Energy and Industrial Strategy (BEIS, 2021a, 2021b).

Burlinson et al. (2021) have shown that past prices can increase the strength of IVs, most likely due to the more recent and greater use of fixed term contracts which are based on prices set prior to when the data is collected. However, BEIS' price data starts from 2010 and prevents this avenue of analysis in this particular study. Notwithstanding, similar to

[8] Kahouli (2020) suggests that energy prices could be endogenous if changes in prices initiate a trade-off between energy and health related expenditures. Though a concern, this view can be countered if energy price changes are considered too small, as a proportion of total expenditure, to trigger a marked substitution effect away from or towards health expenditures (Kahouli, 2020; Awaworyi Churchill et al., 2020).

Burlinson et al. (2021), we simultaneously reduce multicollinearity and increase the strength of the IVs by using a single pair: electricity unit prices and the fixed charge for gas supply.

We match prices to individual-level data in the UKHLS sample by region, year, fuel type and payment method – see Appendix B (Table B1). Table B2 (Appendix B) presents summary statistics for the annual average gas and electricity prices, between 2010 and 2012, used as instrumental variables in our analysis.

The first stage of our IV analysis, can be specified as follows:

$$\mathrm{FUELPOV}_i^* = \alpha_I + \mathrm{PRICES}_I^{'}\gamma + X_I^{'}\rho + \omega_t + \mu_r + u_i \qquad (3)$$

where, *PRICES*$_i$ represents the vector of electricity unit prices and gas standing charges, γ represents the vector of coefficients for prices, u_i represents the first stage regression error term, and X_i is the set of our covariates that are used in our base-case specification as defined earlier (Specification 1).

Whilst the IVs statistically satisfy the exclusion restriction condition, we find the first-stage F-statistic sometimes falls below Staiger and Stock (1997)'s rule-of-thumb of 10 and always below Lee et al. (2020)'s threshold of 104.7. Indeed, weak correlations between energy prices (IV) and fuel poverty indicators (the endogenous variable) have been reported previously in the literature (e.g., Munyanyi et al., 2021). Therefore, we correct for weak instruments in three ways: 1) all estimates use the limited information maximum likelihood estimator (LIML) which is considered more robust in the presence of weak instruments (Angrist and Krueger, 2001); 2) we calculate more conservative critical values and their respective "tF 0.05 standard errors" as proposed by Lee et al. (2020)[9]; and, 3) we adopt Lewbel (2012)'s approach by combining the external price-based IVs with internal instruments generated using heteroskedasticity in the data. As an additional analysis, we also employ the Lewbel IV estimator, with external and internally

[9] For brevity the adjusted standard errors are available upon request since the results remain qualitatively similar.

generated instruments, whilst balancing the covariates using inverse-propensity score weighting (IV-internal-external-PSW) (Aizer and Doyle, 2015).

Compared to standard IVs, Lewbel's (2012) approach can result in noisier estimates. On the other hand, in the presence of weak instruments, internally generated IVs have served as a useful comparator in relevant literature and has the added advantages of being an efficient estimator that also bypasses the exclusion restrictions condition (see, e.g., Awaworyi Churchill et al., 2020; Bukari et al., 2021; Pan et al., 2021).

3.3 Fixed effects panel data models

Panel regressions models are in principle feasible for our self-reported health and wellbeing outcomes, as they are also measured longitudinally in UKHLS, but not for our set of biomarkers (biomarker data are only available as a cross-section). Similarly, a set of the covariates included in Specifications 2–4 is missing or not collected consistently beyond Wave 2, hence our panel estimations are based on our base case specification (Specification 1). Moreover, the *IHEAT* variable, one of our fuel deprivation indicators and a component for our composite fuel deprivation indicators, is not available at UKHLS waves 5 and 7 (but is available in all other waves used in our panel data analysis), making the panel unequally spaced in time. Given these limitations, our panel data regression models should be viewed as further robustness tests for our base-case analysis upon account for the time-invariant unobserved heterogeneity.

We adopt fixed effects estimators for a subset of outcomes (*LIFESAT, PCS-12* and *MCS-12*) to eliminate unobserved time-invariant heterogeneity. Specifically, we employ longitudinal UKHLS data on Waves 1-10 and augment specification 1 to include Wave fixed effects alongside the year and month fixed effects already included in specification 1. For the panel data models all price and income variables are deflated using the retail price index (base year, 2009) (ONS, 2021); all time-variant covariates included in specification 1 are defined longitudinally for the needs of these models.

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.[10] 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.

[10] 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 indicators of fuel deprivation

Specification	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) and, 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 indicators 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 protein on indicators of fuel deprivation

Panel A. Fibrinogen				
Fuel deprivation measure	**Specification 1†**	**Specification 2‡**	**Specification 3♯**	**Specification 4♯♯**
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 3♯**	**Specification 4♯♯**
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)
♯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.

4.2. 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.

Table 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 indicators of fuel deprivation.

Specification	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†	-1.114***	0.035***	0.056***	0.086***	0.062***	0.031***	-0.194***	-0.076***
	(0.261)	(0.013)	(0.019)	(0.023)	(0.011)	(0.007)	(0.047)	(0.011)
Specification 2‡	-1.087***	0.032**	0.053***	0.083***	0.062***	0.033***	-0.191***	-0.073***
	(0.260)	(0.013)	(0.018)	(0.023)	(0.011)	(0.006)	(0.048)	(0.011)
Specification 3♯	-1.062***	0.031**	0.051***	0.081***	0.062***	0.034***	-0.188***	-0.071***
	(0.264)	(0.012)	(0.018)	(0.023)	(0.012)	(0.006)	(0.049)	(0.011)
Specification 4♯♯	-0.811***	0.019**	0.034**	0.059***	0.051***	0.036***	-0.142***	-0.058***
	(0.269)	(0.009)	(0.015)	(0.023)	(0.015)	(0.003)	(0.051)	(0.014)
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 indicators of fuel deprivation

Panel A. PCS-12				
Fuel deprivation measure	**(1†)**	**(2‡)**	**(3♯)**	**(4♯♯)**
IHEAT-LIHC indicator	-0.039	-0.032	-0.027	-0.020
	(0.047)	(0.045)	(0.043)	(0.044)
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	-0.142*	-0.135*	-0.133*	-0.112
	(0.076)	(0.077)	(0.078)	(0.079)
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”.

We also conduct analysis separately by gender and age groups to explore the potential heterogeneity of our associations of interest across demographic groups. Overall, we find limited differences in the association between our composite fuel deprivation measures and life satisfaction by gender and between age groups (<65 vs $\geq$ 65 age group); in the majority of cases, the estimated coefficients do not systematically differ (at the 10% level) between gender and age groups (Table A2, Appendix). Moreover, Table A3 (Appendix) further confirms that there is limited evidence of the presence of systematic associations between our self-reported measures of physical and mental health (*MSC-12* and *PSC-12*), given the inclusion of material deprivation as an additional control variable (specification 4).[11]

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

		Panel A. Fibrinogen		
Fuel deprivation measure	**Specification 1†**	**Specification 2‡**	**Specification 3⌗**	**Specification 4⌗⌗**
IHEAT-LIHC indicator	0.047**	0.039*	0.038*	0.033
	(0.023)	(0.023)	(0.023)	(0.023)
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	-0.203	-0.233	-0.240*	-0.265*
	(0.146)	(0.142)	(0.141)	(0.142)
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.

4.3 Bounding analysis, IV models and further specification checks

4.3.1 Bounding approach

In this sub-section we present results from our bounding analysis to account for the potential role of omitted variables bias in our analysis. Specifically, 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

[11] Sample size limits the reliability of our analysis by age groups in the case of fibrinogen (as biomarker data are available for a much smaller sub- sample because of collection and consent considerations); this is further constrained by the low prevalence of fuel deprivation, when based on our composite fuel deprivation measures, in the case of splitting our sample by age groups.

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 are 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 (i.e., statistically significant at 1% or 5% levels) 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 wellbeing on indicators of fuel deprivation##

	(1)	(2)	(3)
Panel A. Life satisfaction			
Fuel deprivation measure	$\hat{\beta}(\delta=0)$	$\beta^{*}(\min\left\{1,\ 1.3\hat{R}^{2}\right\}, \delta=1)$	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	-0.641***	-0.410	[-0.641, -0.410]
IHEAT-FP10 indicator	-0.743***	-0.505	[-0.743, -0.505]
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	-0.020	0.005	[-0.020, 0.005]
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	-0.112	-0.074	[-0.112, -0.074]
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	0.033	0.022	[0.033, 0.022]
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	-0.265*	-0.334	[-0.334, -0.265]
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, and material deprivation.
*p<0.1, **p<0.05, ***p<0.01.

4.3.2 Instrumental variable (IV) models

In Table 10, column 1 presents the IV results for *LIFESAT* using external instruments (electricity unit prices and gas standing charges); column 2 contains the estimates using internally generated instruments, and column 3 the corresponding estimates in the case of external and internal IVs. Overall, these results reinforce our finding so far on the negative association between fuel deprivation and life satisfaction; this is also evident for the case of our composite energy deprivation measures when less weak instruments are identified (first-stage F-statistic)

Turning to physical (*PCS-12*) and mental health (*MCS-12*) outcomes (Table 11), these results are consistent overall with our analysis so far, suggesting that there is limited evidence to support a systematic association between fuel deprivation and physical health. Internally generated IVs, and/or in combination with external IVs, (Table 11, columns 2 and 3) provide less weak instruments for the case of our mental health functioning regression, with the relevant results further confirming those presented previously on the negative influence of fuel deprivation on mental health functioning.

Our results that the composite fuel deprivation measures are more strongly and systematically linked to fibrinogen, an inflammatory biomarker, are further confirmed here. Table 12 shows a positive and systematic link between our fuel deprivation indicators and fibrinogen, particularly when relying upon the more proximal and composite indicators of fuel deprivation.

As an additional robustness check, we implement the Lewbel IV estimator (with external and internally generated instruments), whilst balancing the covariates using inverse-propensity score weighting (Tables 10-12, column 4, IV-internal and external-PSW). These results are mainly consistent with those discussed above and further alleviate concerns surrounding selection bias (Aizer and Doyle, 2015; Burlinson et al., 2021).

Table 10. IV (two-stage least squares), Lewbel and Lewbel-PSW regressions for measures of life satisfaction on indicators of fuel deprivation using electricity unit prices and gas fixed charges as instruments.

Fuel deprivation measure	$\hat{\beta}$ (IV-external) (1)	$\hat{\beta}$ (IV-internal) (2)	$\hat{\beta}$ (IV-internal and external) (3)	$\hat{\beta}$ (IV-internal and external-PSW) (4)
LIHC indicator	-2.043**	-0.312**	-0.326**	-0.244
	(1.025)	(0.151)	(0.151)	(0.284)
F-statistic	10.85	50.13	51.03	15.16
J-(p-value)	0.325	0.773	0.636	0.435
FP10 indicator	-1.128**	-0.171	-0.197	-0.240
	(0.495)	(0.127)	(0.125)	(0.199)
F-statistic	24.53	45.35	49.83	31.28
J-(p-value)	0.527	0.550	0.482	0.227
IHEAT				
	-2.294**	-0.842***	-0.853***	-1.079***
	(1.158)	(0.159)	(0.159)	(0.306)
F-statistic	11.67	37.56	40.63	12.16
J-(p-value)	0.217	0.148	0.146	0.010
IHEAT-LIHC				
	-6.289	-0.839***	-0.845***	-1.046***
	(4.042)	(0.273)	(0.273)	(0.248)
F-statistic	4.630	74.11	78.94	29.13
J-(p-value)	0.142	0.407	0.329	0.000
IHEAT-FP10				
	-3.872*	-1.051***	-1.059***	-1.324***
	(2.058)	(0.204)	(0.204)	(0.257)
F-statistic	8.633	43.100	43.30	18.94
J-(p-value)	0.191	0.604	0.550	0.002

Notes: IV-internal and external-PSW stands for the Lewbel IV estimator, with external and internally generated instruments, whilst balancing the covariates using inverse-propensity score weighting. *p<0.1, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

Table 11. IV (two-stage least squares), Lewbel and Lewbel-PSW regressions of PCS-12 and MCS-12 on indicators of fuel deprivation using electricity unit prices and gas fixed charges as instruments.

Panel A. PCS-12				
Fuel deprivation measure	$\hat{\beta}$ (IV-external) (1)	$\hat{\beta}$ (IV-internal) (2)	$\hat{\beta}$ (IV-internal and external) (3)	$\hat{\beta}$ (IV-internal and external-PSW) (4)
LIHC indicator	-0.194	0.017	0.015	0.035
	(0.172)	(0.024)	(0.024)	(0.033)
F-statistic	10.85	50.13	51.03	15.16
J-(p-value)	0.459	0.033	0.028	0.008
FP10 indicator	-0.110	0.023	0.019	0.006
	(0.088)	(0.020)	(0.020)	(0.023)
F-statistic	24.53	45.35	49.83	31.28
J-(p-value)	0.597	0.005	0.007	0.002
IHEAT indicator	-0.214	-0.033	-0.035	0.005
	(0.198)	(0.024)	(0.024)	(0.046)
F-statistic	11.67	37.56	40.63	12.16
J-(p-value)	0.401	0.065	0.083	0.010
IHEAT-LIHC indicator	-0.551	0.020	0.019	-0.084**
	(0.595)	(0.037)	(0.037)	(0.042)
F-statistic	4.630	74.11	78.94	29.13
J-(p-value)	0.315	0.278	0.293	0.001
IHEAT-FP10 indicator	-0.357	-0.017	-0.018	-0.120*
	(0.342)	(0.032)	(0.032)	(0.066)
F-statistic	8.633	43.10	43.30	18.94
J-(p-value)	0.370	0.473	0.504	0.010
Panel B. MCS-12				
Fuel deprivation measure	$\hat{\beta}$ (IV-external) (1)	$\hat{\beta}$ (IV-internal) (2)	$\hat{\beta}$ (IV-internal and external) (3)	$\hat{\beta}$ (IV-internal and external-PSW) (4)
LIHC indicator	0.042	-0.071**	-0.0709**	-0.013
	(0.160)	(0.035)	(0.035)	(0.043)
F-statistic	10.85	50.13	51.03	15.16
J-(p-value)	0.167	0.231	0.156	0.136
FP10 indicator	0.00524	-0.041*	-0.039	-0.019
	(0.082)	(0.024)	(0.024)	(0.029)
F-statistic	24.53	45.35	49.83	31.28
J-(p-value)	0.161	0.739	0.717	0.909
IHEAT indicator	0.0718	-0.127***	-0.126***	-0.223***
	(0.186)	(0.042)	(0.042)	(0.060)
F-statistic	11.67	37.56	40.63	12.16
J-(p-value)	0.177	0.671	0.613	0.116
IHEAT-LIHC indicator	0.311	-0.164*	-0.164*	-0.033
	(0.562)	(0.097)	(0.097)	(0.029)
F-statistic	4.630	74.11	78.94	29.13
J-(p-value)	0.207	0.372	0.415	0.003
IHEAT-FP10 indicator	0.141	-0.136**	-0.135**	-0.117***
	(0.324)	(0.067)	(0.067)	(0.044)
F-statistic	8.63	43.10	43.30	18.94
J-(p-value)	0.182	0.702	0.719	0.143

Notes: IV-internal and external-PSW stands for the Lewbel IV estimator, with external and internally generated instruments, whilst balancing the covariates using inverse-propensity score weighting. *p<0.1, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

Table 12. IV (two-stage least squares), Lewbel and Lewbel-PSW regressions of fibrinogen and CRP on indicators of fuel deprivation using electricity unit prices and gas fixed charges as instruments.

Panel A. Fibrinogen				
Fuel deprivation measure	$\hat{\beta}$ (IV-external) (1)	$\hat{\beta}$ (IV-internal) (2)	$\hat{\beta}$ (IV-internal and external) (3)	$\hat{\beta}$ (IV-internal and external-PSW) (4)
LIHC indicator	0.248*	0.015	0.0166	0.033
	(0.144)	(0.018)	(0.018)	(0.031)
F-statistic	10.85	50.13	51.03	15.16
J-(p-value)	0.716	0.218	0.155	0.294
FP10 indicator	0.128*	0.004	0.007	0.029
	(0.074)	(0.019)	(0.018)	(0.024)
F-statistic	24.53	45.35	49.83	31.28
J-(p-value)	0.491	0.544	0.522	0.427
IHEAT indicator	0.291*	0.050**	0.051**	0.133***
	(0.164)	(0.022)	(0.022)	(0.034)
F-statistic	11.67	37.56	40.63	12.16
J-(p-value)	0.849	0.250	0.247	0.210
IHEAT-LIHC indicator	0.815	0.065**	0.0653**	0.026
	(0.496)	(0.028)	(0.028)	(0.027)
F-statistic	4.63	74.11	78.94	29.13
J-(p-value)	0.898	0.948	0.921	0.000
IHEAT-FP10 indicator	0.498*	0.079***	0.0805***	0.0546**
	(0.283)	(0.026)	(0.026)	(0.024)
F-statistic	8.63	43.10	43.30	18.94
J-(p-value)	0.923	0.503	0.467	0.008
Panel B. CRP				
Fuel deprivation measure	$\hat{\beta}$ (IV-external) (1)	$\hat{\beta}$ (IV-internal) (2)	$\hat{\beta}$ (IV-internal and external) (3)	$\hat{\beta}$ (IV-internal and external-PSW) (4)
LIHC indicator	1.000	-0.038	-0.033	-0.098
	(0.745)	(0.100)	(0.100)	(0.186)
F-statistic	10.85	50.13	51.03	15.16
J-(p-value)	0.351	0.858	0.860	0.304
FP10 indicator	0.476	-0.017	-0.004	0.080
	(0.381)	(0.094)	(0.092)	(0.149)
F-statistic	24.53	45.35	49.83	31.28
J-(p-value)	0.241	0.695	0.674	0.562
IHEAT indicator	1.219	0.112	0.117	0.387*
	(0.863)	(0.116)	(0.115)	(0.233)
F-statistic	11.67	37.56	40.63	12.16
J-(p-value)	0.404	0.950	0.940	0.269
IHEAT-LIHC indicator	3.621	-0.1614	-0.1605	-0.289*
	(2.640)	(0.174)	(0.174)	(0.168)
F-statistic	4.630	74.11	78.94	29.13
J-(p-value)	0.581	0.793	0.733	0.000
IHEAT-FP10 indicator	2.124	-0.013	-0.008	0.096
	(1.505)	(0.146)	(0.146)	(0.224)
F-statistic	8.63	43.10	43.30	18.94
J-(p-value)	0.452	0.846	0.800	0.033

Notes: IV-internal and external-PSW stands for the Lewbel IV estimator, with external and internally generated instruments, whilst balancing the covariates using inverse-propensity score weighting. *p<0.1, **p<0.05, ***p<0.01. Robust standard errors in parentheses.

4.3.3. Panel data fixed-effects models

Given the limitations our data impose to longitudinal analysis, both in terms of our biomarker outcomes as well as the availability of the explanatory variables used in our analysis beyond UKHLS wave 2, the corresponding fixed effects results are limited to our base-case specification (Specification 1). The results using the panel waves 1 to 10 (excluding waves 5 and 7)[12] and those restricted to the sub-sample following up those individuals with valid biomarker data at wave 2 over time are presented in the Appendix (Table A4, Appendix A). Overall, these results confirm, after eliminating time-invariant unobserved heterogeneity, that our composite deprivation indicators are strongly associated with life satisfaction and mental rather than physical health functioning.

5. Conclusion

Fuel poverty is widely acknowledged as a distinct form of income poverty with far-reaching implications for health and wellbeing. 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 wellbeing 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 wellbeing 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.

[12] Given that the *IHEAT*, one of our fuel deprivation indicators and a component for our composite fuel deprivation indicators, is not collected at UKHLS waves 5 and 7, the panel data used here are not equally spaced in time.

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 wellbeing 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 wellbeing. 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. We further attenuate concerns surrounding endogeneity using IV models, and panel data analysis. Overall, the results from these analyses reinforce the baseline findings and highlight a relationship between composite fuel deprivation indicators with wellbeing and inflammation, measured using a blood-based biomarker (fibrinogen); on the other hand, there is limited evidence for the presence of systematic associations between fuel deprivation and self-reported measures of physical health These findings complement the relevant literature in two ways. First, the relationship between fuel deprivation and self-reported measures of wellbeing and mental health is consistent with preceding studies (e.g. Awaworyi Churchill et al., 2020). The results are also consistent with the relevant literature suggesting that, whilst there may be a relationship between self-reported measures of *overall health* (e.g. Gilbertson et al., 2012; Kahouli, 2020; Awaworyi Churchill and Smyth, 2021), there is limited evidence to support a strong link between fuel deprivation and self-reported measures of *physical health* (Liddell and Morris, 2010). Second, our findings extends the existing literature by revealing that fuel deprivation leads to increased levels of fibrinogen – an inflammatory biomarker; this suggests that further academic research and energy policy analysts may need to focus on more *objective* measures of *physical health* as *self-reported physical health* measures may mask important associations with fuel deprivation as in parts of the existing literature.

Moreover, 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 wellbeing measures. 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). In light of our findings, the UK government's recent change to the fuel poverty definition, from Low-Income-High-Cost (LIHC) to the Low-Income-Low Energy Efficiency (LILEE) indicator, needs further consideration. The latter retains the poverty threshold whilst replacing the energy cost threshold. Hence, LILEE defines fuel poverty as households whose residual income falls below the poverty threshold (adjusting for energy costs) and living in a property with an energy efficiency rating of band D or below. According to this definition, energy expenditure only matters for those close to the poverty threshold, after deducting housing costs from income, and therefore vulnerable to being pushed below this threshold once energy costs are considered (Legendre and Ricci, 2015; Burlinson et al., 2018). Energy expenditure therefore plays a more limited role. For households already below the poverty threshold, regardless of energy costs, the defining factor determining whether a household is fuel poor or not is energy efficiency of the property. This raises the question: who will be able to afford installation of energy efficiency measures and/or are able to install (e.g., tenure, type of dwelling) such measures? The potential distributional effects and concomitant health inequalities impacting those left behind during the green transition are stark and require further scrutiny from policymakers and future research in order to better understand how to support the fuel poor in adapting to and protecting their households from rising energy costs and climate change.

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Appendix A

Table A1. Definition and summary statistics for the covariates used in our analysis

Variable	Definition	Mean	Std. Dev.
MALE (reference)	1 if male, 0 otherwise	0.483	0.500
FEMALE	1 if female, 0 otherwise	0.517	0.500
AGE	Age in years	47.857	17.845
MARRIED (reference)	1 if married/civil partnership; 0 otherwise	0.526	0.499
SEPARATED	1 if separated or divorced; 0 otherwise	0.105	0.307
WIDOW	1 if widowed, 0 otherwise	0.067	0.250
SINGLE	1 if single, 0 otherwise	0.302	0.459
A-LEVEL/DEGREE (reference)	1 if A-level/Degree qualification; 0 otherwise	0.336	0.473
NO/BASIC QUAL	1 if no qualifications/basic qualification; 0 otherwise	0.664	0.473
OWNER (reference)	1 if owns accommodation; 0 otherwise	0.708	0.455
RENT	1 if renting accommodation; 0 otherwise	0.292	0.455
UK-IRISH (reference)	1 if ethnicity is UK or Irish; 0 otherwise	0.876	0.329
NON-UK-IRISH	1 if ethnicity is not UK or Irish, 0 otherwise	0.124	0.329
CHILDREN	Number of children in the household	0.454	0.839
EMPLOYED (reference)	1 if employed; 0 otherwise	0.565	0.496
UNEMPLOYED	1 if unemployed; 0 otherwise	0.053	0.223
RETIRED	1 if retired; 0 otherwise	0.232	0.422
STUDENT	1 if full-time student; 0 otherwise	0.049	0.217
DISABILITY	1 if long-term illness or disability; 0 otherwise	0.036	0.185
OTHER	1 if other economic activity; 0 otherwise	0.066	0.248
NOCARER (reference)	1 if not caring for sick/disabled/elderly in the household; 0 otherwise	0.928	0.258
CARER	1 if caring for sick/disabled/elderly in the household; 0 otherwise	0.072	0.258
NORTH-EAST	1 if in the North East of England, 0 otherwise	0.045	0.207
NORTH-WEST	1 if in the North West of England, 0 otherwise	0.115	0.319
YORKSHIRE	1 if in Yorkshire and Humberside, 0 otherwise	0.088	0.283
EAST MIDLANDS	1 if in the East Midlands, 0 otherwise	0.076	0.265
WEST MIDLANDS	1 if in the West Midlands, 0 otherwise	0.090	0.286
EAST	1 if in the East of England, 0 otherwise	0.098	0.298
LONDON	1 if in London, 0 otherwise	0.111	0.314
SOUTH-EAST	1 if in the South East of England, 0 otherwise	0.149	0.356
SOUTH-WEST	1 if in the South West of England, 0 otherwise	0.095	0.293
WALES	1 if in the Wales, 0 otherwise	0.048	0.215
SCOTLAND	1 if in the Scotland, 0 otherwise	0.085	0.278
NEVER-SMOKER (reference)	1 if never smoker; 0 otherwise	0.398	0.490
EX-SMOKER	1 if ex-smoker; 0 otherwise	0.381	0.486
SMOKER	1 if current smoker; 0 otherwise	0.221	0.415
NOFIVEADAY (reference)	1 if respondent does not eat 5 fruit/vegetables a day, 0 otherwise	0.774	0.418
FIVEADAY	1 if respondent eats 5 fruit/vegetables a day, 0 otherwise	0.226	0.418
ACTIVE	Self-reported sports activity: 0 if “no sports at all” to 10 if “very active”	3.488	2.954

NORESPIRATORY (reference)	1 if never diagnosed with asthma, emphysema or chronic bronchitis; 0 otherwise	0.849	0.358
RESPIRATORY	1 if diagnosed with asthma, emphysema or chronic bronchitis; 0 otherwise	0.151	0.358
NOARTHRITIS (reference)	1 if never diagnosed with arthritis, 0 otherwise	0.832	0.374
ARTHRITIS	1 if diagnosed arthritis, 0 otherwise	0.168	0.374
NOENDOCRINE (reference)	1 if never diagnosed with hyperthyroidism or diabetes, 0 otherwise	0.899	0.302
ENDOCRINE	1 if diagnosed with hyperthyroidism or diabetes, 0 otherwise	0.101	0.302
NOCVD (reference)	1 if never diagnosed with cardiovascular related disease, 0 otherwise	0.762	0.426
CVD	1 if diagnosed with cardiovascular related disease, 0 otherwise	0.238	0.426
NOOTHERCONDITION (reference)	1 if never diagnosed with liver condition, cancer or epilepsy 0 otherwise	0.934	0.249
OTHERCONDITION	1 if diagnosed with liver condition, cancer or epilepsy 0 otherwise	0.066	0.249
NODEPRIVATION (reference)	1 if belongs to a household reported deprivation in less than three goods/services; 0 otherwise.	0.786	0.410
DEPRIVATION	1 if belongs to a household reported material deprivation in three or more goods/services; 0 otherwise.	0.214	0.410

Table A2. Association between life satisfaction and composite fuel deprivation measures by gender and across age groups (Ordered Logit models)⌗

Fuel deprivation	Male	Female	Age<65	Age>=65
IHEAT-LIHC indicator	-1.381**	-0.541*	-0.823***	-0.948
	(0.558)	(0.256)	(0.295)	(0.612)
IHEAT-FP10 indicator	-1.057***	-0.867***	-0.935***	-1.161***
	(0.379)	(0.207)	(0.213)	(0.383)
N	3024	3817	5147	1694

⌗Specification 4.
*p<0.1, **p<0.05, ***p<0.01. Ordered logit coefficients are presented here. Robust standard errors in parentheses.

Table A3. Association between PCS-12, MCS-12 and composite fuel deprivation measures by gender and across age groups (OLS models)⌗

		Panel A. PCS-12		
Fuel deprivation measure	Male	Female	Age<65	Age>=65
IHEAT-LIHC indicator	-0.147	0.049	-0.023	-0.025
	(0.099)	(0.036)	(0.049)	(0.077)
IHEAT-FP10 indicator	-0.127**	0.022	-0.043	-0.007
	(0.063)	(0.028)	(0.033)	(0.063)
		Panel B. MCS-12		
Fuel deprivation measure				
IHEAT-LIHC indicator	-0.037	-0.154	-0.125	-0.003
	(0.050)	(0.117)	(0.088)	(0.070)
IHEAT-FP10 indicator	-0.005	-0.121	-0.086	-0.034
	(0.036)	(0.075)	(0.057)	(0.050)
N	3024	3817	5147	1694

⌗Specification 4.
*p<0.1, **p<0.05, ***p<0.01. OLS regression coefficients are presented here. Robust standard errors in parentheses.

Table A4. Linear fixed effects regression models for life satisfaction, PCS-12 and MCS-12 on indicators of fuel deprivation‡

	(1) Full sample [Waves 1-10]	(2) Waves 1-10 [restricted to those with valid biomarker data]
	Panel A. Life satisfaction	
Fuel deprivation measure		
IHEAT-LIHC indicator	-0.218***	-0.266***
	(0.031)	(0.079)
IHEAT-FP10 indicator	-0.223***	-0.278***
	(0.025)	(0.065)
	Panel B. PCS-12	
Fuel deprivation measure		
IHEAT-LIHC indicator	-0.006	0.00633
	(0.005)	(0.014)
IHEAT-FP10 indicator	-0.005	-0.00922
	(0.004)	(0.011)
	Panel C. MCS-12	
Fuel deprivation measure		
IHEAT-LIHC indicator	-0.031***	-0.0104
	(0.006)	(0.015)
IHEAT-FP10 indicator	-0.036***	-0.0256**
	(0.005)	(0.012)
N	320,067	49,250

‡Specification 1: base model specification.
Notes: Data from UKHLS Waves 5 and 7 are excluded from our analysis. OLS regression coefficients are presented here. *p<0.1, **p<0.05, ***p<0.01.

Appendix B

We match gas and electricity average retail marginal prices and fixed charges, collected annually for each GB region by the Department of Business and Industrial Strategy (BEIS, 2021a, 2021b), to individual-level data in our UKHLS sample. Table B1 presents details on the matching process.

Time period matching

The year is matched to the time period covered by the UKHLS data used in our analysis: 1/2010-3/2012.

Regional matching

Prices are matched by geographical region. For the most part, this is a straightforward match between the 14 regional distribution networks and 12 government office regions (Table B1). In the case of Scotland and Wales, the arithmetic mean of North/South sub-regions is used. Whilst the Northern Wales distribution network also extends across Merseyside, we do not believe that this significantly contaminates the overall results based on the matching process.

Payment method matching

Payment methods include credit (i.e., the default standard variable supplier and/or tariff), direct debit (i.e., a fixed or variable tariff allocated after switching supplier and/or tariff) and prepayment (i.e., pay-as-you-go typically using a key card or token). UKHLS does not declare as to whether electricity consumers use time-of-use (Economy 7) tariffs. Nonetheless, the payment methods remain the same for Economy 7 consumers of whom represent only 6% of meters in Wales and 14% of meters in England and Scotland (BEIS, 2020). Credit prices are matched to those paying each quarter/year (the default method) and other non-standard methods of payment (including frequent cash payments, government schemes). Direct debit prices are allocated to those paying a fixed amount each month by standing order or monthly by direct debit. Prepayment prices are allocated to consumers who pay-as-they-go using a prepaid key, card or token (Table B1). Other configurations of credit and debit prices reveal consistent findings but perform weaker as instruments (i.e., less strongly correlated with the fuel poverty indicators).

Price definitions, summary statistics and within-region variation

Table B2 presents the electricity average retail marginal prices and gas fixed charges. There are 99 prices in total as we have 11 regions, 3 years and 3 payment methods.

Table B1. Matching process

BEIS	UKHLS	
Year	Current prices → Interview year	
2010	2010 → 2010	
2011	2011 → 2011	
2012	2012 → 2012	
Regions	BEIS Region → UKHLS Region	
North East	North East → North East	
North West	North West → North West	
Yorkshire	Yorkshire → Yorkshire and the Humber	
East Midlands	East Midlands → East Midlands	
West Midlands	West Midlands → West Midlands	
Eastern	Eastern → East of England	
London	London → London	
South East	South East → South East	
South West	South West → South West	
Southern*		
Merseyside and North Wales	Average(Merseyside and North Wales, South Wales) → Wales	
South Wales		
South Scotland	Average(North Scotland, South Scotland) → Scotland	
North Scotland		
Northern Ireland**		
BEIS Payment method	BEIS →	UKHLS Payment method
Credit Direct debit Prepayment	Credit →	• A quarterly bill by direct debit or other method • Included in rent, government schemes, frequent cash payments
	Direct debit →	• Fixed amount each month by standing order • A monthly or annual bill by direct debit or other method
	Prepayment →	• Prepayment meter (i.e. pay-as-you-go using key/card)

Notes: * UKHLS separates the South into South East and South West, Southern data not matched. ** BEIS does not collect gas price data for NI, therefore GB only. We use the most recent median typical domestic consumption values (BEIS, 2021a, 2021b).

Table B2. Instrumental variables – summary statistics

Variable	Mean	S.D.
Gas and electricity prices (2010-2012)		
Annual regional average fixed gas charge (£/year)	99.544	9.243
Annual regional average marginal electricity price (£/kWh)	0.119	0.014
N	99	

Notes: N= 11 (regions) x 3 (years) x 3 (methods of payment)=99. All statistics are adjusted to 2009 prices using the retail price all items index (ONS, 2021).