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The Impact of Temperature Changes on Residential Energy Use

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Abstract: In order to explore the impact of climate change on energy use, we estimate an energy demand model that is driven by temperature, prices and income. The estimation is based on an unbalanced panel of 62 countries over three decades. We limit the analysis to the residential sector and distinguish four different fuel types (coal, electricity, natural gas and oil). Compared to previous papers, we have a better geographical coverage and consider both a heating and cooling threshold as well as further non-linearities in the impact of temperature on energy demand and temperature-income interactions. We find that oil, gas and electricity use are driven by a non-linear heating effect: Energy use decreases with rising temperatures due to a reduced demand for energy for heating purposes, but the speed of that decrease declines with rising temperature levels. We cannot find a significant impact of temperature on the demand for cooling energy.

JEL Classification: Q41, Q43

Key Words: Climate change, energy demand, heating and cooling effect, temperature

1. Introduction

During the last century, the global average temperature rose by about one degree Celsius, and may easily rise by another 1.8 to 4.0 degrees over the current century, depending on the emission scenario (IPCC 2007). Among the various economic consequences of a global temperature rise, the impact on energy use is of particular importance and may well represent a large part of the total economic impact of climate change (Tol 2009). Furthermore, greenhouse gases emitted by the energy sector are themselves a main driver of climate change and responsible for a good quarter of global greenhouse gas emissions (IPCC 2007). Energy use thus affects and is affected by both climate change and climate policy. This paper aims to disentangle the impact of temperature changes on energy use and to calculate the temperature sensitivity of energy demand for selected fuels.

By now a number of studies (see below) analyse the driving forces behind the temperature sensitivity of energy under specific conditions. Usually based on micro level data, these analyses tend to take into account as many socio-economically and geographically relevant determinants as possible. For assessing particular policy measures targeted at region specific problems (e.g. number of energy poor households, distributional effects of different policies etc.) or for analysing the energy demand reaction to temperature changes in a specific country or region, this micro-perspective is advantageous. The aim of our paper is to go beyond the single country analysis. Data from multiple countries exhibit a wider range of energy uses, technologies, economic circumstances, and climates. The estimated relationships are therefore better suited for extrapolation to future climate and economic conditions. Information about the temperature sensitivity of energy demand is essential for a thorough understanding of the consequences of climate change – e.g. as a basis for calibrating general equilibrium or integrated assessment models.

We concentrate on *residential* energy demand, because previous studies showed that energy use in the services and manufacturing sectors reacts only minimally to temperature variations; see Bigano et al. (2006) for a discussion on that point.

We add to the existing literature (see Agrawala et al., 2011, for an overview) by combining many of the conceptual achievements of previous studies as well as by introducing new features. Most previous studies, both on the micro and on the macro level, focused solely on electricity use. We extend our analysis to heating oil, natural gas and solid fuels as well. We use a large sample of countries to increase confidence in the estimated relationships, not only because we have more observations, but also because we measure the effects over a wider range of income and temperature levels.

Instead of estimating the temperature effect on energy use only linearly, we allow for the temperature elasticity to depend on temperature itself by estimating non-linear specifications. We account not only for a smooth non-linear dependency, but also account for a discontinuous heating threshold by introducing heating degree months. Additionally, we consider that the temperature elasticity of energy use may also depend on other variables, namely income.

In the following section, we give a brief overview of the existing literature. In Section 0, we describe how we model the determinants of energy use, including the concept of heating degree months. We describe our data in Section 3. In Section 4, we present our results on the heating effect and the cooling effect as well as some supplementary and sensitivity analysis. Section 5 discusses the results and concludes.

2. Existing Work

As mentioned above, most contributions so far addressed the topic either on a micro-level (e.g. Quayle and Diaz 1980; Rosenthal and Gruenspecht 1995; Henley and Peirson 1997, 1998; Florides et al. 2000; Vaage 2000, Zarnikau 2003; Larsen and Nesbakken 2004; Mansur et al. 2005; Mansur et al. 2007) or using country or regional time series data (e.g. Al-Zayer and Al-Ibrahim 1996; Hunt et al. 2003; Mirasgedis et al. 2004; Amato et al. 2005; Pezzulli et al. 2006). Naturally, these studies concentrate on specific countries without aiming at large-scale representativeness. Often, the impact of temperature is not the central focus. Methodologies vary greatly, as do the results.

Studies using multi-country panel data are less common. Bigano et al. (2006) study the impact of temperature changes on several fuels in OECD countries from 1978 to 2000. Even though they include “a few” non-OECD countries, their focus is on the developed world. They find a significant negative impact of average annual temperature on electricity, natural gas and oil use in the residential sector. Elasticities vary between -0.57 for electricity and -3.05 for oil. The authors find a positive effect of temperature changes on coal use, with an elasticity of 2.85.

Asadoorian et al. (2008) study the impact of temperature changes on electricity demand in urban versus rural Chinese provinces from 1995 to 2000, thus including several climate zones and some variation in development levels. They find that the temperature elasticity of electricity demand varies between 0.59 and 0.76. Neither Bigano et al. (2006) nor Asadoorian et al. (2008) report semi-elasticities or marginal effects.[1]

Bessec and Fouquau (2008) study the impact of temperature changes on electricity use in 15 member states of the European Union for the period 1985 to 2000. Since they use a panel threshold model, they can in detail model a smooth, non-linear transition from a heating regime with negative temperature elasticities to a cooling regime with positive temperature elasticities. They conclude that both non-linearity and a cooling effect are not very pronounced in cold countries, as opposed to southern EU member states. They also report an increasing impact of warmer summers on electricity demand for cooling.

Lescaroux (2011) focuses on the impact of income on energy demand, but includes temperature as a control variable. His estimation results report a temperature semi-elasticity of total residential energy use between -0.03% (in the short run) and -0.08% (in the long run) per degree centigrade. Based on a comprehensive panel of 101 countries and three aggregates over the period 1960 to 2006, the results are representative for a large number of development levels and climate zones. However, only country average temperature levels are considered. Since he utilizes an autoregressive specification, he can distinguish short-run and long-run effects. He does not include non-linearities in the reaction of electricity use on temperature changes.

De Cian et al. (forthcoming) study residential energy use in 26 OECD and five non-OECD countries for the period 1978-2000, covering a wider variety of development levels and climate zones than many previous macro-panel studies. They conclude that demand for heating and cooling and its response to changes in temperature depend on region, season and fuel type. They account for non-linearities in the reaction to temperature changes by clustering their sample into three groups, cold, mild and hot, depending on the baseline temperature level of countries. They also distinguish seasonal impact by utilizing four seasonal average temperature levels per year and country. Long-run and short-run temperature elasticities are estimated as constants within climate clusters using an error correction specification. For the different groups and seasons, they estimate long-run temperature elasticities between -3.33 and 5.42 for electricity, -2.6 for natural gas and between -3.45 and 3.36 for oil products. Short-run temperature

[1] By "semi-elasticities", we mean the percentage change in energy use (or any other dependent variable) per one-degree temperature change (or a change in any other explanatory variable by one unit). The use of semi-elasticities instead of real elasticities is advisable in the case of temperature, since temperature in degrees centigrade (as well as Fahrenheit) is measured on an interval scale but not on a ratio scale. The problem does not arise if degree days are used instead of (average) temperature levels.

elasticities are smaller, spanning from -0.39 to 0.92 for electricity, from -0.95 to -0.18 for gas and from -0.7 to -0.02 for oil products.Modeling determinants of residential energy use and empirical strategy

In our model, households adapt their use of energy to income, fuel prices and temperature. The role of income, the price of the fuel, and the price of other fuels is clear from microeconomic theory: for the time being, we assume that energy fuels are normal goods with positive income elasticities, negative price elasticities and zero or positive cross price elasticities towards other energy fuels. We show below that fuels are not necessarily normal or ordinary goods, e.g. due to substitution effects from low-quality fuels such as coal towards high-quality fuels such as natural gas. We assume that households (and thus also countries) need a lag of one year to adapt to changes in prices. This addresses common adaptation lags due to information lags, habit persistence, stock holding or contractual obligations. We cannot implement shorter lags due to the yearly frequency of our data.

We account for differences in temperature as well. With rising temperatures, households need less heating, whereas the demand for cooling is likely to rise. With rising temperatures the heating effect, therefore, reduces energy use, while the cooling effect increases it.

A vital question is the nature of the interdependence between temperature changes and adjustments in the use of energy. Assuming a linear relationship seems rather counterintuitive.[2] One would expect that the impact of temperature changes differs depending on the historical temperature level. Presumably, if temperature rises, the reduced heating demand would be smaller for warmer countries than for colder ones; while increased cooling demand would be larger.[3] To address this issue, firstly, we use heating degree months instead of untransformed temperature values to cover the impact of heating and cooling thresholds (see below for more details on the concept of heating degree months). Secondly, we estimate a non-linear relationship between degree months and energy. For each fuel type we estimate three functional forms, linear, quadratic and logarithmic, and compare with a baseline specification without any temperature impact. Furthermore, we interact temperature and (per-capita) income. Richer households might have a higher ability to adapt to climate change, e.g. by investing in insulation, heating appliances,

[2] See for example Bigano et al. (2006), who identify the use of a linear model as a major drawback of their analysis.

[3] Since the specific process of the adaptation of energy use in the course of changes in temperature depends on local conditions like insulation, heating and cooling equipment, local conventions etc., the link between temperature and energy use may of course be linear on a small scale, e.g. for a country that is located in only one climate zone. In this case, variation in annual average temperature levels in that country is limited. On a global scale however, where annual average temperature varies more, a non-linear relationship is much more likely. The question concerning the interpretation of the results of the global analysis is of course whether patterns derived from comparisons between countries also hold within a country, given that temperatures rise significantly in the future.

air conditioning etc. At the same time, poorer households might be less responsive to changing temperature levels since they are constrained in their adaptation options. The same rationale applies to rich and poor countries – if temperature rises, the decrease in energy use may be steeper if a country is richer. In this case, the level of income has an effect on the temperature elasticity of energy demand – the elasticity will increase (in absolute value) with rising income.

Note that heating demand is insensitive to temperature changes above a certain temperature threshold, the heating threshold. The heating threshold is the temperature level at which it is warm enough so that households feel comfortable enough not to use their heating equipment. The analogue is true for cooling and temperature changes below a cooling threshold. The traditional approach to this problem is the use of heating (HDD) and cooling degree days (CDD),[4] as for example in Al-Zayer and Al-Ibrahim (1996) or Amato et al. (2005). Since HDD and CDD are not available for a sufficiently broad range of countries, their use is not an option for our analysis.

As we investigate annual and national data, we face the problem of how to represent heterogeneous temperature levels (and changes) within countries and years in the aggregate – especially if countries and seasonal temperature variation are large. We therefore use gridded monthly data instead of annual country averages. To account for the heating and cooling thresholds, we construct regionalized heating (HDM) and cooling degree months (CDM) from the monthly, gridded temperature averages. Our regionalized HDM and CDM are closely linked to the concept of heating degree months used in Maddison and Rehdanz (2011). To construct HDM and CDM, we calculate deviations of the monthly mean temperature from the threshold temperature[5] for each 0.5 degree grid cell in the grid. The deviation is set to zero if the monthly mean temperature is higher (lower for CDM) than the threshold temperature. The mean of the remaining differences is the heating/cooling degree value for that month and that country. Finally, all months of a year are summed up and form the yearly (regionalized) HDM/CDM value for the country:

$HDM_{i,t} = \sum_{m \in t} \left(MEAN_{g \in i} \left(POS\left(18.3 - T_{m,g}\right)\right)\right)$ and (1)

[4] Heating degree days are usually defined as the difference between the average temperature of a period and the heating threshold, multiplied with the number of days within that period if the average temperature is below the heating threshold and zero if the average temperature is above (e.g. EUROSTAT 2008). Cooling degree days are the difference between the cooling threshold and the average temperature of the period, also multiplied with the number of days if the average temperature is above the threshold and zero if it is below.

[5] In accordance with the literature, we use 18.3 degrees centigrade as threshold temperature. Cf. e.g. Uri (1979) or Dublin and McFadden (1984).

$$CDM_{i,t} = \sum_{m\in t}\left(MEAN_{g\in i}\left(POS\left(T_{m,g} - 18.3\right)\right)\right), \tag{2}$$

where the function POS returns only positive deviations, $MEAN_{x\epsilon y}$ returns the arithmetic mean over all x within y and $\Sigma_{x\epsilon y}$ returns the sum over all x within y. T is the monthly mean temperature, indices m, t, g and i denote month, year, 0.5-degree grid cell and country, respectively.

Apart from temperature, income and prices, household energy demand is determined by a multitude of factors that are unobservable by nature or for practical reasons, such as limited data availability. This is especially true on a cross-country scale. Since we employ a panel data set, we are able to address the problem of time-invariant, country-specific unobserved determinants of energy use by including fixed effects in our regression model. However, some unobserved characteristics, although being highly persistent, will still be time-variant and therefore unaccounted for in the standard fixed-effects model. This includes classical unobservables like habits, but also long-run changes in the prevailing and available technology, capital stock or government policies. Furthermore, transient (or so perceived) shocks of the explanatory variables will have a smaller impact on energy demand than sustained changes. To include some of the persistent but time-variant omitted explanatory power, and to differentiate between transient and sustained shocks, we include the history of a countries' energy use in the form of a lagged dependent variable additional to the country-specific fixed effects.[6] To rule out that we interpret time-invariant factors as being highly persistent and thus overestimate long-run shocks, we reject any specification with an autoregressive term that is not significantly different from one for standard significance levels. As a sensitivity test, we also estimate each specification with either fixed effects or lagged dependent variables.

Since we include lagged dependent variables in addition to fixed effects, the standard fixed effects least squares estimator will be biased due to endogeneity of the lagged dependent variable (Nickell 1981). The literature on dynamic panel data models contains a variety of estimators that overcome this "Nickell bias" and yield unbiased estimators by instrumenting for the endogenous lagged variable, such as the estimators by Anderson and Hsiao (1981), Arellano and Bond (1991) or Blundell and Bond (1998). However, the generalized-method-of-moments (GMM) estimators by Arellano and Bond as well as by Blundell and Bond are constructed to suit large N, small T panels, while their usefulness for macroeconomic panels (such as ours) with small N and moderate T has been

[6] The interpretation of a lagged dependent variable as a representation of persistent shocks is based on the Koyck transformation. Koyck (1954) showed that an infinite distributed lag model of geometric structure can be transformed into a model with one lagged dependent variable.

doubted based on a root-mean-square error (RMSE) criterion in favor of a corrected least squares dummy variable (LSDVC) estimator proposed by Kiviet (1995; see also Judson and Owen, 1999). Kiviet's LSDVC estimator is meant to combine the merits of the conventional, biased least squares dummy variables estimator in terms of efficiency with the consistency of the GMM approaches. It was extended by Bruno (2005a) to suit also unbalanced panels. Since our panel is a macroeconomic panel similar to the one used in the Monte Carlo study by Judson and Owen (1999), we choose Bruno's (2005a) LSDVC estimator as our estimator of choice. The GMM-based estimator of Arellano and Bond (1991) with Windmeijer's (2005) variance correction for small samples is used to test for sensitivity with regards to the estimator, see Section 4.3.

Unlike many existing studies, we study not only electricity, where data availability is good. We include four fuels that represent the vast majority of fuels used for heating and cooling worldwide: Coal and solid biomass[7] as well as electricity, natural gas and fuel oil. Demands for the four fuels are estimated individually, not as a system. However, we estimate cross price elasticities as a sensitivity analysis.

3. Data

Data on energy use, prices and real GDP are retrieved from ENERDATA (2005) for up to 176 countries and the period 1970 to 2002.[8] Data availability differs considerably between the four fuels, coal, electricity, natural gas and oil types; both regarding use and price data (see Table 1 for details). Data on the use of gas and coal are available for about 70 countries; for oil and electricity there are time series for almost every country in the world. In comparison, data on prices are scarce. Reliable price data are available mostly for developed countries and only from 1978 onwards (for information about the geographical coverage of the data, cf. Figures A1-A4 in the appendix). This limits the estimation sample to 25 years at most if price data are included. Regarding geographic coverage, coal is again the fuel type with the lowest coverage: the price of coal for residential use is available for only 22 countries. Even though the share of coal in residential energy demand is usually of minor (and diminishing) importance, both from a global and from national perspectives, this constitutes a shortcoming of the analysis. It was however impossible to impute the price of residential coal by other prices, e.g. coal prices from other sectors. Data availability

[7] We cannot differentiate between coal and solid biomass due data restrictions. Coal and biomass are represented in one aggregate variable, which we will call coal in the further course of the paper.

[8] Enerdata is a research & consulting firm that compiles and publishes global energy use data. The database is compiled from various international organizations as well as national statistical offices and other national institutions, for details see ENERDATA (2012).

is better for the prices of other fuel types. For natural gas and light fuel oil, more than 30 countries are covered. Electricity prices are available for 63 countries. Nonetheless, also for those energy types, limited availability of price data imposes a drawback of the analysis in terms of representativeness, reliability and quality of the estimation results. We solve this drawback by testing the robustness through regressions without prices on the same sample. As a proxy for household income we use per-capita GDP in purchasing power parities (converted to 1995 international dollars). Compared to information on energy prices and use, data availability is good.

We use monthly average temperature values taken from the High Resolution Gridded Dataset of the Climatic Research Unit of the University of East Anglia (CRU 2008, Mitchell and Jones 2005) available at a 0.5 degree grid. We transform the gridded, monthly temperature averages to annual HDM and CDM on the country level according to the procedure described in Section 0. Temperature data are available for most countries and all years of interest. All temperature variables are in degrees centigrade.

- Table 1 ABOUT HERE -

4. Results

To identify the best (in terms of explanatory power) and most robust specification for each fuel type, we compare three functional forms of temperature impact on energy use, namely linear, quadratic and logarithmic, and one baseline specification without temperature impact. For each functional form, we compare specifications with and without fuel prices. The impact of cross prices and temperature-income interactions is studied as a sensitivity analysis in Section 4.3. To choose our specification-of-choice, we discard all specifications with insignificant temperature impact and choose from the remaining set the specification with the best score on the Akaike Information Criterion (AIC).

4.1. Heating Effect

For all fuels we find a significant heating effect (cf. Table 2). We find that the quadratic specification is superior to the others in terms of parameter significance and AIC for all fuels (for an overview of all relevant specifications, cf. Table A 1).[9] This confirms our hypothesis that the response in energy use to temperature changes is non-linear, even beyond the discontinuity imposed by the heating threshold. While in warmer countries less energy is used for heating

[9] Logarithmic specifications do either not yield significant results or copy the quadratic specification closely. Since fit is usually better for the quadratic specifications, we do not present the logarithmic models here.

than in colder countries, the marginal impact of temperature changes on fuel use decreases in absolute tons of oil equivalents with increasing temperature (see Figure 1). At the same time, the relative impact, i.e. the elasticity, increases with rising temperature levels (see Figure 2).

- Table 2 ABOUT HERE -

- Figure 1 ABOUT HERE -

- Figure 2 ABOUT HERE -

The size of the non-linear effect is different among the four fuels. As Figure 1 shows, electricity demand is almost constant, even for very cold countries, and the squared parameter is small compared to coal, gas and oil. This is reasonable since electricity has a multitude of other uses apart from space heating that accordingly reduce temperature dependence of the fuel. Non-linearities play a much larger role for the other three fuels. For temperatures below 90 HDM, where 75 % of the observations are located, predicted coal, gas and oil use is particularly curved, leading to a decelerating rise in the temperature elasticity of fuel use. For example, we estimate that a country with only around 10 HDM (e.g. Saudi Arabia, India or Namibia), although 15 times hotter than a country with around 150 HDM (e.g. China, the USA or North Korea), has a short-run temperature elasticity of oil that is only 10 times smaller (0.32 versus 3.12) – all other explanatory variables equal. Non-linearities aside, coal is the most temperature-elastic fuel in the short run, followed by gas, oil and electricity.[10] Interestingly, this order is changed in the long run due to the relatively low persistence of shocks of coal use. Short-run and long-run elasticities are compared in Figure 2. Persistence of shocks is similar for electricity, gas and oil products.

Because of the differences in methodology, data and especially due to the use of degree months, our results are not easily comparable to the results of previous studies (cf. Section 2). For average HDM levels, our estimated elasticities are about the same order of magnitude as those in Bigano et al. (2006) for electricity and natural gas, while our elasticity is larger for coal and smaller for oil. Compared to the results of De Cian et al. (forthcoming), our elasticities are within the range of their estimates for electricity and oil, but larger for natural gas. De Cian et al. (forthcoming) do not estimate coal use.

[10] Note that the representativeness of our coal model is limited, since it uses only 270 observations from 20 countries. For an overview of the regional coverage of our data for the different fuels, see Figure A2 to Figure A5.

Although not at the core of our analysis, the estimated price and income elasticities of the four fuels show interesting differences (for a detailed picture, see Figure A 1 in the appendix). Electricity, gas and oil are normal goods. This is not true for coal. Coal use reacts negatively to changes in income and positively to changes in coal price. Coal is an inferior good. The income effect more than offsets the substitution effect in the price reaction, leading to an overall positive price elasticity. Thus, coal is a Giffen good according to our estimation. As mentioned before, our coal model relies on a relatively small sample and is not as representative as in the cases of the other fuels (cf. Footnote 10). In all countries except China, residential coal use has remained constant or declined over the last decades, both per capita and in absolute terms. Nowadays coal plays a substantial role for residential space heating only in a limited number of countries, namely in the CIS countries and China. In the rest of the world, it competes on a very low level with oil and gas on the one hand and with firewood on the other.

Gas reacts most strongly to changes both in income and price. Gas is the superior fuel. Not surprisingly and supposedly due to the broad use of electricity for a large variety of applications with few substitution possibilities, income and price elasticities of electricity use are lowest. Since persistence of shocks is similar for electricity, gas and oil, the responsiveness ranking between those three does not change in the long run.

4.2. Cooling Effect

An increase in cooling demand is one of the predicted effects of climate change. Although quantifying the cooling effect was one of our declared goals, we are unable to find a significant cooling effect on energy use, irrespective of the functional form and irrespective of whether we estimated the cooling effect jointly with the heating effect or separately. This does not necessarily mean that there is no cooling effect. The geographical scope of our data set is broad, it includes developed as well as many developing countries. So far on the macro scale, the cooling effect has been derived mainly for developed countries (De Cian et al., forthcoming, for example cover the OECD countries and in addition South Africa, India, Thailand and Venezuela; Bessec and Fouquau 2008 cover the EU-15 countries). However, households in developing countries will most probably respond differently to temperature changes. Although most developing countries are located in warm climates, the endowment with air conditioning and other cooling devices is supposedly below average, since the households' incomes are so low. Also, including only per-capita GDP might not be sufficient for capturing these structural differences. Furthermore our sample covers a rather long time period, starting in the 1970s. Since cooling is a relatively new phenomenon in the household sector outside the USA, the cooling effect might be obscured by the long time span.

Then again, estimations restricted to all OECD countries, to all warm OECD countries, and to the European Mediterranean did not yield a significant cooling effect either, even if we restrict the sample to the 10 most recent years. However, the estimation of a single-country time series model based only on data for the US suggested a significant cooling effect.[11] We conclude that within our observation period cooling is still only a regional issue, if not an US-issue – although this finding is likely to change in the future.[12]

While Bigano et al. (2006) do not test for a cooling effect, De Cian et al. (forthcoming) find a significant positive influence of summer temperature on electricity demand for a subsample of mild and hot countries. Asadoorian et al. (2008) find a cooling effect for the residential sector in China. We cannot confirm their result with our data.

4.3. Supplementary and sensitivity analyses

4.3.1. The price of oil

To capture the impact of substitutes or complements, we include oil prices into the various specifications. Since the oil price and the prices of the other three fuels are highly correlated, we refrain from including more than one cross price to avoid multi-collinearity.[13] Generally, the oil price does not have a significant impact on the demand for any of the fuels, for most of the functional forms and especially for our specifications of choice. A notable exception is natural gas. Gas and oil prices are either both significant or both insignificant. We therefore exclude oil prices from the final natural gas specification, not least for consistency reasons. The impact of prices on gas use is to a considerable extent governed by a small group of outliers, as we describe below.

4.3.2. Sample size

As mentioned in Section 3, data availability is low for residential energy prices. We therefore repeat the analysis without prices to determine the impact of sample size. See Figure A2 to Figure A5 in the appendix. To differentiate between the effect of increased sample size and the effect of including prices, we additionally estimate all specifications restricted to the sample for which price data is available. In the case of coal, we find that the income effect is lower in the large sample. The temperature effect has about the same size, but the quadratic term becomes

[11] For the USA, the cooling effect turned out to be linear, with a short-run elasticity of 0.13 and a long-run elasticity of 0.26. The cooling effect is significant on the 1% level, but it has to be kept in mind that this single-country estimation is based on 24 observations only.
[12] Note that our observation period ends already 2002.
[13] Correlation coefficients (p-values) with oil prices are -3.8 (0.0) for coal prices, 0.3 (0.0) for gas prices and -0.1 (0.03) for electricity prices.

insignificant (the linear term remains significant). The persistence parameter is considerably higher, but still significantly different from one. The parameter changes for the lagged dependent variable, income and temperature squared are also present in the small sample and thus attributed to the omitted price variable. For electricity, income and persistence parameters are stable, but the temperature effect is considerably smaller. The linear and quadratic temperature parameters are insignificant individually, but jointly significant. The temperature parameter is also insignificant for the small sample if prices are excluded. In the case of natural gas, the income and temperature effects are lower but still significant, including the quadratic term. The income and HDM parameters do not change as much if prices are excluded from the small sample, suggesting that the changes can indeed be attributed mostly to the larger sample. For oil, the persistence, income and temperature parameters are lower and become insignificant for the large sample. Contrary to the income effect, the temperature effect is also insignificant for the small sample if prices are excluded, meaning that the insignificance of the temperature effect might be caused by the exclusion of the oil price and not the larger sample.

4.3.3. Interactions

Above, we study non-linearities in temperature. Here we turn to non-linearities in income. The impact of changes in temperature on energy demand might not only depend on the level of temperature itself, but also on income. Households with higher income have more options to adapt to temperature changes than low-income households (e.g. by improving insulation or heating systems); the same rationale holds for high and low income countries. If temperatures rise, the decrease in energy use should be steeper if a country is richer. In this case, the level of income has an effect on the temperature elasticity of energy demand – the elasticity will increase (in absolute value) with rising income. We allow for this effect by including an interaction term into the regression. Income-temperature interaction terms are insignificant for practically all specifications and fuels. We find some weak indication for income dependence of the temperature elasticity of fuel use in the case of natural gas. Although the interaction term is in some cases significant, it usually renders the temperature coefficient itself insignificant. We therefore regard the specification without interactions more credible.

4.3.4. Outliers

Natural gas is not only an interesting fuel because it shows some signs of weak impacts of cross prices and income-temperature interaction, but also because the result is driven to some extent by a small number of outliers in the original sample, in particular with respect to the impact of gas prices. For that reason, the results for natural gas presented so far are purged of those outliers. We excluded 14 observations from 7 countries.[14] The outliers were identified by iteratively deleting the most influential observation until the parameter changes remained sufficiently small.[15] The single qualitative difference between the specifications including and excluding outliers is that the gas price parameter is significant if outliers are excluded and insignificant if they are included for all specifications.

4.3.5. Estimator

Some authors have advocated the use of either fixed effects or lagged dependent variables in applied econometrics (cf. Angrist and Pischke 2009), since the price of including both (having to cope with the Nickell bias, cf. Section 0) is too high compared to the gains (being able to correctly map our theoretical model onto an estimation equation). We feel that by choosing the LSDVC estimator we made a viable compromise between estimation effort and validity. Still, as a sensitivity check, we estimate each of our specifications with only fixed effects as well as with only a lagged dependent variable, excluding the respective other. We used standard OLS procedures for the estimation. We found that, apart from electricity, exclusion of either fixed effects or lagged dependent variables leads to a significant, even qualitative, alteration of the results. Especially the omission of time-invariant heterogeneity, i.e. the fixed effects, renders the impact of temperature, income and fuel prices insignificant for all fuels except electricity and for most specifications. The exclusion of lagged dependent variables has a large impact as well, even though it is less consistent throughout all specifications compared to the exclusion of fixed effects. Again, electricity remains comparably stable. Temperature impact remained significant and non-linear for oil but not for coal and gas. We could not confirm a significant effect of income on oil use, while income remained significant for coal and gas. We conclude from our comparison of estimations using either fixed effects or lagged dependent variables or both that it is important to account for both time-variant as well as time-invariant heterogeneity across countries and include both lagged dependent variables as well as fixed effects.

[14] This includes four observations from Chile, three from Romania, two from Bolivia and Finland as well as one from Colombia, Czech Republic and Ireland.
[15] The most influential observation was identified by calculating the changes in the parameter of the most sensitive variable (in this case gas price) if each observation was included or excluded using Stata's -dfbeta- post-estimation routine.

Referring to the debate about what is the most appropriate dynamic panel estimator for small N, moderate T panels, we further compare our results with Arellano and Bond's (1991) GMM estimator (AB estimator from now on).[16] Since the LSDVC estimator has been argued to be favourable based on an RMSE criterion, we expect to find larger standard errors when using the AB estimator. Since the bias will be smaller or about equal for the AB estimator compared to the LSDVC estimator, the difference between the parameter values will give some indication about the unbiasedness of our estimates. We find the differences between the two estimation procedures to be generally small for our specifications of choice, in any case qualitatively. As expected, standard errors estimated using the AB estimator are generally higher. In some cases, this affects the significance of the results. Fuel prices are generally insignificant in the AB model, as are the temperature effects for electricity and oil. The parameter values are remarkably stable. One exception is the parameters of the lagged dependent variables. The AB models estimate a considerably smaller persistence parameter, which at the same time is less significantly different from one. In general, the parameters of the two estimators differ most for the coal model. Since the sample size for coal is considerably smaller than for the other fuels, this is not surprising. Most important, the size of the HDM coefficients is generally unaffected by changing the estimator.

5. Discussion and conclusion

In this paper, we examine the impact of temperature changes on residential energy use and calculate temperature elasticities of energy use. We use heating degree months as a temperature measure. The responsiveness of energy use to temperature changes depends on the temperature level itself, even beyond the threshold effect included in the heating degree months. Energy use is non-linear in temperature, but the curvature differs between fuels. Energy use decreases with rising temperatures (because of a decreased demand for heating), but above the heating threshold the marginal decrease declines with rising temperature levels.

[16] For this sensitivity analysis, we use the two-step GMM estimation procedure of Arellano and Bond's (1991) estimator with Windmeijer's (2005) robust standard errors and forward orthogonal deviations instead of first differences (Arellano and Bover 1995) to avoid loss of observations. As recent debates indicate, a large instrument collection, which easily evolves with panels with sufficiently large time dimension, overfits the model and leads to invalid estimates for the standard errors (cf. e.g. Roodman 2009 on this issue). To confine this problem, we limited the number of instruments used in our estimations by "collapsing" the instrument matrix. "Collapsing" instruments means that one instrument for each variable and lag distance is used, rather than one for each time period, variable and lag distance. See Roodman (2009) and the references given there for details. Arellano and Bond's (1991) estimator was implemented using Stata 10.1 and Roodman's (2006) -xtabond2- procedure.

The geographical scope of our paper is considerably larger than in most previous studies, and covers both developed and developing countries. This allows us to form conclusions of general validity. However, this generality necessarily involves a loss of provision for specific circumstances: For example, we are not able to identify a cooling demand of worldwide impact, a result that is due to the fact that cooling is not a global issue, yet – however it certainly is a regional.

What are the implications of our findings for economic impacts of climate change? Private households would benefit from the reduced spending on heating energy. Energy suppliers would be hit as their markets shrink. This effect is largest in the cold and rich North. According to our elasticity ranking, gas suppliers will suffer most from climate change, since the temperature elasticity of natural gas is highest. Gas is followed by oil and electricity. However, gas is at the same time also most responsive to income changes. Thus the contractive effect of climate change on gas use would be offset by economic growth. The same is true to a lesser extent for oil and electricity. Coal use will decrease due to warming, but also if incomes rise or coal prices fall, due to it being an inferior Giffen good.

The reduction in heating energy demand could be partly or even completely offset by two developments: Firstly, an increased use of cooling devices, though not important in our observation period, could in the future increase energy use. Secondly, economic growth in warm developing countries will increase energy use.

Adding energy demand in industry and services would be a natural extension of this study. Even if the residential sector is the one with the highest sensitivity towards temperature changes with respect to energy demand, other sectors may feature similar effects as well. Furthermore, broadening the analysis to include other fuel types could be a sensible extension. Especially the consideration of (traditional) biomass would lead to a more complete picture of the interrelations in developing countries, since a considerable fraction of residential energy use falls upon fire wood and other biomass-based fuels. Availability of data prevents progress in that respect at the moment. An empirical study of the impact of weather and climate on energy supply would be another valuable extension. All this is deferred to future research.

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Tables and Figures

Table 1: Descriptive Statistics.

Variable	Mean	Std. Dev.	Min	Max	Included Observations		
					N	n	T
Fuel use (tonnes of oil equivalent (toe) per person per year)							
Solid fuels (coal)	44.25	87.33	0.00	632.49	1 346	69	20
Electricity	56.93	98.02	0.15	692.71	4 290	176	24
Gas	90.29	140.66	0.00	806.86	1 580	72	22
Light fuel oil	65.88	127.73	0.03	1 170.27	4 351	174	25
Fuel price (PPP(95USD) per toe)							
Coal	163.53	65.03	13.38	305.23	308	22	14
Electricity	1 329.18	1 014.09	40.45	8 835.40	1 029	63	16
Gas	429.12	233.04	5.10	1 300.17	614	38	16
Light fuel oil	412.79	189.57	112.36	1 352.68	662	33	20
Income (1000 PPP(95USD) per person per year)	6.68	6.82	0.42	43.94	4 265	162	26
Average temperature (°C, country-year-median)[a]	19.74	8.35	-9.00	31.75	6 768	183	37
Regionalized Heating Degree Months (HDM)[b]	44.26	63.84	0.00	331.11	6771	183	37
Regionalized Cooling Degree Months (CDM)[b]	55.29	39.67	0.00	132.57	6771	183	37

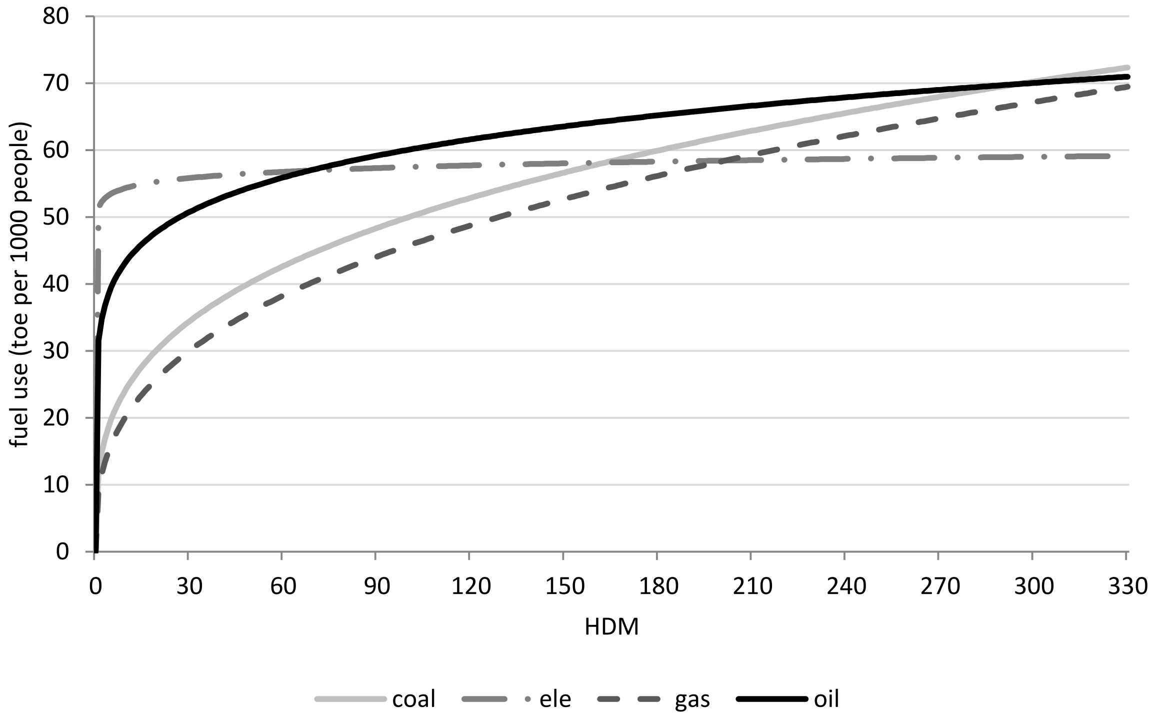
N: Total number of observations; n: Number of countries with at least one observation; T: Average number of periods per country. [a]: Median average temperature is not used in regressions and displayed solely for the information of the reader. [b]: For the definition of Regionalized Heating and Cooling Degree Months (HDM and CDM), cf. Section 2.

Table 2: LSDVC estimation of coal, electricity, gas and oil use for heating purposes.

Dependent variable: log(fuel use per capita)	Coal	Electricity	Gas	Oil
log(fuel use per capita)$_{(t-1)}$	0.83***	0.94***	0.92***	0.95***
	(0.04)	(0.01)	(0.02)	(0.01)
log(gdp per capita in PPP)	-0.82***	0.07***	0.2***	0.1**
	(0.16)	(0.01)	(0.06)	(0.04)
log(fuel price in PPP)$_{(t-1)}$	0.26**	-0.01***	-0.08**	0.03
	(0.11)	(0.003)	(0.04)	(0.02)
log(HDM)	0.21	0.02**	0.31***	0.12*
	(0.21)	(0.01)	(0.07)	(0.06)
$(\log(HDM))^2$	0.05**	0.002*	0.02***	0.01**
	(0.02)	(0.001)	(0.01)	(0.005)
Observations	270	884	527	597
No. of countries	20	56	36	32
AIC	727.25	518.15	1216.4	1540.8
p((b_log(fuel use per capita)$_{(t-1)}$)=1)	0.00	0.00	0.00	0.00

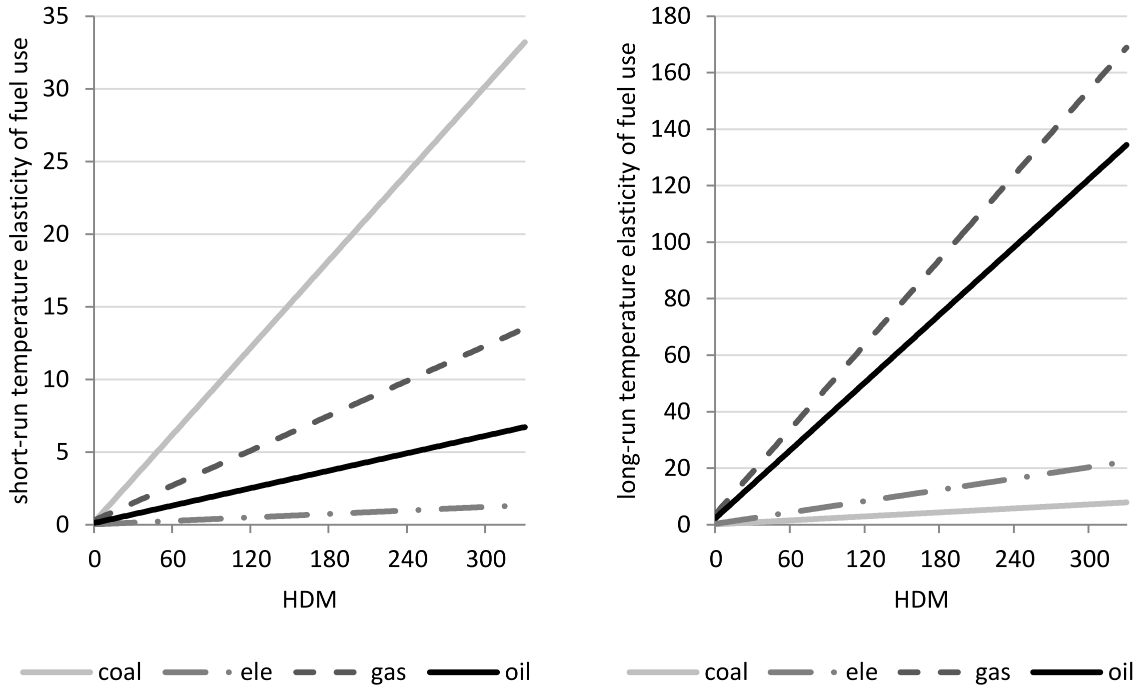
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Gas: Excluding outliers. 14 observations from Bolivia (2), Chile (4), Colombia (1), Czech Republic (1), Finland (2), Ireland (1) and Romania (3) were determined using DFBETA influence statistics. HDM: Regionalized Heating Degree Months.

Figure 1: Non-linear response in energy use to temperature changes.



Predicted values using average explanatory variables.

Figure 2: Short-run and long run temperature elasticity of fuel use.



Predicted values using average explanatory variables. Note the different scales of the vertical axes.

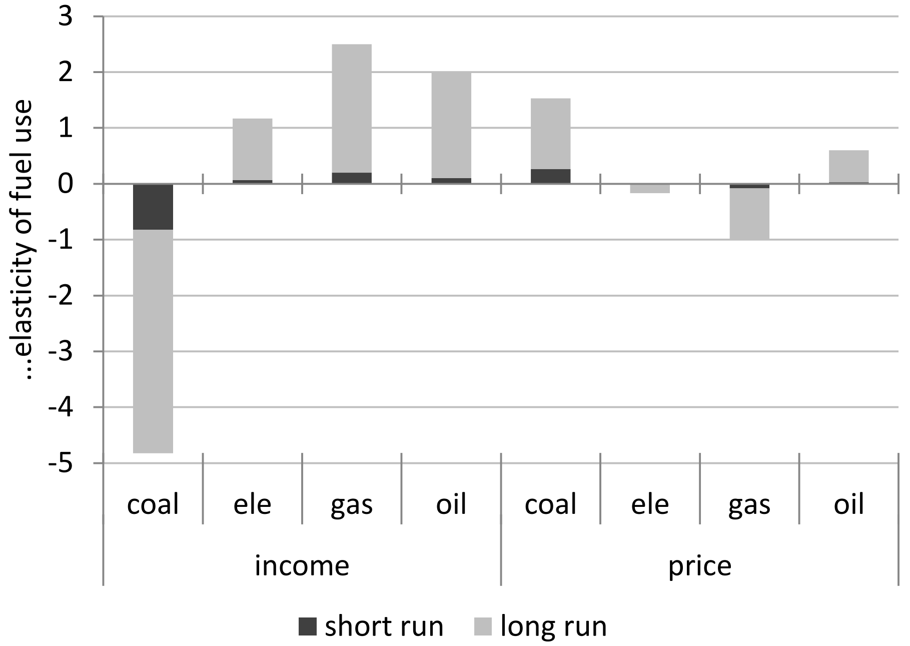
Appendix

Table A 1: LSDVC Estimation results for various functional forms.

	coal			electricity			gas			oil		
	no temp.	linear	quadr.	no temp.	linear	quadr.	no temp.	linear	quadr.	no temp.	linear	quadr.
log(fuel use per capita)$_{(t-1)}$	0.93***	0.83***	0.83***	0.93***	0.94***	0.94***	0.91***	0.91***	0.92***	0.95***	0.95***	0.95***
	(0.03)	(0.04)	(0.04)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
log(gdp per capita in PPP)	-0.64***	-0.86***	-0.82***	0.07***	0.07***	0.07***	0.11*	0.13**	0.2***	0.06	0.07	0.1**
	(0.17)	(0.17)	(0.16)	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.06)	(0.04)	(0.04)	(0.04)
log(fuel price in PPP)$_{(t-1)}$	0.20**	0.25**	0.26**	-0.01***	-0.01***	-0.01***	-0.07**	-0.07*	-0.08**	0.02	0.03	0.03
	(0.1)	(0.11)	(0.11)	(0.004)	(0.004)	(0.004)	(0.03)	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)
log(HDM)		0.35*	0.22		0.01	0.02**		0.12***	0.31***		0.02	0.12*
		(0.19)	(0.21)		(0.01)	(0.01)		(0.05)	(0.07)		(0.05)	(0.06)
(log(HDM))^2			0.05**			0.002*			0.02***			0.01**
			(0.02)			(0.001)			(0.01)			(0.005)
Observations	293	270	270	971	884	884	547	527	527	633	597	597
No. of countries	21	20	20	62	56	56	37	36	36	33	32	32
AIC (smaller is better)	882.2	729.7	727.3	963.5	521.6	518.2	1 304.1	1 233.6	1 216.4	1 663.2	1 547.3	1 540.8
p((b_log(fuel use)$_{(t-1)}$)=1)	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

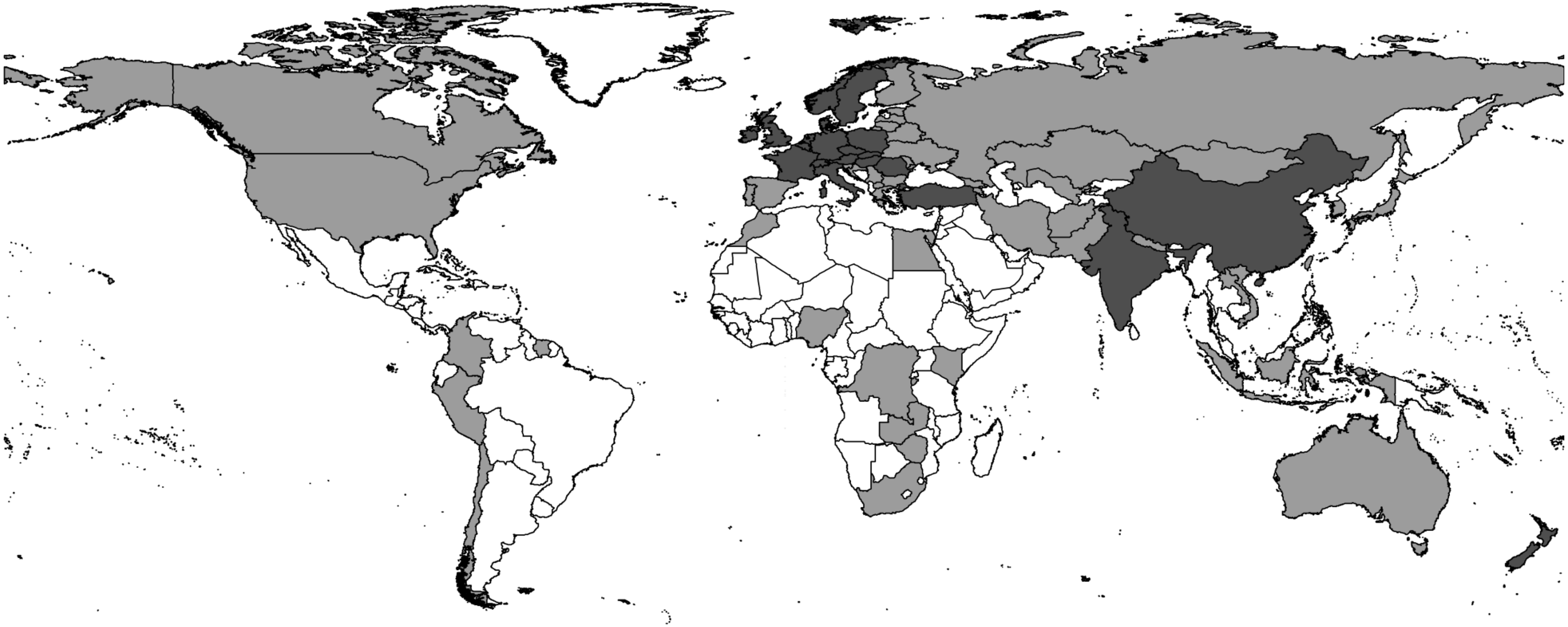
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Gas: Excluding outliers. HDM: Regionalized Heating Degree Months. The logarithmic model does usually not yield significant temperature impact or copies the quadratic specification closely. We therefore do not present the logarithmic model here.

Figure A 1: Income and price elasticities of fuel use.



Predicted values using average explanatory variables.

Figure A2: Geographical coverage of coal data



♦: Use data available; ♦: Use and price data available; blank: no data.

Figure A3: Geographical coverage of electricity data

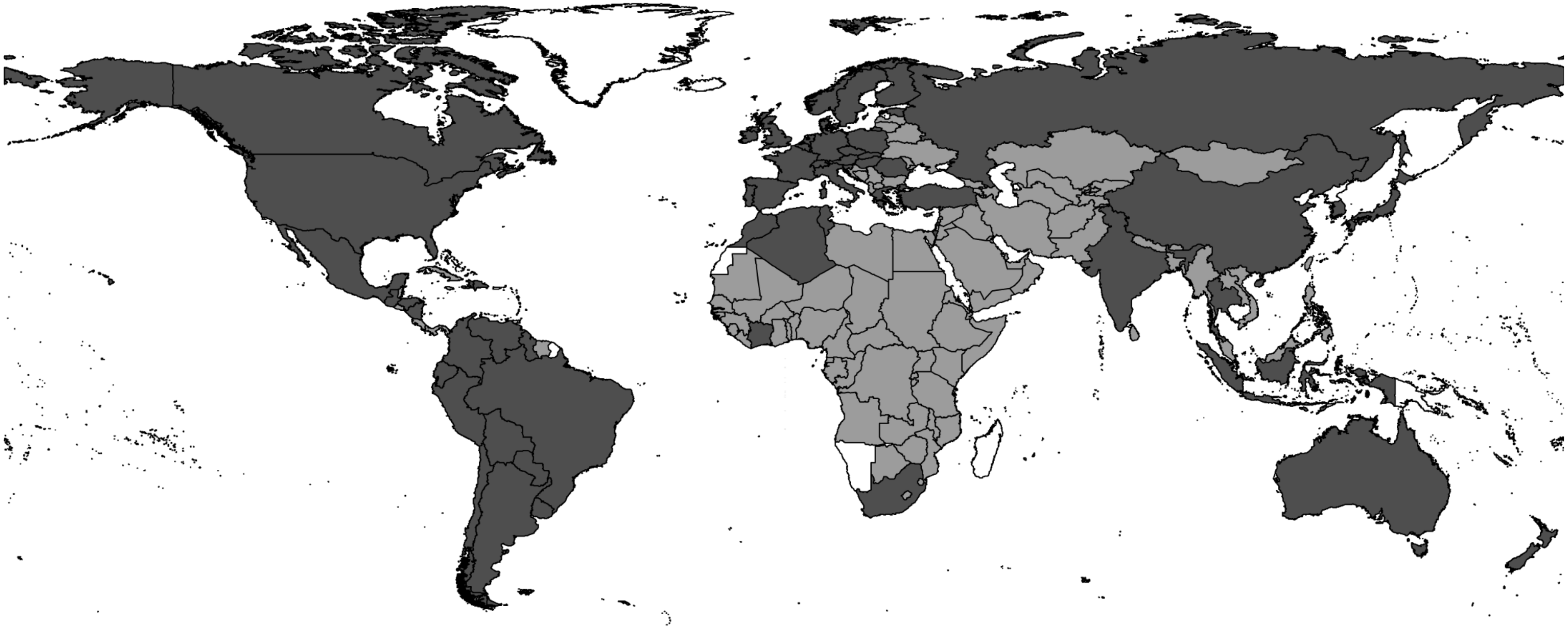


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Figure A4: Geographical coverage of natural gas data

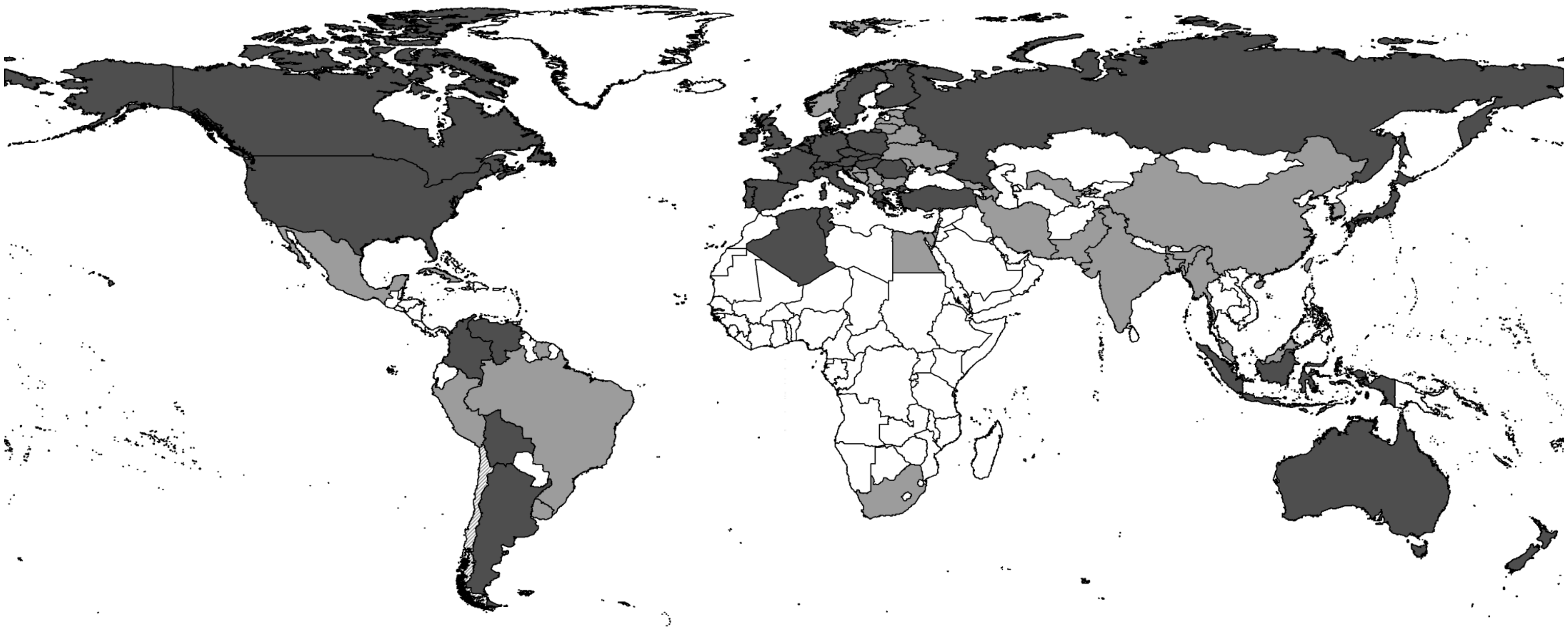

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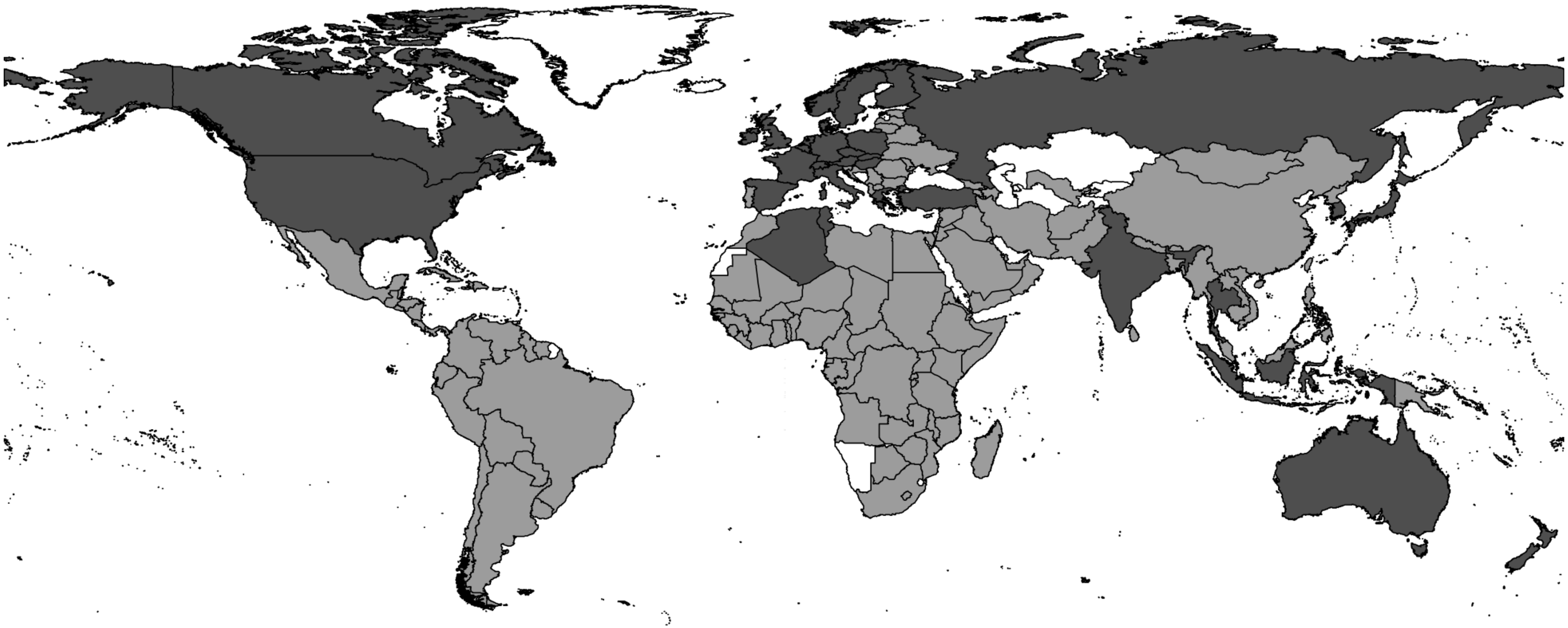
Figure A5: Geographical coverage of oil data



♦: Use data available; ♦: Use and price data available; blank: no data.