The Effect of High Gas Prices on European Mortality

Research Project Report

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Abstract

Inability to afford natural gas and electricity, if used for heating, can lead to a variety of medical conditions. We analyze the effect of a change in the price of natural gas on mortality at different European regional levels, conditional on the temperature in the respective region. To conduct this analysis, we use both official and remotely sensed data and compare standard panel models with fixed effects estimates to the results derived from multi-level models estimated with bayesian techniques.

Supplementary material for this project, including all code and all plots not printed in this submission, is available on GitHub.

Contents

A. Introduction

The Russian invasion of Ukraine in February 2022 took the global community by surprise. The beginning of this war overshadowed the COVID-19 pandemic and confronted European policy-makers with huge challenges. Europe's energy supply was not the most acute problem, but it was one of the biggest for the upcoming months. The energy consumption of many European countries is based to a large extent on natural gas (Eurostat, 2023b) and cheap Siberian gas has led to a strong dependence on Russia over the years. At the beginning, the commitment to secure supply had to be kept, but subsequently European politics had to struggle with the problem of rising energy prices. The disruption of the natural gas supply after Russia's invasion led to an increase of heating prices and pushed lots of additional European households into "fuel poverty". Many families in Europe cannot afford to pay their heating bills during winter and therefore cannot adequately heat their homes. These families are considered to live in energy poverty as their heating costs are so high relatively to their income. In 2021, 7% of European households could not afford to keep their homes adequately warm and according to Eurostat (2023c) this share increased to 9% by 2022. High energy prices introduce a dilemma to households because they must either endure cold homes to save on heating costs or sacrifice other expenses to afford their heating bills. Opting for reduced heating, exposes them to lower ambient temperatures, which have been associated with significantly higher risk of cardiovascular and respiratory disease (World Health Organization [WHO], 2018). On the other hand, if families don't decrease their heating usage as prices rise, their energy bills will escalate, leaving less money for crucial expenditures like food and healthcare, also impacting mortality. Consequently, increasing mortality can arise from higher energy prices.

This project report estimates the effect of energy prices on mortality in Europe. A growing literature describes the impact of energy prices on mortality (Chirakijja et al., 2021). Our approach is tested on data of European countries and regions from 2014 to 2022, where we exclude the period of March 2020 up until March 2022 due to Covid. The project sheds light on the health implications that arise when households struggle to afford adequate heating due to soaring energy prices. Our contribution is twofold. First our research tries to provide a first data-driven assessment of the relationship between energy poverty and mortality in Europe, establishing a link between gas and electricity prices, and public health outcomes. Secondly, the empirical evidence, presented in this report, could inform the policy debate on price fixing versus income subsidies in the face of high energy prices. Overall, our study is intended to offer valuable insights into the effectiveness of policy measures in alleviating energy poverty and its associated health risks.

Our empirical strategy is based on two stages. We first investigate the relationship with classic frequentist panel data methods, controlling for unobserved heterogeneity with time and unit fixed effects. In a second approach we use Bayesian approaches to estimate the two way fixed effect model. Then, we leverage the hierachical structure of our data and estimate a multilevel model with bayesian techniques.

B. Data

Our analysis is centered on Europe during the period from 2014 to 2022. We construct a weekly panel data set encompassing 23 European countries, comprising both monthly country-level (gas price) and weekly region-level information (temperature and mortality). We exclude the period from the first week of march 2020 up until the first week of march 2022 to account for COVID. Our final data set at NUTS-3 level contains 281,505 observations for 902 different NUTS regions.

B.1. Dependent Variable

The dependent variable in our analysis is an age-adjusted mortality measure. In order to eliminate the age structure of individual regions as a factor influencing death rates, we compute an age-adjusted mortality rate for each region and time similar to the approach of Chirakijja et al. (2021). Specifically, we calculate mortality, the ratio of deaths to the population, for each age group, and weight them by using population-level population shares for the respective age groups. We impose one fixed population age structure on each region and scale the death rates in all age groups accordingly. Using this procedure, we can account for differences and changes in the demographic structure for the respective NUTS-regions. The weekly data on deaths and population shares at NUTS-3, 2, 1, and 0-level are extracted from Eurostat (2023a) and Eurostat (2023d). Note that the nested observations at different levels do not perfectly match up. Thus aggregating NUTS-3 at the country level does not exactly line up with the NUTS-0 figures, due to reporting issues.

B.2. Independent Variables

For our analysis, we adopt gas and electricity prices as the key energy price indicators. The data on household prices for electricity and gas were kindly provided by E-Control form the HEPI (2023) research project. The study provides information on prices in cents per kilowatt-hour (kWh) in PPPs (EU27 = 1) covering European capital cities. By utilizing the end-user prices for electricity and gas in these capitals, we approximate the energy prices within the respective countries for our research project.

Additionally, we use the daily weather information from Copernicus (2023), utilizing the remotely sensed E-OBS daily gridded meteorological data set. Subsequently, we extract the weekly average temperature for each NUTS-3 region. To avoid parametric assumptions about the temperature-mortality relationship, we employ the methodology by Barreca et al. (2016) which involves constructing temperature bins.

C. Models and Results

We want to identify the impact of gas prices on mortality. Our identification strategy is twofold. We first estimate the relationship with a set of classic panel data methods. We control for unobserved heterogeneity by employing week and NUTS region fixed effects.

C.1. Frequentist Estimation

We do not include temperature as a continuous variable. The specification would be predicted on a parametric specification of the temperature-mortality relationship (i.e. linear, quadratic, or higher order polynomials for temperature). To facilitate interpretation we recode temperature as categorical variable in eight bins (<0, 0-5, 5-10, 10-15, 15-20, 20-25, 25-30, >30). The assumption behind this variable transformation is that the mortality effects are constant for each bin. We estimate the following relationship.

$$\begin{aligned} \text{Mortality}_{it} = \text{Region}_i + \text{Time}_t + \gamma_j \sum_{j}^{8} \text{Temperature}_{it,j} + \beta_1 \text{ GasPrice}_{it} \\ + \delta_j \sum_{j}^{8} \text{Temperature}_{it,j} * \text{GasPrice}_{it} + \varepsilon_{it} \end{aligned} \tag{B1}$$

In all specifications we use the lagged logarithm of the gas price. Based on Auffhammer and Rubin (2018) we expect households to react with a two month lag to price changes. As we have weekly data, we use the 8^{th} lag of the logarithm of gas price. To account for COVID we exclude the period from the beginning of 1.3.2020 up until 1.3.2022 in all specifications.

C.1.1. The effect of energy prices on mortality

Table 2 presents the results of regressing the lagged gas and electricity prices on mortality. All specifications include NUTS-3 and time fixed effects. Standard errors are clustered at the

NUTS-3 level. We find a strong and statistically significant association between electricity prices and mortality. However gas prices are not associated with higher mortality. Column 3 and 4 present the results including a winter dummy, to investigate differential effects among seasons. While the effect of electricity prices increases during the cold season, there is no evidence for a stronger impact of gas prices on mortality during the winter.

C.1.2. Energy prices, temperature and mortality

Table 1 presents the first baseline panel data methods with temperature. All specifications include NUTS-3 and time fixed effects. Standard errors are clustered at the NUTS-3 level. Column (1) presents the results for the temperature-mortality relationship, excluding energy prices. The baseline bin is 10-15 degrees. The temperature mortality relationship is U-shaped. Low temperatures increase mortality, moderate ones reduce them, and high temperatures increase mortality. A week with an average temperature of above 30 degrees yields on average 4.434 more deaths per 100.000 compared to a week with 10-15 degrees.

Next we investigate how energy prices moderate the temperature-mortality relationship. Column 2 presents the results when we interact gas prices with temperature. We do not find evidence, that a high gas price in combination with low temperatures increases mortality. However gas prices seem to statistically significantly increase the effect of heat. For temperatures above 30 degrees, we find that a one percent increase in gas prices is associated with 2.69 more deaths per 100.000. Higher energy prices, making adaptive measures more expensive, could thus amplify the mortality effects of heat.

Column 3 reports the results when we interact the electricity price and temperature. Higher electricity prices seem to increase mortality. The differential impact of electricity prices on mortality varies significantly with temperature bins. However, there is no evidence that a high electricity price increases mortality for both extremely high and low temperatures. For all bins however, a higher electricity price is associated with higher mortality.

C.2. Bayesian Estimation

C.2.1. Two Way Fixed Effects Model

We now estimate the baseline model specification F1 with bayesian techniques. We restricted the sample to the country level to alleviate computational issues. The number of observations at the country level is comparatively small with 8607 observations for 26 countries. This has, however, significant drawback, as temperature data is at the country level and thus might be lacking granularity. We use the standard priors from the rstanarm package. For the coefficients, the priors are centered at zero, and have a variance of 0.00045-0.00029, as they are adjusted according to the variation of the outcome, age-adjusted mortality per capita. At the country level there were no observations with average temperatures above 30 degrees. Thus we aggregated the last two bins ">30" and "25-30" to ">25".

$$\text{Mortality}_{it} = \text{Country}_i + \text{Time}_t + \gamma_j \sum_j^7 \text{Temperature}_{it,j} + \beta_2 \,\text{GasPrice}_{it} + \delta_j \sum_j^7 \text{Temperature}_{it,j} * \text{GasPrice}_{it} + \varepsilon_{it} \quad \text{(B1)}$$

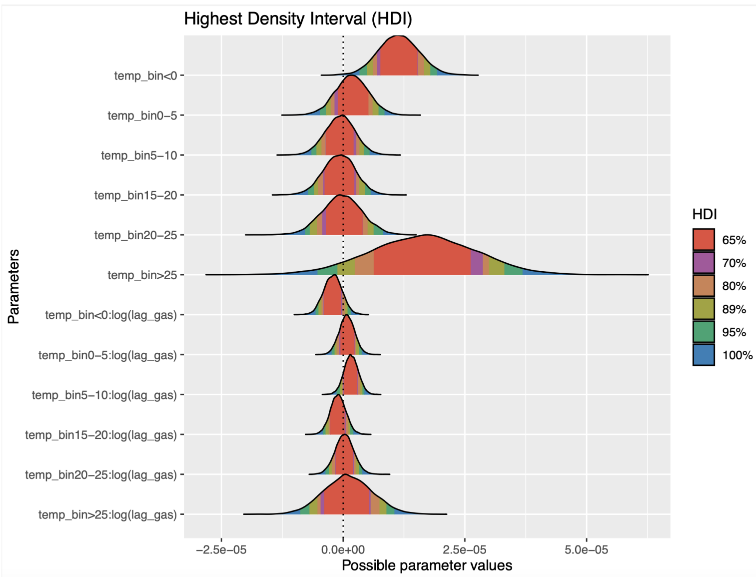

Figure 1: HDI of coefficiens

Figure 1 displays the highest density interval for the coefficients of interest. Both extremely high and very low temperatures are strongly associated with increased mortality. However we do not find evidence that the interaction of gas prices and temperature increases mortality. This contrasts to the frequentist estimation at NUTS-3 level, where we found a strong and significant impact of high temperatures and gas prices. For the lowest temperatures, there even seems to be suggestive evidence for a negative effect of gas prices on temperature. A posterior predictive check, which can be found in the appendix, also highlighted some deficiencies in the ability of the model to replicate the actual data.

C.2.2. A Very Simple Bayesian Multi-Level Model

We begin by specifying arguably the simplest multilevel model that we can apply to our research question. To do this, we first filter the data so that only observations where the weekly mean temperature is below 5 degrees Celsius remain. The data contains 5,438 observations. We then estimate[1]:

$$\begin{aligned}\text{Mortality}_{i,c_i,t} = {} & \text{Time}_t + \\ & A^{c_i} + \\ & B_1^{c_i} \cdot \log(\text{Gas Price})_{i,c_i,t} + \\ & E_{i,c_i,t},\end{aligned} \tag{B2}$$

where i denotes the region (NUTS 1), c_i denotes the country the region is in, and t denotes the week. In addition, A^{c_i} is a country-specific intercept, while $B_1^{c_i}$ is a country-specific slope coefficient. We denote Bayesian coefficients by capital letters to distinguish them from the coefficients from the frequentist models before and to honor their probabilistic character.

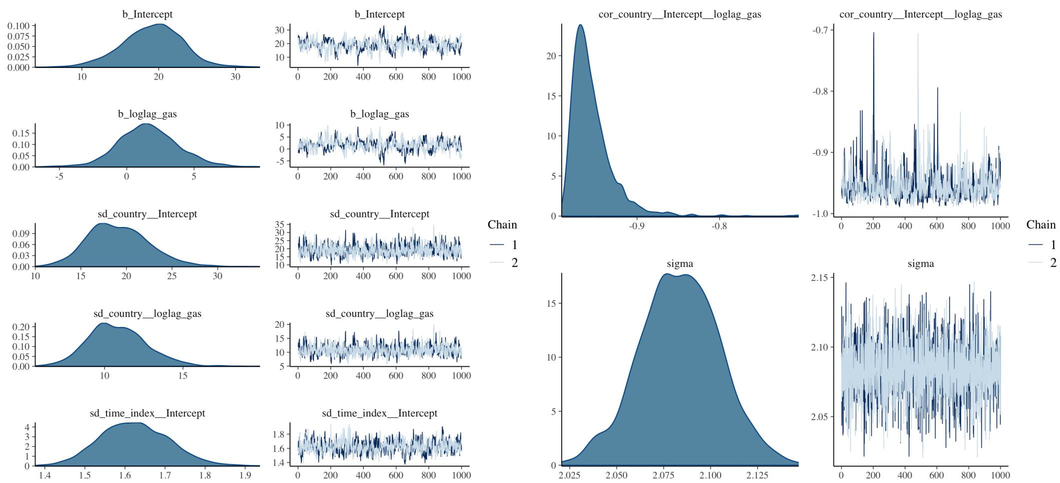

Figure 2: Trace and density plots of Model B2.

From the above trace plots, we can see that the two chains we ran have mixed at least decently,

[1] In our code, this model is called `model7g`.

and definitely much better than in our copious unsuccessful tries. In addition, there are no signs of divergence, indicating that we can interpret the values that we get from our coefficients.

Note that we use the default priors from the brms package, which includes flat priors on the population level coefficient. This may not be plausible, however, trying different priors did not affect our posterior estimates strongly while stronger priors sometimes led to computational issues.

In this model, there is only one population level coefficient, and its highest density intervals can be seen in Figure 3. We get a posterior distribution whose probability mass sits chiefly to the right of the zero mark, but whose highest density intervals of 65 or more percent all have their lower bound below zero.

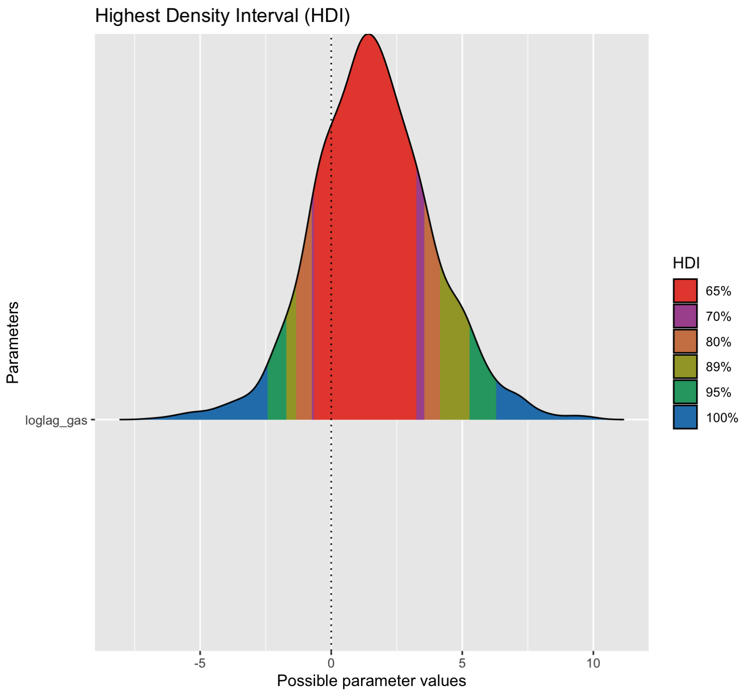

Figure 3: Highest density intervals of Model B2.

However, since we estimated a multi-level model and sampled posterior distributions at the country level, we can also examine them. Country-level estimates are reported in Table 1.

Unfortunately, this does not paint a clearer picture regarding the effect of an increase in the logged gas price on mortality. If anything, it tells us that there is probably an issue with the posterior for Serbia and that the other effects are somewhat ambiguous. However, this was our simplest multi-level specification and served a good job in introducing us to this kind of model.

	Estimate	Est.Error	Q2.5	Q97.5
AT	-1.185	3.980	-8.884	7.015
BE	-5.086	4.070	-12.941	3.169
BG	18.105	4.514	9.470	27.000
CH	-7.897	5.047	-17.438	2.406
CZ	0.608	4.156	-7.350	9.157
DK	-0.403	4.091	-8.155	7.631
EE	-0.919	4.556	-9.654	8.620
EL	2.512	4.614	-6.307	11.954
ES	0.264	5.469	-10.304	11.070
FR	-6.452	4.056	-14.391	1.722
HR	13.056	5.768	2.035	24.630
HU	9.202	4.409	1.075	18.065
IT	-0.717	4.042	-8.442	7.498
LT	8.648	4.567	-0.007	18.134
LU	4.649	4.348	-3.371	13.729
LV	8.860	4.057	1.076	16.896
NL	-0.306	4.010	-8.033	7.818
PL	8.868	4.396	0.342	17.440
RO	12.623	4.057	4.893	20.877
RS	-90.702	12.959	-115.431	-65.695
SE	0.088	4.867	-9.148	9.774
SI	2.197	5.047	-7.555	12.312
SK	9.430	5.113	-0.675	19.473
UK	5.880	4.964	-3.614	15.833

	Estimate	Est.Error	Q2.5	Q97.5
AT	-1.241	2.259	-5.896	3.050
BE	-0.107	2.323	-4.784	4.472
BG	-4.244	2.404	-9.021	0.511
CH	0.368	2.706	-5.113	5.549
CZ	-0.265	2.308	-4.996	4.207
DK	-1.144	2.298	-5.872	3.304
EE	0.984	2.530	-4.424	5.852
EL	-2.837	2.553	-7.991	2.152
ES	-2.984	2.900	-8.879	2.560
FR	-0.125	2.302	-4.758	4.395
HR	-5.157	3.143	-11.387	0.841
HU	-1.739	2.542	-7.036	2.946
IT	-2.217	2.278	-6.927	2.093
LT	-1.660	2.504	-6.871	3.122
LU	-5.520	2.580	-10.867	-0.679
LV	-1.171	2.293	-5.786	3.266
NL	-1.124	2.266	-5.768	3.073
PL	-3.970	2.428	-8.890	0.857
RO	-3.857	2.303	-8.654	0.514
RS	53.707	7.041	39.926	67.335
SE	-1.902	2.462	-6.895	2.828
SI	-2.490	2.696	-7.769	2.685
SK	-3.585	2.812	-9.151	1.879
UK	-4.210	2.983	-10.150	1.551

Table 1: Posteriors for A^{c_i} and $B_1^{c_i}$ by country (Model B2).

C.2.3. A Still Simple Bayesian Multi-Level Model

As a next step, we undo the subsetting step from before, take the full dataset at the NUTS-1 level, with 27,235 observations and estimate the following model[2]:

$$\begin{aligned}\text{Mortality}_{i,c_i,t} = {} & \text{Time}_t + \\ & A^{c_i} + \\ & B_1^{c_i} \cdot \text{Temperature}_{i,c_i,t} + \\ & B_2^{c_i} \cdot \log(\text{Gas Price})_{i,c_i,t} + \\ & \Gamma_1^{c_i} \cdot \text{Temperature}_{i,c_i,t} \cdot \log(\text{Gas Price})_{i,c_i,t} + \\ & E_{i,c_i,t},\end{aligned} \tag{B3}$$

where the notation matches the one explained previously. Importantly, we use a simpler approach to binning temperature than in the previous, frequentist, models. Instead of using multiple bins, we use a single dummy variable indicating a "cold" climate where and whenever the weekly average temperature was below 5 degrees Celsius. We did this because more complicated models like the one described next generally took more than 24 hours of computation time. We used the default priors from the brms package, including flat priors for the population level

[2] In our code, this model is called `model8`.

coefficients. We are again well aware of the deficiencies, however, because of the large sample size, the posterior distributions were not strongly sensitive to the priors. Figure 4 shows highest density intervals for the posterior distributions of the now three parameters. We can see that the largest uncertainty is associated with the temperature variable (and its effect on mortality), while the plain gas price effect has more probability mass below zero than above it, and the interaction effect is most probably positive, but also more uncertain. Country-level estimates are reported in the appendix.

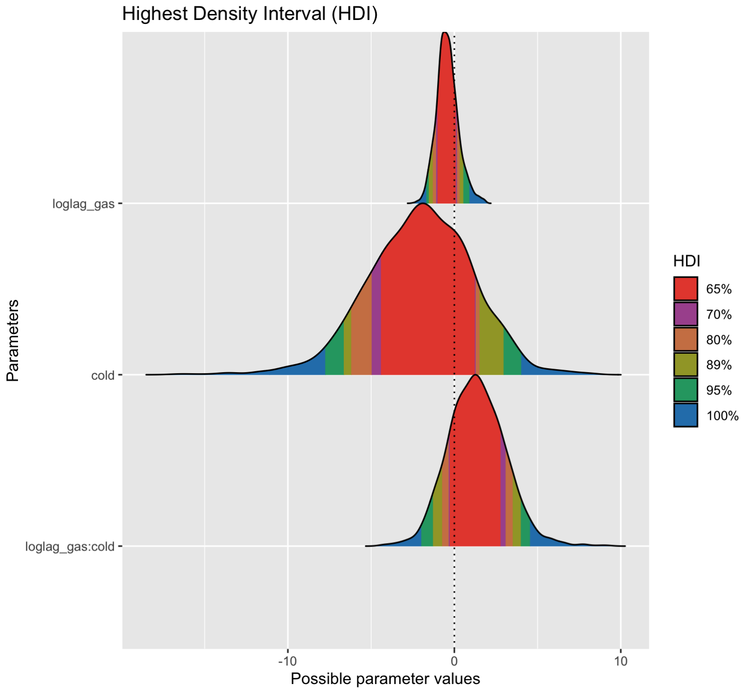

Figure 4: Highest density intervals of Model B3.

C.2.4. A More (Or Rather, Too) Complex Bayesian Multi-Level Model

In addition, we tried specifying a more complex model at the NUTS-3 level, which can be represented like this[3]:

$$
\begin{aligned}
\text{Mortality}_{i,r_i,c_i,t,\tau} = {} & A^{r_i,c_i,t,\tau} + \\
& B_1^{r_i,c_i,t,\tau} \cdot \text{Temperature}_{i,r_i,c_i,t,\tau} + \\
& B_2^{r_i,c_i,t,\tau} \cdot \log(\text{Gas Price})_{i,r_i,c_i,t,\tau} + \\
& \Gamma_1^{r_i,c_i,t,\tau} \cdot \text{Temperature}_{i,c_i,t} \cdot \log(\text{Gas Price})_{i,r_i,c_i,t,\tau} + \\
& E_{i,r_i,c_i,t,\tau},
\end{aligned} \tag{B4}
$$

[3] In our code, this model is called `model3`.

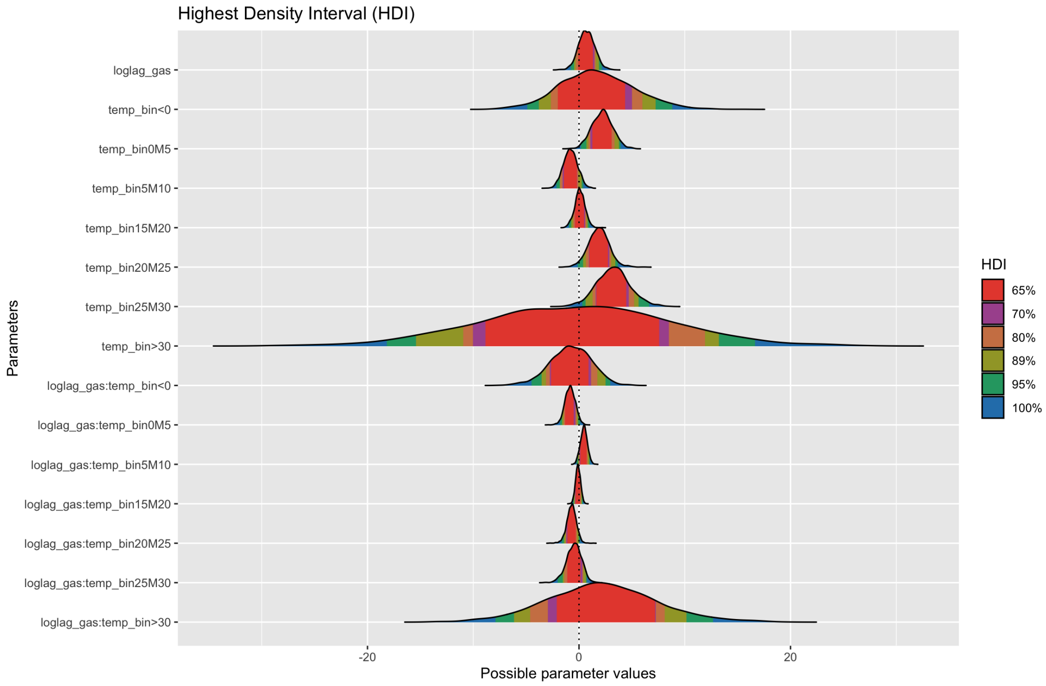

Figure 5: Highest density intervals of Model B4.

where i denotes the region (NUTS 2), r_i denotes the larger region (NUTS 1) the region is in, c_i denotes the country the region is in, t denotes the year, and τ denotes the month. In this model, coefficients vary between regions, countries, years and months. Temperature is again binned in 8 categories, as explained above using frequentist estimation techniques. We specified a normal prior $N(0, 10)$ on the population coefficients, which capture plausible effect sizes reasonably well.

Unfortunately, estimating the model like this yields 12,560 posterior coefficient distributions, which would be difficult to represent on paper, even in the appendix. In this model, the population-level posterior coefficients have the highest density intervals shown in Figure 4.

D. Conclusion and Limitations

Our initial plans for the Bayesian (i.e., main) part of our analysis were obstructed by the issues of computational complexity we encountered, in addition to challenges regarding mixing and convergence in multiple models that we had to drop before hand-in. For a more robust analysis, we could continue by exploring different model specifications, run with more iterations than the models we estimated. However, continuing on this path was not feasible for the present project since the Bayesian models presented needed, in some cases, more than 24 hours of computation time, despite efforts to tweak the sampler or the prior specification. Therefore, a "trying out" approach could not have been conducted within the time frame of this project.

Overall our modelling approaches paint a complex and ambigious picture. The standard frequentist panel regressions employing fixed effects do not provide evidence that high gas prices impact mortality. However, we do find evidence that gas prices have a statistically significant effect when temperatures are very high. Electricity prices seem to be strongly associated with higher mortality. However, we do not find clear evidence of a differential impact of electricity prices when temperatures are extremely low or high. To simplify our analysis, we decided to focus in the subsequent Bayesian estimation on the impact of gas prices only.

We leveraged the hierachical structure of the data (since we have observations nested in NUTS regions) by estimating multilevel models. This allowed us to account for the unit level heterogeneity in a more sophisticated fashion than by simply clustering the standard errors in panel fixed effect regression. The rather simple approach B2 shows that there is somewhat suggestive evidence that higher gas prices are associated with higher mortality. Specification B3 also presents rather tentative evidence that gas prices are associated with higher mortality.

Regarding further options, we could improve data quality, include covariates, specify different priors, and try out new empirical strategies. One approach to more credibly identify a causal effect would be to include an IV strategy, since changes in the gas price could be endogenous to mortality. We would then follow Chirakijja et al. (2021) and estimate a shift-share IV. Chirakijja et al. (2021) exploit the differences in the share of gas that are used for heating at a country level. Variations in the relative price of price over electricity would thus have a differential impact on mortality, based on how dependent a region is on gas for heating. To account for endogenous adjustments of those shares, one uses the share of heating coming from gas in the first period. First, rather promising, tries, including the downloaded shares from Eurostat, can be found on GitHub.

A. Appendix

Table 2: The effect of energy prices on mortality

	Dependent variable:			
	age_adjusted_mortality			
	(1)	(2)	(3)	(4)
log(lag_elect)	0.944***		0.822***	
	(0.118)		(0.130)	
log(lag_gas)		−0.009		0.014
		(0.124)		(0.138)
log(lag_elect):winter			0.308***	
			(0.110)	
log(lag_gas):winter				−0.057
				(0.101)
Observations	299,285	293,201	299,285	293,201
R^2	0.001	0.00000	0.001	0.00001
Adjusted R^2	−0.003	−0.004	−0.003	−0.004
F Statistic	346.956*** (df = 1; 297997)	0.039 (df = 1; 291913)	192.162*** (df = 2; 297996)	0.954 (df = 2; 291912)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3: Temperature, energy prices, and mortality

	Dependent variable:		
	age_adjusted_mortality		
	(1)	(2)	(3)
temp_bin<0	0.705***	0.707*	0.247
	(0.085)	(0.370)	(0.579)
temp_bin0-5	0.343***	0.270	−0.095
	(0.053)	(0.207)	(0.333)
temp_bin5-10	0.261***	0.468***	−0.728***
	(0.031)	(0.146)	(0.278)
temp_bin15-20	−0.344***	0.029	1.472***
	(0.033)	(0.148)	(0.267)
temp_bin20-25	−0.120*	0.067	1.654***
	(0.067)	(0.293)	(0.450)
temp_bin25-30	1.163***	0.213	2.485***
	(0.094)	(0.372)	(0.647)
temp_bin>30	4.434***	−1.675	1.768
	(0.548)	(2.575)	(5.956)
log(lag_gas)		0.013	
		(0.133)	
temp_bin<0:log(lag_gas)		0.049	
		(0.178)	
temp_bin0-5:log(lag_gas)		0.007	
		(0.099)	
temp_bin5-10:log(lag_gas)		−0.130*	
		(0.072)	
temp_bin15-20:log(lag_gas)		−0.151**	
		(0.073)	
temp_bin20-25:log(lag_gas)		−0.025	
		(0.139)	
temp_bin25-30:log(lag_gas)		0.494***	
		(0.173)	
temp_bin>30:log(lag_gas)		2.687**	
		(1.132)	
log(lag_elect)			1.032***
			(0.134)
temp_bin<0:log(lag_elect)			0.175
			(0.189)
temp_bin0-5:log(lag_elect)			0.128
			(0.108)
temp_bin5-10:log(lag_elect)			0.316***
			(0.092)
temp_bin15-20:log(lag_elect)			−0.576***
			(0.088)
temp_bin20-25:log(lag_elect)			−0.526***
			(0.142)
temp_bin25-30:log(lag_elect)			−0.383*
			(0.206)
temp_bin>30:log(lag_elect)			0.863
			(1.858)
Observations	310,228	285,465	291,549
R^2	0.005	0.006	0.008
Adjusted R^2	0.001	0.002	0.003
F Statistic	232.538*** (df = 7; 308909)	118.617*** (df = 15; 284185)	149.416*** (df = 15; 290269)
Note:			*p<0.1; **p<0.05; ***p<0.01

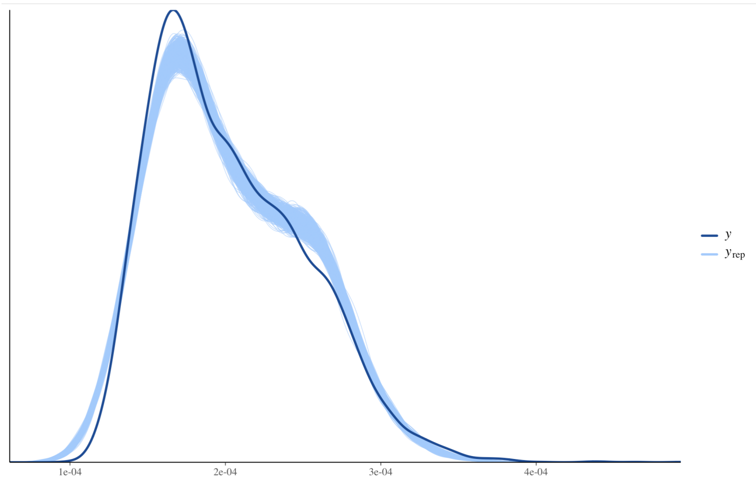

Figure 6: Model B1: Posterior predicitive check with 1000 repitions

Table 4: Intercept

	Estimate	Est.Error	Q2.5	Q97.5
AT	-2.034	1.228	-4.264	0.459
BE	-8.032	1.194	-10.295	-5.564
BG	6.982	1.508	4.043	10.098
CH	-3.212	2.348	-7.900	1.435
CZ	0.023	1.445	-2.755	3.051
DK	-1.072	1.485	-3.877	1.903
EE	-3.422	2.147	-7.633	0.630
EL	-4.534	1.230	-6.872	-2.059
ES	-3.852	1.190	-6.092	-1.459
FR	-7.307	1.170	-9.448	-4.914
HR	2.757	1.902	-0.953	6.433
HU	1.795	1.479	-0.977	4.716
IT	-3.119	1.198	-5.377	-0.679
LT	6.769	2.000	2.955	10.682
LU	1.364	1.386	-1.249	4.098
LV	9.722	1.593	6.737	12.868
NL	-2.017	1.183	-4.264	0.398
PL	2.628	1.505	-0.209	5.764
PT	1.363	1.489	-1.558	4.296
RO	3.601	1.262	1.164	6.195
RS	-14.824	4.631	-24.164	-5.870
SE	4.662	2.092	0.700	8.853
SI	1.105	1.803	-2.320	4.745
SK	0.341	2.126	-3.776	4.479
UK	11.536	1.591	8.460	14.593

Table 5: log_gas

	Estimate	Est.Error	Q2.5	Q97.5
AT	-0.269	0.677	-1.742	0.943
BE	1.937	0.672	0.435	3.189
BG	0.291	0.754	-1.347	1.688
CH	-1.019	1.146	-3.306	1.183
CZ	0.558	0.754	-1.065	1.959
DK	-0.148	0.784	-1.786	1.316
EE	2.789	1.124	0.573	4.999
EL	0.904	0.677	-0.615	2.154
ES	-0.493	0.658	-1.937	0.727
FR	0.956	0.655	-0.475	2.123
HR	0.080	1.024	-2.013	2.102
HU	1.755	0.840	0.068	3.397
IT	-0.294	0.660	-1.704	0.917
LT	-0.549	1.019	-2.666	1.372
LU	-3.332	0.827	-5.069	-1.784
LV	-1.739	0.879	-3.493	-0.070
NL	0.232	0.659	-1.222	1.422
PL	-0.476	0.803	-2.141	1.028
PT	-0.650	0.753	-2.282	0.777
RO	0.845	0.704	-0.726	2.159
RS	11.764	2.550	6.980	16.939
SE	-2.670	0.909	-4.490	-0.960
SI	-1.643	0.921	-3.540	0.110
SK	1.426	1.131	-0.844	3.647
UK	-8.301	0.944	-10.183	-6.528

Table 6: cold

	Estimate	Est.Error	Q2.5	Q97.5
AT	0.296	3.215	-5.597	6.728
BE	2.041	3.264	-4.208	8.583
BG	7.932	3.740	0.614	15.505
CH	-2.096	4.170	-10.170	6.094
CZ	0.536	3.448	-5.936	7.509
DK	0.415	3.395	-5.896	7.156
EE	0.818	3.965	-6.661	8.506
EL	4.341	3.874	-3.167	12.494
ES	2.426	4.270	-5.484	11.015
FR	-0.604	3.229	-6.585	6.109
HR	10.730	4.918	1.702	20.582
HU	7.814	3.642	1.272	15.601
IT	1.463	3.267	-4.492	8.241
LT	3.829	4.021	-3.708	11.758
LU	3.644	3.507	-2.909	10.904
LV	-0.274	3.471	-6.777	6.810
NL	1.035	3.191	-4.770	7.475
PL	8.730	3.598	1.668	15.965
PT	1.844	12.702	-23.288	27.771
RO	8.210	3.382	2.135	14.900
RS	-78.834	12.630	-103.520	-54.315
SE	0.501	3.697	-6.857	7.968
SI	0.766	4.007	-7.084	8.720
SK	10.011	4.597	1.375	19.285
UK	1.500	4.185	-6.681	9.858

Table 7: log_gas:cold

	Estimate	Est.Error	Q2.5	Q97.5
AT	-0.498	1.755	-3.994	2.726
BE	-1.420	1.798	-5.102	2.001
BG	-2.996	1.901	-6.752	0.737
CH	0.451	2.179	-3.884	4.669
CZ	-0.562	1.840	-4.353	2.935
DK	-0.636	1.829	-4.303	2.739
EE	-0.628	2.127	-4.841	3.396
EL	-2.241	2.069	-6.588	1.699
ES	-1.587	2.227	-6.065	2.490
FR	-0.181	1.764	-3.787	3.126
HR	-5.364	2.623	-10.550	-0.521
HU	-3.705	2.048	-8.042	-0.036
IT	-1.294	1.770	-4.951	1.900
LT	-1.783	2.127	-5.972	2.180
LU	-2.424	2.002	-6.627	1.383
LV	0.487	1.896	-3.314	4.025
NL	-0.784	1.739	-4.265	2.380
PL	-4.502	1.917	-8.390	-0.789
PT	-0.992	6.962	-15.569	12.660
RO	-4.102	1.850	-7.755	-0.790
RS	43.698	6.848	30.397	56.920
SE	-0.667	1.863	-4.389	2.914
SI	-0.503	2.095	-4.605	3.656
SK	-5.336	2.468	-10.296	-0.769
UK	-0.460	2.497	-5.443	4.331

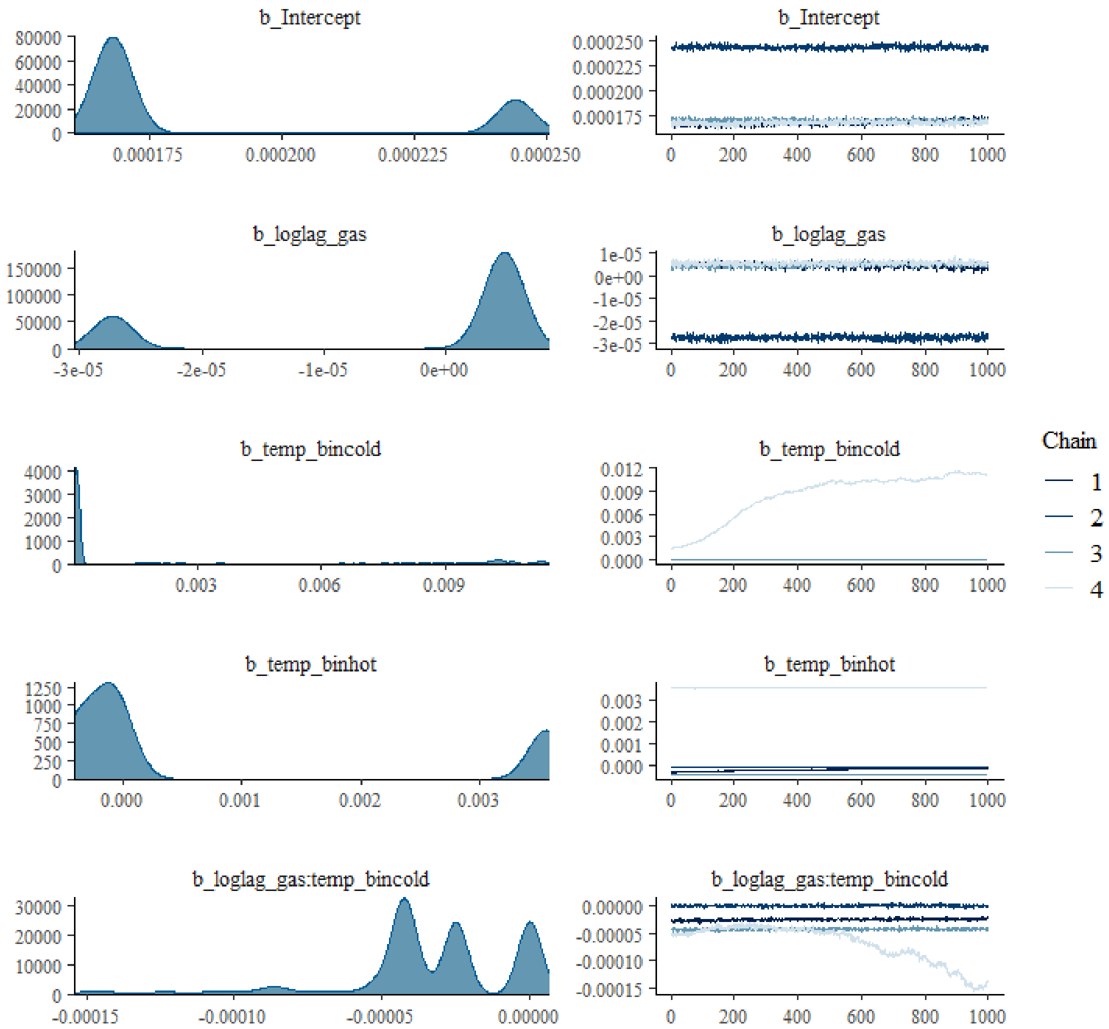

Figure 7: Trace and density plots of test model 7b.

We tried running a complex model more efficiently by manually fixing the step size within the process of exploring the posterior distribution. We did so by setting - control = list(adapt_delta = 0.795, max_treedepth = 10) - within the code for our model 7b. Unfortunately, we were not able to obtain any meaningful result because the chains have not mixed. As a result, posterior means and medians as well as posterior variances and tail quantiles are unreliable.

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