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Observational evidence of the seasonal and demographic variation in experienced temperature from 77,743 UK Biobank participants

Authors:
Kennard, H. R.[1*] (Postgraduate Student), Huebner, G. E.[1] (Senior Research Associate), Shipworth, D.[1] (Professor)

1) University College London

*corresponding author's address: UCL Energy Institute Central House, 14 Upper Woburn Place, London, WC1H 0NN, United Kingdom.

Harry.kennard.13@ucl.ac.uk

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Abstract

Background
Exposure to cold is known to be associated with severe health impacts. The primary epidemiological evidence for this is the seasonal variation in mortality. However, there is a paucity of directly measured data for personal cold temperature exposure. This paper develops the concept of experienced temperature, and reports how it varies with season, demographics and housing factors.

Methods
This study uses data from 77,743 UK Biobank participants. A novel method to directly measure participant's exposure to low temperatures using a thermistor in a wrist-worn activity monitor is described. These readings are combined with demographic and housing factor variables in a multiple regression model to understand underlying relationships.

Results
The study reveals a significant difference in experienced temperature of approximately 1.8°C between the periods of coldest and hottest external temperature. A number of demographic differences were also observed – such as people of Chinese ethnic background experiencing 0.65°C lower temperatures than other groups.

Conclusions
This paper presents primary evidence for a seasonal variation in experienced temperature. This variation likely contributes to cold related mortality and morbidity. It is hypothesised that this relationship would be less strong in countries which suffer fewer impacts of cold winter temperatures.

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Introduction

In the UK the most widely used epidemiological evidence for the negative health impacts of cold exposure is the winter peak in mortality[1]. Often characterised as the ratio of average daily winter deaths to non-winter deaths – the use of excess winter deaths (EWD) has been the subject of recent debate; a large number of EWDs occur outside the winter period[2] and regional variation in the duration of the coldest months makes cross country comparison difficult[3].

Some evidence has begun to emerge which paints a complex picture of the health impacts of cold, with some studies suggesting mild cold exposure may stimulate brown adipose fat production and positively benefit metabolic health[4]. The use of whole body cryotherapy remains controversial in athlete recovery programs[5], but is widely used in the treatment of specific conditions[6 7]. Despite such studies, the consensus remains that prolonged cold exposure, especially for vulnerable individuals, can have significant impacts on physical and mental well-being. However, particularly in the domestic setting, establishing specific threshold temperatures at which exposure to cold becomes dangerous is difficult, and supported by little direct evidence[8]. This is due in part to the underlying complexity of the thermal exchange mechanisms involved and a paucity of large scale directly measured temperature data.

This paper introduces a novel technique for determining exposure to cold by developing a concept due to Kuras et al., named here the *experienced* temperature[9]. The experienced temperature aims to characterise the immediate thermal environment of an individual, measured here by a wrist worn sensor. As part of the UK Biobank, 103,707 participants wore an activity monitor on the wrist for a week. Alongside accelerometer data the sensor recorded temperature. Pilot studies for this project demonstrated that the sensor's temperature is influenced by both the ambient environmental temperature and heat from the wrist. As such, it is suitable for characterising the experienced temperature of an individual.

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Methods

A full research plan was submitted to an online pre-registration repository prior to the analysis of the data[10]. This allows research questions and hypotheses to be recorded and guards against data mining or significance hacking[11].

Sources of data

All variables except external temperature (see below) are drawn from the UK Biobank dataset. The UK Biobank is an on-going cross-sectional health study of UK adults, which recruited over 500,000 people from the general population. Of these, 236,519 participants[12] were invited to wear an Axivity AX3 wristband sensor for one week to provide data on physical activity. The Axivity device encodes accelerometer, temperature and lux light level data into a single data file. 103,707 such files were available for analysis in this study. The age of the participants at the time of wearing the wristband ranged from 43 to 79, the median age was 64. An examination by Fry et al. of the whole UK Biobank sample found evidence of the 'healthy volunteer' bias, that participants smoke, drank alcohol and were obese at lower rates than the general population[13]. Figure 1 gives the approximate geographical distribution of participants.

Experienced temperature

The thermal environment of humans is complex[14]. The primary pathways for heat transfer are conduction, convection, radiation and evaporative exchange. Since these pathways can be highly anisotropic and influenced by local heating, clothing, air movement, moisture levels and many other factors, characterising this environment is difficult. No single temperature will capture an individual's thermal environment fully. However, a wrist worn temperature sensor reflects the thermal environment well, since it is not dramatically influenced by core body heat. Wrist temperature varies diurnally with a peak during sleeping hours[15 16]. However, there is little variation in amplitude as a function of either gender[17] or age[18]. It is therefore most likely the best location to capture experienced temperature.

Baseline demographic data collection was completed in 2010. The wristband data were collected between June 2013 and December 2015, with an approximately flat distribution of wear-period start times across the data collection duration. The total number of participants in each season across the 2.5 years of data collection were winter: 16,130, spring: 21,301, summer 17,689, autumn 22,623. There were no wear-periods which began in the first week of the year.

The data from the UK Biobank were processed in the following manner. 80,050 participants remained after a wear-time requirement of 90% was imposed and the data down sampled to a 5-second interval (in line with the study by Doherty et al. using the same device[12]). 78,578 remained after participants with conditions associated with abnormally cold hands (such as Raynaud's disease) or disrupted circadian rhythms (dementia and Alzheimer's disease) were excluded[19]. Participants carrying out shift-work were also excluded at this stage[20 21 22]. Outliers with an experienced temperature above 40°C or below 20°C were excluded, as were participants with missing data or those who opted to withdraw, leaving 77,743 participants in the study.

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The experienced temperature variable was derived from the temperature time series in the following manner: First, the first and last day's data were excluded to remove transient effects at the start and end of the trial period. Second, all data points with an activity reading above the median value were excluded in order to remove times at which participants were active or exercising. The resultant time series was not trivial to summarise. However, the decision was made at the Pre-analysis stage that the first decile be taken to represent the coldest temperatures experienced. The minimum was not used as it is susceptible to being biased by single brief cold temperature readings, and the mean is dominated by the warm microclimate of the bed while sleeping.

External temperature

The external temperature for the week during which the Axivity wristband was worn was given by gridded NASA MEERA-2 dataset[23]. Each participant's approximate home location was matched to the corresponding grid square and the 5-day average of the 2-meter air temperature calculated. The grid resolution in the NASA MEERA-2 dataset is 0.625°×0.5° which corresponds to approximately 70×35 km – around 200 grid squares cover the UK[24].

Multiple regression

The research was designed to allow for the use of multi-level modelling to account for regional grouping of the data. However, a calculation of the variance partition coefficient, which measures the amount of the variance that is explained by regional differences, was found to be less than 0.2%. Given that 99.8% of the variance was not due to regional differences, a simpler multiple regression model was adopted.

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Results

Table 1 reports the regression model for 77,743 participants using the variables external temperature, age, sex, accommodation and tenure types, household income and size, employment status, whether the home has gas or solid fuel appliances and ethnicity. Table 2 reports additional variables of financial situation satisfaction and heating type for a smaller sample of 29,646 individuals – all other coefficients agreed with those in table 1, but with wider confidence intervals. The variance inflation factor was less than 2.1 for all variables, indicating a low risk of multi-collinearity.

External temperature vs experienced temperature

The experienced temperature falls by 0.08°C for every degree drop in external temperature. The experienced temperature recorded during coldest periods is therefore 1.8°C colder than the warmest periods. This relationship is illustrated in figure 2.

Demographic and building factors

The model revealed a number of significant differences of at least 0.1°C at the <1% level. For every year of age increase for participants, the experienced temperature was found to increase by 0.02°C, which means, on average, a 75-year-old had an experienced temperature 0.7°C higher than a 40-year-old. Participants with a Chinese ethnic background were found to have an experienced temperature 0.65°C colder than white participants.

The experienced temperature of those renting from the local authority was 0.16°C higher than those who owned their homes outright. Those who live in flats were 0.10°C warmer than in house/bungalows. Participants who lived in homes with oil/kerosene heating systems were 0.14°C colder than those with gas central heating. Those who make regular use of open solid fuel fires were 0.15°C colder than the majority who have a gas hob or cooker – this slightly unusual comparison results from the UK Biobanks variables.

Participants unable to work due to sickness or disability had experienced temperatures 0.18°C higher than those in employment. There is some evidence that financial situation satisfaction negatively correlates with experienced temperature; those who report being very unhappy with their financial situation were 0.28°C warmer than those who were extremely happy, although no other significant differences in this category were found.

Uncertainty analysis

The quoted confidence intervals account for statistical uncertainty only. Substantial unquantified uncertainty exists regarding whether the participant remained close to their home address for the duration of the trial. Furthermore, the accuracy of an individual Axivity device is ±1°C[25] – this accounts for some of the variance visible in figure 2. Uncertainties exist as to whether the demographic variables collected in the initial baseline data collection exercise were still accurate at the time of wearing the Axivity device.

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Discussion

Main finding of this study

The experienced temperature of sedentary older UK adults drops by 0.08°C for every degree decrease in external temperature, corresponding to around a 1.8°C difference between the warmest and coldest periods of the year. A key hypothesis that results from this finding is that countries which suffer lower levels of cold related illness might have a less steep gradient in experienced temperature against external temperature. Whether the observed gradient of 0.08°C is sufficient to explain the prevalence of cold related illness in the UK is still an open question. Furthermore, it is important not to interpret this figure in a way that ignores the large degree of heterogeneity in experienced temperatures, both between different demographic groups and within an individual's daily experience.

What is already known on this topic

To date, no work has been conducted attempting to record the personal thermal environment of people at the population level. At the small sample level, the individual experienced temperature (IET) was defined by Kuras et al. for which 23 participants in Boston wore iButton temperature sensors record the IET during a 6-day period which included a heat wave[9]. IETs were 3.7°C lower than the outdoor ambient temperature, and 1°C higher than those recorded during a reference period which was 6.5°C cooler than the heat wave.

The largest recent survey (N=821) of internal temperatures and dwelling characteristics of English homes found several significant differences in living room temperatures[26]. Those living in local authority homes were 1.8°C warmer than in owner occupied dwellings. The living rooms of retired people were 1°C higher than those of people in full-time employment.

A nationally representative estimate of average UK internal domestic temperatures found them to decrease by 0.17°C for every centigrade drop in external temperature[27]. This is steeper decline than the 0.08°C figure reported here, and consistent with the observation that the microclimate of the bed provides warmer experienced temperatures than suggested by room temperature measurements.

What this study adds

This is the first study to have examined the variation of experienced temperature in a large sample of the population. The regression model reveals significant differences between demographic groups and certain building characteristics. This approach allows for specifically targeted interventions to be developed, which might more effectively combat the negative health impacts of cold. The relationship between the experienced temperature and health outcomes will appear in a future manuscript.

The lower experienced temperature of those with oil/kerosene heating systems and open fires accords with the current understanding of fuel poverty in the UK. The result that people of a Chinese ethnic background have significantly lower experienced temperatures

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warrants further investigations – this might be cause for concern, or merely reflective of different heating practices, such as the use of electric blankets.

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Limitations of this study

The relationship between ambient and experienced temperature is complex, and makes interpretation difficult. Before further work is conducted, the significant differences that this study has revealed should only be used as justification for further enquiry. The temperature sensor's position on the wrist means that this measure of experienced temperature may not agree with readings taken with sensors placed at other locations on the body. Furthermore, since the temperature readings contain a component of body heat, they are generally higher than the local ambient temperature. Therefore, care must be taken not to conflate the values of measured experienced temperature reported here with other bodily or ambient temperatures

Clothing which covers the wrist increases the temperature reading of the sensor, all other things being equal. Therefore, the method used here records cold exposure more reliably than high temperature exposure. This is because there is an ambiguity at high recorded temperature whether the reading is a result of a high ambient temperature or a sensor worn under a heavy coat, for example. Conversely, there are no physical mechanisms which could result in colder temperature readings in the absence of cold ambient temperatures, so this ambiguity does not exist for cold temperatures.

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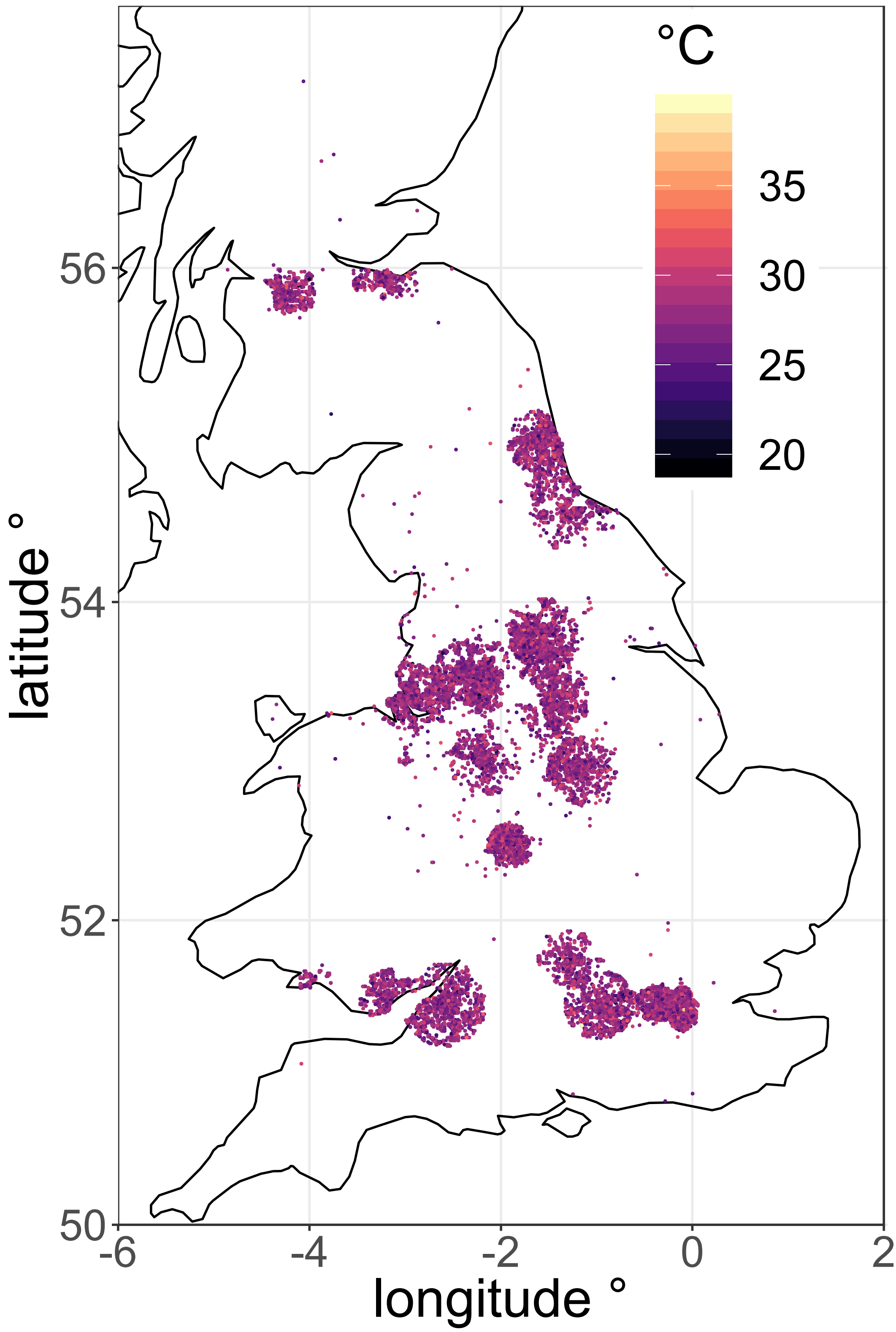

Figure 1 The approximate location of the study participants with the seasonally corrected experienced temperature

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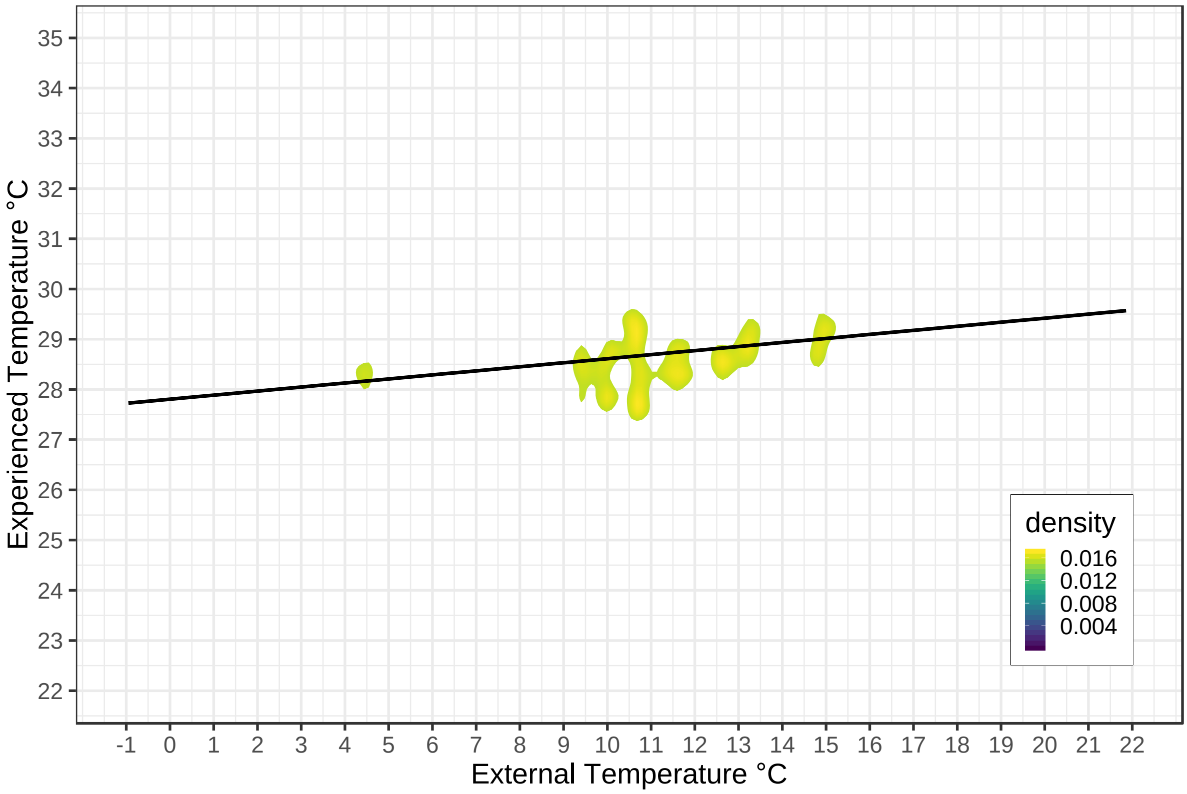

Figure 2 The seasonal variation of experienced temperature, as a function of external temperature. Due to the high number of data points, they are represented as a density cloud. The gradient of the regression line is 0.08

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Table 1 Regression results for the full sample of 77,743 study participants

Predictor variable (relative subcategory, N)	Sub-category (N)	*b*	*b* 95% CI [LL, UL]
(Intercept)	-	26.48**	[26.32, 26.64]
External temperature	-	0.08**	[0.08, 0.08]
Age	-	0.02**	[0.02, 0.02]
Sex (Female, 43758)	Male (33985)	-0.08**	[-0.10, -0.05]
Accommodation type (House/bungalow, 71508)	Flat (6084)	0.10**	[0.05, 0.15]
	Temporary (54)	0.07	[-0.42, 0.57]
	None of above (84)	-0.17	[-0.56, 0.23]
	Prefer not to answer (13)	-0.22	[-1.25, 0.81]
Tenure type (Own outright, 44528)	Mortgage (28469)	0.03	[0.00, 0.06]
	Rent Local Authority (2105)	0.16**	[0.07, 0.24]
	Rent private (1506)	-0.07	[-0.17, 0.03]
	Shared (173)	0.03	[-0.25, 0.31]
	Rent free (470)	0.03	[-0.14, 0.20]
	None of above (277)	0.04	[-0.18, 0.26]
	Prefer not to answer (215)	-0.20	[-0.45, 0.06]
Household Income £ (Less than 18,000, 10613)	18,000 to 30,999, (17753)	0.08**	[0.03, 0.12]
	31,000 to 51,999 (20002)	0.04	[-0.01, 0.09]
	52,000 to 100,000 (17017)	0.04	[-0.01, 0.09]
	Greater than 100,000 (4855)	0.02	[-0.04, 0.09]
	Prefer not to answer (5478)	0.10**	[0.04, 0.17]
	Do not know (2025)	0.17**	[0.08, 0.26]
Household size	-	0.00	[-0.01, 0.02]
Employment status (In paid employment or self-employed, 39810)	Retired (27422)	0.04*	[0.00, 0.08]
	Looking after home and/or family (3230)	-0.05	[-0.12, 0.02]
	Unable to work because of sickness or disability (1436)	0.18**	[0.08, 0.28]
	Unemployed (904)	-0.06	[-0.18, 0.06]
	Doing unpaid or voluntary work (3751)	-0.05	[-0.11, 0.02]
	Full or part-time student (741)	-0.14*	[-0.27, -0.00]
	None of the above (350)	-0.19	[-0.39, 0.00]
	Prefer not to answer (99)	0.10	[-0.27, 0.46]
Gas or Solid Fuel (Gas hob or gas cooker, 55130)	Gas fire (6750)	-0.01	[-0.06, 0.03]
	An open solid fuel fire (2302)	-0.15**	[-0.23, -0.08]
	None of the above (13509)	0.08**	[0.04, 0.12]
	Prefer not to answer (41)	0.42	[-0.15, 1.00]
	Do not know (11)	-0.99	[-2.08, 0.10]
Ethnicity (White, 75333)	Asian (662)	0.15*	[0.01, 0.29]
	Black (584)	0.09	[-0.06, 0.24]
	Chinese (157)	-0.65**	[-0.94, -0.37]
	Mixed (398)	-0.10	[-0.28, 0.08]
	Other ethnic group (397)	-0.13	[-0.32, 0.05]
	Prefer not to answer (192)	-0.22	[-1.02, 0.59]
	Do not know (20)	-0.01	[-0.28, 0.25]

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Table 2 Regression results for additional variables for a smaller sample of 29,646 participants.

Predictor variable (relative subcategory, N)	Sub-category (N)	*b*	*b* 95% CI [LL, UL]
Financial situation satisfaction (Extremely happy, 2770)	Very happy (10881)	0.01	[-0.06, 0.09]
	Moderately happy (12845)	0.01	[-0.06, 0.09]
	Moderately unhappy (2080)	0.07	[-0.04, 0.18]
	Very unhappy (646)	0.28**	[0.12, 0.45]
	Extremely unhappy (328)	0.13	[-0.09, 0.35]
	Prefer not to answer (50)	-0.36	[-0.88, 0.15]
	Do not know (46)	-0.02	[-0.56, 0.51]
Heating type (Gas central heating, 27442)	Electric storage heaters (670)	0.07	[-0.08, 0.22]
	Oil (kerosene) central heating (832)	-0.14*	[-0.28, -0.00]
	Portable gas or paraffin heaters (8)	-0.79	[-2.06, 0.49]
	Solid fuel central heating (98)	-0.25	[-0.62, 0.13]
	Open fire without central heating (82)	-0.31	[-0.72, 0.09]
	None of the above (485)	-0.04	[-0.21, 0.13]
	Prefer not to answer (13)	1.22*	[0.06, 2.38]
	Do not know (16)	-0.77	[-1.69, 0.14]

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