Recent decreases in domestic energy consumption in the United Kingdom attributed to human influence on the climate

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Abstract
Domestic energy consumption in the United Kingdom depends on both meteorological and socio-economic factors. The former are dominated by the effect of temperature during the colder months of the year, with the energy demand increasing as the temperature decreases. Warming of the UK climate under the influence of anthropogenic forcings is therefore expected to lead to a reduction in domestic energy consumption. Here, we present an end-to-end attribution study that investigates whether the anthropogenic effect on consumption is already evident in the United Kingdom. We analyse data of gas and electricity use in UK households during 2008–2019 and use a simple linear model to express the temperature dependence. Uncertainties in the resulting transfer functions are derived with a recent methodology, originally introduced for downscaling purposes, but adapted here for use in impact studies. The transfer functions are applied to temperature data from simulations with and without the effect of human influence on the climate, generated by 11 state-of-the-art climate models. We thus assess the anthropogenic impact on energy consumption during the reference period by comparing it with what it might have been in a climate without anthropogenic climate change, but at the same level of adaptation. We find that without human influence on the climate, UK households would consume on average about 1,400 kWh more per year, which would increase the annual energy bills by about 70 GBP. Our attribution assessment provides useful evidence of an impact that has already emerged, which can help inform UK’s adaptation plans as the climate continues to warm.

Keywords
climate change attribution, climate change impacts, general circulation models, UK energy consumption

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1 | INTRODUCTION

There is strong interconnection between energy consumption and climate change driven by human activity. On the one hand, energy use is a major contributor to anthropogenic greenhouse gas emissions (Wier et al., 2001; Blanco et al., 2014). On the other hand, a warming climate may heavily influence energy systems via, for example, changes in demand peaks linked to the changing frequency of weather extremes, impacts on hydropower generation linked to changes in water availability, or impacts on the efficiency of power transmission (Ebinger and Vegara, 2011; Carleton and Hsiang, 2016). A reduction in energy demand is deemed imperative for the success of limiting global warming to 2 or 1.5°C (Semieniuk et al., 2021). This, however, is challenging as adaptation solutions often rely on more intense energy demand, for example, for domestic heating or cooling (Davis and Gertler, 2015; Biardeau et al., 2020).

The relationship between energy demand and temperature has been shown to display a characteristic U-shape that reflects a rising cooling demand at higher temperatures and heating demand at lower temperatures (Isaac and van Vuuren, 2009; Auffhammer and Aroonruengsawat, 2011). While a warming climate is anticipated to affect demand, the impacts need to be considered both in the context of different countries or regions (van Ruijven et al., 2019; Zhu et al., 2019), as well as different sectors like, for example, the residential sector, industry, the commercial sector, or public services. Household energy consumption plays a key role in man-made climate change as it constitutes 72% of the total greenhouse gas emissions on a global level (Hertwich and Peters, 2009). Our study focuses on domestic consumption in the United Kingdom, partitioned between gas and electricity, the two main energy types used at present. Anthropogenic warming in the wider region of northern Europe has already been detected (Stott et al., 2010) and seasonal temperatures in the United Kingdom are projected to further increase in the coming 50 years by as much as 4 or 5°C relative to the period 1981–2000 (Lowe et al., 2018).

Heating demand overshadows cooling demand in UK households, and this is unlikely to change significantly during the course of the century (Collins et al., 2010) despite the steeply increasing frequency of summer heatwaves (Christidis et al., 2020). Hence, one might expect that warmer winters may drive an overall reduction in domestic energy consumption, at least until air-conditioning becomes more common in British homes. Given that human activity has made UK winters about a degree warmer (Christidis et al., 2018), it is important to ask whether a human-driven reduction in household energy is already manifest. While the science of climate change attribution has been developing research methods to address such questions, it has largely concentrated on meteorological variables establishing, for example, how mean or extreme temperature and rainfall have been impacted by anthropogenic forcings (Bindoff et al., 2013). Taking a step forward, end-to-end attribution studies linking weather variables to actual impacts (Otto, 2016) would provide essential scientific evidence that can inform decision-making and encourage adaptation planning. However, unlike meteorological data, long and reliable records of impact variables are more difficult to obtain and as a result such studies still remain scarce. Here, we present a simple attribution methodology and use it to analyse recent changes in the UK’s domestic energy consumption, though we envisage our approach could be adopted and applied to a range of other weather-driven impacts.

Using the basic framework of risk-based attribution studies (Stott et al., 2016), we assess the impact of anthropogenic forcings on domestic energy consumption by comparing climate model simulations of the actual climate, influenced by all external forcings (ALL), with simulations of a hypothetical natural world (NAT) without the effect of human influence. As the models do not provide energy diagnostic variables, we develop transfer functions to estimate consumption from modelled temperature data, given that temperature is the dominant weather driver of electricity and gas demand in the United Kingdom (Thornton et al., 2016). Apart from weather, energy demand is also affected in the long run by socio-economic changes (Psiloglou et al., 2009; Thornton et al., 2016). Consequently, our analysis typifies the mean level of adaptation in the United Kingdom during the reference 12-year period considered in the study (2008–2019) and our findings should not be extrapolated to other periods, without accounting for possible changes in socio-economic or demographic factors.

The remainder of the paper is structured as follows: Section 2 presents the observed and modelled temperature data and the domestic gas and electricity consumption data used in the study. The derivation of the transfer functions and the attribution methodology are discussed in Section 3. Results are shown in Section 4, including estimated changes in both mean and high levels of energy consumption due to anthropogenic climate change and how this translates to cost reduction per household. Finally, some concluding remarks are given in Section 5.
2 | DATA

2.1 | Observed and simulated temperature data

The bulk of heating demand for UK households is anticipated to fall in the colder months of the year, which we specify here as January–March and October–December. We estimate the UK mean temperature averaged over these 6 months for different years using observational and modelled data. We employ temperature data from HadUK-Grid (Hollis et al., 2019), a dataset constructed with observations from a network of meteorological stations across the United Kingdom and interpolated onto a uniform grid to provide full land coverage. Timeseries of observed temperature anomalies since 1884 (Figure 1a) reveal a warming trend of 0.96 °C/decade.

UK mean temperature anomalies over land are also computed with data from 11 coupled climate models that took part in the World Climate Research Programme’s Coupled Model Intercomparison Project phase 6 (CMIP6; Eyring et al., 2016). We use models that provided simulations with both natural and anthropogenic forcings (ALL) and with natural forcings only (NAT). The NAT experiment includes changes in volcanic aerosols and the solar irradiance, whereas the ALL experiment also includes historical changes in well-mixed greenhouse gases, aerosols, ozone and land use. Unlike the NAT simulations, which end in year 2020, the ALL simulations end in year 2014 and are extended to present-day with the medium emissions scenario SSP2-4.5 (Riahi et al., 2017). More details about the models are given in the supporting information Table S1. In total, the models provide 58 ALL and 64 NAT simulations. In common with previous attribution studies, temperature anomalies are constructed relative to the 1901–1930 baseline which is used as a proxy of the pre-industrial climate. The timeseries of the model simulations are also plotted in Figure 1a. In agreement with the observations, the ALL simulations suggest a positive trend over the observational period with a mean of 0.85 °C/decade, while the NAT experiment does not indicate a notable long-term change and yields a mean trend of 0.01 °C/decade.

FIGURE 1 UK mean temperature anomalies averaged over the 6 months January–March and October–December. (a) Timeseries of the temperature anomalies computed with HadUK-Grid (black), 58 ALL simulations (red), and 64 NAT simulations (green). The vertical dashed lines mark the analysis period 2008–2019. (b) Normalized distributions of the temperature anomaly for the observational period 1884–2019 constructed with data from HadUK-Grid (histogram) and the ALL simulations (red line). The p-value of the Kolmogorov–Smirnov test indicates no significant difference between the distributions. (c) Trends over the observational period from individual ALL simulations (vertical bars) and HadUK-Grid (black dashed line). The red dashed line corresponds to the ALL ensemble mean. (d) Power spectra from HadUK-Grid (black) and the ALL simulations (orange). (e) Quantile–quantile plots for each of the ALL simulations. Temperature anomalies are relative to 1901–1930.
As attribution assessments rely on modelled data, it is essential to establish that the models we use are fit for purpose. We therefore carry out a number of standard evaluation tests for multi-model ensembles (Christidis et al., 2020) to examine the level of consistency between the CMIP6 ALL simulations of the historical climate and the HadUK-Grid observations. First, we construct the distribution of the temperature anomaly over the period 1884–2019 using observations and the multi-model ALL ensemble (Figure 1b). A Kolmogorov–Smirnov test suggests that the ALL distribution is indistinguishable from the observed one (p-value >0.1). The observed trend over the same period is also within the range of the trends from individual simulations and in good agreement with the ensemble mean (Figure 1c). We next use power spectra to assess the modelled variability across different timescales and again find that the observed variability lies within the range of the modelled spectra (Figure 1d). Finally, quantile–quantile plots for each simulation do not raise concerns about the modelled representation of the UK temperature (Figure 1e). In addition, we also confirm that the modelled representation of the North Atlantic Oscillation (NAO) agrees well with the NAO based on HadSLP2 sea-level pressure observations (Allan and Ansell, 2006; supporting information Figure S1). We therefore conclude that the modelled data used here are reliable and certainly suitable for our analysis.

2.2 | Energy consumption

The UK Government publishes tables with annual consumption data for different sectors, which provide the energy data used in this study. Energy consumption is driven by the seasonal cycle, temperature variability and underlying trends. Apart from actual consumption, the Government’s tables also include consumption figures with the seasonal cycle and temperature variability effects removed, as the residual offers a clearer view of the underpinning trend linked to socio-economic changes. This adjustment is performed in two steps. First, for each fuel type, the monthly consumption is multiplied by a given factor to account for temperature departures from the 1981 to 2010 long-term average. Subsequently, the seasonal adjustment is performed using an ARIMA model. The adjustment process is described in more detail in Rahman (2011). The temperature adjustment is based on observational temperature data from a network of 17 stations. Using a more complete network would be beneficial but was found to have a negligible impact on the adjusted consumption estimates (McCarthy et al., 2014).

While the underlying trends after adjustment are important for policy purposes, it is precisely the temperature component of consumption that is removed during the adjustment, which is key to understanding consumption changes as the climate warms. This temperature-related component can be easily inferred by the difference between the actual and the temperature-adjusted consumption values. Using the published Government data for years 2008–2019, we calculate the average domestic temperature-related gas and electricity consumption per household by subtracting the temperature-adjusted from the actual consumption. The resulting values are listed in the supporting information Table S2. Years with positive values indicate that more energy was used than anticipated, as a result of anomalously cold temperatures in the United Kingdom, while the opposite is the case for negative values. Table S2 shows that most years in the reference period have negative temperature-related consumption which could be indicative of the effect of long-term warming, while positive values are linked to the cold winters of 2010 and 2013.

We next investigate the relationship between the temperature-related consumption and the mean January–March and October–December temperature. Developing a simple model that describes this relationship, would allow us to derive temperature-related consumption estimates from CMIP6 temperature data. It should be stressed again that as these relationships are derived from data in years 2008–2019, the consumption estimates reflect the mean level of adaptation in this near-present period only.

3 | METHODS

3.1 | Transfer functions

The dependence of the temperature-related electricity (ELC) and gas (GAS) consumption per household on the mean temperature anomaly for the cold months of the year can be described well by a simple linear relationship, as illustrated in Figure 2a–c. We employ the approach of Christidis et al. (2020) to develop transfer functions that estimate consumption from temperature anomalies and account for the effect of different sources of uncertainty. The approach was originally developed as a statistical downscaling technique to relate local to regional temperatures, but we demonstrate here how it can be adapted for use in impact studies. Using ELC as an example, its dependence on the mean temperature anomaly of the cold months, ΔT, can be estimated with the linear model:

\[
ELC = \alpha_0 + \alpha_1 \Delta T
\]  

(1)

The regression coefficients are computed with ordinary least squares applied to observed annual values of
ELC and $\Delta T$ during 2008–2019. We find a strong linear dependence of energy consumption on the temperature of the colder months (correlation coefficient $-0.96$). We also confirm that inclusion of the warmer months (i.e., using the annual mean temperature as a predictor) would not strengthen the anticorrelation, suggesting that heating during the colder months indeed dominates the temperature-related consumption. Using the mathematical formulas of Christidis et al. (2020), also given in the supporting information Appendix S1, we next compute confidence intervals for the response variable for different quantiles of the $t$ distribution. These are represented by the orange lines in Figure 2d for the 1st–99th percentiles. Hence, instead of a single transfer function, we now have a set of 100 alternative functions to account for the range of possible values of the response variable (ELC).

The same procedure is applied to GAS and the sum ELC + GAS.

As we only have a limited number of 12 years for our regression model, we also need to account for the effect of sampling uncertainty. This is done by a Monte Carlo bootstrapping procedure, which resamples the observed data 1,000 times and yields 1,000 alternative transfer functions represented by the grey lines in Figure 2g–i. Each of these grey lines has an associated set of 100 alternative functions to describe the uncertainty in the response. In conclusion, for each type of energy (ELC, GAS, ELC + GAS) we have a set of 100 transfer functions to estimate consumption from CMIP6 models, and additional sets from bootstrapping to assess the sampling uncertainty. While our transfer functions model the consumption dependence on temperature over the entire
United Kingdom, regional functions may also be developed in a similar way, provided that regional energy data are available, and the models represent well temperatures over smaller areas.

### 3.2 Attribution

Risk-based attribution enables us to compare the distribution of energy consumption in years 2008–2019 with what it might have been in a colder natural world without anthropogenic climate change, but under the same level of adaptation. Given the anti-correlation between temperature and consumption, we expect the NAT distribution to shift towards higher consumption compared to ALL. Apart from changes in the mean demand, probability estimates of high consumption levels can also be obtained from the ALL and NAT distributions to assess the impact of human influence in colder years. To construct the ALL distribution, we extract years 2008–2019 from the 58 ALL simulations and apply our transfer functions to modelled temperature anomalies for all the years in this period (58 simulations × 12 years). As the NAT climate is stationary in the long run, we construct the NAT distribution using all years since 1884 (64 simulations × 137 years). As mentioned earlier, we compute temperature anomalies relative to 1901–1930, which are expected to account for most of the anthropogenic effect. The energy consumption estimates, however, use the period 1981–2010 to establish the “normal” (baseline) consumption levels, which is already influenced by human activity. This simply means that as the NAT climate is colder than this baseline, the NAT distribution of energy consumption will not be centred at zero but will be shifted towards positive values (i.e., higher demand than normal in the colder NAT climate).

### 4 RESULTS

#### 4.1 Changes in the distribution of energy consumption

We first construct normalized probability distributions of the temperature-related energy consumption from model-based energy estimates, by applying the 100 transfer functions (Figure 2d–f) to ALL and NAT temperature anomalies. The resulting distributions are illustrated in Figure 3. As expected, if the 2008–2019 UK climate reverted to the colder NAT conditions (but under the same level of adaptation), consumption would increase. The ALL distribution is somewhat broader than the NAT, which is mainly due to the uncertainty in the temperature trend across different models. The mean increase in consumption in the colder NAT climate (NAT minus ALL) calculated as the difference between the 50th percentile of the energy distributions is reported in Table 1. Using the alternative transfer function sets from bootstrapping, we also recalculate the mean change and estimate the associated 5–95% uncertainty range. The CMIP6 models suggest that anthropogenic climate change leads to a mean decrease in the annual energy consumption of 74 and 1,305 kWh per household per year for ELC and GAS, respectively.

![Figure 3](image_url)

**FIGURE 3** Change in (a) ELC, (b) GAS and (c) combined ELC + GAS consumption per UK household due to anthropogenic forcings. Normalized distributions of the energy consumption are plotted with (red) and without (green) the effect of human influence. The distributions are constructed using consumption estimates based on temperature data from the CMIP6 ALL and NAT simulations. The vertical lines mark the 50th percentile. Higher consumption is evident in the NAT climate.

#### Table 1

|         | Change in consumption | Uncertainty range |
|---------|-----------------------|-------------------|
| ELC     | 74                    | 65–95             |
| GAS     | 1,305                 | 1,136–1,664       |
| ELC + GAS | 1,381            | 1,157–1,774       |
4.2 | Changes in high consumption levels

While changes in the mean consumption are useful, it is also important to understand changes in years when energy demand is expected to be high. Using different thresholds of energy consumption, we estimate the probability of exceeding them in the ALL and NAT climate and plot the resulting return times (inverse probability) against the different energy thresholds (Figure 4). The results reveal a notable reduction in household consumption across all return times. Common levels of consumption that would be expected to be exceeded every other year (return time = 2) in the NAT world are now less frequent with an estimated return time for ELC + GAS of 7–17 years. Higher levels of consumption exceeded, for example, every 50 years in the NAT world, now have a near-zero likelihood, as such events are associated with cold temperatures that have become extremely rare in our warmer climate. High levels of energy demand in the NAT climate are in other words extremely unlikely to be seen in UK’s warmer climate.

4.3 | Savings in a warmer climate

We finally estimate how the reduction in energy consumption linked to warming translates into savings per UK household. We use the official published tables of annual domestic ELC and GAS bills to calculate the mean cost per household per kWh during the decade 2010–2019. The energy cost averaged over this reference decade amounts to 15.6 pence for ELC and 4.5 pence for GAS. Applying these values to the estimated consumption reduction (Table 1), we compute the mean savings per household illustrated in Figure 5. Our analysis suggests that during 2010–2019 UK’s annual energy cost per household was on average 70.2 GBP lower (11.5 for ELC and 58.7 for GAS) relative to the natural climate.

5 | DISCUSSION

Although links between domestic energy demand and weather have been explored before and used, for example, in the context of seasonal forecasting for demand planning (Thornton et al., 2019), there is a lack of attribution perspectives in the literature on the impact of climate change that may have already been materialized. We estimate here that in recent years the annual domestic electricity and gas consumption per household in the United Kingdom has decreased by about 1,400 kWh due to human influence on the climate, leading to a decrease in energy bills of about 70 GBP. There are several uncertainties in the above estimates, like, for example, modelling dependencies, sampling effects, changes in adaptation, or

![Figure 4](image1.png)  
**Figure 4** Return time (inverse probability) estimates corresponding to different levels of annual domestic (a) ELC, (b) GAS, and (c) combined ELC + GAS consumption per UK household with (ALL, red) and without (NAT, green) human influence on the climate. The solid lines mark the best estimate (50th percentile) and the coloured areas the 5–95% uncertainty range. The horizontal arrows in Panel (c) mark the change in return time for events that occurred 1-in-2 and 1-in-50 years in the NAT climate.

![Figure 5](image2.png)  
**Figure 5** Estimated mean decrease in the annual cost of ELC and GAS per UK household during 2010–2019. The horizontal lines mark the best estimate and the coloured boxes the 5–95% uncertainty range.
uncertainties in the Government’s estimates of temperature-related consumption. Our methodology provides a range of possible outcomes that account for much of the uncertainty effects and we suggest that our results can adequately describe the overall change during the reference period. Future work may also consider application of our methodology to different periods, individual seasons, or regions within the United Kingdom.

While energy consumption is shown to be strongly linked to the colder months of the year, the effect of warm summers may become more prominent in the future, as new adaptation measures may be required to account for the risk of overheating in UK homes (Gupta and Gregg, 2012). It should also be stressed that although our results refer to a very recent period, they may still not be typical of years 2020–2021, when the COVID-19 pandemic had a strong impact on energy systems (Bertram et al., 2021) and its effect may also be reflected in domestic consumption, as homeworking has become commonplace. Despite adaptation considerations, our study provides valuable evidence of a clear relationship between anthropogenic climate change and domestic energy consumption in recent years, adding to the scientific basis that can aid decision and policymaking.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

AUTHOR CONTRIBUTIONS

Nikolaos Christidis: Conceptualization; data curation; formal analysis; methodology; software; writing-original draft; writing-review and editing. Mark McCarthy: Methodology; supervision. Peter A. Stott: Supervision.

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ENDNOTES

1 https://www.gov.uk/government/statistics/energy-consumption-in-the-uk.

2 https://www.gov.uk/government/statistical-data-sets/annual-domestic-energy-price-statistics.

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