Kiel
Working Papers

Kiel Institute
for the World Economy

The Impact of Temperature Changes on Residential Energy Consumption

by Sebastian Petrick, Katrin Rehdanz and Richard S. J. Tol

No. 1618 | April 2010

Kiel Working Paper No. 1618 | April 2010

The Impact of Temperature Changes on Residential Energy Consumption

Sebastian Petrick, Katrin Rehdanz and Richard S. J. Tol

Abstract:
To investigate the link between rising global temperature and global energy use, we estimate an energy demand model that is driven by temperature changes, prices and income. The estimation is based on an unbalanced panel of 157 countries over three decades. We limit the analysis to the residential sector and distinguish four different fuel types (oil, natural gas, coal and electricity). Compared to previous papers, we have a better geographical coverage and consider non-linearities in the impact of temperature on energy demand as well as temperature-income interactions. We find that oil, gas and electricity use are driven by a non-linear heating effect: Energy use not only 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. Furthermore we find evidence that the temperature elasticity of energy use is affected by the level of temperature as well as the level of income.

Keywords: Climate change, energy demand, heating and cooling effect, temperature

JEL classification: Q41, Q43

Sebastian Petrick
Kiel Institute for the World Economy
24100 Kiel, Germany
Telephone: +49 431 8814 263
E-mail: sebastian.petrick@ifw-kiel.de

Katrin Rehdanz
Kiel Institute for the World Economy
Department of Economics, Kiel University, Kiel, Germany

Richard S. J. Tol
Economic and Social Research Institute, Dublin, Ireland
Institute for Environmental Studies, Vrije Universiteit, Amsterdam, The Netherlands
Department of Spatial Economics, Vrije Universiteit, Amsterdam, The Netherlands

1. Introduction and existing work

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 next century, depending on the scenario (IPCC 2007). Among the various economic consequences of a global temperature rise, the impact on energy consumption 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 consumption thus affects and is affected by both climate change and climate policy. This paper aims to disentangle the impact of temperature changes on energy consumption.

So far, most contributions addressed the topic on a micro-level, concentrating on specific countries (e.g. Quayle and Diaz 1979; Li and Sailor 1995; Rosenthal and Gruenspecht 1995; Al-Zayer and Al-Ibrahim 1996; Henley and Peirson 1997, 1998; Florides et al. 2000; Vaage 2000, Hunt et al. 2003; Zarnikau 2003; Mirasgedis et al. 2004; Amato et al. 2005; Giannakopoulos et al. 2005; Mansur et al. 2005; Pezzulli et al. 2006; Asadoorian et al. 2007; Mansur et al. 2007). However, studies that focus on a single country are necessarily limited in scope, since they consider only the range of climates experienced and the variety of technologies used in that country. It is therefore useful to look at all countries simultaneously – although we acknowledge that the broader insights may well come at the expense of detail and depth.

Studies on many countries are few. Bigano et al. (2006) investigate the energy consumption of the residential, industrial and service sectors of up to 26 OECD countries, distinguishing between five different fuel types. They find significant impacts of temperature only for residential energy demand. Energy use of the industrial and service sectors are not significantly influenced by temperature changes. Bessec and Fouquau (2008) focus on total electricity use in the EU-15 and do not differentiate between specific sectors. By applying a smooth threshold regression model they account for non-linearities in the link between energy use and temperature. Furthermore, they find that the non-linear pattern is more pronounced in warm countries. The only study with a global scope – in the sense that it covers a heterogeneous group of countries all over the world – is by De Cian et al. (2007). They restrict their analysis to the residential sector but include 31 OECD and five non-OECD countries, covering a wider variety of development levels and climate zones than previous studies. They conclude that demand for heating and cooling and its response to changes in temperature depend on region, season and fuel type.

In this paper, we further extend the analysis of De Cian et al. (2007). First, we add more countries to the sample. This should 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. Second, we allow for non-linear responses. Winter heating is one example. One would expect less demand for winter heating in warmer countries, but heating demand goes to zero if winters are warm enough. Regarding cooling, air conditioning varies from an extravagance to a necessity depending on summer heat. Energy is a luxury good for households with little income, a necessary good for richer people, and maybe even a saturated good for those with the highest incomes. Furthermore, solid fuels are often inferior goods, and richer households tend to use more energy-efficient equipment. There is, therefore, no reason to assume a simple, linear relationship between energy use on the one hand and climate and income on the other.

The paper is build up as follows: Section 2 provides an overview over the determinants of residential energy consumption including income, fuel prices as well as temperature and how they affect it. This is followed by considerations regarding the econometric estimation. We present the data in section 3. The results of the econometric analysis are discussed in section 4. Section 5 concludes.

2. Modelling determinants of residential energy consumption

Our study covers information on the use of different fuel types in the residential sector, namely light fuel oil, natural gas, solid fuels (excluding biomass, so mainly coal) and electricity. We include only the residential sector because previous studies confirmed 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. In our model, households adapt their use of energy to changes in 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 and ordinary goods with positive income elasticities, negative price elasticities and zero or positive cross price elasticities towards other energy fuels.

In our analysis we account for differences in temperature as well. With rising temperatures, households will heat less, whereas the demand for cooling will rise – while the heating effect reduces energy consumption, the cooling effect increases it in the course of a rise in temperature. A vital question is the nature of the interdependence between temperature changes and adjustments in the consumption of energy. Assuming a linear relationship seems rather counterintuitive.[1] One would expect that the impact of a changed temperature differs substantially depending on the original temperature level. Presumably, if

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

temperature rises, the reduced heating demand would be smaller for warmer countries than for colder ones; while increased cooling demand would be larger.[2]

The use of heating (HDD) and cooling degree days (CDD),[3] as for example in Al-Zayer and Al-Ibrahim (1996) or Amato et al. (2005), already presents a transformation of temperature data that is intended to cover this non-linearity. However, degree days do not provide a smooth adaptation of the temperature elasticities to the respective prevailing temperature, but simply introduce a discontinuous jump at a threshold value. The choice of the heating or cooling threshold is usually more or less arbitrary, and the assumption of an identical threshold value for all countries might be vulnerable to criticism if enough countries are included. An alternative approach is presented in De Cian et al. (2007). Instead of using degree days, they cluster their sample of countries into three groups (hot, mild and cold countries), for each of which a separate (linear) energy demand equation is estimated.

In this paper we follow a different approach to assess the non-linearities in the response to temperature changes by estimating one non-linear demand equation per fuel for the whole sample. We use linearizable functions to avoid unnecessary complexity and to facilitate the estimation as well as the interpretation of results. We consider different functional forms including quadratic polynomials as well as logarithmic and inverse functions.[4] Linear equations are estimated as a benchmark and for comparison to previous papers. To distinguish between the heating and cooling period, we use the average temperatures of the hottest and coldest months unlike Bigano et al. (2006) who use annual averages only. We refrain from using HDD or CDD (as in Al-Zayer and Al-Ibrahim 1996 or Amato et al. 2005) because of the difficulties to define the (globally representative) heating and cooling thresholds. Furthermore, data availability would reduce geographical and temporal coverage significantly.

---

[2] 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. Here, variation in yearly average temperatures is limited. On a global scale however, where average temperatures varies more, a non-linear relationship is much more likely. The question concerning the interpretation of the results derived for the global scale is of course, whether patterns derived from comparisons between countries also hold within a country, given that temperatures rise significantly in the future.

[3] Heating degree days are usually defined as the difference between the average temperature of a period and an arbitrary threshold temperature (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 an arbitrary *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.

[4] For most specifications, cubic polynomials were tested as well but generally inferior to the functional forms mentioned here.

The impact of changes in temperature on energy demand does not only depend on the level of temperature itself, as implemented by including non-linearities, but probably also on other variables, especially 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 consumption should be steeper, if a country is comparably 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.

In the short run, the speed of adjustment of energy use to changes in the explanatory variables is limited as it is largely restricted to behavioural changes. Extensive adjustment is only possible in the long run and implies changes, e.g. in the prevailing and available technical equipment and government policy. Furthermore, transient (or so perceived) shocks of the explanatory variables will have a smaller impact on energy demand than sustained changes. To account for this inertia, we include the energy use of the preceding period into the equation. Thereby we implicitly take into account the whole history of the exogenous variables.[5]

The whole model can be summarized as

$$(1) \qquad e_{i,t} = f\left(tmin_{i,t}, tmax_{i,t}, y_{i,t}, pe_{\mathrm{i,t}}, ps_{i,t}, e_{\mathrm{i,t\text{-}1}}, \delta_i\right),$$

where $e_{i,t}$ is county *i*'s per-capita consumption of fuel *e* in year *t*, $tmin_{i,t}$ is the daily mean temperature of the coldest, $tmax_{i,t}$ the daily mean temperature of the hottest month in one year, $y_{i,t}$ denotes per-capita income, $pe_{i,t}$ is fuel *e*'s price, $ps_{i,t}$ is the cross price (possibly a price vector) of substitutable fuels and δ_i are a set of country specific effects. At this stage, the functional form is not yet specified. In the following, we will compare different functional forms, namely linear and quadratic polynomials as well as logarithmic and inverse functions. The different functional forms for heating demand are summarized in Table 1. To estimate the cooling effect, *tmin* is replaced by *tmax*. To estimate both effects jointly, both *tmin* and *tmax* were included in the same equation.

[5] If a geometrically decreasing (i.e. decreasing by a constant proportion) impact of past lags of an exogenous variable is assumed, including all past lags of this variable can be transformed into including a lagged endogenous variable (lagged by one period) by the Koyck-transformation (cf. Koyck 1954, pp. 19 ff.). The parameter of the lagged dependent variable then represents the adjustment speed implied in the geometric relation between the lagged exogenous variables.

Table 1: Different functional forms of the regression equation (heating effect)

Linear: $e_{i,t} = \beta_1 tmin_{i,t} + \beta_3 tmin_{i,t} \cdot y_{i,t} + \gamma_1 y_{i,t} + \gamma_2 pe_{\mathrm{i,t}} + \gamma_3 ps_{i,t} + \gamma_4 e_{\mathrm{i,t-1}} + \delta_i$

Quadratic: $e_{i,t} = \beta_1 tmin_{i,t} + \beta_2 tmin_{i,t}^2 + \beta_3 tmin_{i,t} \cdot y_{i,t}$

$+ \gamma_1 y_{i,t} + \gamma_2 pe_{\mathrm{i,t}} + \gamma_3 ps_{i,t} + \gamma_4 e_{\mathrm{i,t-1}} + \delta_i$

Logarithmic: $e_{i,t} = \beta_1 \log\left(tmin_{i,t}\right) + \beta_3 tmin_{i,t} \cdot y_{i,t} + \gamma_1 y_{i,t} + \gamma_2 pe_{\mathrm{i,t}} + \gamma_3 ps_{i,t} + \gamma_4 e_{\mathrm{i,t-1}} + \delta_i$ [a]

Inverse: $e_{i,t} = \beta_1 tmin_{i,t}^{-1} + \beta_3 tmin_{i,t} \cdot y_{i,t} + \gamma_1 y_{i,t} + \gamma_2 pe_{\mathrm{i,t}} + \gamma_3 ps_{i,t} + \gamma_4 e_{\mathrm{i,t-1}} + \delta_i$ [a]

a: For the logarithmic specification, *tmin* was added to 25 to prevent loss of observations when taking logarithm of negative temperatures. The same is true for the inverse specification to force the discontinuous jump outside the observed domain.

3. The data

We use data on annual average temperature derived from monthly data 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 and converted to country averages. This procedure does not take into account to what extent particular areas of a country are populated. This might be especially important for large and diverse countries, like Canada, the United States of America, or Russia. The majority of Canadians live close to the US border and not in the Arctic Circle. We, therefore, calculated population-weighted country averages to test for robustness. Population data was retrieved from the HYDE database (before 1990, Klein Goldewijk 1995) and the GPWv3 database (from 1990 onwards, CIESIN and CIAT 2005). The population weights used are available only on a 10 year (until 1990) and 5 year (from 1990 onwards) frequency; the bias thus introduced for other years is unclear so we use the area-weighted temperatures as our main variable. Temperature data are available for all countries and periods of interest.

Data on energy consumption, prices and real GDP are retrieved from ENERDATA (2005) for the period 1970 to 2002. We distinguish between four major fuel types, viz. oil, gas, solid fuels (i.e. coal) and electricity. Sample sizes differ considerably with respect to the different fuel types – both regarding consumption and price data, see Table 2 for details. Data on the consumption 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 rare. 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. Regarding geographic coverage, coal is again the fuel type with the lowest coverage: the price of coal for residential consumption 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 approximate the price of residential coal by other prices, e.g. coal prices from other sectors. Data availability 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 fuel types, limited availability of price data impose 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 auxiliary regressions (see Section 4). As a proxy for household income we use per-capita GDP in purchasing power parities (converted to 1995 international dollars). Compared to energy price and consumption variables, data availability is good.

Table 2: Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	Included Observations		
					N	n	T
Fuel use (tonnes of oil equivalent per person per year)							
Light fuel oil	65.88	127.73	0.03	1 170.27	4 351	174	25
Gas	90.29	140.66	0.00	806.86	1 580	72	22
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
Fuel price (PPP(95USD) per toe)							
Light fuel oil	412.79	189.57	112.36	1 352.68	662	33	20
Gas	429.12	233.04	5.10	1 300.17	614	38	16
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
Income (1000 PPP(95USD) per person per year)	6.68	6.82	0.42	43.94	4 265	162	26
Daily average temperature in the coldest month (°F)	54.64	22.22	-23.36	81.86	6 771	183	37
Daily average temperature in the hottest month (°F)	77.41	9.09	50.39	101.23	6 771	183	37

N: Total number of observations; n: Number of countries with at least one observation; T: Average number of periods per country.

4. Results

To estimate the four fuel demand models, we use the two-step GMM estimation procedure for dynamic panels proposed by Arellano and Bond (1991) 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 and restricting instrumentation to a certain lag level (depending on the model between three and five lags).[6]

4.1 The heating effect

For each fuel type, we estimate the linear and the three non-linear equations for a number of specifications that differ with respect to price variables included and the treatment of income-temperature interaction. We first evaluate which of the fuel prices has a significant influence on the consumption of which fuel. It turns out that only the price of oil is significant for other fuels. Oil and gas consumption furthermore depend on their own prices. The price for neither coal nor electricity have any significant effect on the use of any fuel type.

Having determined the set of meaningful price variables, we contrast the four equations with and without an interaction term for income and temperature. Based on parameter significance, sign of the temperature and income variables, the size of the autoregressive parameter and on the Akaike Information Criterion, we choose one equation for each fuel type that best explains the use of this fuel. Our choices are presented in Table 3, the alternative specifications can be found in the appendix (Tables A1-A4).

The results are robust to replacing area-weighted temperature data by population-weighted data – only the size of the effects increases in some cases if population weighted-temperature data is used, significance remains unchanged. Detailed results for population weighted-temperature data can be found in the appendix (Table A5).

We find a significant heating effect for all four fuel types (cf. Figure 1). Non-linearity of the heating effect can be confirmed for oil, gas and electricity. For coal the linear model is superior. Oil and electricity consumption exhibit quadratic patterns, while the logarithmic specification was most appropriate for natural gas.

---

[6] "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.

The property of allowing for a positive slope in the case of the quadratic functions if temperatures become sufficiently high takes effect only for temperatures outside our sample (warmer than 80°F/26°C in the case of oil and 140°F/60°C in the case of electricity).

In the following we discuss the results presented in Table 3 for each fuel type individually before we make comparisons.

In the short run, oil has the highest temperature semi-elasticity of the four fuel types – if temperature increases by one degree Fahrenheit, per-capita oil consumption decreases by 1% for the average level of per-capita income and temperature (cf. Figure 2).[7], This corresponds to 2.5 toe per capita. However, the picture is quite different for some countries. For a relatively warm and poor country like India the semi-elasticity is -8% and the marginal effect is only -0.97 toe per capita for a one degree Fahrenheit temperature change. In contrast, for a relatively cold and rich country like Norway the semi-elasticity is -3%, corresponding to a marginal effect of -3.29 toe per capita.[8] This illustrates the effects of non-linearity and income-temperature interaction – the absolute effect of a temperature change is higher if a country is relatively cold and rich. Although in a warmer and poorer country the absolute effect is accordingly smaller, the change in relative terms can easily be higher, since the initial level of per-capita consumption of energy is lower in the first place. Figure 1shows how, for average income, energy use depends on the temperature level. Figure 3 shows how, for the average temperature, long-run temperature semi-elasticities depend on the income level.

The same reasoning holds true for natural gas, the other fuel that features both non-linearity and temperature-income interaction. However, with -0.6% the short-run average semi-elasticity is much smaller than in the case of oil. In fact, the response to temperature changes is smallest for natural gas among the four fuel types. Also, because of the logarithmic specification, the non-linearity is less pronounced over the whole temperature domain than in the case of oil. It is limited mainly to very cold winters, which in our sample were frequent only in Canada, Russia and Central Asia. For average winter temperatures, the curve resembles an almost linear pattern. Also income seems slightly less important in explaining differences in energy consumption compared to oil, as can be seen from the shallower slope of the natural gas line in Figure 3.

In all countries except China, residential coal use has remained constant or declined over the last decades, per capita but also in absolute terms. Nowadays

[7] The use of semi-elasticities is necessary since we arbitrarily measure temperature in degrees Fahrenheit.
[8] Of course the calculated effects for single countries suit illustrative purposes only, since the underlying parameters were estimated for the whole panel and thus represent a global mean. The same parameters will probably evolve differently from a single country estimation.

Table 3: Energy demand models for oil, gas, coal and electricity

	oil (quadratic)	gas (logarithmic)	coal (linear)	electricity (quadratic)
fuel use in (t-1)	0.897***	0.858***	0.970***	0.939***
	(0.021)	(0.044)	(0.036)	(0.014)
tmin	-2.134***		-0.449***	-0.575***
	(0.702)		(0.170)	(0.154)
$tmin^2$	0.017*			0.004*
	(0.009)			(0.002)
log(tmin)		-11.351*		
		(6.073)		
GDP-interaction	-0.064*	-0.053*		
	(0.038)	(0.032)		
GDP per capita (PPP)	2.643**	2.606***	0.133	0.411***
	(1.101)	(0.965)	(0.244)	(0.141)
gas price		-0.049**		
		(0.024)		
oil price	-0.104***	0.042***	0.041*	
	(0.034)	(0.013)	(0.023)	
N	627	466	540	3455
No. of countries	33	29	30	157
AIC	6255	4200.3	4049.4	22244.2
Wald chi^2	6332.3***	1092.3***	1250.4***	7535.4***
No. of instruments	30	18	20	115
Hansen J-statistic	24.2	14.3	22.5	126.9
P-value of Hansen J-stat.	0.45	0.28	0.13	0.14

*** significant at 1%, ** significant at 5%, * significant at 10%. Standard errors in parentheses. Arellano/Bond autocorrelation tests were computed up to order 6 and generally rejected the null hypothesis for autocorrelation of second or higher order at the ten percent level of significance.

coal plays a significant 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. Coal is usually regarded as an inferior good. It is the only fuel type that does not exhibit a non-linear heating effect, and the income-temperature interaction is not significant either. Despite responding linearly, the semi-elasticity for coal is quite high in the short run and with -0.9% only slightly smaller than for oil.

However, the explanatory power of the coal model is limited. Coal is the only case in which the autoregressive parameter, which models the inertia of reaction, is for some specifications larger than one, and also in our specification of choice not significantly different from one (p-value: 0.2, one-sided test).[9] This suggests an extremely sluggish response of residential coal consumption. Consumption does not change significantly from one year to the other, temperature and price effects cancel out while income changes do not matter. Graphical inspection confirms invariance of residential coal consumption for a considerable number of countries (graphs not shown).

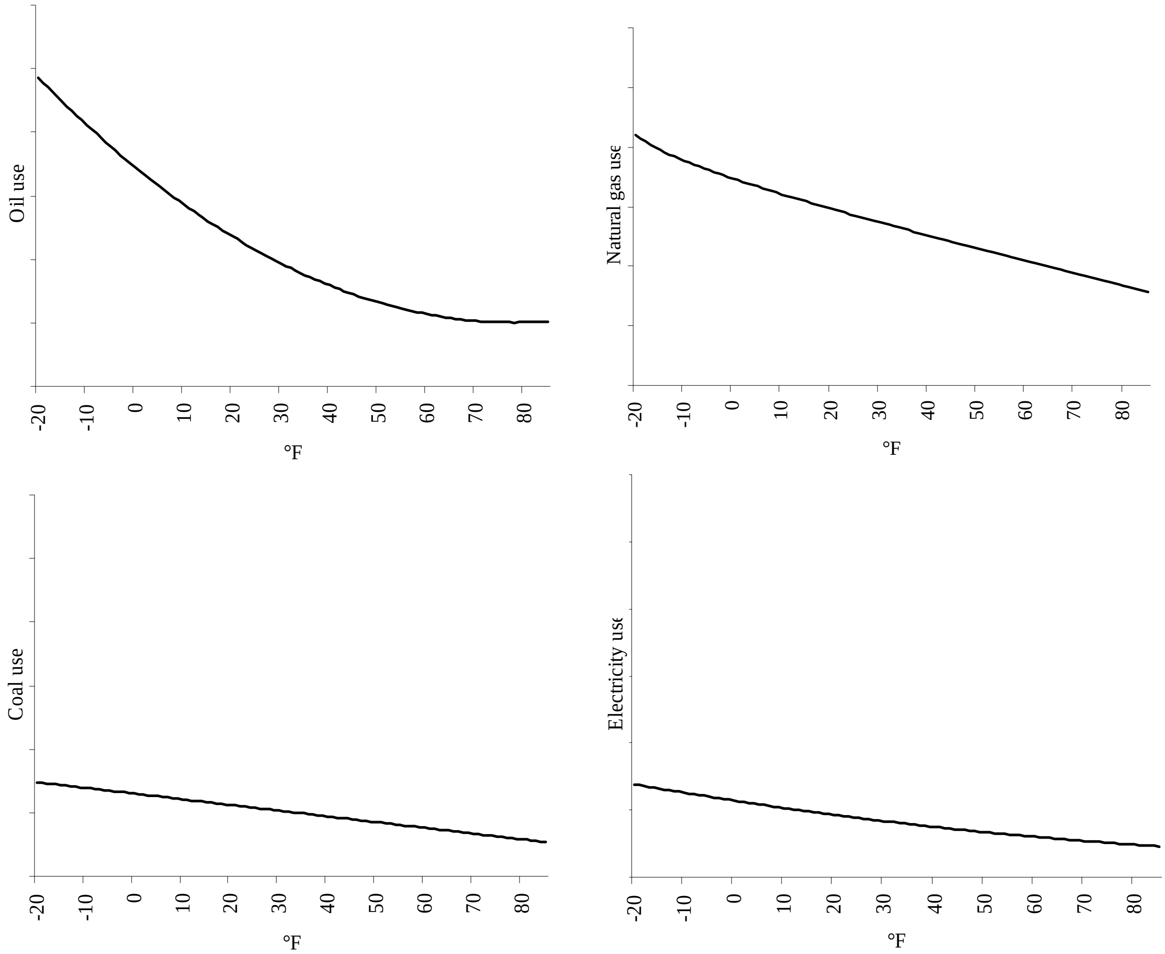
Electricity is the only fuel type that is used both for heating and for cooling.[10] While we focus on the heating effect in this section, the cooling effect is discussed below. The short-run average temperature semi-elasticity of residential electricity consumption being only -0.6%, electricity use is among the least temperature-sensitive fuels. This does not come as a surprise since electricity is used for a range of services, including not only heating and cooling but also services that are less responsive to climate and weather, such as lighting and home appliances. The response of electricity consumption on temperature changes nevertheless follows a non-linear (quadratic) pattern, but interactions between temperature and income are not present.

As explained before, households' adaptation to temperature changes is inert, mainly because of habits and technological constraints. Including an autoregressive parameter into the regressions enables us to differentiate between short-run and long-run effects, the latter giving the overall impact in the year in which the initial shock faded out. The more inert a model is, i.e. the larger the autoregressive parameter is, the higher will be the final impact of the initial (short-run) shock. In the case of our four fuel demand models the long run elasticities are probably more relevant than the short-run elasticities and present a slightly different picture. Still oil consumption reacts more to temperature changes than

[9] For all other fuels, the autoregressive parameter is significantly smaller than one.

[10] Of course it is in principle possible that households use their own generator to produce electricity from oil products themselves. The cooling effect could then also affect the consumption of oil. Apart from the fact that this effect is supposedly only of minor importance, most of it is statistically covered by the transport sector and not by the household sector anyway, which leaves it beyond the scope of this study.

Figure 1: Fuel use as a function of temperature (for average income)



One scale division is 50 toe, the axis intercept depends on each countries fixed effect and the income and possibly price levels.

Figure 2: Temperature semi-elasticities of fuel use (for average temperature and income)

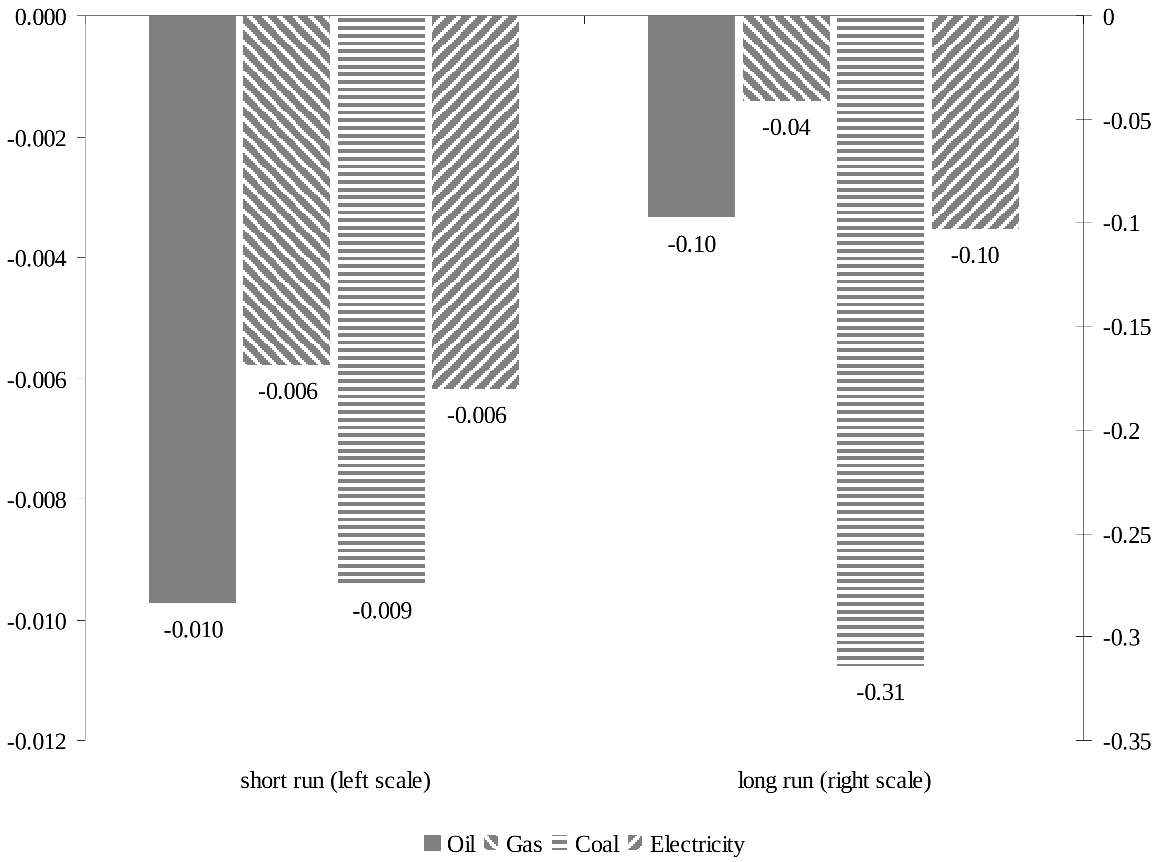
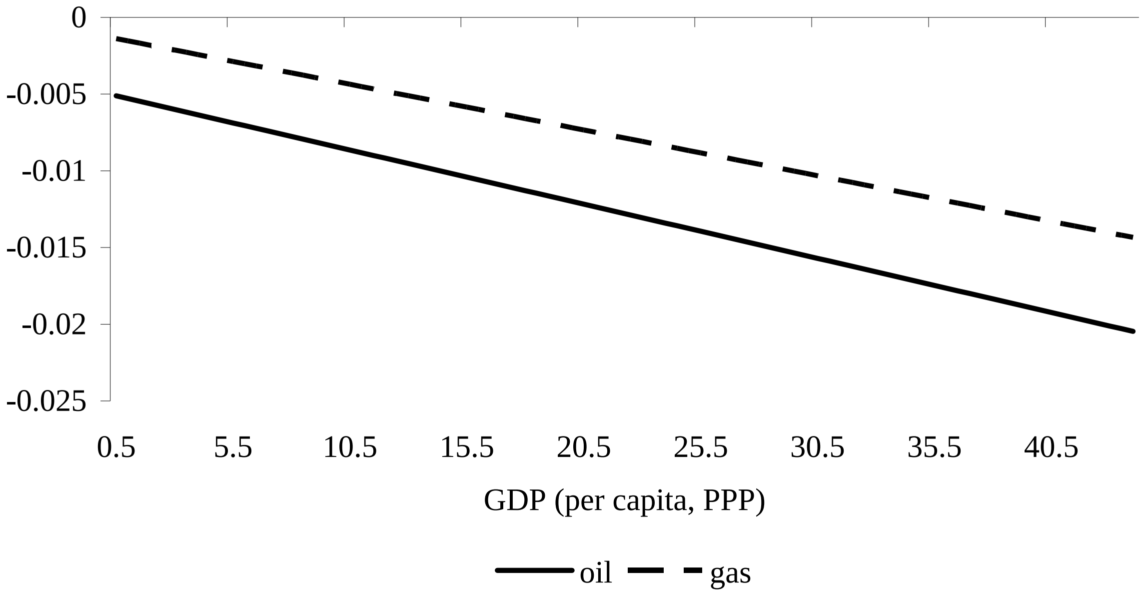


Figure 3: Long-run temperature semi-elasticities (for the average temperature) as a function of income.



natural gas – one degree Fahrenheit warmer leads ceteris paribus and on average to a ten percent decrease in oil consumption in the long run compared to a four percent decrease in consumption of natural gas (cf. Figure 2). But in the long run electricity use reacts to a great extent, too, and decreases by ten percent. This reflects the slower speed of adjustment of electricity use compared to other fuels. Accordingly, the median lag for electricity is 11.2 years, compared to 6.6 and 4.6 years for oil and gas.[11] For coal, the high autoregressive term results in a long-run average semi-elasticity of 31%, implying a median lag of 22.8 years. As indicated above, the results for coal need to be treated with care.

Turning to the economic variables, the impact of income and price changes on energy use is as expected. See Figures 4 and 5. Natural gas is the most superior fuel; its average income elasticity is highest (0.11) in the short run, followed by oil (0.06) and electricity (0.05). The coefficient for coal is insignificant. Two effects might cancel out here: On the one hand the income effect leads to an expansion of coal use, while simultaneously the substitution effect diminishes coal use as oil or gas are substituted for coal due to its inferior character. In the long run, the picture changes accordingly to the autoregressive terms – the average income elasticity of electricity is highest, followed by gas and oil.

The oil price is the most influential price variable – it enters into the oil demand equation and as a cross price also into the gas and coal demand equations. Gas consumption depends also on the gas price and the direct price effect is higher than the oil price effect. Neither coal nor electricity use is influenced by the price of coal or electricity respectively. Both in the short and in the long run, price dependence is highest in the case of coal, followed by oil and gas. Electricity is the only fuel that is not price-dependent at all. Note that all prices are household sector prices.

A comparison with results from previous studies is difficult, since methodology as well as data differ significantly. In general, the average temperature semi-elasticities resulting from our study are significantly smaller in absolute values than those of Bigano et al. (2006) and De Cian et al. (2007).[12] The same is true for income and, with few exceptions, price elasticities.

4.2 The 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, the existence of a cooling effect had to be rejected irrespective of the functional form on a global scale and irrespective of whether we estimated the cooling effect

[11] The median lag is the time that is needed for half of the impact of an initial shock to materialize.

[12] This is not true for coal, where Bigano et al. (2006) find a positive temperature elasticity. Since Bigano et al. (2006) and De Cian et al. (2007) present only elasticities and no semi-elasticities, we had to convert their elasticities using the relevant average temperatures from our data base.

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. 2007 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 might 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 rather new phenomenon in the private household sector, the cooling effect might be obscured by the long time span. Then again, estimations restricted to all and also to especially warm OECD countries from 1995 onwards did not yield a significant cooling effect either. However, the estimation of an error correction model based only on data for the USA suggested a significant cooling effect.[13] We conclude that within our observation period cooling is still only a regional issue, if not an US-issue – although this conclusion is likely to be rectified for the future.[14]

While Bigano et al. (2006) do not test for a cooling effect, De Cian et al. (2007) find a significant positive influence of summer temperature on electricity demand for a subsample of mild and hot countries. We cannot confirm their result with our data.

4.3 Sensitivity analysis

Including price variables into the model cuts the number of observations and countries quite considerably, since price data is available only from 1978 onwards and for a limited number of countries (details can be found in the appendix, cf. Figures A1 to A4). To accommodate that trade-off, we estimated the models for oil, gas and coal not only on a small sample with price variables and on a large sample without price variables, but also without price variables for the small sample that is limited by the availability of price data. We postulate that if the two estimations without price variables come to approximately the same results, we can conclude that deviations between the outcomes from the small sample (including prices) and the large sample (excluding prices) are only due to including or excluding price variables and not to including or excluding certain countries. We find that in most cases and at least with respect to significance or non-significance the two estimations without price variables come to

[13] For the USA, the cooling effect turned out to be linear. Interdependencies between temperature and income were not present. It has to be kept in mind, that this single-country estimation is based on only 27 observations (the time period from 1976 to 2002).
[14] Recall that our observation period ends already 2002.

Figure 4: Short-run income and price elasticities of fuel use (for average temperature, income and price)

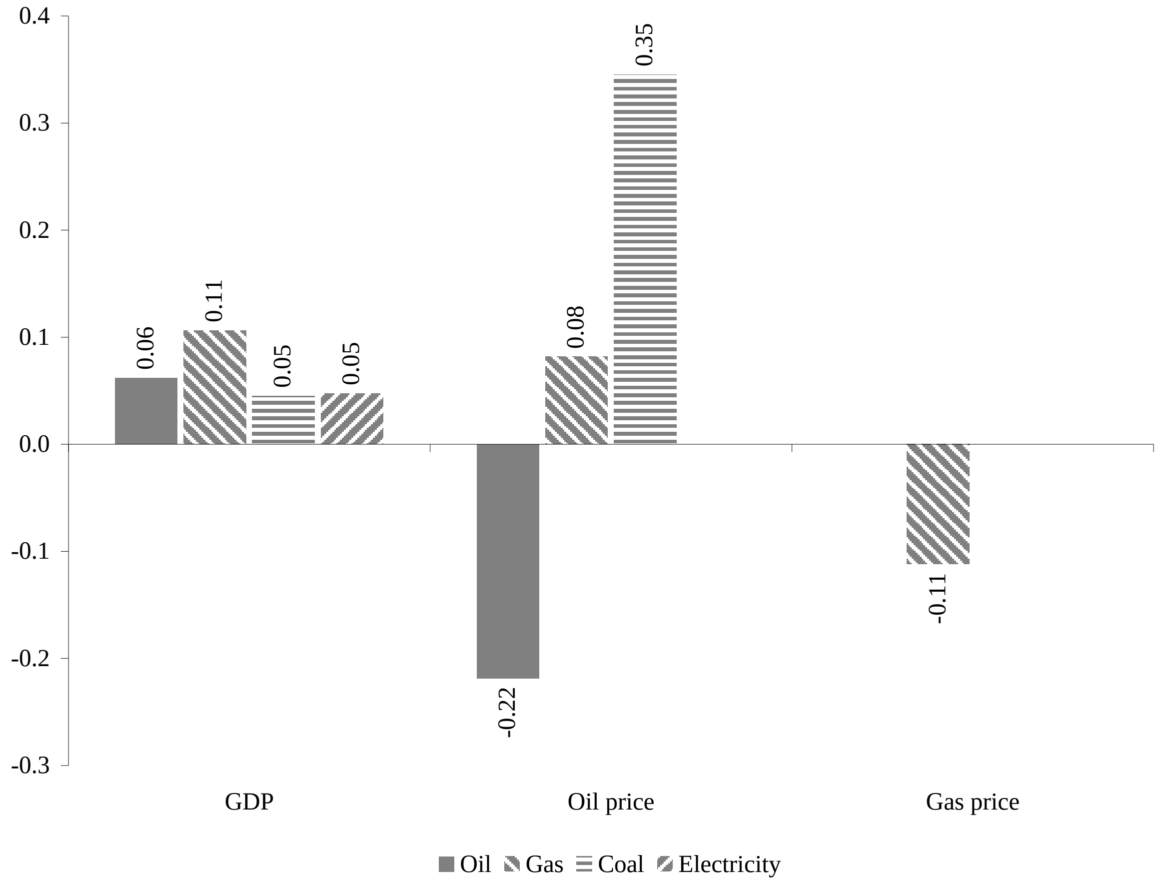


Figure 5: Long-run income and price elasticities of fuel use (for average income, price and temperature)

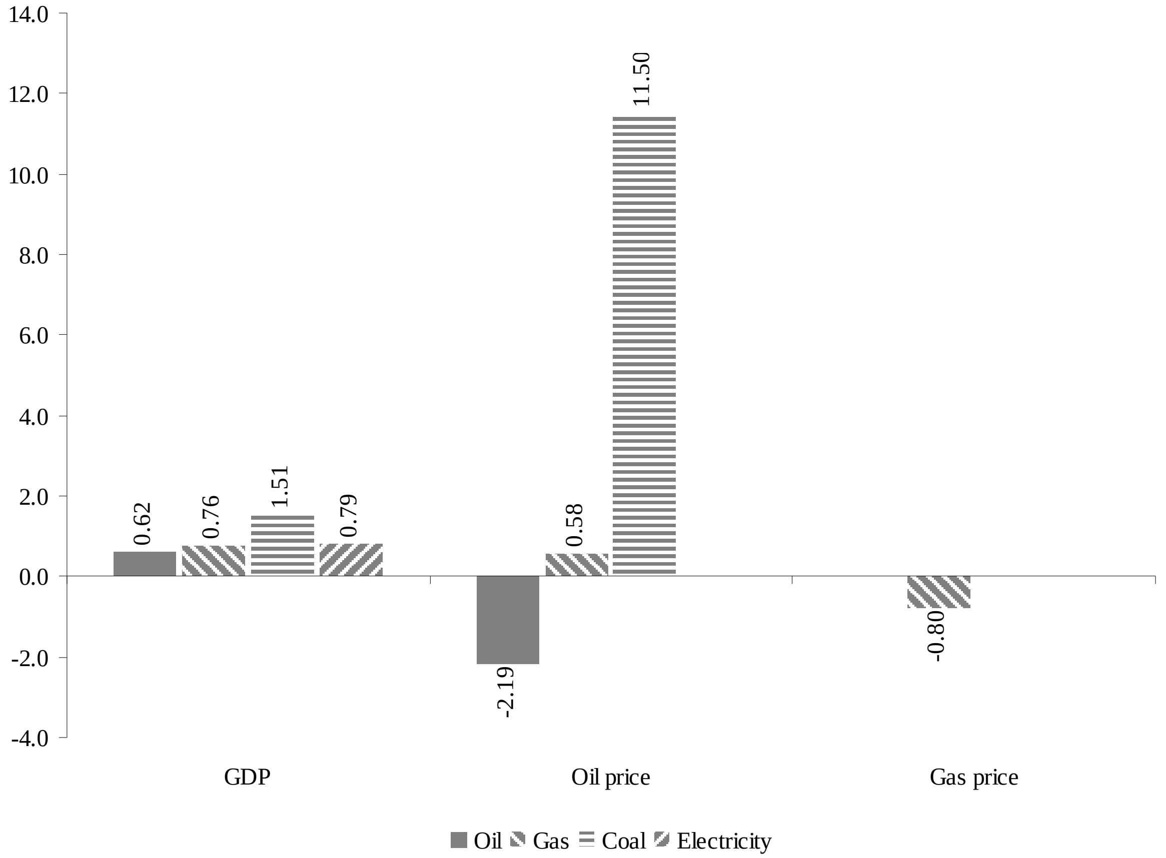


Table 4: Regression results with and without information on prices for different sample sizes

	oil			gas			coal		
	small sample		large sample	small sample		large sample	small sample		large sample
fuel use (t-1)	0.90***	0.90***	0.91***	0.86***	0.91***	0.80***	0.97***	0.98***	1.02***
tmin	-2.13***	-1.92***	-1.18*				-0.45***	-0.62**	-0.44*
tmin²	0.02*	0.02**	0.01**						
log(tmin)				-11.35*	-18.44***	-13.35**			
GDP-interaction	-0.06*	-0.07	-0.03	-0.05*	-0.06*	-0.03**			
GDP per capita (PPP)	2.64**	3.12**	1.7	2.61***	2.85**	2.98***	0.13	0.20**	0.26**
oil price	-0.10***			-0.05**			0.04*		
gas price				0.04***					
N	627	627	3482	466	466	1351	540	540	1100
No. of groups	33	33	155	29	29	67	30	30	65
AIC	6255.0	6823.3	29168.8	4200.3	4467.5	11768.3	4049.4	4734.4	8667.2
Wald chi²	6332.3***	12028.2***	5481.2***	1092.3***	2360.5***	968.3***	1250.4***	3176.1***	15331.6***
No. of instruments	30	30	141	18	18	20	20	20	18
Hansen J-statistic	24.20	24.72	140.66	14.29	18.13	21.95	22.4951	16.8748	21.3686
P-value of Hansen J-stat.	0.45	0.48	0.37	0.28	0.20	0.14	0.1279	0.4629	0.1255

*** significant at 1%, ** significant at 5%, * significant at 10%. Arellano/Bond autocorrelation tests were computed up to order 6 and generally rejected the null hypothesis for autocorrelation of second or higher order and the ten percent level of significance.

approximately the same result (cf. Table 4 for details). Only the significance of the effect of income on oil use seems to depend to some extent on the small sample size and our results should be interpreted with care in that respect.

5. Discussion and conclusion

In this paper, we examine the impact of temperature changes on residential energy consumption, emphasizing the evaluation of different functional forms of that impact and the interaction between household income and responsiveness to temperature changes. Despite differences among different fuel types, energy use is in general non-linear in temperature: Energy use drops as the temperature rises (because of a reduced demand for heating), but the rate of that drop declines with rising temperature levels (as heating demand approaches zero). Furthermore we find evidence that the size of the heating effect is not only affected by the temperature level, but also by the level of income: Households in richer countries respond more strongly to a temperature change.

The geographical scope of our paper is considerably larger than in 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 issue and as such it has already been analyzed and will hopefully going to be analyzed in the future. Whether a global cooling demand develops in the future remains to be seen.

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 relatively cold and rich North.

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 of effect in our observation period, could in the future increase energy use, not only on a regional, but also on a global scale. Secondly, if the international community succeeds in fighting poverty in the comparably warm developing countries, this will not only by means of an income effect increase energy use, it will also amplify the global demand for cooling.

Considering different economic sectors, especially 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 consumption falls upon fire wood and other biomass-based fuels. Availability of data prevents progress in that respect at the moment. A more methodological extension would be the use of explicitly non-linear estimators instead of linearizable non-linear functions. This is left for further research.

Acknowledgements

The DFG provided welcome financial support through the Excellence Initiative Future Ocean. We thank Anne-Katrin Heinrichs and Andreas Bernetzeder for their invaluable support in data collection. All errors and opinions are ours.

References

Al-Zayer, J. and A. A. Al-Ibrahim (1996): *Modelling the Impact of Temperature on Electricity Consumption in the Eastern Province of Saudi Arabia.* Journal of Forecasting 15, pp. 97-106.

Amato, A. D., M. Ruth, P. Kirshen and J. Horwitz (2005): *Regional Energy Demand Responses to Climate Change: Methodology and Application to the Commonwealth of Massachusetts.* Climatic Change 71, pp. 175-201.

Arellano, M and S. Bond (1991): *Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations.* Review of Economic Sciences 58, pp. 277-297.

Arellano, M. and O. Bover (1995): *Another look at the instrumental variables estimation of error-component models*. Journal of Econometrics 68, pp. 29-51.

Asadoorian, M. O., R. S. Eckaus and C. A. Schlosser (2007): *Modelling Climate Feedbacks to Electricity Demand: The Case of China.* Energy Economics 30, pp. 1577-1602.

Bessec, M. and J. Fouquau (2008): *The non-linear link between electricity consumption and temperature in Europe: A threshold panel approach.* Energy Economics 30, pp. 2705-2721.

Bigano, A., F. Bosello and G. Marano (2006): *Energy demand and Temperature: A Dynamic Panel Analysis.* FEEM Nota Di Lavoro 112.2006.

CIESIN (Center for International Earth Science Information Network, Columbia University) and CIAT (Centro Internacional de Agricultura Tropical) (2005): *Gridded Population of the World Version 3 (GPWv3): Population Density Grids*. Available from the Socioeconomic Data and Applications Center (SEDAC), Columbia University at http://sedac.ciesin.columbia.edu/gpw. (2009-07-03).

CRU (University of East Anglia Climate Research Unit) (2008): *CRU TS3.0 Dataset*. Available from the British Atmospheric Data Centre (BADC), download from http://badc.nerc.ac.uk/data/cru (2009-07-06).

De Cian, E., E. Lanzi and R. Roson (2007): *The Impact of Temperature Change on Energy Demand: A Dynamic Panel Analysis.* FEEM Nota Di Lavoro 46.2007.

ENERDATA (2005): Multiple Databases on Energy Consumption, Energy Prices and Other Indicators. More Information on http://www.enerdata.fr/enerdatauk/eshop/index.php.

EUROSTAT (2008): *Heating Degree-days. Eurostat Metadata in SDDS format: Summary Methodology.* Download from http://epp.eurostat.ec.europa.eu/cache/ITY_SDDS/EN/nrg_esdgr_sm1.htm (2009-02-03).

Florides, G. A., S. A. Kalogirou, S. A. Tassou and L. C. Wrobel (2000): *Modelling of the Modern Houses of Cyprus and Energy Consumption Analysis.* Energy 25, pp. 915-937.

Giannakopoulos, C., B. E. Psiloglou and S. Majithia (2005): *Weather and Non-weather Related Factors Affecting Energy Load Demand: A Comparison of the Two Cases of Greece and England.* Geophysical Research Abstracts 7,06969. Download from http://www.cosis.net/abstracts/EGU05/06969/EGU05-J-06969.pdf (2009-02-02).

Henley, A. and J. Peirson (1997): *Non-Linearities in Electricity Demand and Temperature: Parametric versus Non-parametric Methods.* Oxford Bulletin of Economics and Statistics, 59,1, pp. 149-162.

Henley, A. and J. Peirson (1998): *Residential energy demand and the interaction of price and temperature: British experimental evidence.* Energy Economics 20, pp. 157-171.

Hunt, L.C., G. Judge and Y. Ninomiya (2003): *Modelling Underlying Energy Demand Trends.* Surrey Energy Economics Discussion paper Series (SEEDS) 105.

IPCC (2007): *4th Assessment Report "Climate Change 2007: Synthesis Report".* Download from http://www.ipcc.ch/ipccreports/ar4-syr.htm (2008-11-24).

Klein Goldewijk, C.G.M., and J.J. Battjes (1995): *The Image 2 Hundred Year (1890-1990) Data Base of the Global Environment (HYDE)*. Report No. 481507008, RIVM.

Koyck, L. M. (1954): *Distributed lags and investment analysis*. Amsterdam: North-Holland, ch. II.5, pp. 19-25.

Li, X. and D. J. Sailor (1995): *Electricity use sensitivity to climate and climate change.* World Resource Review 7(3), pp. 334-446.

Mansur, E. T., R. Mendelsohn and W. Morrison (2005): *A Discrete-Continuous Choice Model of Climate Change Impacts on Energy.* Yale School of Management Working Paper ES-43.

Mansur, E. T., R. Mendelsohn and W. Morrison (2008): *Climate Change Adaptation: A Study of Fuel Choice and Consumption in the U.S. Energy*

Sector. Journal of Environmental Economics and Management 55(2), pp. 175-193.

Mirasgedis, S., Y. Sarafidis, E. Georgopoulou, D. P. Lalas, M. Moschovits, F. Karagiannis, D. Papakonstanntinou (2004): *Models for mid-term electricity demand forecasting incorporating weather influences.* Energy 31, pp. 208-227.

Mitchell, T. D. and P. D. Jones (2005): *An improved method of constructing a database of monthly climate observations and associated high-resolution grids*. International Journal of Climatology 25, pp. 693-712.

Pezzulli, S., P. Frederic, S. Majithia, S. Sabbagh, E. Black, R. Sutton and D. Stevenson (2006): *The seasonal forecast of electricity demand: A hierarchical Bayesian model with climatological weather generator.* Applied Stochastic Models in Business and Industry 22, pp. 113-125.

Quayle, R. G. and H. F. Diaz (1978): *Heating Degree Day Data Applied to Residential Heating and Energy Consumption.* Journal of Applied Meteorology 19, pp. 241-246.

Roodman, D. (2009): *A Note on the Theme of Too Many Instruments*. Oxford Bulletin of Economics and Statistics 71 (1), pp. 135-158.

Rosenthal, D. H. and H. K. Gruenspecht (1995): *Effects of global warming on energy use for space heating and cooling in the United States.* Energy Journal 16, pp. 77-97.

Tol, R. S. J. (2009): *The economic effect of climate change.* Journal of Economic Perspectives 23(2), pp. 29-51.

Vaage, K. (2000): *Heating technology and energy use: A discrete continuous choice approach to Norwegian household energy demand.* Energy Economics 22, pp. 649-666.

Windmeijer, F. (2005): *A finite sample correction for the variance of linear efficient two-step GMM estimators*. Journal of Econometrics 126, pp. 25-51.

Zarnikau, J. (2003): *Functional forms in energy demand modelling.* Energy Economics 25, pp. 603-613.

Appendix

Table A1: Estimation results for residential consumption of oil products

	including oil prices				excluding oil prices			
	linear	quadratic	logarithmic	inverse	linear	quadratic	logarithmic	inverse
oil use in (t-1)	0.89***	0.90***	0.90***	0.89***	0.91***	0.91***	0.92***	0.92***
	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
tmin	-1.82**	-2.13***			-0.56	-1.18*		
	(0.79)	(0.7)			(0.61)	(0.72)		
tmin²		0.02*				0.01**		
		(-0.01)				(0.00)		
log(tmin)			-20.89**				-18.3	
			(9.12)				(13.25)	
$tmin^{-1}$				138.37***				69.86
				(26.29)				(70.51)
GDP-interaction	-0.05	-0.06*	-0.12***	-0.17***	-0.04	-0.03	-0.06	-0.09***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.03)
GDP per capita (PPP)	1.64	2.64**	4.48***	5.59***	1.97	1.7	2.66**	3.77***
	(1.14)	(1.1)	(1.19)	(1.22)	(1.69)	(1.62)	(1.33)	(1.11)
oil price	-0.11***	-0.10***	-0.11***	-0.16***				
	(0.04)	(0.03)	(0.04)	(0.06)				
N	627	627	627	627	3482	3482	3482	3482
No. of countries	33	33	33	33	155	155	155	155
AIC	6327.9	6255.0	6337.9	6 501.4	29674.2	29168.8	29476.6	29 626.2
Wald chi²	5324.9***	6332.3***	4155.5***	3303.0***	4635.6***	5481.2***	4283.8***	3204.5***
No. of instruments	25	30	25	25	109	141	109	109
Hansen J-statistic	24.4	24.2	26.4	23.26	138.9**	140.7	125.8*	120.2
P-value of Hansen J-stat.	0.22	0.45	0.15	0.28	0.02	0.37	0.08	0.15

*** significant at 1%, ** significant at 5%, * significant at 10%. Standard errors in parentheses. Arellano/Bond autocorrelation tests were computed up to order 6 and generally rejected the null hypothesis for autocorrelation of second or higher order and the ten percent level of significance.

Table A2: Estimation results for residential consumption of natural gas

	including gas and oil prices				excluding prices			
	linear	quadratic	logarithmic	inverse	linear	quadratic	logarithmic	inverse
gas use in (t-1)	0.87***	0.85***	0.86***	0.86***	0.77***	0.87***	0.80***	0.80***
	(0.04)	(0.04)	(0.04)	(0.05)	(0.10)	(0.04)	(0.11)	(0.13)
tmin	-1.13	-0.41			-0.60**	-0.59		
	(0.69)	(0.96)			(0.30)	(0.39)		
tmin²		-0.02				0		
		(0.02)				(0.01)		
log(tmin)			-11.35*				-13.35**	
			(6.07)				(5.82)	
$tmin^{-1}$				83.42***				18.33
				(17.89)				(37.53)
GDP-interaction	-0.03	0	-0.05*	-0.07**	-0.02	-0.02	-0.03**	-0.06**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)
GDP per capita (PPP)	1.90**	1.38*	2.61***	3.28***	2.82*	1.85**	2.98***	3.96***
	(0.87)	(0.79)	(0.96)	(1.00)	(1.47)	(0.72)	(1.11)	(1.34)
gas price	-0.04**	-0.04*	-0.05**	-0.05**				
	(0.02)	(0.02)	(0.02)	(0.03)				
oil price	0.04***	0.04***	0.04***	0.04**				
	(0.01)	(0.01)	(0.01)	(0.02)				
N	466	466	466	466	1351	1351	1351	1351
No. of countries	29	29	29	29	67	67	67	67
AIC	4232.5	4254	4200.3	4226.1	12121.3	11419.3	11768.3	11855.3
Wald chi²	1249.6***	1033.7***	1092.3***	2251.7***	1029.9***	1869.9***	968.3***	682.8***
No. of instruments	18	21	18	18	20	25	20	20
Hansen J-statistic	16.6	15.7	14.3	15.3	19.7	25.1	22	23.1
P-value of Hansen J-stat.	0.17	0.33	0.28	0.22	0.23	0.20	0.14	0.11

*** significant at 1%, ** significant at 5%, * significant at 10%. Standard errors in parentheses. Arellano/Bond autocorrelation tests were computed up to order 6 and generally rejected the null hypothesis for autocorrelation of second or higher order and the ten percent level of significance.

Table A3: Estimation results for residential consumption of coal

	including oil prices				excluding oil prices			
	linear	quadratic	logarithmic	inverse	linear	quadratic	logarithmic	inverse
coal use in (t-1)	1.02***	1.02***	1.02***	1.02***	0.97***	0.96***	0.97***	0.97***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)	(0.04)
tmin	-0.44*	-0.18			-0.45***	-0.26		
	(0.23)	(0.43)			(0.17)	(0.17)		
$tmin^2$		-0.01				0		
		(0.01)				(0.01)		
log(tmin)			2.98				-10	
			(6.17)				(7.42)	
$tmin^{-1}$				31.04				27.64
				(33.97)				(26.35)
GDP per capita (PPP)	0.26**	0.29**	0.20**	0.21**	0.13	0.06	0.09	-0.04
	(0.11)	(0.12)	(0.08)	(0.09)	(0.24)	(0.27)	(0.22)	(0.17)
oil price					0.04*	0.04*	0.04*	0.03
					(0.02)	(0.02)	(0.02)	(0.02)
N	1100	1100	1100	1100	540	540	540	540
No. of countries	65	65	65	65	30	30	30	30
AIC	8667.2	8945.7	8270.9	8270.9	4049.4	4102.7	3987.1	3928.0
Wald chi²	15331.6***	18217.1***	17881.9***	20894.3***	1250.4***	1363.9***	1238***	1302.5***
No. of instruments	18	24	18	18	20	25	20	20
Hansen J-statistic	21.4	24.6	17.7	20.7	22.5	24.4	21.2	17.2
P-value of Hansen J-stat.	0.13	0.22	0.28	0.15	0.13	0.23	0.17	0.37

*** significant at 1%, ** significant at 5%, * significant at 10%. Standard errors in parentheses. Arellano/Bond autocorrelation tests were computed up to order 6 and generally rejected the null hypothesis for autocorrelation of second or higher order and the ten percent level of significance.

Table A4: Estimation results for residential electricity consumption for heating purposes

	linear	quadratic	logarithmic	inverse
electricity use in (t-1)	0.92***	0.94***	0.91***	0.91***
	(0.01)	(0.01)	(0.01)	(0.01)
tmin	-0.43***	-0.57***		
	(0.13)	(0.15)		
$tmin^2$		0.00*		
		(0.00)		
log(tmin)			-11.60*	
			(6.41)	
$tmin^{-1}$				3.87
				(18.86)
GDP per capita (PPP)	0.58***	0.41***	0.61***	0.57***
	(0.11)	(0.14)	(0.11)	(0.12)
N	3455	3455	3455	3455
No. of countries	157	157	157	157
AIC	23918.9	22244.2	22711.3	23122.0
Wald chi^2	8995.5	7535.4	7669.2	6088.8***
No. of instruments	149	115	149	149
Hansen J-statistic	154.6	126.9	148.2	143.5
P-value of Hansen J-stat.	0.30	0.14	0.43	0.54

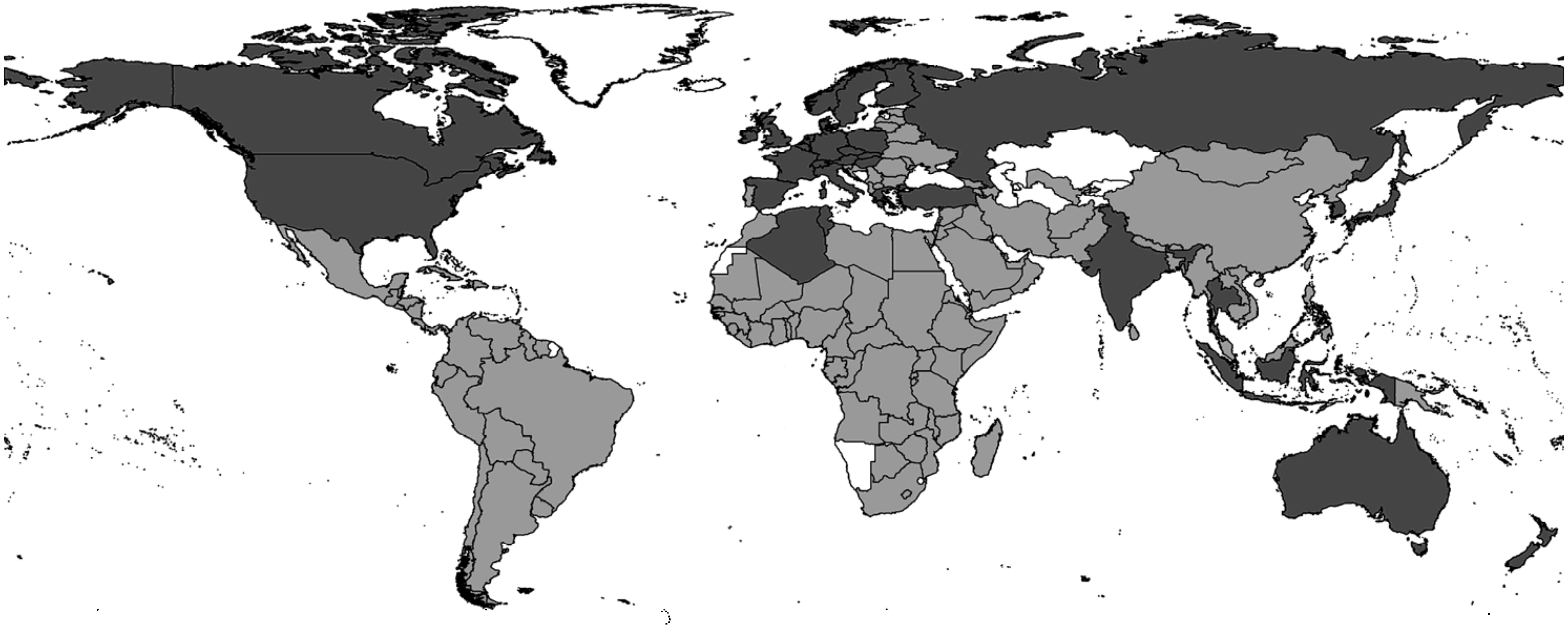
*** significant at 1%, ** significant at 5%, * significant at 10%. Standard errors in parentheses. Arellano/Bond autocorrelation tests were computed up to order 6 and generally rejected the null hypothesis for autocorrelation of second or higher order and the ten percent level of significance.

Table A5: Estimation results using population-weighted temperature data

	oil (quadratic)	gas (logarithmic)	coal (linear)	electricity (quadratic)
gas use in (t-1)	0.93***	0.84***	0.97***	0.94***
	(0.02)	(0.08)	(0.04)	(0.01)
tmin	-1.87*		-0.47***	-0.57***
	(1.10)		(0.17)	(0.15)
tmin²	0.03**			0.00**
	(0.01)			(0.00)
log(tmin)		29.81		
		(31.84)		
GDP-interaction	-0.13**	-0.13**		
	(0.06)	(0.05)		
GDP per capita (PPP)	6.21***	6.13***	0.2	0.45***
	(2.15)	(1.61)	(0.25)	(0.14)
gas price		-0.05**		
		(0.02)		
oil price	-0.09**	0.04***	0.04*	
	(0.04)	(0.01)	(0.02)	
N	627	466	540	3455
No. of countries	33	29	30	157
AIC	5952	4237.3	4037.3	22275.4
Wald chi²	3556.9***	617***	1313.2***	7603.2***
No. of instruments	24	24	20	115
Hansen J-statistic	16.6	19.9	22.5	120.8
P-value of Hansen J-stat.	0.55	0.34	0.13	0.25

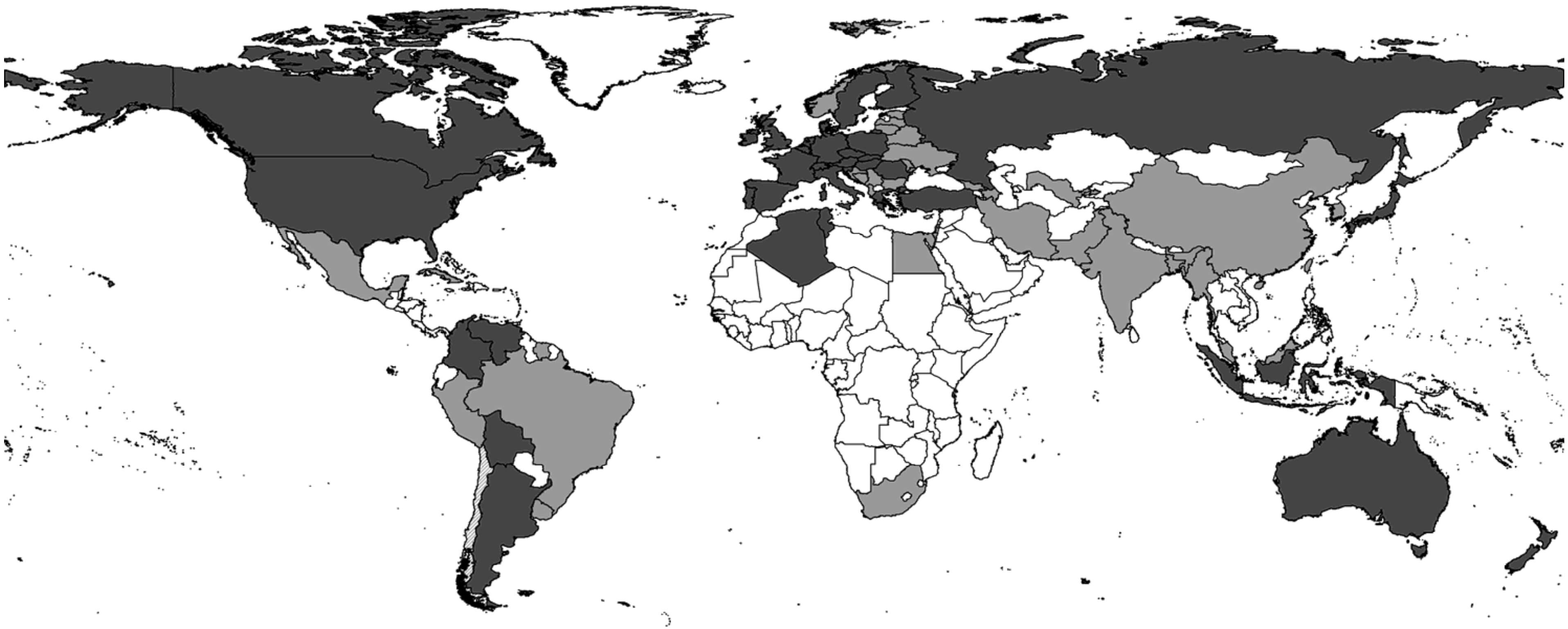
*** significant at 1%, ** significant at 5%, * significant at 10%. Standard errors in parentheses. Arellano/Bond autocorrelation tests were computed up to order 6 and generally rejected the null hypothesis for autocorrelation of second or higher order and the ten percent level of significance.

Figure A1: Geographical coverage of oil data



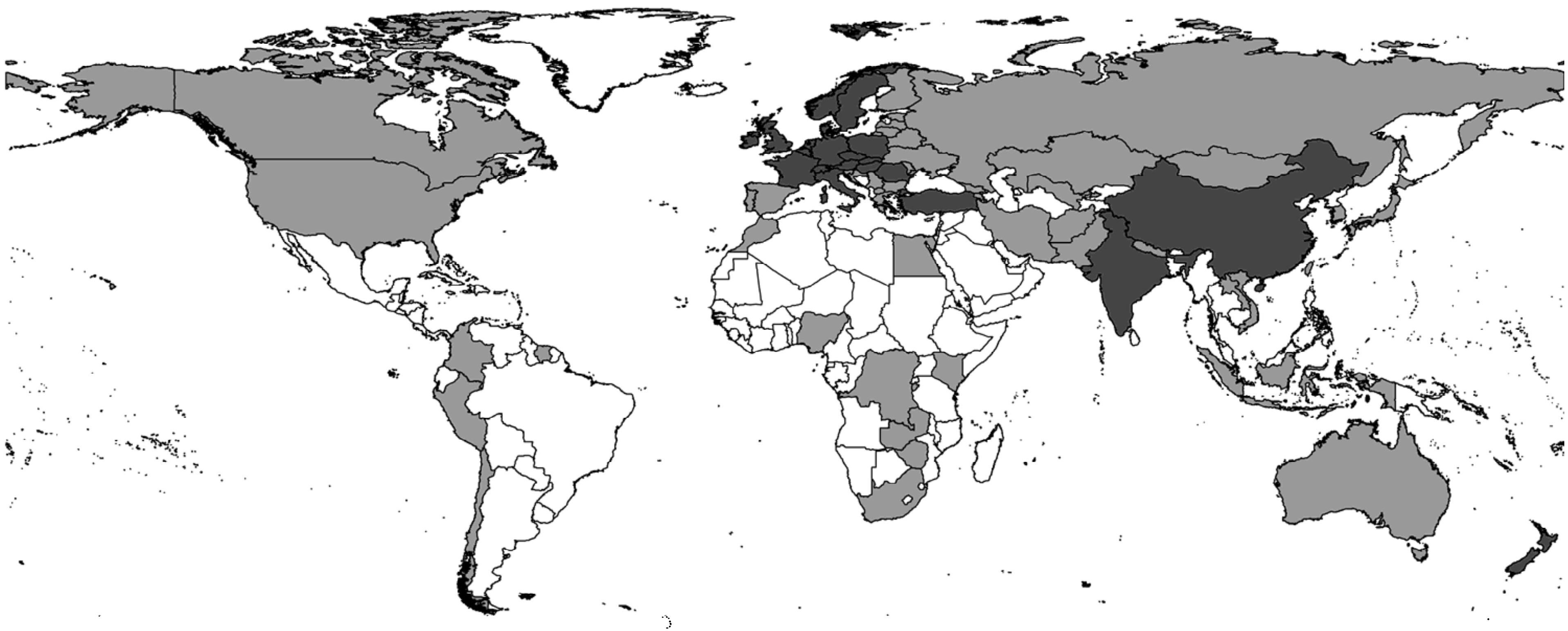
♦: Consumption data available; ♦: Consumption and price data available; blank: no data.

Figure A2: Geographical coverage of natural gas data



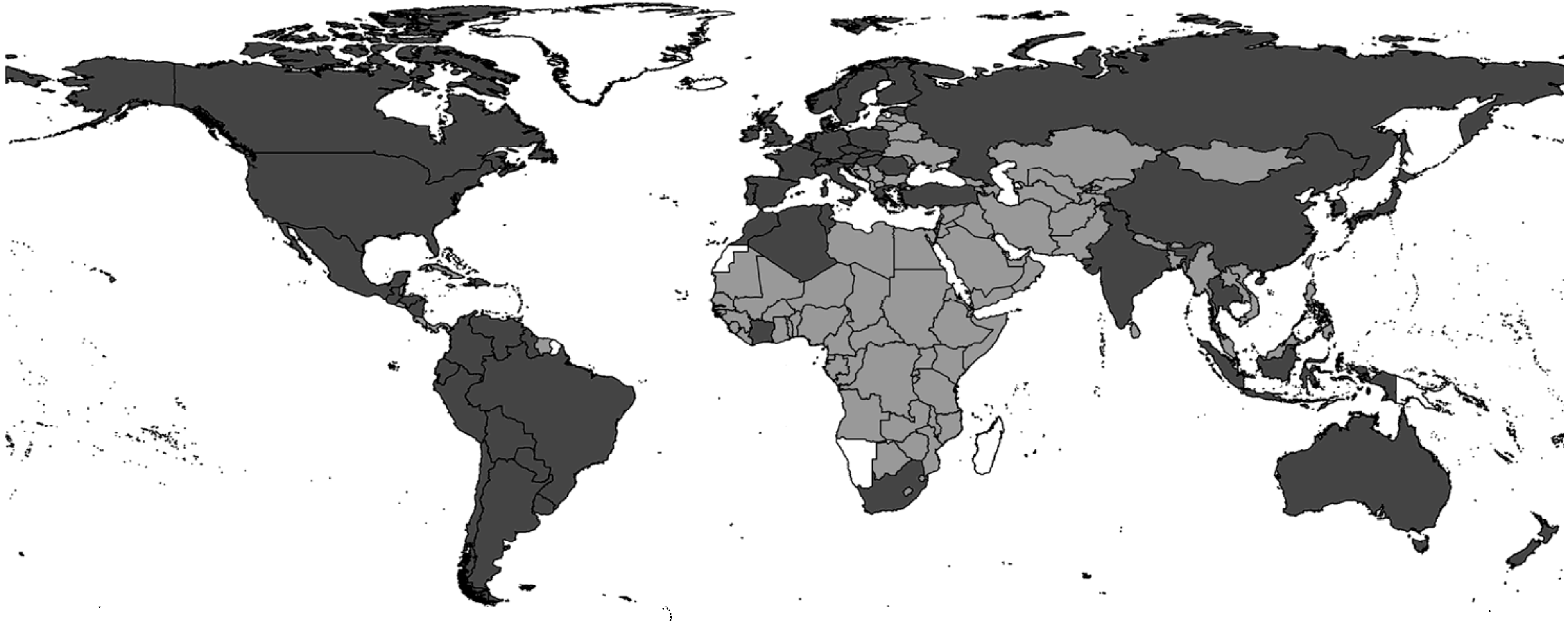
♦: consumption data available; ♦: Consumption and price data available; blank: no data.

Figure A3: Geographical coverage of coal data



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

Figure A4: Geographical coverage of electricity data



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