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# Winter demand falls as fuel bills rise: Understanding the energy impacts of the cost-of-living crisis on British households

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ABSTRACT

In October 2022 British households entered a heating season amidst exceptionally high energy prices – squeezing household incomes and increasing fuel poverty. This study analyses electricity and gas consumption in 5594 households from October 2022 to March 2023 using XGBoost counterfactual models trained on historic data. With survey data collected in early 2023 we investigate how consumption reduction correlated with energy-saving actions, household and dwelling characteristics, and indicators of underheating and fuel poverty.

Our analysis showed that electricity consumption was 8.4% lower and gas consumption 10.8% lower than the previous winter (accounting for weather), saving consumers around £29/month. Despite this and a government subsidy, energy bills were still around £34/month higher than the previous winter (£158/month (median); £500/month (95th percentile)); price elasticity was −0.10 for electricity and −0.07 for gas consumption. Greatest consumption reduction correlated with largest reported changes to heating practices, in particular heating for fewer hours and turning thermostats down lower. We find evidence of greater fuel poverty and underheating among the greatest energy reducers.

This paper presents novel methods for analysing energy saving using smart meter data for changes without a control group, plus novel findings related to short-term price elasticity and the energy-saving impacts of behaviour change.

## 1. Introduction

Since early 2022 households in Great Britain (GB[1]) have been experiencing exceptional rises in inflation and interest rates, particularly in food, fuel and energy prices [1]. As a result, many households have been struggling to pay bills, keep warm and fed, and stay healthy [2]. A combination of a global gas shortage following Russia's invasion of Ukraine in February 2022 and economic downturn during the COVID-19 pandemic has led to what the IEA has called a "full-blown global energy crisis" [3], with billions facing the "greatest cost-of-living crisis in a generation" [4].

This study focuses on the impact of the cost-of-living crisis during winter 2022/23, since in Britain this is when domestic energy consumption is highest due to heating demand. In September 2022 the pound (GBP) dropped to its lowest value[2] (73.61) since the first lockdown in 2020, down from 82.94 in January 2022, and had only partially recovered to 78.90 by the end of March 2023 [5]. 2022 also saw high inflation in GB (up to 11.1%, a 41-year high) caused by a combination of high global demand for consumer goods and disrupted supply chains linked to the COVID-19 pandemic, and "soaring energy and fuel prices" largely driven by Russia's invasion of Ukraine [6]. Following the invasion oil prices saw an immediate rise and petrol and diesel prices at the pump set new records in July 2022 (191.6p/litre and 199.2p/litre, respectively), with prices falling only gradually over the next 12 months. Wholesale gas prices had started rising in the second half of 2021, which were slowly passed on to consumers.

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[1] Great Britain consists of the United Kingdom (UK) excluding Northern Ireland (which is part of the Irish power grid and hence not part of this study).
[2] Broad Effective exchange rate index, Sterling (January 2005 = 100).

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In 2017 Ofgem[3] introduced a price cap (a limit on the daily standing charge and kWh unit cost) for customers on pre-payment meters, and in 2019 a price cap for most other domestic customers, *i.e.* those on a standard variable tariff. From the start of 2021 these were combined into the 'Default Tariff Cap' or 'energy price cap'. In early 2022 this increased by 54%, so that the 'typical' direct-debit household would see annual energy bills rise from £1277 to £1971 per year. To prevent a further rise of 80% above the early 2022 cap, from 1st October the Energy Price Guarantee (EPG) was introduced to keep 'typical' annual bills at around £2500/year.[4] Additionally, the Energy Bill Support Scheme delivered a £400 subsidy over six months from October 2022 to March 2023 to dual-fuel customers (equivalent support was available for single-fuel customers) [6,7].

Recent decades have seen gas prices rise in real terms while demand has dropped (due to a number of factors, from improved home insulation to changes in heating behaviours) [8]. The relationship between price and demand is complex but generally the price elasticity, a measure of how much demand changes with a given change in price, is considered low for energy, both in the short and long term. Estimates for domestic gas price elasticity in the UK have ranged from −0.10 to −0.28 (*i.e.* for a 10% increase in price we would expect gas demand to decrease by between 1% and 2.8%), with some indications that lower income households show greater price elasticity (greater sensitivity to rising prices) [8]. Pellini estimates long-run electricity price elasticity in the UK to be −0.607, similar to Sweden (−0.668) and Spain (−0.699) but much greater than the Netherlands (−0.081) and France (−0.266) [9]. A *meta*-analysis estimated short-term and long-term electricity price elasticity in the US to be −0.35 and −0.85, respectively [10]. One of the challenges of estimating energy price elasticity is that households may choose (or feel compelled) to reduce their energy consumption due to multiple cost-of-living pressures, not simply rising energy bills.

To tackle rising inflation the Bank of England increased interest rates every month from December 2021 (at 0.1%) to August 2023 (5.5%). Rising rates affected mortgage payments while private renters saw average rent rises of 5.5% from August 2022 to August 2023 [6]. One survey found 29% of UK adults with a mortgage and 34% of renters saw their payments increase between August 2022 and January 2023 [11]. Over the same period food prices rose by over 28%,[5] peaking in March 2023 at 19.1%; the highest rate of food price increase since 1977 [12]. In March 2023 a survey of over 10,000 people found that almost 20% of respondents had to eat less or skip meals in the preceding month (43% of those receiving benefits) [13]. Between April 2022 and March 2023, the Trussell Trust distributed almost 3 million emergency food parcels; over twice as many compared with five years previously. The Trussell Trust reports a particular increase in employed people requiring help whose incomes are insufficient to afford essential items [14]. A survey by the Financial Conduct Authority of over 5000 people in January 2023 found that the number of adults missing bill/credit payments in at least three of the past six months increased from 4.2 million (8%) in May 2022 to 5.6 million (11%), with many more finding them a 'heavy burden' (7.8 million (15%) to 10.9 million (21%)). Additionally, over half of UK adults (28.4 million people) reported greater anxiety or stress due to the rising cost of living [11].

Low-income households are disproportionately affected by rising inflation due to spending a greater proportion of their income on energy and food, with electricity and gas bills making up 7.4% of total spending of those in the lowest income decile in 2021/22, while those in the highest income decile only spent 3.5% on energy bills [6]. The number of households in fuel poverty[6] by the end of winter 2022/23 is yet to be reported, but between 2021 and 2022 the number in England is estimated to have risen by around 100,000 households (from 13.1% to 13.4%). At the same time the average 'fuel poverty gap' (the fuel bill reduction needed to lift the average household out of fuel poverty) rose 33% to £338 [15]. The percentage in fuel poverty is projected to rise to 14.4% in 2023 [16]. However, a data-driven study on fuel poverty and meter disconnection led the authors to conclude that "the English definition of fuel poverty considerably underestimates need" and that a better definition is required [17]. A study that defined fuel poverty as spending more than 20% of net income on fuel estimated that from April 2023 20% of households would have been fuel poor if not for increased support for those on social security; with the support, around 15% of households would be fuel poor [18]. When households are unable to afford their energy bills homes end up cold and may have issues with mould and damp. Such living conditions have been linked to excess winter deaths, cardiovascular and respiratory diseases, mental health problems, exacerbation of conditions such as arthritis, as well as lower educational attainment and emotional wellbeing among children [19–21]. Figures compiled by the End Fuel Poverty Coalition estimate that living in a cold home caused 4706 excess winter deaths in winter 2022/23 in GB [22].

To date there have been few studies on the impact of the cost-of-living crisis on actions taken by householders to reduce their energy consumption and on their resulting energy consumption and energy bills (a gap we address in this paper). Consumer group Which? report an estimated 13 million UK households (46%) have not been turning on their heating in cold weather; 51% of those with a household income below £20,000; 32% of those with income over £80,000. The most popular actions taken to avoid energy use were wearing extra layers indoors (54%), reducing oven use (41%) and taking fewer or shorter showers (33%) [23]. Early analysis of the 2023 SERL Energy Survey by Huebner *et al.* [24] found householders generally reported making increased efforts to save energy, in particular closing curtains at night and turning lights off in unused rooms. Putting on more clothes to reduce heating use was one of the five most popular actions, and 40% of those surveyed reduced their boiler flow temperature. A related study reported a rise in the proportion of households setting their thermostat lower than 18 °C from 6.7% in winter 2020/21 to 15.2% in winter 2022/23 [25].

During the pandemic electricity and gas use increased, particularly during winter lockdowns, but by summer 2021 energy use had returned to pre-pandemic levels, and through winter 2021/22 gas use was slightly down on pre-pandemic levels [26]. In 2022 average household electricity consumption was down by 6% compared to 2021 (after temperature adjustment) and annual domestic gas use was 12% lower than 2021 when temperature adjusted. The Office for Budget Responsibility estimated in March 2023 that weather-adjusted household gas demand in winter 2022/23 was around 15% lower than before Russia's invasion of Ukraine [27]. Compared to Q1 (Quarter 1) in 2022, Q1 2023 temperature-adjusted domestic energy consumption is estimated to have been down overall by 9.5% (11% reduction in industrial consumption) [28]. National Grid ESO (Electricity System Operator) reported national electricity demand was lower than expected throughout most of winter 2022/23 except for during the coldest periods [29]. A study of 11,519 households (of which a higher proportion than average was believed to be vulnerable consumers with very low pre-price rise energy consumption) found annual gas and electricity use dropped by 20% and 3%, respectively, in 2022/23 [17].

[3] Ofgem (the Office of Gas and Electricity Markets) is the energy regulator in Great Britain.

[4] Note that the energy price cap and EPG set maximum standing charges and unit costs for electricity and gas rather than limiting the amount a household pays in total; actual bills depend on location and electricity/gas consumption.

[5] The last time food prices had risen by 28% was over the previous 13 years (April 2008 – August 2021).

[6] By the government definition households in England are classed as fuel poor if their dwelling has Energy Performance Certificate (EPC) rating band D or below and if, were they to heat their home to the required level, their remaining income would be below the official poverty line.

In this study we investigate the electricity and gas consumption in 5594 GB households from October 2022 to March 2023 (henceforth referred to as 'winter 2022/23') and use survey data from early 2023 to understand changes in energy consumption, energy-saving behaviours, and the impact of rising prices and demand reduction on household energy bills. We train and test machine learning (extreme gradient boosting (XGBoost)) counterfactual/predictive models for 5594 homes with electricity and gas data in GB using smart meter, weather and calendar data from winter 2021/22 and produce counterfactuals for winter 2022/23 (our estimate for energy demand if conditions in winter 2022/23 had been the same as in winter 2021/22). Comparing the counterfactuals with observed daily demand allows us to estimate the impact of the cost-of-living crisis in GB. Combining this analysis with survey data collected early in 2023 reveals how different types of households and dwelling may have achieved different levels of savings, and how self-reported energy-saving actions correlated with observed energy reduction. We address the following research questions using an innovative method to predict a weather-corrected counterfactual during a natural experiment.

1. *What was the impact of the cost-of-living crisis on household electricity and gas consumption during October 2022–March 2023 ('winter 2022/23')?*
2. *How did energy bills change in winter 2022/23 compared to the previous winter, and how did any energy consumption reduction translate to bill savings?*
3. *How did savings vary between different types of household and dwelling (e.g., financial wellbeing, presence of children and the elderly, dwelling type, dwelling energy efficiency)?*
4. *Which self-reported energy-saving actions showed the greatest correlation with reduction in total energy consumption?*
5. *Were those who saw the greatest reduction in energy consumption more likely to be struggling financially and/or to experience problems related to underheating?*

While the small amount of previous analysis of the cost-of-living crisis in winter 2022/2023 has either reported on survey results or energy data, this is the first peer-reviewed study to combine both and address the questions above. The SERL dataset provides smart meter data for thousands of households in GB dating back several years allowing for household-level analysis of change over time in energy consumption. Combined with the survey sent out to the same households in January 2023, this dataset provides unique insights into how householders adapted (or otherwise) their behaviours during the first heating season of the cost-of-living crisis and how their electricity and gas consumption changed, accounting for changes in weather using predictive models.

This paper is structured as follows. In Section 2 we describe the methods including the datasets, data preparation and predictive modelling. Section 3 presents the results with discussion of implications and limitations. Conclusions are summarised in Section 4 along with plans for further research.

## 2. Methods

Self-reported changes in behaviour in winter 22/23 are compared with longitudinal gas and electricity data from 5594 GB homes. The energy saving is calculated by comparing the metered energy during the cost-of-living crisis to a counterfactual. The counterfactual is calculated using a machine learning algorithm trained on data prior to the cost-of-living crisis that is then run with the weather during the cost-of-living crisis. Often a counterfactual is measured using data from properties that have not been subject to the intervention being studied *i.e.* a cross-sectional study with a control group, however, in the case of a natural experiment such as the cost-of-living crisis, there is no natural control group as all homes are subject to the intervention and so a counterfactual needs to be calculated from historic data correcting for weather.

Appendix B contains detailed information about the model training, selection and performance. All code used for data preparation, analysis and figure creation is publicly available on GitHub (https://github.com/ellenwebborn/Winter-demand-falls-as-fuel-bills-rise). All data processing, modelling and analysis was performed using the programming language R version 4.1.2 [30] and R packages: broom [31], caret [32], data.table [33], doParallel [34], epitools [35], forcats [36], ggplot2 [37], ggpubr [38], glmnet [39], lubridate [40], mlbench [41], monochromeR [42], purrr [43], RColorBrewer [44], stringr [45], timeDate [46], and xgboost [47].

### 2.1. Data pre-processing

We use the 6th edition Smart Energy Research Lab (SERL) [48–52] datasets comprising electricity, gas (where available), survey and weather data for around 13,000 homes in Great Britain. Initially households were removed from the sample who indicated having installed/replaced a heat pump or acquired an electric vehicle (EV) in the previous 12 months in the 2023 SERL Energy Survey (described below) as the predictive models are trained on the previous winter (before the heat pump installation or EV charging began/increased). After further filtering for energy data quality and model accuracy (described below), 5594 households remained in the sample (all of which had both gas and electricity data). See Appendix A for a summary of sample representativeness.

#### 2.1.1. Energy data

Models were trained and tested on data from the previous winter (1st October 2021–31st March 2022). Data from earlier winters were excluded to prevent capturing the effects of the COVID-19 pandemic [26,53]. The counterfactual (prediction) period was 1st October 2022–31st March 2023 ('winter 2022/23'). Although energy prices had already started to increase during winter 2021/22 (the training/testing period), the increases were much lower than the large rises in April 2022 [7]. There is no perfect separation of the pandemic effects and the start of the cost-of-living crisis, and therefore our analysis aimed to show the effects of the cost-of-living crisis on energy consumption compared to consumption during the economic conditions of winter 2021/22. Zapata-Webborn *et al.* [26] estimate that winter 2021/22 electricity demand remained around 2% higher than pre-pandemic levels, while gas demand was around 2% lower – possibly due to the initial rise in gas prices at this time.

Households required at least 25 days' valid data in every month of the training/testing period and at least 90% valid days' data in winter 2022/23 (at least 164 days) for inclusion in the study. Daily consumption used the sum of half-hourly data for the day if available, otherwise daily reads were used, and gas demand was converted from cubic metres to kWh.[7] Households were also excluded if over 50% of their electricity reads or 90% of their gas reads[8] were zero in either the training/testing or prediction periods, likely due to data collection issues. Additional filtering was applied at the modelling stage to exclude households without a sufficiently accurate predictive model (described below), and households without both gas and electricity data were removed due to fuel price assumptions requiring dual fuel customers. The final sample size was 5594 households.

[7] Gas volume (kWh) = Gas volume ($m^3$) * 1.02264 * calorific value / 3.6 and we used a calorific value of 39.5 $MJm^{-3}$.

[8] The threshold was higher for gas reads since households which only use gas for space heating could feasibly only heat their homes 10% of the time in winter.

**Table 1**
*T*-test results for the alternative hypothesis: observed consumption was lower than predicted consumption in winter 2022/23. CI: confidence interval, upper bound infinite as 1-sided *t*-test. Mean difference: difference in means between predicted and observed consumption (>0 implies predicted higher).

| | Mean difference (kWh/day) | t-value | P-value | 95% CI |
|---|---|---|---|---|
| Electricity | 0.937 | 24.995 | < 0.001 | (0.876, Inf) |
| Gas | 6.941 | 45.822 | < 0.001 | (6.691, Inf) |

#### 2.1.2. Survey data

Two surveys were used for this study – the initial survey given to SERL participants at sign up and the 2023 SERL Energy Survey; available under 'Data Documentation' in [54] and documented in [55]. The 2023 study contains the most up-to-date information and focuses on questions relating to the cost-of-living crisis. It was therefore the main source of contextual information. A postal copy was sent to 12,001 SERL participants on 2nd February 2023 with a weblink for optional online response and data collection ended on 7th April 2023. The response rate was 49% although not all questions were completed by all participants. The response rate for the sample in this study was also 49% (2733 households). For details of the initial sign-up survey see [50,56].

#### 2.1.3. Weather, date and time data

Mean, maximum and minimum daily temperature, mean daily solar irradiance, total daily precipitation, and mean and maximum wind speed from the ECMWF [57] (linked at the household level in the SERL dataset) were selected to be the predictor weather variables, as these have been shown to be predictors of energy consumption [58]. Mean temperature and mean solar irradiance on the preceding day were also included in some models as they contribute to building thermal response and so heating demand. All regression formulas included a (single) indicator variable for the date being a weekend or national holiday. In addition, sinusoidal transforms were applied to day-of-the-year to capture seasonal effects using the methods in [17, Appendix B]. See Appendix B3 for details of how all variables were used in the models.

#### 2.1.4. Energy prices

To calculate energy costs in October 2022–March 2023 we assumed that all participants were paying the capped rates set by the UK government's Energy Price Guarantee (EPG). The EPG set out the maximum daily standing charge and unit rates for gas and electricity that could be charged to domestic consumers and varies by energy supply region and payment method [59,60]. It is likely that some households had tariffs below the EPG levels. Some consumers (mostly living in flats) pay for their electricity as part of their rent or service charge and this may be set at business rates to which the EPG does not apply. Other consumers may have long-term or special tariff contracts with their supplier. However, there were very few tariffs at a level lower than the EPG available in winter 2022/23 [61].

For winter 2021/22 we assumed tariff rates were the Default Tariff Cap [62] (described above). It is less likely that all consumers were paying the cap level in winter 2021/22 than were paying the EPG in 2022/23, with an unknown number on fixed price tariff contracts at lower levels taken out in the preceding year. The difference in costs between the two time periods is therefore a conservative estimate, since the actual difference for those with lower tariffs than the cap in the first winter will be greater.

Note that unit rates and standing charges vary by region in GB, so LSOA geographic area matched with geographic energy supply region [63] was used to link SERL participants with the relevant unit rates and standing charges. For the small number of LSOAs on the boundary of multiple supply regions the mean tariff level was taken. Households were assumed to pay by direct debit (the most common payment method in the UK [64]) unless they indicated otherwise on the 2023 SERL energy survey (question C2 on payment methods). Price data statistics are presented in Appendix C.

### 2.2. Counterfactual modelling

We based our counterfactual modelling on the approach used in [26], which created counterfactual models for each household separately. We used extreme gradient boosting (XGBoost) as this was the most successful algorithm used in that study. XGBoost is an ensemble-based predictive machine learning technique that employs 'boosting' to iteratively learn from combining lots of different models. The training dataset is reweighted each iteration such that the less well predicted datapoints are the focus of later iterations, and a final model is created by averaging over the models used [65,66]. XGBoost improves upon standard gradient boosting in terms of reducing over-fitting and computational efficiency with proven success in machine learning competitions [67,68]. For examples of the use of XGBoost for predicting energy consumption see, for example, Zapata-Webborn *et al.* [26]. The model training and selection processes are described in Appendix B including details of hyperparameters, regression formulas, and final model performance.

## 3. Results and discussion

### 3.1. Energy consumption changes in winter 2022/23

Our first research question asks what impact the cost-of-living crisis had on domestic energy consumption in winter 2022/23. Table 1 shows the results of a repeated-measures *t*-test with the 1-sided alternative hypothesis that observed consumption was lower than predicted consumption in winter 2022/23. The results confirm that there was a significant difference between mean observed and mean predicted electricity and gas consumption for the sample.

Table 2 presents statistics for the predicted and observed daily energy consumption along with the estimated 'reduction' in consumption. Reduction (kWh) is the difference between a household's predicted and observed consumption; reduction (%) is the kWh reduction divided by the predicted consumption. We consider medians to be more reliable estimates for average than mean as they are more resistant to skew by outliers (which can be caused by households with exceptionally high consumption or change in consumption, or by inaccurate model predictions). We find that on (median) average, consumers reduced their electricity consumption by 0.6 kWh/day (8.4%) and their gas consumption by 4.9 kWh/day (10.8%, similar to the 9.5% estimated reduction for Q1 2023 by Harris [28]; lower than the 15% estimate for winter 2022/23 by Bolton [27]).

Fig. 1 shows the distribution of the data summarised in Table 2. While most households reduced their energy consumption compared to the previous winter, some saw energy consumption rise (negative reduction) by up to around 50%. Conversely, some households saw very large reductions of over 50%. In later sections we investigate these differences in terms of household characteristics and self-reported energy-saving actions.

### 3.2. Impact of price rises and energy reduction on energy bills

Using the fuel price assumptions described in Section 2.1.4 we can estimate the energy bills each winter and the impact of energy consumption reduction on energy bills. As described above, energy prices rose significantly in 2022 and the UK government introduced the Energy Bill Support Scheme (£400 for dual fuel bills spread out from October 2022 to March 2023). In order to show the estimated costs/cost reductions we split this subsidy between electricity and gas bills in a 2:3 ratio (our observed cost ratio from the data). This equates to a monthly subsidy of £26.67 for electricity and £40 for gas.

Fig. 2 shows how bills changed compared to the previous winter and compared to the predicted bills from the energy counterfactuals. On

**Table 2**
Average winter results for the sample (N = 5594). IQR: interquartile range, sd: standard deviation. Negative reduction implies consumption was higher than predicted.

| | Predicted (kWh/day) | | Observed (kWh/day) | | Reduction (kWh/day) | | Reduction (% of prediction) | |
|---|---|---|---|---|---|---|---|---|
| | Median (IQR) | Mean (sd) | Median (IQR) | Mean (sd) | Median (IQR) | Mean (sd) | Median (IQR) | Mean (sd) |
| Electricity | 8.14 (5.72, 11.92) | 9.82 (6.57) | 7.40 (5.11, 10.76) | 8.89 (5.95) | 0.61 (−0.03, 1.60) | 0.94 (2.80) | 8.38 (−0.48, 17.56) | 7.08 (24.24) |
| Gas | 47.92 (33.03, 66.48) | 53.12 (29.82) | 41.63 (28.06, 58.82) | 46.18 (26.99) | 4.94 (0.46, 11.30) | 6.94 (11.33) | 10.78 (1.19, 22.44) | 11.74 (24.86) |

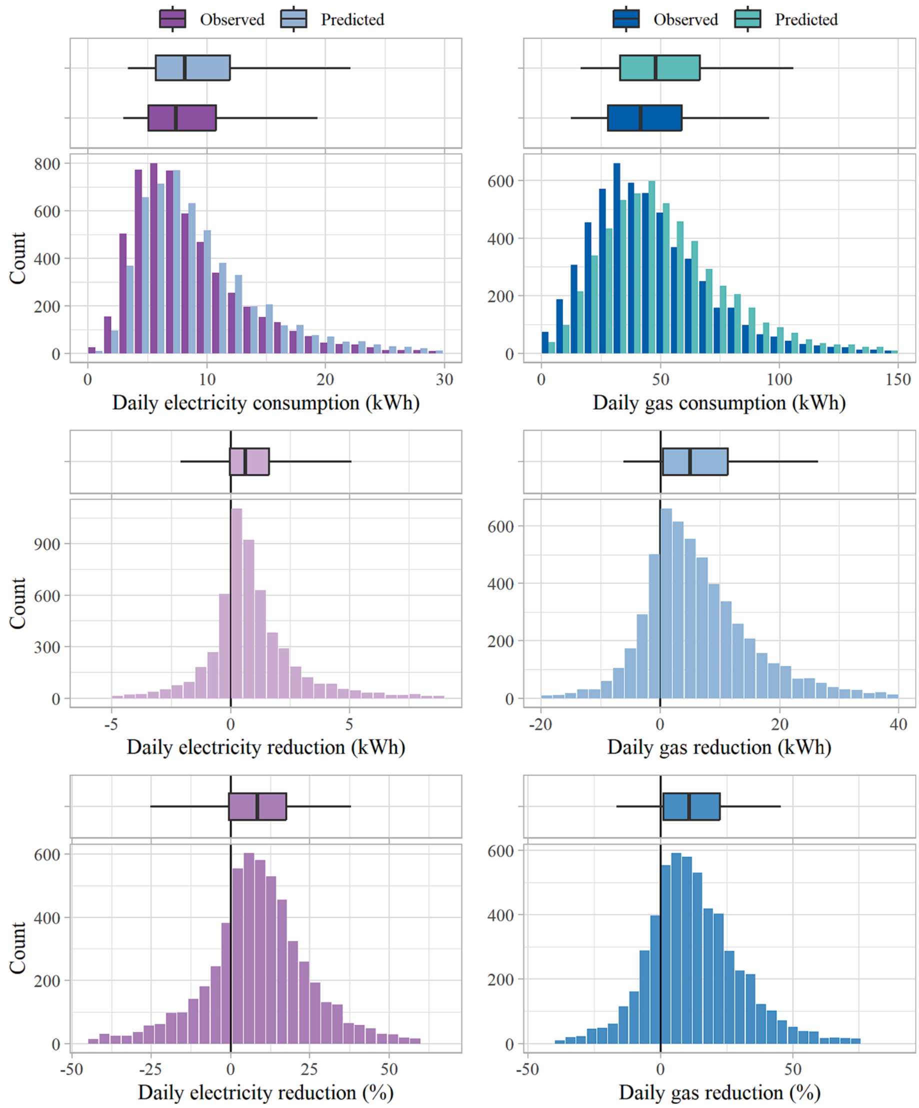


**Fig. 1.** Histograms and box plots showing observed and predicted daily electricity and gas consumption and consumption reduction compared to the previous winter (N = 5594). Counts < 10 not shown for statistical disclosure control. Summary statistics in Table 2.

average the estimated reduction in energy consumption reduced electricity bills by £7.81/month and gas bills by around £20.78/month. Despite the efforts of households to reduce consumption and the government subsidy, median total energy bills increased from around £125/month to £158/month. Those in the top 5% of bill payers saw total energy bills rise from almost £300/month to £500/month. On average the combination of energy consumption reduction and government subsidy reduced bills by around £100/month; approximately one quarter of which was due to lower energy consumption. For more detailed statistics on the change in energy bills see Appendix C.

Monthly analysis reveals that average bills were highest in December 2022 (coinciding with the lowest temperatures and Christmas holidays), when median total energy bills before the government subsidy was £296, (£413 and £674 at the 75th and 95th percentiles). Pay-as-you-go customers (in particular those on pre-payment meters) would be particularly affected by high costs in a particular month, because their bills do not benefit from being averaged over multiple months and they are at risk of being cut off if unable to keep up with payments [17]. Note also that around 1% of households were ineligible for the £400 subsidy [69] while renters were at risk of missing out on various support if

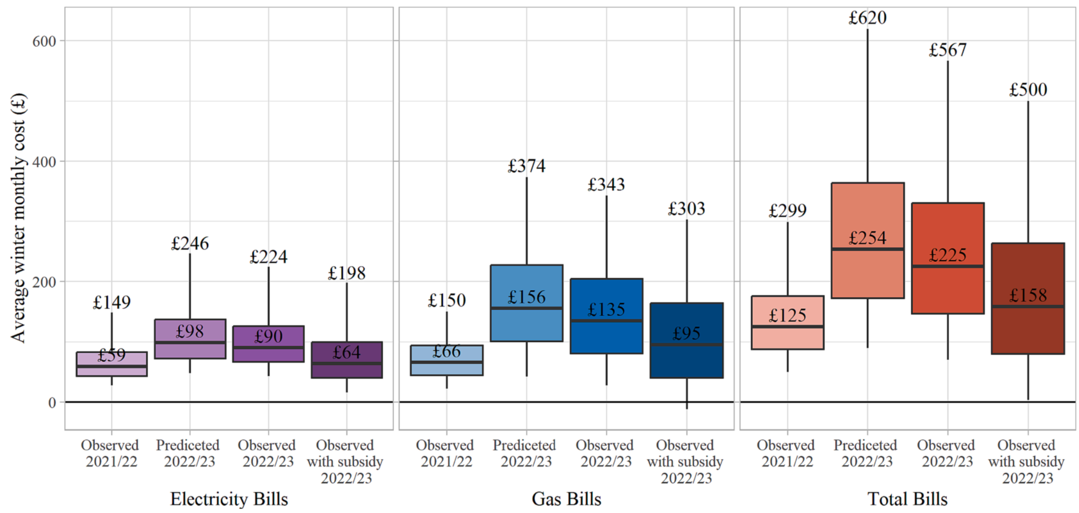


**Fig. 2.** Observed and predicted electricity, gas and total monthly energy bills in winter 2021/22 and 2022/23. Subsidy described in the text. Boxes show the interquartile range, 'whiskers' extend to the 5th and 95th percentiles.

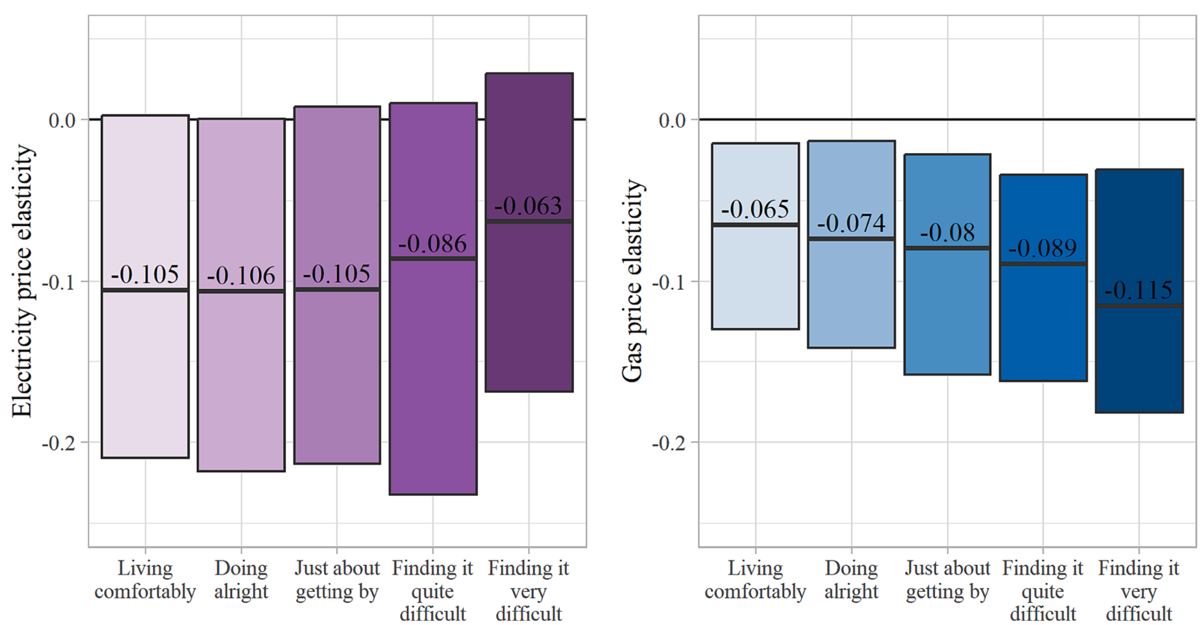


**Fig. 3.** Electricity (left) and gas (right) price elasticity by self-reported financial wellbeing (2023 SERL Survey). Figures show the median, boxes show the interquartile ranges. N = 815 (living comfortably), 1157 (doing alright), 549 (just about getting by), 108 (finding it quite difficult), 52 (finding it very difficult).

paying via a landlord who did not pass subsidies on [70].

### 3.2.1. Price elasticity

We find that the median (IQR) price elasticity[9] for winter 2022/23 compared with winter 2021/22 was −0.099 (−0.223, 0.016) for electricity and −0.071 (−0.144, −0.010) for gas, respectively. These values show lower price elasticity than typical values in the literature [8–10]. It has been suggested that those with lower income are more sensitive to price changes [8], and so we calculated the price elasticity by fuel and by 'financial wellbeing' (Fig. 3). We find opposite trends in the electricity and gas elasticities; more affluent households are more responsive to increases in electricity price (higher absolute elasticity) while those struggling financially are more responsive to rising gas prices. This could be because wealthier households have more electric appliances that they can turn off standby or choose to use less or have the capital to buy more efficient appliances such as low energy lighting, while those struggling financially are more willing to reduce their (typically gas) heating to save money. There is also an interaction between electricity and gas use, for instance reducing lighting increases the need for extra heating, while use of an electric heater to reduce gas use will drive up electricity consumption, despite potentially reducing energy consumption overall depending on the way heating is used in the rest of the home. This will be the focus of future work.

[9] Each household's price elasticity is calculated monthly for winter 2022/23 as monthly % energy reduction / % difference between winter 2021/22 unit cost and unit cost in that month. The mean of the 6 months' elasticities gives mean winter elasticity per household, of which we take the mean and interquartile range (IQR).

**Table 3**
Linear regression results for household and dwelling characteristics previously found to be significant individually when regressed against % total energy reduction (N = 1208). Categorical variable base cases: financial wellbeing (high), dwelling (semi-detached), EPC (band C), tenure (owner-occupier), any aged 85+ years (no). Std. Err.: standard error. ***($p < 0.001$), **($0.001 \leq p < 0.01$), *($0.01 \leq p < 0.05$).

| Term | Estimate (%) | Std. Err. | P-value |
|---|---|---|---|
| Dependent variable: % total energy reduction | | | |
| Intercept*** | 8.878 | 2.169 | **0.000** |
| Financial wellbeing: low** | 1.547 | 0.516 | **0.003** |
| Dwelling: detached | 0.813 | 0.584 | 0.164 |
| Dwelling: terraced | 0.524 | 0.564 | 0.354 |
| Dwelling: flat/maisonette/apartment | −0.529 | 0.564 | 0.349 |
| EPC: A-B | 0.747 | 0.517 | 0.149 |
| EPC: D | 0.708 | 0.586 | 0.227 |
| EPC: E-G | 0.608 | 0.575 | 0.291 |
| Number of bedrooms | 0.265 | 0.577 | 0.646 |
| Tenure: private renter | 0.556 | 0.502 | 0.268 |
| Tenure: social renter | −0.981 | 0.548 | 0.074 |
| Tenure: live rent free | −0.480 | 0.488 | 0.326 |
| Any aged 85yrs+ | −0.552 | 0.490 | 0.260 |

### 3.3. Household and dwelling characteristics: correlation with percentage consumption reduction

Section 3.1 revealed a wide distribution of energy reduction, with most households changing consumption within ± 50% of their predicted amount. Exploratory analysis reveals that absolute (kWh) reduction is most strongly correlated with predicted consumption, *i.e.* those who typically consume the most reduced their energy by the most, possibly those with low consumption to start with had little potential to lower their energy use. In this analysis we therefore study percentage reduction, in particular percentage of total (electricity + gas) energy. Table 3 shows the results of a linear regression of total energy reduction percentage against household and dwelling characteristics selected following individual regressions (those which on their own showed significant correlation with energy reduction)[10], where the 'high/low' financial wellbeing classification is defined as in [26][11]. Once combined, the only variable with significant correlation with energy reduction is financial wellbeing; low financial wellbeing is associated with greater energy reduction. This may not be surprising since those struggling financially are more likely to be motivated by rising energy prices (as we found for gas price elasticity) and dwelling and household characteristics are more likely to correlate with total consumption and therefore kWh rather than percentage energy reduction.

### 3.4. Energy-saving actions and energy consumption reduction

#### 3.4.1. Overall engagement with energy-saving actions

There are a number of reasons why a household may reduce their energy consumption from one winter to the next, such as occupant-related changes (*e.g.* the number of occupants or their working statuses), energy efficiency improvements such as loft insulation or double glazing), or specific energy-saving actions taken by the occupants on a one-off or regular basis (*e.g.* reducing boiler flow temperature or avoiding using the oven). The reasons behind efforts to reduce consumption could include the cost-of-living crisis, environmental concerns, or efforts to support the war in Ukraine by reducing gas demand [71]. It is not possible to pinpoint the reasons for the energy reduction we observe in each household, but the 2023 SERL Energy Survey data reveals whether people were reducing consumption deliberately, what actions were being taken, and some of the challenges faced (such as being unable to keep warm or afford to use the heating).

Of the 2710 households in our sample who responded to the question *"How much effort, if any, would you say your household makes to limit or reduce the amount of gas or electricity used?"* 38% reported making "a great deal of effort", 47% reported "some effort", 13% reported "a little effort", while only 1% responded "no effort at all". This shows that most households were actively making efforts to reduce their energy consumption this winter, which is likely to explain, at least in part, the reductions presented in Section 3.1.

Fig. 4 shows the percentage of respondents who report doing each action 'always' or responded 'yes' when asked if they do them (depending on the question response options). The most popular (more than 60% of respondents 'always' perform them, shown in purple) are closing blinds/curtains at night, taking showers rather than baths and switching off lights in unused rooms. We would not expect to see a large correlation between these actions and energy reduction because their response indicates that these actions did not change between the two periods of interest. In contrast, if typically unpopular actions (orange and yellow) show high correlation with energy reduction, or are unusually popular with those who reduced consumption the most, then they might be actions that more people should be performing if they wish to reduce consumption, and a potentially underutilised approach to energy saving worthy of greater publicity. To understand which actions might be most effective for energy consumption reduction we begin by comparing the actions of those who reduced consumption by the most with the rest of the sample followed by regression analysis of electricity and gas reduction against energy-saving actions, and lastly investigate their change in thermostat settings and gas use with external temperature compared to the rest of the sample.

#### 3.4.2. Energy-saving actions and total consumption reduction

To understand how energy-saving actions may have contributed to energy consumption reduction we begin by comparing the survey responses of those who reduced by the most with the rest of the sample. We split the sample into five 'energy reduction quintiles' where quintile 5 were in the top 20% of total percentage energy reducers and quintile 1 had the 20% lowest total energy reduction (in fact all saw consumption increase). See Appendix D for details about the quintile groups including by how much each quintile reduced consumption.

Those who reduced their total energy consumption the greatest percentage (quintile 5) were 2.6 times more likely (risk ratio with 95% CI (2.2, 3.0), p-value < 0.001) to report making "a great deal of effort" to reduce consumption (61% of this group whereas the sample average was 38% and among the lowest reducers, (quintile 1) 26%. In response to question A6 about whether any of 16 actions were taken 'a lot more', 'a little more', 'a lot less', *etc.* compared to the previous winter, quintile 5 reported taking an average of 4.4 actions 'a lot more' than previously, the highest of all quintiles, with quintile 1 only averaging 2.1 actions taken 'a lot more' than in the previous winter. There was little difference between the quintiles in reporting doing actions 'a little more'[12]; therefore, for subsequent analysis we reduce these variables to binary outcomes 'a lot more' than last winter or 'not a lot more' for the purposes of comparing quintiles and for linear regression.

Next, we investigate which actions tended to be taken a lot more than previously, and whether they were generally popular (purple and green)

[10] Those tested but excluded from the final model due to non-significance at the $p < 0.05$ level were: index of multiple deprivation (IMD) quintile; number of occupants; binary indicators for: any children aged 0–15 years, any children under 6 years, and anyone aged 75+ years; dwelling age, presence of solar PV, solar water heating, a battery, and an electric vehicle.

[11] We define households with 'high' financial wellbeing if their survey response to the question about how they themselves were managing financially was "Living comfortably" or "Doing alright". Households are classed as having 'low' financial wellbeing if they responded "Just about getting by", "Finding it quite difficult", or "Finding it very difficult".

[12] Appendix D.2 includes a figure of these results including all response categories.

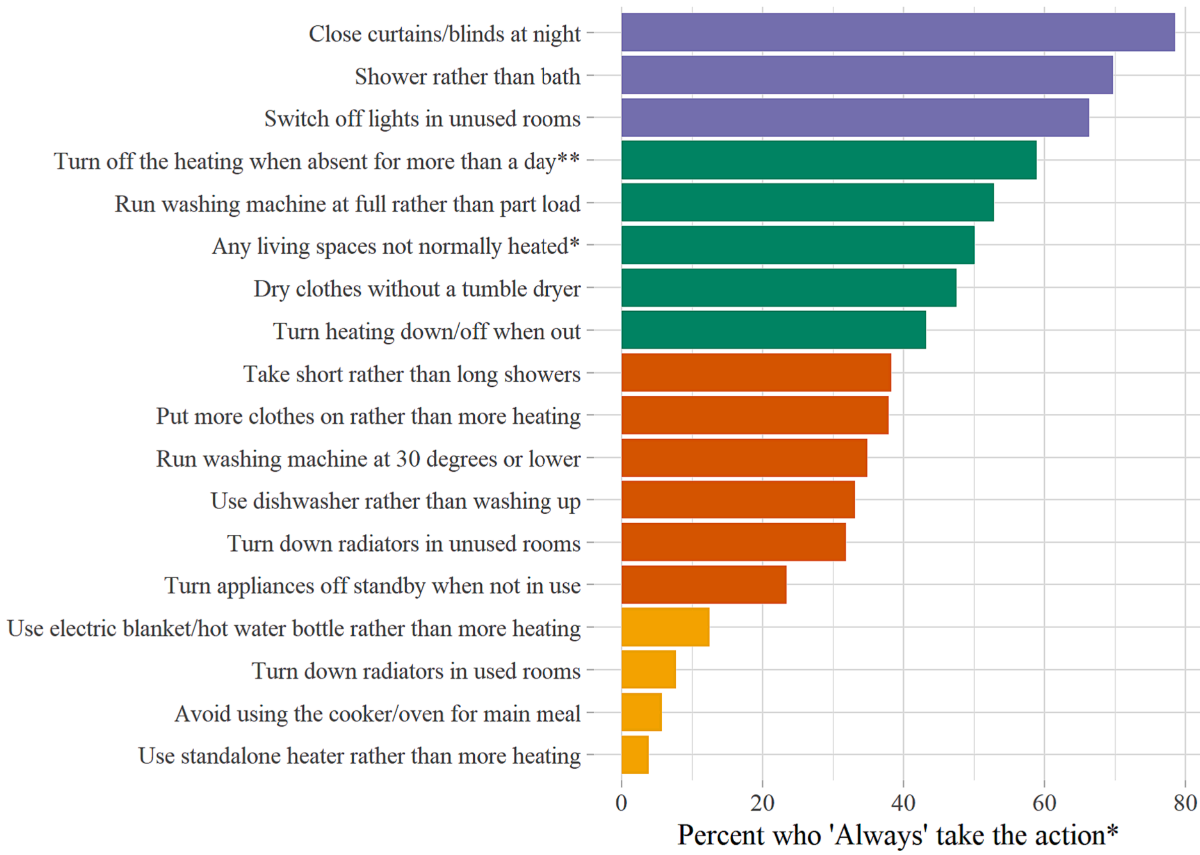


**Fig. 4.** The percent of respondents who reported 'always' performing the actions shown, *except for the question about 'any living spaces not normally heated' (responded yes). Questions have been abbreviated, in particular 'turn the heating off when absent for more than a day'. Percents given out of the total responses excluding those who answered 'not applicable, cannot do this'. Colours group by bands of 20% for use in later analysis.

actions that most people were 'always' performing (see Fig. 2) or if they were less commonly performed and their recent adoption/increase by quintile 5 was atypical of the sample more widely. We calculate the risk ratio of quintile 5 performing each action a lot more than in the previous winter compared to the rest of the sample[13] (left-hand subplot of Fig. 5). Actions with the highest risk ratios saw the biggest differences between quintile 5 and the rest of the sample in terms of whether they did the action 'a lot more' (or not) than in the previous winter. The percentage of respondents who performed each action a lot more than previously are shown in the right-hand subplot of Fig. 5, where black circles (and numbers to the right) represent quintile 5, grey circles (and numbers to the left) show the percentage of quintile 1, and white circles show the percentage of the full sample.

While more than half of the sample heated their home for fewer hours than in the previous winter, quintile 5 were over 4.3 times more likely to do this than the rest of the sample – by far the biggest risk ratio of all the actions, and their most popular action to adopt/increase, with 88% of quintile 5 heating their homes for fewer hours than before compared with only 42% of the lowest reducers. Five actions that less than 40% of the sample reported 'always' doing (orange or yellow from Fig. 2) were around twice as likely (risk ratios 2.0–2.2) to be done a lot more this winter by the greatest reducers than by the rest of the sample. They all relate to using less energy for heating, either by turning down radiators (in both used and unused rooms), putting on more clothes, using an electric blanket or hot water bottle, or using a standalone heater. The percentage of quintile 5 who did these actions a lot more than in the previous winter ranged from 24% to 59%, which, while similar to many other actions shown, tended to see much bigger differences compared to quintile 1 (their range was 8%–24% for these actions). Being actions that most people were not always doing or increasing since the previous winter, these may have the greatest untapped potential for energy consumption reduction (as discussed above).

All SERL participants have a smart meter, although not all have a working in-home display (IHD). There has been some controversy as to the benefits of smart meters for helping reduce energy consumption. Interestingly, of those with a working IHD, quintile 5 were 1.8 times more likely to use to their IHD a lot more than in the previous winter compared to the rest of the sample, with 56% of the greatest energy reducers using it a lot more than previously, compared to 41% of the sample and 28% of the lowest energy reducers. How effective they were in supporting households with energy reduction would be a question for future research, yet people making efforts to save energy reported engaging with them a lot more than previously, which may indicate greater regular interaction, rather than, say, a one-off check.

### 3.4.3. Correlation between energy-saving actions and energy reduction

As discussed above, the greatest energy reducers were more likely to do actions 'a lot more' than the previous winter compared to the rest of the sample, whereas they did a similar number 'a little more' (Appendix D2). Therefore, to understand the correlation between energy-saving actions and energy reductions we transformed the responses of questions relating to action change since the previous winter to binary

[13] Risk ratio (also known as 'relative risk') of 1 implies the chance of quintile 5 doing the action 'a lot more' is the same as for the rest of the sample. Risk ratio > 1 implies a higher chance for those in quintile 5.

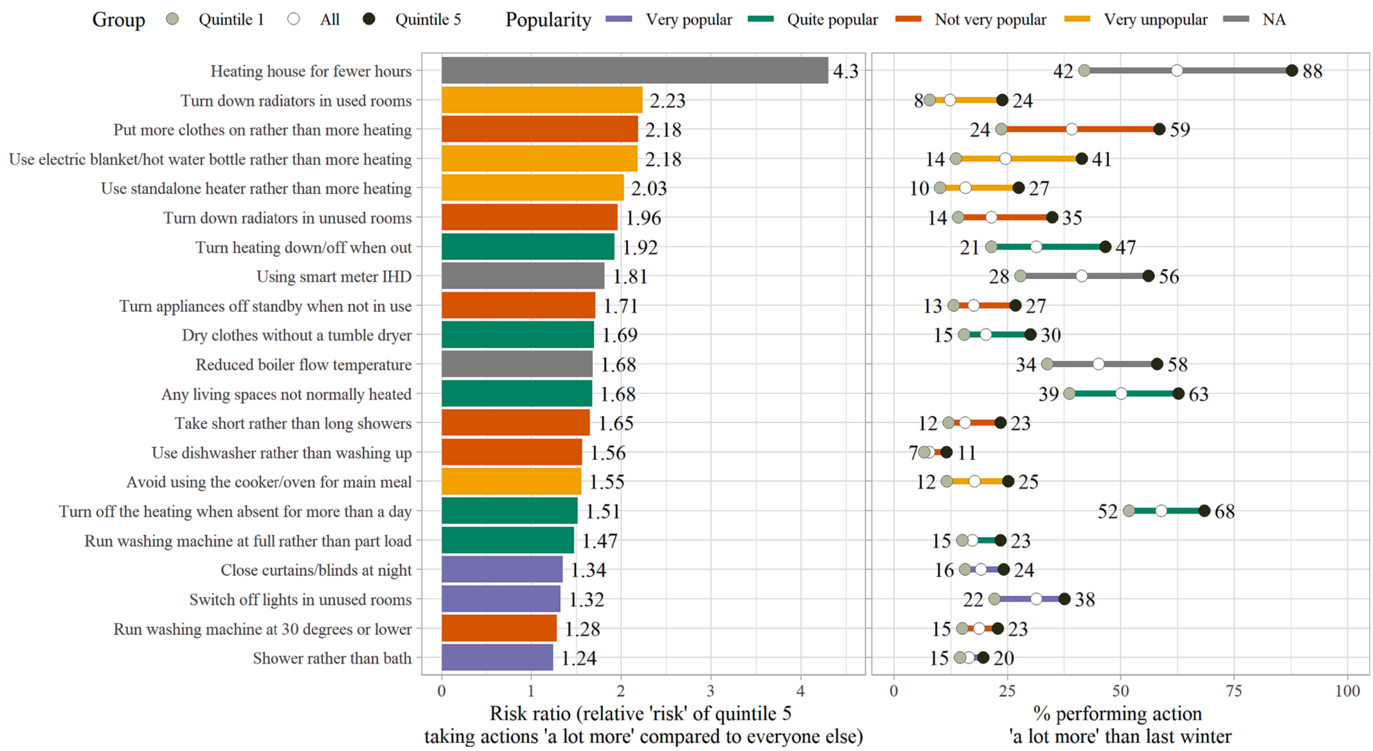


**Fig. 5.** Left: risk ratio for energy reduction quintile 5 to perform an action 'a lot more' this winter compared to the rest of the sample. All risk ratio p-values < 0.037 with 17/21 < 0.001. Right: the percentage of survey respondents who performed each action 'a lot more' than in the previous winter; numbers show the percent of quintile 1 (left) or quintile 5 (right). Colours indicate popularity (the percentage of the sample who 'always' perform each action (see Fig. 4)). Grey used for actions where the propensity to perform the action 'always' is not applicable or unknown.

**Table 4**
Linear regression of percentage reduction in electricity and (separately) gas consumption against energy-saving actions (N = 2006). Following regression with all actions with responses about change since the previous winter, the 10 most important variables were retained for the final regressions shown (10 or fewer actions were shown to have significance at the p < 0.05 level in the initial regression). Estimate (kWh/day) = estimate (% reduction) × median predicted consumption (Table 2), Estimate (pence/day) = Estimate (kWh/day) × January–March 2023 unit costs (Table). ***(p < 0.001), **(0.001 ≤ p < 0.01), *(0.01 ≤ p < 0.05).

| | Term | Response | Estimate (% reduction) | Estimate (kWh/day) | Estimate (pence/day) | Std. Err. | P-value |
|---|---|---|---|---|---|---|---|
| Electricity | **Intercept*** ** | | 5.891 | 0.479 | 15.64 | 0.688 | **<0.001** |
| | **Use standalone heater rather than more heating*** ** | A lot more | −2.359 | −0.192 | −6.26 | 0.446 | **<0.001** |
| | **Dry clothes without a tumble dryer*** | A lot more | 1.091 | 0.089 | 2.90 | 0.492 | **0.027** |
| | **Turn down radiators in unused rooms*** | A lot more | 1.113 | 0.091 | 2.96 | 0.489 | **0.023** |
| | **Put more clothes on rather than more heating*** | A lot more | 1.208 | 0.098 | 3.21 | 0.485 | **0.013** |
| | Avoid using the cooker/oven for main meal | A lot more | 0.765 | 0.062 | 2.03 | 0.467 | 0.102 |
| | **Shower rather than bath*** | A lot more | −1.109 | −0.090 | −2.94 | 0.504 | **0.028** |
| | Any living spaces not normally heated | Yes | 0.631 | 0.051 | 1.68 | 0.432 | 0.144 |
| | Use dishwasher rather than washing up | A lot more | −0.640 | −0.052 | −1.70 | 0.468 | 0.172 |
| | Turn appliances off standby when not in use | A lot more | 0.458 | 0.037 | 1.22 | 0.480 | 0.339 |
| | Use electric blanket/hot water bottle rather than more heating | A lot more | 0.479 | 0.039 | 1.27 | 0.476 | 0.314 |
| Gas | **Intercept*** ** | | 1.887 | 0.904 | 8.90 | 0.840 | **0.025** |
| | **Heating house for fewer hours*** ** | Yes | 3.807 | 1.824 | 17.95 | 0.446 | **<0.001** |
| | **Use electric blanket/hot water bottle rather than more heating*** ** | A lot more | 2.015 | 0.965 | 9.50 | 0.464 | **<0.001** |
| | **Any living spaces not normally heated*** ** | Yes | 1.498 | 0.718 | 7.06 | 0.417 | **<0.001** |
| | **Reduced boiler flow temperature*** | Yes | 1.026 | 0.492 | 4.84 | 0.421 | **0.015** |
| | **Put more clothes on rather than more heating*** | A lot more | 1.051 | 0.503 | 4.95 | 0.482 | **0.030** |
| | **Use smart meter in-home display*** | More often | 0.964 | 0.462 | 4.54 | 0.428 | **0.024** |
| | **Use standalone heater rather than more heating*** | A lot more | 0.965 | 0.463 | 4.55 | 0.436 | **0.027** |
| | **Turn down radiators in used rooms*** | A lot more | 1.140 | 0.546 | 5.37 | 0.461 | **0.014** |
| | **Shower rather than bath*** | A lot more | −1.133 | −0.543 | −5.34 | 0.461 | **0.014** |
| | **Turn appliances off standby when not in use*** | A lot more | 0.978 | 0.469 | 4.61 | 0.453 | **0.031** |

outcomes 'a lot more' or 'not a lot more'[14] and performed linear regression of these variables against percentage reduction in electricity and gas consumption separately. Initially we included all possible actions with reported change since the previous winter, of which 10 or fewer showed significant correlation with electricity or gas reduction. Table 4 shows the results of the final regressions for electricity and for gas reduction against the 10 most important variables for each fuel.

Actions correlated with the greatest energy reduction were those that reduced gas heating demand, with heating the house for fewer hours

[14] In the case of questions with yes/no responses these were left as yes/no.

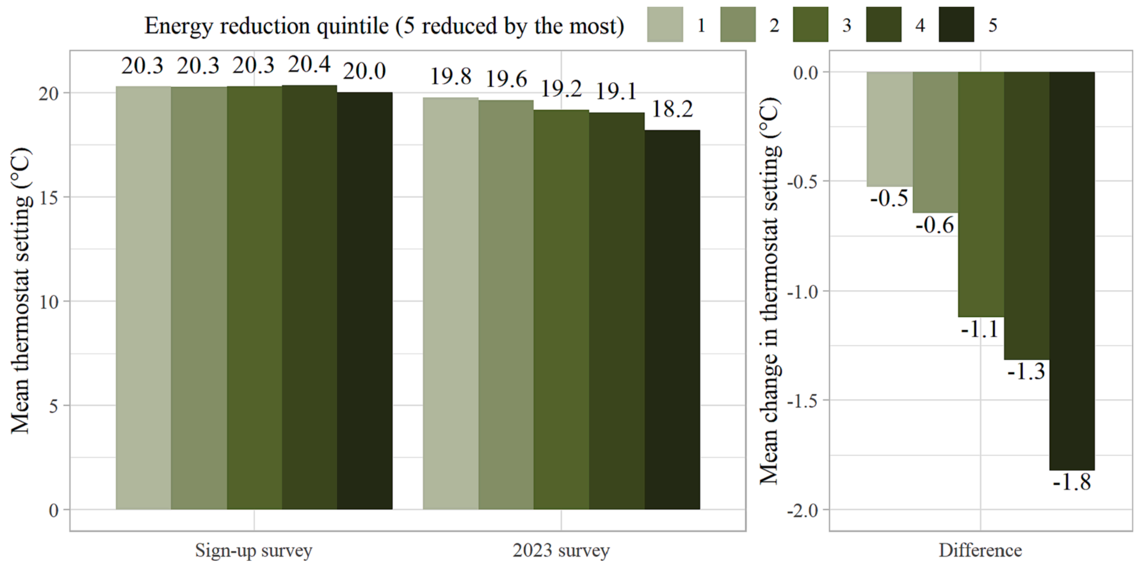


**Fig. 6.** Thermostat settings in the sign-up and 2023 energy survey and the difference in reported settings, by energy reduction quintile.

**Table 5**
Linear regression, gas consumption percentage reduction against change in thermostat setting, N = 2074. Estimate (kWh/day) = estimate (% reduction) × median predicted consumption (Table 2), Estimate (pence/day) = Estimate (kWh/day) × January–March 2023 unit costs (Table C1).

| | Term | Estimate (% reduction) | Estimate (kWh/day) | Estimate (pence/day) | Std. Err. | P-value |
|---|---|---|---|---|---|---|
| Electricity | **Intercept*** ** | 7.499 | 0.610 | 19.91 | 0.482 | **<0.001** |
| | Reduction in thermostat setting in °C | −0.279 | −0.023 | −0.74 | 0.422 | 0.501 |
| Gas | **Intercept*** ** | 9.201 | 4.409 | 43.38 | 0.710 | **<0.001** |
| | **Reduction in thermostat setting in °C*** ** | 3.839 | 1.840 | 18.10 | 0.622 | **<0.001** |

reducing consumption by the most of any single action taken/taken a lot more than in the previous winter. There is strong agreement with the risk ratios in Fig. 6 (the behaviours more likely to be increased by the greatest reducers). On average using a standalone heater increased electricity use (required for standalone heaters) by 0.19 kWh/day but reduced gas use (normally used for central heating) by 0.46 kWh/day, resulting in an overall reduction in energy use of 0.27 kWh/day. However, since the unit cost of electricity was higher than for gas, on average using a standalone heater increased bills by 1.7p/day (~£0.51/month). Therefore, when discussing the potential benefits of standalone heaters it is important to consider how much they will be used compared to use of the heating system and (if cost is the main driver) the relative price/kWh of electricity and gas.

Avoiding using the tumble dryer understandably correlates with lower electricity consumption, although care must be taken not to cause mould or damp issues if drying clothes indoors in cold weather or compensating by turning up the space heating. A few heating-related actions showed significant correlation with electricity reduction, despite most of these households having gas heating; possibly due to a certain set of behaviours being common among the greatest energy reducers irrespective of whether they individually contribute to the lower electricity consumption.

Increased use of a smart meter IHD also correlated with reduced gas use which may be due to insights gained from the IHD about energy consumption or it could be an indicator that a household is making real efforts to reduce consumption (as is likely the case with turning appliances off standby, which clearly does not lower gas use). Showering rather than taking a bath correlated with increased electricity and gas use; an unexpected finding; perhaps complicated by factors such as people showering more frequently than taking baths, and very few households taking this action a lot more than before (16%). An added complexity is that some showers are electrically heated or pump assisted. Either way, showering compared to bathing does not appear to reduce energy consumption.

### 3.4.4. *Thermostat settings*

Changes to thermostat settings are not easily compared with the actions analysed above so we analyse them separately. 2074 households in our sample reported their thermostat temperature setting in both their original SERL ("sign-up") survey and in the 2023 SERL energy survey. The mean setting was 20.3 °C in the original survey and 19.2 °C in the 2023 survey (a mean reduction of 1.1 °C). Standard deviation for all three variables was approximately 2.0 °C or 2.1 °C; standard error of the mean 0.04 °C or 0.05 °C.

Fig. 6 shows the mean thermostat settings reported in the survey at sign up (between 2019 and 2021 due to three recruitment waves[15]) and the mean change by energy reduction quintile. While all quintiles initially reported a thermostat setpoint of approximately 20 °C, thermostat reduction increased with energy saving quintile, with the greatest energy reducers lowering their setpoints by 1.8 °C on average; around twice the mean reduction of the rest of the sample (0.9 °C). Therefore, not only were the greatest reducers 4 times more likely to heat their homes for fewer hours than the rest of the sample, and to avoid using the heating or turning it up by using alternatives such as hot water bottles or wearing more layers, but in general they kept their homes at lower temperatures, thus reducing the heating demand while the heating was on.

Given these results, we performed linear regression of change in thermostat setting against gas (and for consistency, electricity) consumption percentage reduction (Table 5). As expected, there is

[15] Thermostat settings showed no significant difference between sign-up years when analysed by Hanmer and Zapata-Webborn [25].

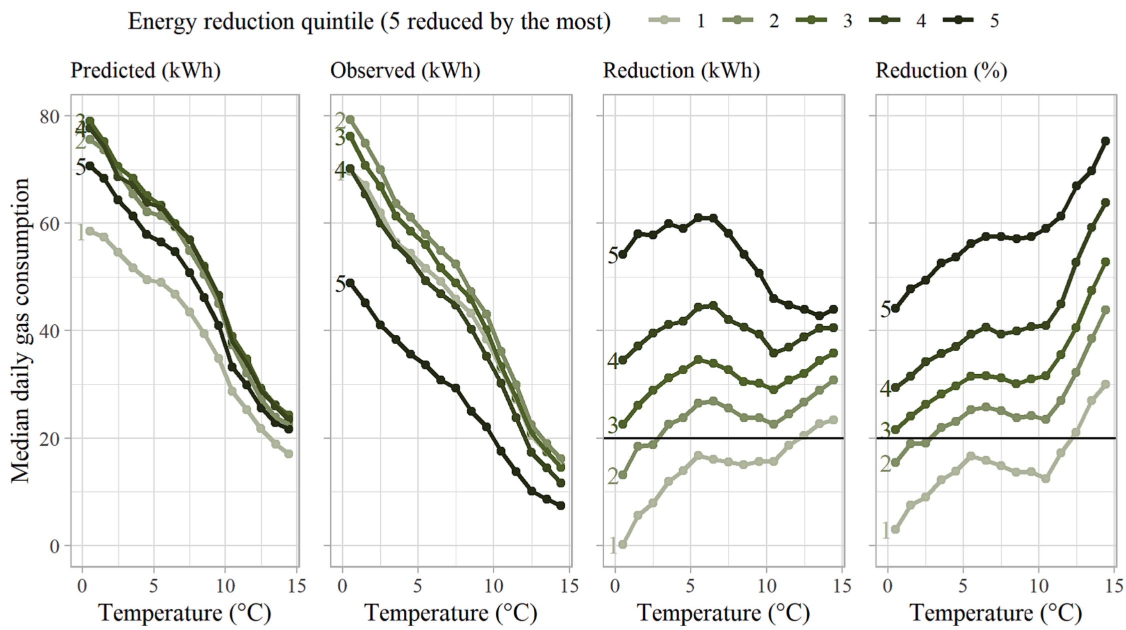


**Fig. 7.** Median gas consumption predictions, observations, and reductions against external temperature by energy reduction quintile.

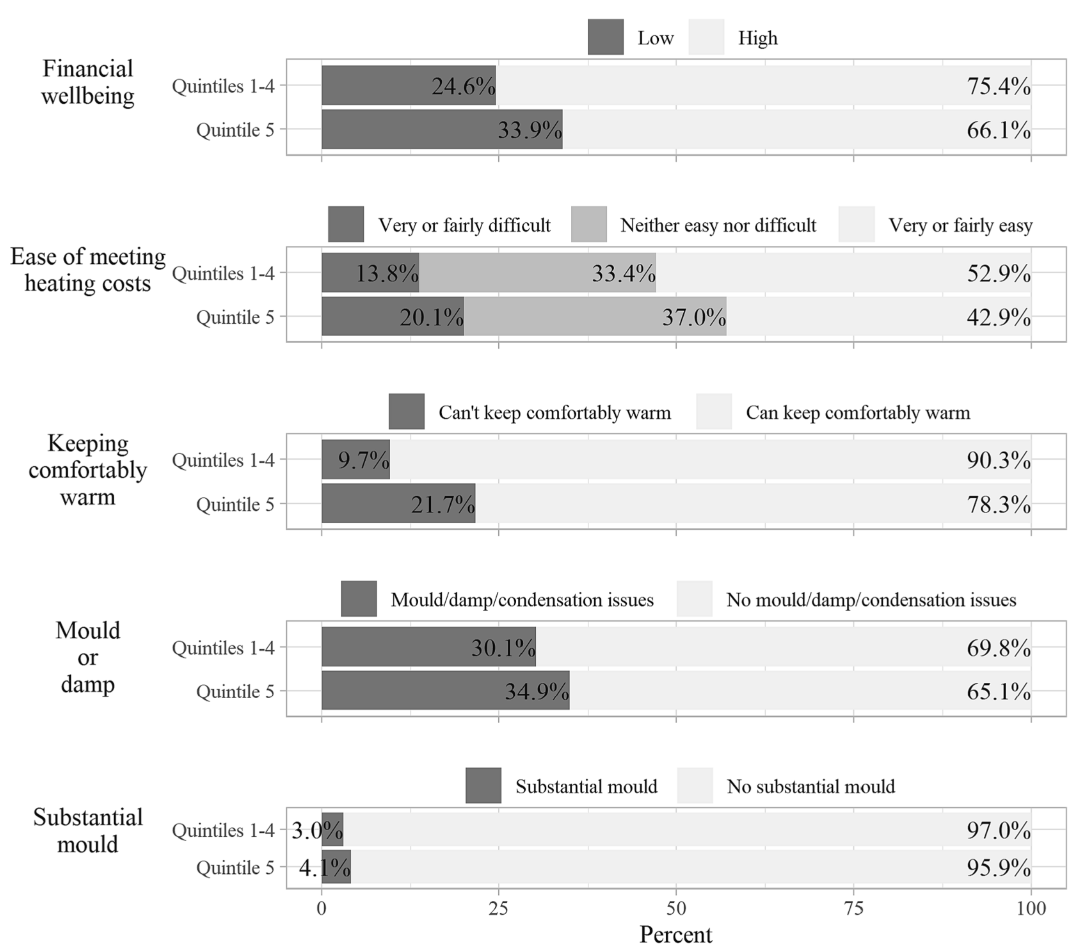


**Fig. 8.** Comparing rates of fuel poverty and underheating-related survey variables between those who reduced total energy consumption by the most (energy reduction quintile 5) with the rest of the sample. N per variable between 2550 and 2695, smallest subgroup N = 20 (quintile 5 with substantial mould).

significant correlation between thermostat reduction and gas consumption; on average for every 1 °C reduction in thermostat setpoint gas consumption reduced by almost 4% or around £5.43/month (an average that will be highly influenced by external temperature each month). There was no statistically significant correlation found with electricity reduction. Previous studies have reported energy and cost savings associated with thermostat settings, but these are either based on theoretical models or observational data, whereas this is the first report of the impact of interventions.

### 3.5. The effects of external temperature

Energy consumption for domestic heating is highly influenced by external temperature [58,72]. We have already found correlation between gas consumption reduction and heating homes for fewer hours and reducing thermostat settings. Next, we explore how gas consumption and reduction varied with external temperature. We focus on gas consumption since this is the main heating source for most of the sample, and exploratory analysis of electricity use against temperature showed weak trends. For each household, daily gas consumption was split into temperature bins of width 1 °C. It was important that the same households contributed equally to all temperature bins,[16] so that the data did not become biased as temperatures changed (for example over-representing households in the North during the coldest weather). A balance was therefore struck between temperature range and number of households – temperatures between 0 and 15 °C gave a sample of 5124 (with at least 1013 in each energy saving quintile).

Fig. 7 reveals several interesting features of the data. Firstly, quintile 1 (whose consumption actually increased (Appendix D1)) had the lowest predicted gas consumption at all temperatures (and particularly in cold weather), while their actual gas use with temperature was very similar to quintiles 2–4. Secondly, quintile 5 used less gas at higher temperatures than the other quintiles and also increased their gas use by less than the others as weather turned colder. Indeed, quintile 5 was typically consuming around 49 kWh/day (gas) in 0–1 °C weather (IQR 29–72 kWh/day) compared to 74 kWh (median of the rest of the sample, IQR 52–101 kWh). This resulted in gas reduction of over 20% at these temperatures for quintile 5, while for the rest of the sample gas consumption was approximately at predicted levels (*i.e.* no reduction) at these temperatures.

Overall, gas consumption reduction as a percentage increased with temperature, likely due to people delaying turning their heating on during October/November, avoiding using the heating in relatively warmer autumn/winter weather, and/or the effects of reduced thermostat settings. In absolute (kWh) terms reduction was greatest at around 6 °C (the average heating season external temperature). At colder temperatures (below 5 °C) both the absolute and percentage reduction in gas demand reduced. For future winters it is important to note that the potential to save energy reduces significantly in colder weather, so vulnerable consumers struggling financially may be unable to afford their heating when they need it most. Additionally, if future winters are significantly colder than winter 2022/23 then we would expect that overall gas consumption may rise compared with this winter.

### 3.6. High energy reduction: A potential cause for concern?

Quintile 5 (greatest energy reducers) on average used less gas during cold weather (Fig. 7), set their thermostats at lower temperatures (Fig. 6), and were more likely to reduce the hours of heating in their homes, turn down radiators and use alternatives such as extra clothing to avoid turning the heating on/up (Fig. 5). They were also more likely to be struggling financially (Table 3). While energy reduction can be highly commendable as we move towards net zero and vital for households in financial difficulty, a lack of energy consumption, and in particular underheating, can cause or exacerbate physical and mental health issues [19–21] and even excess winter deaths [22]. Given the increasing levels of fuel poverty in GB [15,16] (which is also reflected in the SERL sample[17]), our final analysis investigates whether high energy reduction in winter 2022/23 could indicate underheating practices and related issues.

Fig. 8 shows the percentage of the greatest energy reducers (quintile 5) in each fuel poverty or underheating-related survey variable group compared to the rest of the sample. Risk ratio analysis (Appendix D3) reveals that quintile 5 were 2.3 times more likely to be unable to keep comfortably warm in their living room, 1.5 times more likely to find it 'very' or 'fairly' difficult to meet their heating costs and 1.4 times more likely to suffer from low financial wellbeing. They were only slightly more likely (1.2 times (95% CI 1.0–1.32)) to report problems with condensation, mould or damp and showed no significant difference in terms of issues of 'substantial mould', which only affected around 3.3% of respondents (83 households).

While it is reassuring that when the survey was completed (February–April 2023) those reducing their energy consumption the most were not significantly more likely to suffer substantial mould issues, it is possible that sustained underheating could cause such issues in future. However, that 31% of the sample reported issues with condensation, mould or damp regardless of their energy reduction is concerning for GB households generally. These results paint a picture of a significant proportion of households struggling financially, finding it difficult to meet heating costs, and feeling cold in their homes. The evidence from our sample points to greater support needed to ensure those struggling financially are not left choosing between eating and heating due to unaffordable heating costs, particularly in cold weather. Effective policies could include greater financial support combined with improved home energy efficiency to reduce the cost of keeping homes warm.

### 3.7. Limitations

The results presented here must be considered within the context in which they were obtained in order to understand their potential limitations in terms of generalisability and reliability. Appendix A summarises sample bias from the data available but cannot capture all sources of bias. Of those who completed the 2023 energy survey, there is likely some response bias, which we have attempted to mitigate by considering specific groups of households, such as those with different levels of financial wellbeing. Households were excluded if we knew they had acquired a heat pump or electric vehicle within the last 12 months (since their predictions would be invalid), or if they had insufficient electricity or gas data, which excluded those without a mains gas supply.

Unfortunately, we did not have access to actual energy prices/bills throughout both winters, and so we assumed that all households were on the Default Tariff Cap in 2021/22 and the Energy Price Guarantee (EPG) the following winter. It is likely that most households were paying similar prices to the EPG in 2022/23 but that more households were paying less than the price cap the previous winter. Therefore, we are likely to have underestimated the bill increase from winter 2021/22 to winter 2022/23.

Finally, it is not possible to know the reliability of the survey data. We hope that participants answer honestly and that their memory of actions taken the previous winter compared to this winter was accurate, but respondents may have chosen to answer in ways that imply greater

[16] A household's contribution was its mean gas consumption (kWh) over all temperatures within the bin. The median of the individual means was then taken to reduce skew by outlier households.

[17] Comparing the financial wellbeing responses of the sign-up SERL survey with the 2023 survey, the percentage 'living comfortably' dropped from 47% to 31%, while those 'just about getting by' or finding 'quite' or 'very' difficult increased from around 15% to 26% (total N = 2498).

efforts to reduce energy due to a sense that it was the 'right' thing to be doing, they may have misremembered actions taken previously, or have been unaware of actions taken by other household members.

## 4. Conclusions

This paper investigated the change in domestic electricity and gas consumption in 5594 households in GB from October 2022 to March 2023 ('winter 2022/23′) compared to the same period in the previous year, which we attribute in large part to the cost-of-living crisis and associated rise in energy prices. We used counterfactual (predictive) modelling with XGBoost to compare measured energy consumption with predicted consumption (accounting for differences in weather conditions), had all other conditions remained the same from one winter to the next. We used daily energy demand data, national price cap data, and detailed survey data from the start of 2023 to analyse energy consumption and energy bills, self-reported energy-saving actions, and conditions linked to underheating and fuel poverty.

The analysis provided the following answers to the original research questions[18]:

1. *What was the impact of the cost-of-living crisis on household electricity and gas consumption during October 2022–March 2023 ('winter 2022/23′)?*

Electricity and gas consumption decreased significantly in winter 2022/23 compared to the previous winter; by 8.4% (median), (IQR −0.5%–17.6%) and 10.8% (1.2%–22.4%), respectively. These figures are likely to be higher for the wider population due to the sample's slight underrepresentation of those struggling financially, who were more likely to reduce consumption by greater amounts. Note that these results will not match annual figures since electricity demand plays a much larger role outside of the heating season when total consumption is generally lower.

2. *How did energy bills change in winter 2022/23 compared to the previous winter, and how did any energy consumption reduction translate to bill savings?*

The energy reductions saved consumers an average of £28.60/month (IQR £25.84 - £34.09) off their total (dual) fuel bills. Despite these savings and the £66.67/month government subsidy, total energy bills still rose on average by £33.72/month (IQR £−7.54 – £87.34). While average energy bills were around £158/month (including savings and subsidy), the highest 5% of household energy bills rose to over £500/month (up from around £300/month the previous winter).

3. *How did savings vary between different types of household and dwelling (e.g. financial wellbeing, presence of children and the elderly, dwelling type, dwelling energy efficiency)?*

The only household/dwelling/low carbon technology characteristic found to correlate significantly with total energy reduction (as a percentage of predicted consumption) was self-reported 'financial wellbeing'; those with low financial wellbeing (defined above) made greater energy consumption reductions.

Only 1% of the 2710 survey respondents reported making 'no effort at all' to save energy, while 38% and 47% reported making 'a great deal' or 'some' effort, respectively.

4. *Which self-reported energy-saving actions showed the greatest correlation with reduction in total energy consumption?*

Energy-saving actions that reduce heating demand were the most strongly correlated with reduced gas consumption, in particular: lowering the thermostat setting, heating the house for fewer hours, using an electric blanket/hot water bottle and putting on more clothes rather than more heating, avoiding heating some living spaces, reducing boiler flow temperature, and turning down radiators. Fewer actions correlated with a reduction in electricity demand, likely due to observed reductions being lower than for gas. Drying clothes without a tumble dryer a lot more than previously was the one action that showed a reduction in electricity consumption that did not relate to heating. Increased use of a standalone heater reduced total energy consumption but the transfer of heat from gas to electricity tended to increase bills. Those who switched from baths to 'a lot more' showers saw electricity and gas use rise, possibly due to showering more often than bathing or transfer of water heating from gas to electricity.

5. *Were those who saw the greatest reduction in energy consumption more likely to be struggling financially and/or to experience problems related to underheating?*

Those struggling financially showed greater sensitivity to gas price increase and lower sensitivity to electricity price increase compared to more affluent households. Median price elasticity was −0.099 for electricity consumption and −0.071 for gas consumption (compared to the previous winter).

Households who reduced their energy consumption the most (*i.e.* the highest 20% of total energy percentage reduction) tended to report doing more energy-saving actions 'a lot more' than in the previous winter compared to the rest of the sample, were over four times as likely to heat their homes for fewer hours than before, and were around twice as likely to avoid using the heating through actions such as wearing more layers or using an electric blanked or hot water bottle, and their mean change in thermostat setting was −1.8 °C (from 20.0 °C to 18.2 °C) (twice the mean reduction of the rest of the sample).

Below 5 °C households were much less likely to reduce their gas consumption than in warmer weather. Within 10 °C–15 °C gas reduction increased with temperature, which may indicate households delaying the start of their personal heating season, or a greater willingness to handle cooler temperatures indoors when it was still relatively warm outside. The greatest energy reducers increased gas use less in cold weather compared to the rest of the sample, with the top 20% of energy reducers using around 49 kWh/day at temperatures close to freezing compared to 74 kWh/day (sample median).

The greatest energy reducers were more likely to have low financial wellbeing, to find it difficult to meet their heating costs, to be unable to keep comfortably warm in their living rooms and were slightly more likely to experience problems with condensation, mould or damp. This indicates that those found to be making large reductions in energy consumption could be vulnerable to health and wellbeing issues related to underheating, and in need of greater financial assistance and support to improve the energy efficiency of their homes, particularly in relation to insulation and boiler efficiency.

The above contribution to knowledge has been achieved by accessing comprehensive gas and electricity longitudinal data that predates the cost-of living crisis. In addition, it is complemented by self-reported changes in behaviour and detailed contextual weather data and other property data. This combined with novel methods of producing counterfactuals accounting for changes in weather has enabled the quantification of a range of changes in behaviour and a detailed calculation of price elasticity, and the impact of measures such as changes to boiler flow temperatures. Historically, the impact of individual changes in behaviour have largely been calculated theoretically rather than empirically because detailed energy, contextual and behaviour data has not been accessible for a large enough sample to obtain meaningful statistical results [82]. Also, this study has for the first time enabled the quantification of the impact of measures normally recommended to save

[18] Where 'average' is the median unless otherwise stated, as explained above.

energy such as showering rather than bathing but which do not appear to correlate with energy reductions.

This research has already been utilised by policymakers to help provide advice to occupants as to how to cope with the even higher fuel prices that homeowners will experience this coming heating season (2023–24) when the energy price guarantee and £400 subsidy has been removed. There is also considerable interest in looking at long-term price elasticity as fuel prices are now predicted to stay high for the coming years.

Further research should investigate more fully the experiences of those in fuel poverty including those who are making large reductions to their energy use and those with no ability to reduce their consumption further as they already have very low consumption. Improving home energy efficiency could be very valuable to such households, and identifying those with greatest need could be the subject of further research. We identified a range of energy-saving actions that showed potential to make significant energy savings, many of which have not yet been adopted as regular practice by most households. Understanding why not, and who might benefit from better communication would be valuable to enable greater energy reduction without causing issues such as underheating among those already making great efforts to save energy.

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**CRediT authorship contribution statement**

**Ellen Zapata-Webborn:** Conceptualization, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Clare Hanmer:** Conceptualization, Writing – original draft, Writing – review & editing. **Tadj Oreszczyn:** Funding acquisition, Methodology, Writing – review & editing. **Gesche Huebner:** Conceptualization, Funding acquisition, Writing – review & editing. **Eoghan McKenna:** Conceptualization, Funding acquisition. **Jessica Few:** Writing – review & editing. **Simon Elam:** Funding acquisition. **Martin Pullinger:** Writing – review & editing. **Callum Cheshire:** Conceptualization, Funding acquisition. **Dominic Friel:** Conceptualization, Funding acquisition. **Harry Masters:** Conceptualization, Funding acquisition. **Alex Whittaker:** Conceptualization, Funding acquisition.

**Declaration of competing interest**

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Ellen Zapata-Webborn, Clare Hanmer, Tadj Oreszczyn, Gesche Huebner, Eoghan McKenna, Jessica Few, Martin Pullinger, and Simon Elam report financial support was provided by Engineering and Physical Sciences Research Council. Callum Cheshire, Dominic Friel, Harry Masters, and Alex Whittaker report financial support was provided by National Grid Electricity Distribution.

**Data availability**

Data is available to accredited researchers working on approved projects. See www.serl.ac.uk for information about how to apply for data access.

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**Appendix A: Sample representativeness.**

Table A1 describes the representativeness of our sample compared with national estimates using 2021 England & Wales Census data [73], Scotland's 2022 Census data [74], Ordnance Survey's Address Base dataset [75], and the English Housing Survey (EHS) [76].

Regionally our sample is broadly representative of GB, with a slight over-representation of households in Wales, the West Midlands and North West and a slight under-representation of households in Scotland. Our sample slightly under-represents households in areas with the greatest deprivation (IMD quintile 1) and over-represents those in areas with the greatest affluence (IMD quintile 5). This is likely to mean our sample-level results slightly under-estimate energy reductions since we found low financial wellbeing to correlate with greater energy reductions. Childless households are particularly over-represented in our sample, in particular households with a single occupier aged under 65 years and those with two adults both aged over 65 years, while households with children are a little under-represented. However, we did not find correlation between the presence of the elderly or of children and percentage total energy reduction.

The most and least efficient dwellings are over-represented in our sample, at the expense of dwellings in EPC band C, while band B dwellings are represented fairly (and the most common category). It is unclear how this may affect the results, particularly as recent analysis has shown that EPC band is a poor predictor of energy use for bands C-G [77]. In general the SERL dataset struggled to be representative by dwelling and tenure type due to the uneven rollout of smart metering [50], and thus our sample is biased towards detached dwellings and owner-occupiers and under-represents flats/apartments and renters. This is likely to have increased our estimates of energy reduction as those in larger dwellings had greater potential to reduce consumption. However, our use of percentage reduction for most of the analysis meant that no correlation between the variables in this table and percentage energy reduction was established (effectively normalising for predicted consumption).

[19] https://smarter.energynetworks.org/projects/nia_wpd_059/.

**Table A1**
Sample breakdowns by various categories where data is available and comparable population estimates exist. Some categories have been merged for statistical disclosure control due to low counts. *Census data excludes caravans, mobile and temporary structures as they are not included in our sample. **Census data uses 66 as the upper age limit rather than 65 years.

| **Category** (number with data) | **Subgroup** | **Sample** (%) | **Population estimate** (%) | **Source** |
|---|---|---|---|---|
| Region (5594) | East Midlands | 8.5 | 7 | 2021 England & Wales Census, 2022 Scotland Census |
| | East of England | 9.3 | 9 | |
| | Greater London | 11.4 | 12 | |
| | North East | 3.7 | 4 | |
| | North West | 12.9 | 11 | |
| | Scotland | 7.0 | 8 | |
| | South East | 13.8 | 13 | |
| | South West | 8.7 | 8 | |
| | Wales | 6.2 | 4 | |
| | West Midlands | 10.0 | 8 | |
| | Yorkshire | 8.5 | 8 | |
| Index of Multiple Deprivation (IMD) quintile (5594) | 1 (greatest deprivation) | 19.7 | 21 | Address Base |
| | 2 | 22.3 | 21 | |
| | 3 | 18.3 | 21 | |
| | 4 | 18.7 | 20 | |
| | 5 (greatest affluence) | 21.1 | 18 | |
| EPC rating (3091) | Bands A & B | 5.1 | 2 | EHS 2019 to 2020: headline report data |
| | C | 30.7 | 38 | |
| | Band D | 46.6 | 47 | |
| | Bands E-G | 17.6 | 14 | |
| Dwelling type* (5369) | Detached house or bungalow | 30.1 | 23 | 2021 England & Wales Census |
| | Semi-detached house or bungalow | 34.7 | 32 | |
| | Terraced house or bungalow | 26.3 | 23 | |
| | Flat, maisonette or apartment | 9.0 | 22 | |
| Tenure (5370) | Owned outright, with mortgage or loan or shared ownership | 84.8 | 63 | 2021 England & Wales Census |
| | Private rented or lives rent free | 6.7 | 20 | |
| | Social rented | 8.5 | 17 | |
| Household size (5420) | 1 person | 25.5 | 32 | 2021 England & Wales Census |
| | 2 people | 43.6 | 37 | |
| | 3 people | 13.4 | 17 | |
| | 4 people | 12.4 | 14 | |
| | 5 or more people | 5.1 | 7 | |
| Household composition** (5316) | 1 adult 65+, no children | 15.5 | 13 | 2021 England & Wales Census |
| | 1 adult < 65, no children | 9.7 | 17 | |
| | 1 adult 65 + and 1 adult < 65, no children | 6.0 | 4 | |
| | 2 adults 65+, no children | 19.5 | 9 | |
| | 2 adults < 65, no children | 16.9 | 18 | |
| | 3 + adults, no children | 12.3 | 12 | |
| | 1 + children | 20.2 | 26 | |

## Appendix B: Model training, selection and performance.

### *B.1 Summary*

All code used is publicly available on GitHub at https://github.com/ellenwebborn/Winter-demand-falls-as-fuel-bills-rise. The training period (1st October 2021–31st March 2022) was split into a train and test set, by randomly selecting five days in each month to be the test set, and the rest were the training set. All households were modelled separately and used the same train/test split (regardless of the occasional missing data) to allow for sample-level daily error analysis. Five-fold cross-validation was used on the training set, and data was scaled and centred before modelling. This study employed XGBoost with R packages *xgboost* [47] and *caret* [32] with booster 'xgbTree'. For each household a model was selected based on its mean monthly coefficient of variation of the root mean squared error; CV(RMSE) and normalised mean bias error; (NMBE), defined as follows:

$$\mathrm{CV(RMSE)} = \frac{1}{\bar{y}}\sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n-1}} \times 100 \quad \text{(B1)}$$

$$\mathrm{NMBE} = \frac{1}{\bar{y}}\frac{\sum (y_i - \hat{y}_i)}{n-1} \times 100 \quad \text{(B2)}$$

where $n$ is the number of observations, $y_i$ is the mean observation the $i^{th}$ month, $\hat{y}_i$ is the mean prediction in the $i^{th}$ month, and $\bar{y}$ is the mean of the observations. ASHRAE guidelines [78] recommend requiring monthly CV(RMSE) < 15% and NMBE within ± 5%. Households were excluded from our sample if, after all models had been trained, none met these criteria. After each round of modelling (see the Procedure below), the latest trained model was accepted (and further model training stopped) if its monthly NMBE was within ± 5% and its monthly CV(RMSE) < 10% (lower than the final 15% cutoff to allow for model improvement). After model evaluation, the final set of households was restricted to those with both a sufficiently accurate electricity and gas model (final sample size 5594 households). Final model performance is reported in Appendix B4.

### B.2 Procedure

For each household, initially a model was trained using a simple formula and a small set of hyperparameters (‘set A’). If the model accuracy was acceptable then training stopped. Otherwise, a more complex formula was introduced (defined below). If model accuracy was still too low, a wider range of hyperparameters were tested (‘set B’) using the most accurate formula from the previous models. The following algorithm describes the process of model development following data pre-processing and filtering, up to the creation of the counterfactuals. Table B3 below defines the hyperparameters used and examples tested in related studies.

Model training and selection procedure

```
0: for each fuel (electricity and gas) do
1:   for each household in the filtered fuel set do
2:     i = 0
3:     while i < 4 do
4:       Train model on the training set with formula f_i and hyperparameter set A
5:       if CV(RMSE) < 10% and |NMBE| < 5% then
6:         Save model as m* and skip to line 18
7:       else
8:         i = i + 1
9:       end
10:    end while
11:    f* is the formula of the model with the lowest CV(RMSE)
12:    Train model with f* and hyperparameter set B
13:      if CV(RMSE) < 15% and |NMBE| < 5% then
14:        Save model as m*
15:      else
16:        Exclude household from the analysis. Stop.
17:      end
18:    Predict the test set consumption using m*
19:    Calculate train and test errors
20:    Retrain model with the formula and hyperparameters of m* on the full training and testing set
21:    Save retrained (final) model as M*
22:    Use M* to predict counterfactual consumption during winter 2022/23
23:  end
24: end
```

### B.3 Hyperparameters and formulas

For each household the following regression formulas were used, starting with $f_0$ and only continuing to the next formula if the model accuracy was too low (see Procedure above). National holidays were defined using the ‘holidayLONDON’ function from R package ‘timeDate’ [81] which does not include national holidays in Scotland or Wales. Sinusoidal calendar variables $\sin_{day}$ and $\cos_{day}$ are as defined in [26].

$f_0$ (used for 5432 electricity and 5311 gas models):

$$\begin{aligned}\text{daily}_{\text{energy}} = {} & \beta_1 \sin_{\text{day}} + \beta_2 \cos_{\text{day}} + \beta_3 \text{weekend or holiday indicator} + \beta_4 \text{mean temperature at 2m above surface level} + \beta_5 \text{mean solar radiation} \\ & + \beta_{10} \text{total precipitation} + \beta_{11} \text{mean wind speed}\end{aligned}$$

$f_1$ (used for 98 electricity and 159 gas models):

$$\begin{aligned}\text{daily}_{\text{energy}} = {} & \beta_1 \sin_{\text{day}} + \beta_2 \cos_{\text{day}} + \beta_3 \text{weekend or holiday indicator} + \beta_4 \text{mean temperature at 2m above surface level} \\ & + \beta_5 \text{minimum temperature at 2m above surface level} + \beta_6 \text{maximum temperature at 2m above surface level} \\ & + \beta_7 \text{mean temperature at 2m above surface level on previous day} + \beta_8 \text{mean solar radiation} + \beta_9 \text{mean solar radiation on previous day} \\ & + \beta_{10} \text{total precipitation} + \beta_{11} \text{mean wind speed} + \beta_{12} \text{maximum wind speed}\end{aligned}$$

$f_2$ (used for 34 electricity and 52 gas models):

**Table B3**
Hyperparameters tested during model development (see procedure above for use of sets A and B). Set A was sufficient for 5552 households’ electricity models and 5500 households’ gas models; set B was used for 42 households’ electricity models and households’ gas models.

| Hyperparameter | Description | Set A | Set B | Literature examples |
|---|---|---|---|---|
| eta | Learning rate (step size for each iteration) | 0.1, 0.3 | 0.05, 0.1, 0.3 | 0.05 [79] |
| n rounds | Maximum number of iterations (number of decision trees in the forest) | 100 | 100, 200, 300 | 300 [79] |
| max depth | Maximum depth of the tree | 6 | 0.5, 1, 5, 10 | 6 [79]; 5 [80] |
| min child weight | Minimum sum of weights in a subset | 1 | 1, 3, 6 | 3 [79]; 1 [80] |
| gamma | Weights for tree pruning – controls regularization | 0 | 0 | 0.1 [79]; 0 [80] |
| subsample | Controls the number of samples (observations) supplied to a tree | 1 | 1 | 0.9 [80] |
| colsample bytree | Controls the number of features (variables) supplied to a tree | 1 | 0.4, 0.6, 0.8, 1.0 | 0.9 [80] |

$$\begin{aligned}\text{daily}_{\text{energy}} = {} & \beta_1 \sin_{\text{day}} + \beta_2 \cos_{\text{day}} + \beta_3 \text{weekend or holiday indicator} + \text{weekend or holiday indicator} \times (\beta_4 \text{mean temperature at 2m above surface level} \\ & + \beta_5 \text{minimum temperature at 2m above surface level} + \beta_6 \text{maximum temperature at 2m above surface level} \\ & + \beta_7 \text{mean temperature at 2m above surface level on previous day} + \beta_8 \text{mean solar radiation} + \beta_9 \text{mean solar radiation on previous day} \\ & + \beta_{10} \text{total precipitation} + \beta_{11} \text{mean wind speed} + \beta_{12} \text{maximum wind speed})\end{aligned}$$

$f_3$ (used for 30 electricity and 72 gas models):

$$\begin{aligned}\text{daily}_{\text{energy}} = {} & \beta_1 \sin_{\text{day}} + \beta_2 \cos_{\text{day}} + \beta_3 \text{weekend or holiday indicator} + \beta_4 \text{mean temperature at 2m above surface level} \\ & + \beta_5 \text{minimum temperature at 2m above surface level} + \beta_8 \text{mean solar radiation} + \beta_{10} \text{total precipitation} + \beta_{11} \text{mean wind speed} \\ & + \beta_{12} \text{maximum wind speed} + \text{weekend or holiday indicator} \times (\beta_4 \text{mean temperature at 2m above surface level} \\ & + \beta_5 \text{minimum temperature at 2m above surface level} + \beta_6 \text{maximum temperature at 2m above surface level} \\ & + \beta_7 \text{mean temperature at 2m above surface level on previous day} + \beta_8 \text{mean solar radiation} + \beta_9 \text{mean solar radiation on previous day} \\ & + \beta_{10} \text{total precipitation} + \beta_{11} \text{mean wind speed} + \beta_{12} \text{maximum wind speed})\end{aligned}$$

### B.4 Selected model performance

Table B4 shows the performance metrics of the selected models. The errors are lower than the seven machine learning algorithms tested in [79] that predicted electrical heating load (lowest training MAPE and RMSE 3.25 and 35.63, respectively; lowest testing MAPE and RMSE 5.21 and 59.75, respectively), although when compared with our gas model results (since their focus was heating demand which may be more comparable), their MAPE training and testing errors were slightly lower while their RMSE were both far higher. Nine models to predict space cooling tested in [80] showed similar or higher RMSE training errors to our final models. Our models were selected based on the ASHRAE guidelines [78] recommending monthly CV(RMSE) $<$ 15% and NMBE within $\pm$ 5%, and the sample-level final models are well within this range. CV(RMSE) and NMBE were similar to model performance in [26] (where training CV(RMSE) for electricity and gas were 3.86% and 3.19%, respectively and training NMBE for electricity and gas were 0.21% and $-$0.10%, respectively). The similarity of the training and testing errors gives us confidence that the models did not suffer unduly from overfitting and would be capable of generalising to the following winter.

**Table B4**
Predictive model performance metrics (sample level).

| Performance | Electricity | | Gas | |
|---|---|---|---|---|
| | Training | Testing | Training | Testing |
| MAPE (%) | 2.00 | 2.28 | 5.32 | 5.69 |
| RMSE (kWh) | 0.27 | 0.32 | 3.26 | 3.64 |
| R-squared (%) | 0.91 | 0.91 | 0.97 | 0.96 |
| CV(RMSE) (%) | 2.73 | 3.27 | 6.18 | 6.78 |
| NMBE (%) | 0.57 | 1.36 | 0.85 | 1.80 |

## Appendix C: Energy bill statistics.

Table C1 shows the price assumptions used based on the Energy Price Cap and Energy Price Guarantee (see Section 2.1.4 for details).

Table C2 presents more detailed statistics of how energy bills were predicted and observed to increase, along with the impact of energy consumption reduction, both with and without the government subsidy (as described in Section 3.2).

**Table C1**
Price assumptions based on local Energy Price Cap (October 2021–March 2022) [62] and local Energy Price Guarantee (October 2022–March 2023) [59,60].

| Period | | Electricity | | | Gas | | |
|---|---|---|---|---|---|---|---|
| | | Oct 2021–Mar 2022 | Oct 2022–Dec 2022 | Jan 2023–Mar 2023 | Oct 2021–Mar 22 | Oct 2022–Dec 2022 | Jan 2023–Mar 2023 |
| Standing charge (pence/day) | Mean | 23.41 | 45.59 | 43.42 | 24.88 | 28.50 | 27.12 |
| | Minimum | 22.20 | 33.20 | 31.57 | 24.88 | 28.50 | 27.12 |
| | Maximum | 26.09 | 52.60 | 50.13 | 24.88 | 28.50 | 27.12 |
| Unit cost (pence/kWh) | Mean | 19.83 | 32.58 | 32.62 | 3.87 | 9.84 | 9.84 |
| | Minimum | 19.12 | 30.71 | 30.35 | 3.77 | 9.72 | 9.71 |
| | Maximum | 20.95 | 34.27 | 34.71 | 4.00 | 10.01 | 10.01 |

**Table C2**
Average monthly change in energy bills in winter 2022/23 compared to the previous winter: predicted and observed. Subsidy is the Government subsidy of £400 for the winter for electricity and gas (total) which we split 40:60 between electricity and gas as this is approximately the average bill split. Consumption reduction impact is the unit cost multiplied by the average monthly energy consumption reduction (predicted – observed).

| | | Predicted increase in energy bills* (£/month) | | Observed increase in energy bills* (£/month) | | Consumption reduction impact (£/month) | |
|---|---|---|---|---|---|---|---|
| | | Median | IQR | Median | IQR | Median | IQR |
| *Without subsidy* | **Electricity** | 39.53 | *(29.29, 54.69)* | 31.71 | *(23.63, 43.61)* | 7.81 | *(5.66, 11.08)* |
| | **Gas** | 89.46 | *(55.68, 133.40)* | 68.68 | *(35.50, 110.40)* | 20.78 | *(20.18, 23.00)* |
| | **Total** | 128.99 | *(84.97, 188.09)* | 100.39 | *(59.13, 154.01)* | 28.60 | *(25.84, 34.09)* |
| *With subsidy* | **Electricity** | 12.86 | *(2.62, 28.02)* | 5.04 | *(−3.04, 16.94)* | – | – |
| | **Gas** | 49.46 | *(15.68, 93.40)* | 28.68 | *(−4.50, 70.40)* | – | – |
| | **Total** | 62.32 | *(18.30, 121.42)* | 33.72 | *(−7.54, 87.34)* | – | – |

## Appendix D: Energy reduction quintiles

### *D.1 Energy reduction statistics*

The energy reduction quintiles are defined by the quintiles of total energy percentage reduction. Quintile 5 reduced consumption by the highest amount (over 23.8%) while quintile 1 increased consumption by more than 0.1%. Table D1 provides some basic statistics about the energy reduction of each quintile group.

**Table D1**
Energy reduction statistics for each energy reduction quintile.

| Energy reduction quintile | | | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|---|---|
| % total energy reduction | Range (definition) | | (−107.2, −0.1) | [−0.1, 7.1) | [7.1, 14.0) | [14.0, 23.8) | [23.8, 86.2) |
| % reduction | Total | Median | −5.8 | 3.8 | 10.5 | 18.4 | 32.3 |
| | | IQR | (−13.1, 2.7) | (1.9, 5.4) | (8.8, 12.1) | (16.1, 21.0) | (27.4, 40.3) |
| | Gas | Median | −7.7 | 3.3 | 10.7 | 19.6 | 35.1 |
| | | IQR | (−16.5, −3.4) | (1.0, 5.5) | (8.2, 13.1) | (16.5, 22.6) | (29.4, 45.2) |
| | Electricity | Median | 1.9 | 5.9 | 8.9 | 11.8 | 14.6 |
| | | IQR | 1.9 | 5.9 | 8.9 | 11.8 | 14.6 |
| kWh reduction | Total | Median | −2.8 | 2.1 | 6.3 | 11.5 | 18.7 |
| | | IQR | (−5.8, −1.2) | (0.9, 3.4) | (4.4, 8.8) | (8.0, 15.7) | (12.9, 27.0) |
| | Gas | Median | −3.0 | 1.5 | 5.3 | 10.0 | 16.8 |
| | | IQR | (−6.0, −1.3) | (0.4, 3.0) | (3.4, 7.9) | (6.8, 14.2) | (11.5, 25.1) |
| | Electricity | Median | 0.1 | 0.5 | 0.7 | 0.9 | 1.0 |
| | | IQR | (−0.7, 0.8) | (−0.1, 1.2) | (0.0, 1.7) | (0.2, 2.0) | (0.3, 2.5) |

### *D.2 Number of energy-reduction actions performed 'a lot more' in winter 2022/23 than in winter 2021/22*

The 2023 SERL energy survey question A6 asked respondents how often each of 16 actions were performed compared with the previous winter. Fig. D1 shows the number of actions participants in each energy-saving quintile reported doing 'a lot more', 'a little more', *etc.* compared with the previous winter. Those who saved the most energy (energy reduction quintile 5) reported doing more actions 'a lot more' than the rest of the sample, and that doing more actions 'a lot more' than last winter increased with saver quintile (from 2.1 actions on average for quintile 1 up to 4.4 actions on average for quintile 5). Conversely, the greatest energy reducers tended to report doing fewer actions 'about the same' (7.1 on average) compared to the other quintiles (up to 9.3 actions on average for quintile 1).

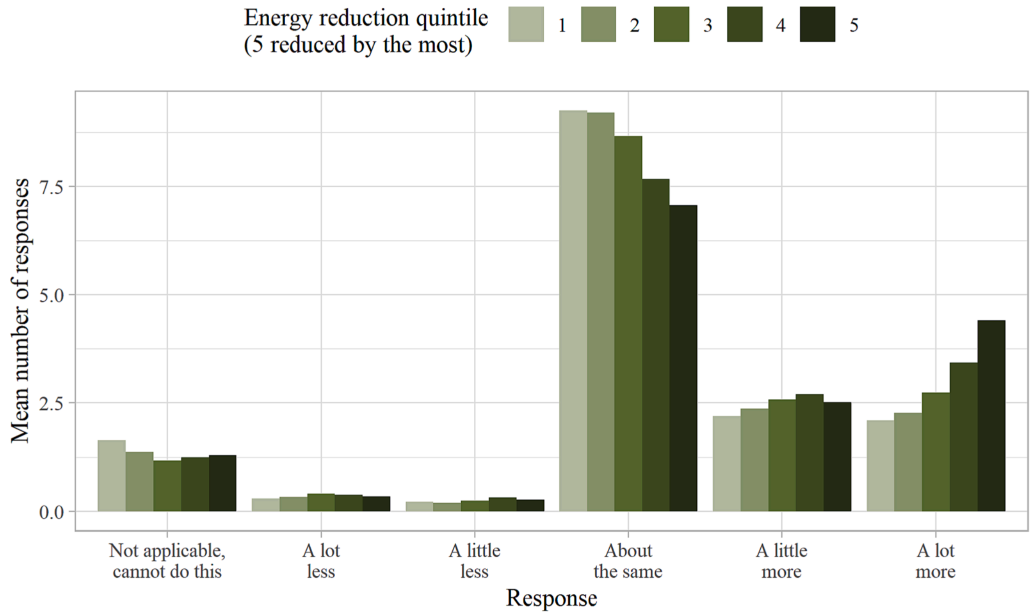


**Fig. D1.** Mean number of responses by energy reduction quintile (see text) of each type to question A6 comprising 16 energy-saving actions. Participants were asked to what extent these actions were done compared with the previous winter.

### *D.3 Risk of fuel poverty and underheating-related issues*

Table D2 shows the results of risk ratio analysis for how much more likely energy reduction quintile 5 were to have each of the variables in column 1 than the rest of the sample. All variables showed significance ($p < 0.05$) except for substantial mould which did not establish a significant difference between quintile 5 and quintiles 1–4.

**Table D2**
Fuel poverty and underheating-related variable risk ratios for quintile 5 (Q5) versus the rest of the sample (Q1-4). Risk ratio of 1 indicates that quintile 5 had the same 'risk' of being in the survey group as the rest of the sample. Risk ratio > 1 implies the greatest savers were more likely to be in a given group than the rest of the sample. ***($p < 0.001$), **($0.001 \le p < 0.01$), *($0.01 \le p < 0.05$).

| Fuel poverty/underheating survey variable | % (N) | | Risk ratio | Risk ratio 95% CI | p-value |
|---|---|---|---|---|---|
| | Q(1-4) | Q5 | | | |
| Low financial wellbeing*** | 24.6% (531) | 33.9% (178) | 1.377 | (1.20, 1.58) | **<0.001** |
| Very or fairly difficult to meet heating/fuel costs*** | 20.6% (299) | 31.9% (105) | 1.546 | (1.28, 1.86) | **<0.001** |
| Unable to keep comfortably warm in the living room*** | 9.6% (210) | 21.7% (112) | 2.250 | (1.83, 2.77) | **<0.001** |
| Problems with condensation, mould or damp* | 30.2% (654) | 34.9% (183) | 1.158 | (1.01, 1.32) | **0.036** |
| Substantial mould on the windows, in the bathroom, on walls or on any furnishings | 3.1% (63) | 4.1% (20) | 1.345 | (0.82, 2.29) | 0.255 |

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