Climate change impacts on household electricity expenditure: the contribution of air conditioning in OECD countries

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Abstract

This paper contributes to expand the empirical evidence on adaptation to climate change through the adoption of air conditioning machines and the use of electricity for a sample of households living across eight different OECD countries outside the United States (US). Our identification strategy relies on the cross-country and cross-household variation, as we combine a geocoded household survey on energy behaviours with high-resolution climate data to compute heating and cooling degree days. The empirical strategy to assess the impact of air conditionig on electricity expenditure makes use of a Control Function approach in order to address the potential endogeneity of air conditioning. We show that the adoption of air conditioning increases significantly the expenditure on electricity, absorbing the effect of global warming captured by the long-term average cooling degree days which is a key variable in explaining the adoption decision.

JEL Codes: N5, O13, Q1, Q54

Keywords: Control Function, climate, adaptation, energy demand.

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1 Introduction

Climate change is already increasing the risk of conditions associated with more frequent mortality and morbidity events not only in tropical regions, but also in mid-latitude temperate areas where more warming will be experienced compared to higher latitudes (Mora et al. 2017). Various forms of social adaptation[1] seem to have contributed to attenuate the mortality risk associated with heat during the last decades, with significant evidence in the United States (US), Japan, Spain, and Canada (Gasparrini et al. 2015). Yet, the specific role of the drivers of such observed changes, such as acclimatization, infrastructural changes, air conditioning, access to health care, remains to be identified. The empirical evidence mostly based on US data suggests that space cooling has been of critical importance at reducing mortality (Barreca et al. 2016, Deschênes and Greenstone 2011). Studies covering different countries highlight how air conditioning has been key to sustain labour productivity in hot countries located in tropical and sub-tropical regions where climatic conditions are already harsh (Niemelä et al. 2002, Hsiang 2010).

While the topic of the health benefits of social adaptation such as air conditioning is still at an infancy stage and mostly limited to the US (see Gasparrini et al. 2015 for a review), equally underinvestigated is how air conditioning affects energy demand and expenditure (Auffhammer and Mansur 2014). The environmental and economic implications of climate-driven energy use is also of special concern because it relates to the broader question of how adaptation might lead to higher emissions (Isaac and van Vuuren 2009) and exacerbate energy poverty (Mastrucci et al. 2019).

A broad literature has investigated the direct impact of temperature variables on energy demand (intensive margin) using reduced-form equations not explicitly accounting for the role of air conditioning. Most of the studies exploit panel data to estimate short-run and long-run elasticities of energy demand to climatic variables for Europe (Eskeland and Mideska 2010, Wenz et al. 2017), the US (Deschênes and Greenstone 2011, Auffhammer et al. 2017), and multiple countries (De Cian and Sue Wing, 2017). Studies using cross-sectional data (Morrison and Mendelsohn 1999, Mendelsohn 2001, Mansur et al. 2008) and time-series data (Franco and Sanstad 2008, Considine 2000) also exist, mostly for the US. Another set of studies focusing on price and income elasticities of residential energy demand might (Alberini et al. 2011) or might not (Krishnamurthy and Kriström, 2015) include climatic variables as a control.

Fewer studies have analyzed the impact of climate or weather conditions on the air conditioning (henceforth AC) adoption decision (extensive margin). They are mostly confined to the US, which accounts for about 40% of the global installed cooling capacity, and where already in the 1980s half households had AC at home (Sailor and Pavlova 2003, Biddle 2008, Rapson 2014), providing researchers with a

[1]The Intergovernmental Panel on Climate Change, IPCC, defines adaptation as adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderate harm or exploits beneficial opportunities, IPCC 2007.

good historical record of data. Only a limited number of studies has examined the implications of AC ownership on either electricity demand conditional on the use of AC. The energy demand equation is estimated only for those households having AC (Davis & Gertler, 2015) or using a two-stage procedure as described in Dubin and McFadden (1984), (e.g. Asaadoorian et al. 2008). Earlier studies (Branch 1993) have included the AC ownership dummy in the demand equation withouth addressing the endogeneity that arises from the relationship between the two decisions of adopting and using AC (Dubin and McFadden 1984). One exception is Barreca et al. (2016). They apply a Control Function (CF) approach to address the endogeneity of AC using a function of climate indicators as instrument. They show that AC shifts electricity demand to the right, and that households with AC consume on average 11% more electricity.

This paper contributes to advance the empirical understanding of the demand for air conditioning, the intensity of its use, and the implications for residential electricity expenditure across multiple countries located outside the US. By combining geocoded cross-sectional data on households in eight different OECD countries (Australia, Canada, France, Japan, Netherlands, Spain, Sweden, Switzerland) with climatic data, we are able to exploit the great heterogeneity in socio-economic and climatic conditions to disentangle the role of different determinants in the adoption and use decision. We identify the effect of climate and air conditioning from cross-sectional variation across a sample of 3711 geocoded households located in different OECD countries interviewed in 2011 (Kriström 2014, OECD 2014). Since household demand for air conditioning and electricity share unobservable common determinants (Dubin and McFadden 1984) difficult to measure in a cross sectional setting, we use a Control Function (CF) approach (Wooldrige, 2015) to address the endogeneity of AC, with past AC imports as exclusion restriction.

Our results show that AC is endogenous, and that it significantly increases the electricity expenditure bill. Households with AC spend on average 10% more on electricity a year. We also show that the main effect of climate on electricity expenditure is modulated by the AC utilization, and that once AC is correctly specified in the electricity expenditure equation, long-term climate conditions influence electricity expenditure only indirectly, through the effect on air conditioner acquisition. For the set of OECD countries analyzed, we show that changes in climatic conditions, by pushing up AC adoption, will also be of great importance as driver of electricity expenditure, with an impact that is comparable to that of per capita income and the number of other electricity-using appliances. The actual impact will depend on the interaction between exposure to warm days and sensitivity, which varies with the way climatic conditions are computed. We conclude discussing how climate change, by increasing the average number of warm days and by deepening AC penetration for a given level of income, could increase energy poverty even in industrialized countries.

The remainder of the paper is organized as follows. Section 2 describes some recent trends in AC use and climatic variables, motivating the regional focus of this paper. Section 3 provides the theoretical and empirical framework. Section 4 describes the datasets used. Section 5 discusses the empirical results and Section 6 concludes with a discussion of the broader implications of our findings.

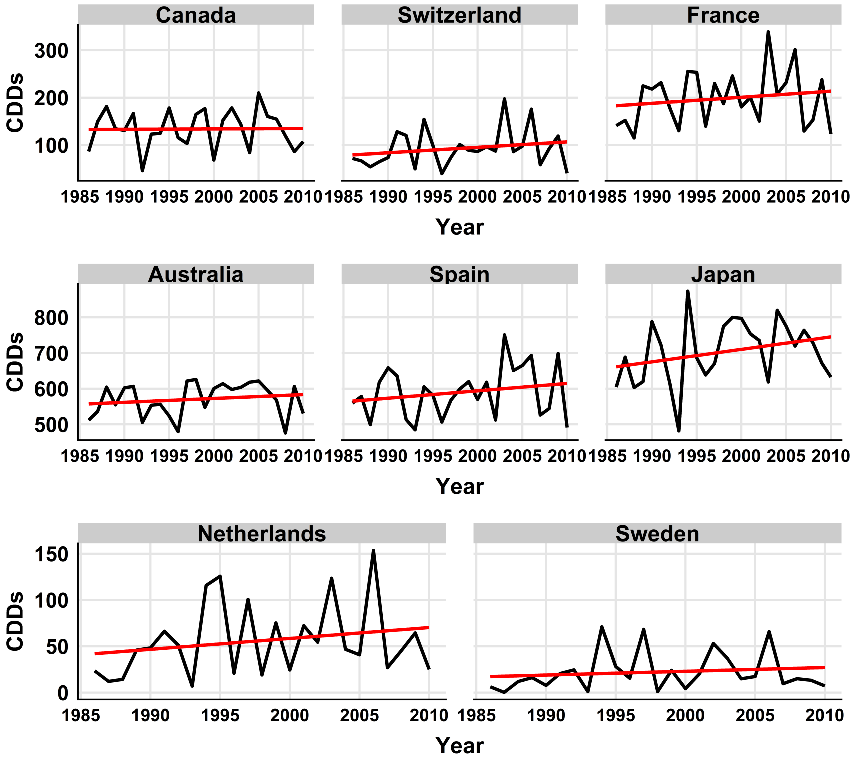
2 Air Conditioning trends in OECD countries

Space cooling is a key energy service of increasing importance in a changing climate. Demand has been growing rapidly, with a threefold expansion since 1990s (IEA, 2018). A key concern are the emerging trends of developing countries, where improved income conditions, rapid urbanization, and warming from a baseline temperature and humidity level that is already of concern, are expected to dramatically increase AC penetration (McNeil and Letschert 2011). While AC has first spread in the US as a way to ensure thermal comfort in the afforable and attractive booming houses during the 1980s (Biddle 2008), access to cooling is now becoming an equity issue, as it can worsen the energy poverty gap (Mastrucci et al. 2019). Yet, climate change is posing a greater health risk related to threshold temperature and humidity levels also at mid-latitudes, where lethal heat events are increasingly being reported (Mora et al. 2017). Well-known examples are the major events in Chicago (1995), Paris (2003), Moscow (2010), though many other exist.[2] Historical trends in Cooling Degree Days (henceforth CDDs), defined as the cumulative number of days over a year exceeding a temperature thresholds of typically 18°C[3] exhibit a gentle growing trend also in subtropical or temperate countries. Figure 1 shows the time series of CDDs computed using daily mean surface temperature from a reanalysis dataset Global Land Data Assimilation System (GLDAS, Rodell et al. 2004), for the eight OECD countries under investigation. Notwithstanding the interannual varaibility, the positive trend is evident in all countries.

[2] See `https://maps.esri.com/globalriskofdeadlyheat/`

[3] ASHRAE (2001) defines Cooling Degree Days (CDDs) and Heating Degree Days (HDDs) as follows: $CDD = \sum_{d=1}^{365}(\gamma_d)(T - 18°C)$ and $HDD = \sum_{d=1}^{365}(1 - \gamma_d)(18°C - T)$

Figure 1: Cooling Degree Days (CDDs) computed at a base temperature of 18°C in selected OECD countries.



At present two third of the AC units are concentrated in China, US, and Japan, whereas the above mentioned OECD countries, with the exception of Japan, have historically had low adoption rates. While the US uses about 20% of final residential electricity for cooling, this percentage is much lower for the other countries, as shown in Table 1. Even these eight OECD countries are quite heterogeneous in terms of electricity for AC, with the share varying between very small values in the Netherlands, up to 5 and 6% in Japan and Australia, respectively. Patterns of electricity use in the final residential mix also vary quite a lot, from the Netherlands which only uses 18% of electricity to Australia and Japan where the share is around 50%. Some of these countries also use a significant share of electricity for heating, Canada (39%) and Sweden (34%).

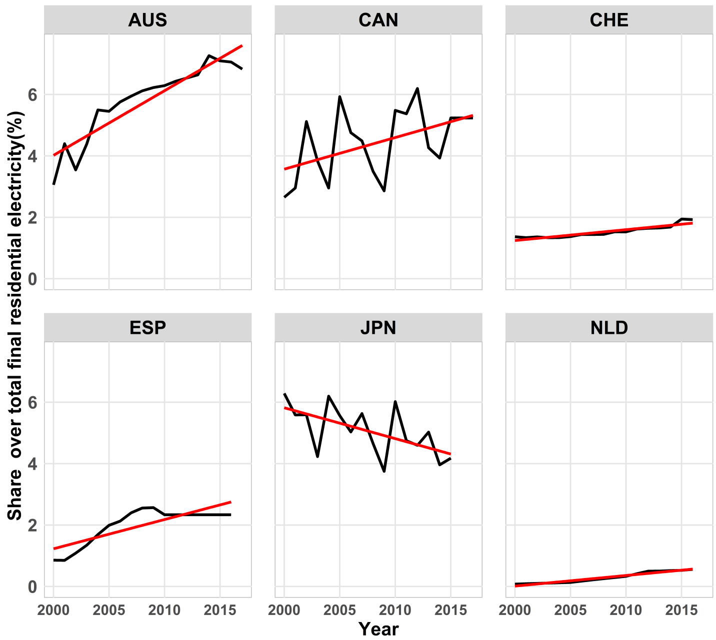
Table 1: Average electricity share (%) in the US and selected OECD countries between 2000 and 2017.

	AUS	CAN	CHE	ESP	FRA	JPN	NLD	SWE	US
Electricity for end-use	49.0	40.3	25.5	37.6	29.1	50.3	17.9	48.4	44.2
Electricity for heating	6.4	38.7	22.1	18.8	29.2	7.7	5.8	34.5	9.1
Electricity for cooling	5.8	4.4	1.5	2.0	NA	5.1	0.3	NA	20.4

Data source: `https://www.enerdata.net/`. France and Sweden do not report statistics for air conditioning energy.

Figure 2 displays the recent trends in the share of electricity expenditure on cooling relative to total final residential electricity. With the exception of Japan, where adoption rates were about 90% already in 2011 (see Table 2),[4] the share of electricity being allocated to cooling has been increasing even in the coldest countries of our sample, Switzerland and Netherlands.

Figure 2: Share of AC electricity consumption relative to total electricity.



Data source: `https://www.enerdata.net/`. France and Sweden do not report statistics for air conditioning energy.

3 Theoretical and Empirical framework

People combine electricity, natural gas, heating oil with durable goods in order to obtain energy services such as cooking, lighting, space heating and cooling. Consumers use durables at the intensity level that provides the necessary service. Yet the choices of purchasing appliances and of how intensively using them are related. We can therefore model the utility of energy services as follows:

$$U = U(\mathbf{ES}, \mathbf{D}, C; \mathbf{X}, \mathbf{W}) \tag{1}$$

where **ES** is a vector of energy sources like electricity, the vector **D** represents durables goods that affect the marginal utility of energy use like air conditioning and C stands for aggregate consumption. The utility function is then affected by a set of household characteristics (**X**) as well as weather and climatic conditions (**W**), which also influence the marginal utility of energy services. A household

[4]The declining trend in the share observed in Japan might be due to other policies and regulations that have been implemented in order to reduce cooling demand.

maximizes utility by choosing **ES**, **D**, and C subject to her budget constraint:

$$Y - P_{es}\mathbf{ES} - C = 0 \tag{2}$$

where Y is household income, P_{es} the price of energy sources while the price of aggregate consumption is normalized to 1.

Utility maximizing energy demand is also a function of weather and climatic conditions, $\mathbf{ES}^*(\mathbf{W})$, and households choose energy and durables in order to control the interior temperature W_{in} by adopting new energy-using appliances such as air conditioners (extensive margin) and by adjusting actual energy use (intensive margin). Together the adoption of energy goods and the quantity of electricity determine the desired level of temperature or more generally the level of thermal comfort, W^*, which depends on the absolute difference between interior, W_{in}, and external W_{out} temperature:

$$\mathbf{ES} = ES(|W_{in} - W_{out}|\mathbf{D}; Y, \mathbf{X}) \tag{3}$$

We focus on the demand for electricity, which we denote with Q, and how that is being affected by the acquisition of air conditioners.[5] Electricity demand is modelled using a log-functional form:

$$lnQ_i = \beta_i + \beta_{cdd}CDD_i + \beta_{hdd}HDD_i + \beta_{ac}AC_i + \beta_p lnP_i + \beta_y lnY_i + \beta_x\mathbf{X}_i + \epsilon_i \tag{4}$$

Eq.(4) is the equation of interest (using Wooldrige 2015's terminology it is the structural equation) describing electricity demand for household i in kWh (intensive margin) as a function of electricity price (P), air conditioning (AC), a set of climate variables describing Cooling and Heating Degree Days, CDD and HDD, see footnote 3, for the geo-located household i, income (Y), and a set of additional household-specific control variables ($\mathbf{X}$) including other electricity-using appliances, house characteristics (size, type, insulation), household size, location in urban areas, education, age, sex, as well as attitudes towards energy efficient behaviors. The error term ϵ is assumed to be normally distributed with zero mean and variance of one.

As shown in Krishnamurthy and Kriström (2015), Eq.(4) can be expressed in term of electricity expenditure (E):

$$lnE_i = \beta_i + \beta_{cdd}CDD_i + \beta_{hdd}HDD_i + \beta_{ac}AC_i + \tilde{\beta}_p lnP_i + \beta_y lnY_i + \beta_x\mathbf{X}_i + \epsilon_i \tag{5}$$

where $\tilde{\beta}_p = (1 + \beta_p)$.

Given the equivalence between Eq.(4) and (5),[6] our empirical model uses electricity expenditure as

[5]While we control for the number of other appliances that use electricity, the survey does not report information on the ownership of electric heaters for heating.

[6]The coefficient $\tilde{\beta}_p$ in Eq. (5) is not the price elasticity, which can be computed as $\beta_p = \tilde{\beta}_p - 1$

dependent variable, being this variable available for a larger number of households.[7]

Household demand for air conditioning and electricity are related (Dubin and McFadden 1984) and share unobservable common determinants difficult to measure in a cross sectional setting. We identify at least three potential sources of endogeneity for AC, E(AC_i, $\epsilon_i \neq$0), the adoption decision. First, unobserved factors could simultaneously affect the adoption of air conditioning as well as the actual quantity of electricity used (for example, individual body characteristics that affect the balance point for thermal comfort). Second, selection bias, which refers to the selectivity of people who tend to adopt AC. For example, households with more income are more likely to adopt all the possible comfort appliances including air condition and it is impossible to identify the effect of air conditioning adoption on quantity just by comparing the characteristics of households with and without air condition. Third, the adoption of air conditioning is a small investment that might be affected by households's risk adversion, a characteristics that we do not perfectly observed then, the problem of omitted variable bias arise.

We address endogeneity of AC, which has a binary nature, by adopting the well-known Control Function (CF) approach as in Wooldridge (2015).[8] The CF is a variable that when added to the regression makes an endogenous variable of interest exogenous. The reduced form Eq.(6) expresses the endogenous variable (AC) as a function of all exogenous variables included in Eq.(4) plus the exclusion restriction that we identify in the average value of past imports of air conditioning machines for the period 1990-2000 (IMP) :

$$AC_i = \gamma_i + \gamma_{cdd} CDD_i + \gamma_{hdd} HDD_i + \gamma_{imp} IMP_i + \gamma_p lnP_i + \gamma_y lnY_i + \gamma_x \mathbf{X}_i + \mu_i \tag{6}$$

where $\mu \sim$ Normal (0, 1). The key assumptions are the relevance of the exclusion restriction in Eq.(6) and its orthogonality with electricity demand in Eq.(4), aside from the indirect route via AC, E(IMP_i, ϵ_i =0).

Since our dataset is a cross-section, we do not have information on past AC demand at the same resolution of our data. The past average value of air conditioning machine imports represents a good proxy for air conditioning demand, considering that the majority of countries included in the analysis are AC importers. Only Japan has been among the top exporters as well, with a share over world exports of 25% in 1990, of 10% in 2000, and of 6% in 2010. Trade data is the only source available at high industrial classification that makes it possible to identify AC machines,[9] while production and demand data are not available at global scale. We use the decade 1990-2000 to avoid contemporaneous

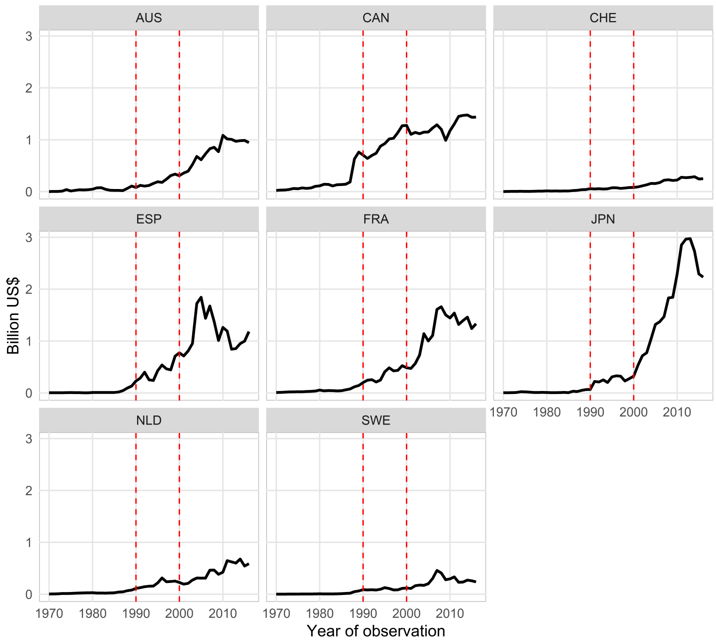
[7]Only 18.8 % of our sample reports information on the quantity of electricity consumed against the 56.7 % of those reporting their electricity expenditure.

[8]Wooldridge (2015) shows that the control function approach can be applied either to linear or not linear setting.

[9]Our import data are from UNComtrade and uses the product category, 71912, air conditioning machines, according to the Standard International Trade Classification SITC Rev.1. Data downloaded from `https://comtrade.un.org/data/` on January 24 2019.

correlation between the AC imports and electricity consumption. The use of a 10-year time window is motivated by the average lifetime of AC machines. As shown in Figure 3, starting from the 1990s all countries under investigation exhibit a constant increasing trend in AC imports. Past AC import data are available only at the country level. In order to redistribute imports to the geocoded households, we use the distance from the Equator measured by the Latitude variable available in our dataset and therefore interact country-level imports with the latitude of households. This procedure makes it possible to create variability at the same spatial level of our data (geocoded points), which we exploit as identification strategy

Figure 3: Value of AC imports in selected OECD countries.



Notes: Red lines mark the period 1990-2000 which is used to define the exclusion restriction.

The CF approach used to address the endogeneity of AC relies on the correlation between the structural error term (ϵ_i) and the reduced-form error (μ_i), whose relationship is described by the following linear equation:

$$\epsilon_i = E(\epsilon_i|\mu_i) + e_i \tag{7}$$

where E(μ_i, $e_i = 0$).

The procedure is implemented in two steps. From the reduced-form regression of the endogenous variable AC against exogenous explanatory variables a new variable, the control function, CF_i, is created and added as an additional variable in the expenditure on electricity equation. As expressed in Eq.(7), ϵ can be decomposed into its mean conditional on μ_i and the deviation around its mean, which by construction is not correlated with μ_i (Train 2009). The conditional expectation, E($\epsilon_i|\mu_i$), is a function of μ_i and it represents our control function (CF), which in the simplest case is $E(\epsilon_i|\mu_i) = \lambda_i\mu_i$. Eq.(4) is then modified as follows:

$$lnE_i = \beta_i + \beta_{cdd}CDD_i + \beta_{hdd}HDD_i + \beta_{ac}AC_i + \lambda_{cf}CF_i + \tilde{\beta}_p lnP_i + \beta_y lnY_i + \beta_x\mathbf{X}_i + e_i \qquad (8)$$

Wooldridge (2015) shows that when the exogenous explanatory variable is a binary variable and the corresponding reduced form equation (5) is estimated through a probit model the derived control function is simply the well-known inverse Mills ratio $CF(\cdot) = \phi(\cdot)/\Phi(\cdot)$.

As presented by Wooldridge, the control function is a flexible approach that can also be used to estimate a random coefficient model which allows for random coefficients to be correlated with the explanatory variable of interest. In our case, the air conditioning adoption may vary across individuals in ways that cannot be observed fully and therefore depends also on unobservables. In our framework, it is possible to combine the problem of self-selection and endogeneity of air conditioning adoption - provided that there is a valid exclusion restriction - with the correlated random coefficient model simply adding to Eq. (8) the interaction between air conditioning adoption and the CF.[10]

$$\begin{aligned} lnE_i = \beta_i + \beta_{cdd}CDD_i + \beta_{hdd}HDD_i + \beta_{ac}AC_i + \lambda_{cf}CF_i + \theta_{rc}AC_iCF_i \\ + \tilde{\beta}_p lnP_i + \beta_y lnY_i + \beta_x\mathbf{X}_i + e_i \end{aligned} \qquad (9)$$

The interaction term, identified in θ, accounts for the random coefficient on AC.

4 Data

The dataset used to estimate Eq.(8) combines the 2011 Environmental Policy and Individual Behaviour Change survey (EPIC, OECD, 2014), which collects data for 12,200 households, with long-term averages (1986-2010) of gridded annual CDDs and HDDs. Stratification and quota sampling on a set of key variables (gender, age, region, income) are used to ensure that the survey is representative at country-level, see Annex B in OECD (2014) for more details. Of the eleven countries that have been covered in the EPIC survey, we retained Australia, Canada, France, Japan, Netherlands, Spain, Sweden and Switzerland, where the location of each family has been geocoded, adding an additional source of cross-sectoral heterogeneity within country.[11]

CDDs and HDDs are the measures commonly used in the energy demand literature to capture the typical intensity and duration of hot and cold climate (Atalla et al. 2018). CDDs and HDDs have been calculated using the daily temperature (degree Celsius) data aggregated from the 3-hourly global surface gridded temperature (0.25° x 0.25° resolution, approximately 27x27 km at the equator) fields obtained from GLDAS (Rodell et al. 2004). We have computed CDDs and HDDs as a proxy for past long-term climatic conditions considering the average from 1986 to 2010, in line with the practice of

[10] See Wooldridge 2015 for applications on linear and non linear models.

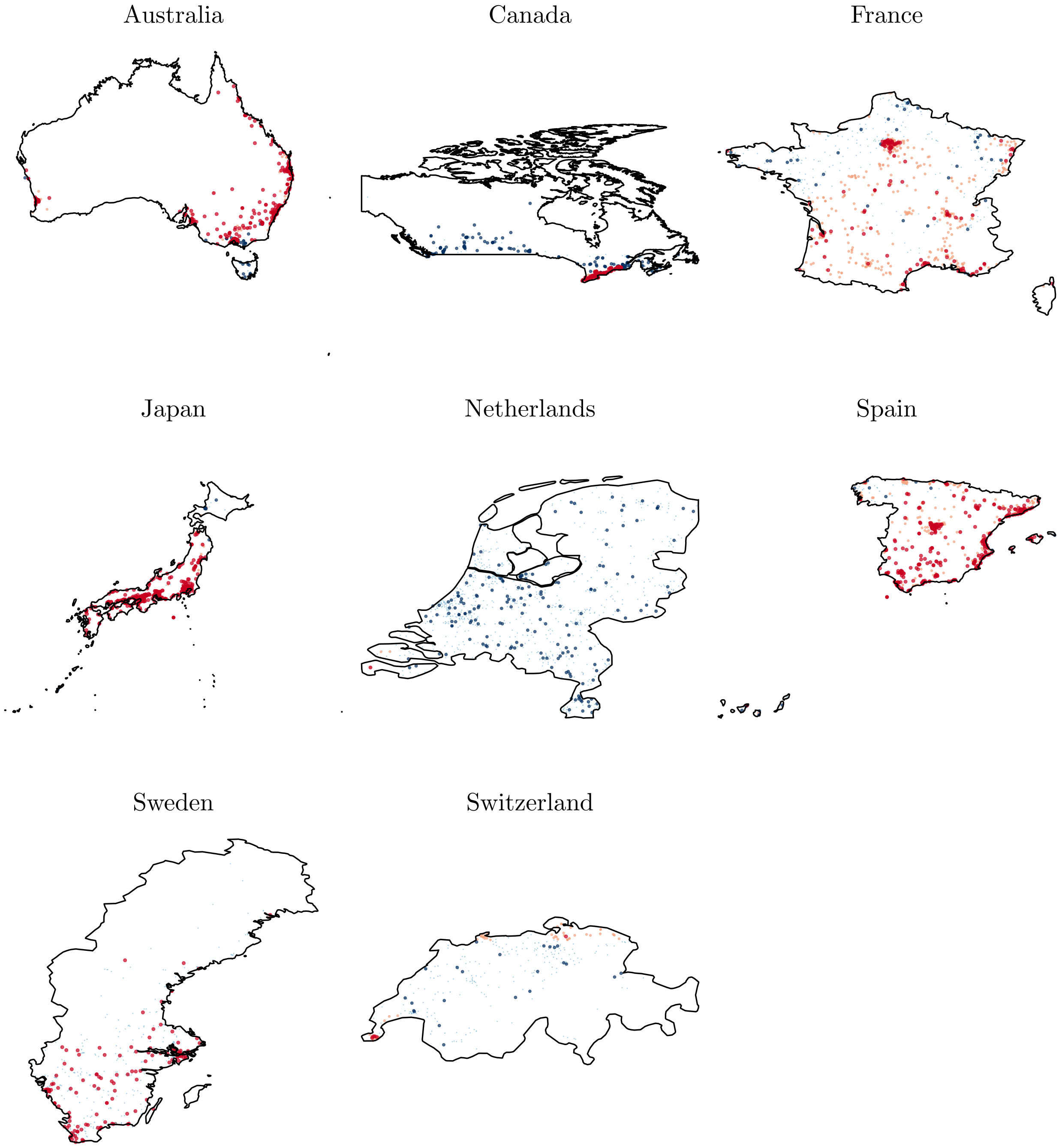
[11] The geocoded households for the countries listed above are 7449.

using long-term climatici conditions in cross-sectional studies (e.g. see Mansur et al. 2008). Since the calculation of CDDs and HDDs is sensitive to the balance point chosen, we test different thresholds between 18 and 25°C. Indeed, although 18°C is the most used temperature threshold in the literature (e.g, Sailor and Pavlova 2003, Akpinar-Ferrand and Singh 2010, Deschênes and Greenstone 2011, Rapson 2014) recent studies have started to explore different thresholds (Levesque et al. 2018). Increasing the threshold at which AC can be turned on is also part of the policy strategies aimed at reducing energy consumption of several countries, for example Japan and India.[12]

Figure 4 plots the spatial distribution of households's ownership of AC along with the long-term average of CDDs and HDDs. Red dots identify households exposed to high CDDs owning an air conditioner. Clusters generally coincide with major urban centers or with the southern part of countries. A number of households especially in France and Spain highlighted in light red did not own AC as of 2011 despite being exposed to relatively warm climatic conditions. The map also shows the households having AC although CDDs are below the sample average (blue dots). The smaller, lighter blue dots are the households without AC and with a relatively low exposure to CDDs. Maps also visualize the great climate variability that is observed within countries across households, as well as the tendency for urban centers to register higher temperature due to the heat island effect (see also Table 2).

[12]The survey and climate data have been merged using the *rgdal* package in R and the DIVA-GIS shapefile provided by the Database of Global Administrative Areas (GDAM). We have used the *extract* function of the *raster* package to extract GLDAS CDD/HDD observations for each OECD participant through geo-location. The CDDs/HDDs grid-cells (pixels) are retained and assigned to each household only where the OECD spatial points fall over them. Each grid cell and each household is then assigned to the region that overlaps with the largest share of the grid-cell. Note that the GLDAS grid-cells close to water have missing values. These households have therefore been dropped.

Figure 4: CDDs 18°C (1986-2010) and AC ownership (EPIC Survey, 2011).



Notes: Red dots: households with high CDDs and with AC. Light red: high CDDs, no AC. Blue: low CDDs, with AC. Light Blue: low CDDs, no AC. High and low CDD levels are defined relative to the sample median across the 8 countries of 160 degree days.

The OECD survey collects a number of energy-related variables including energy expenditure (in euros referring to the last year) and energy consumption (in kWh) that we combine with household socio-demographic characteristics and attitudinal characteristics. As mentioned before, only a subset of households report information on annual quantity of electricity consumed in kWh.[13]Given that the survey collects data also on annual electricity bills we follow Krishnamurthy and Kriström (2015)

[13]In our selected sample only 1402 provide this information which represent 18.8% of the sample.

and use total annual expenditure instead of the quantity of electricity as our variable of interest. To ensure outlier values do not influence results, we trimmed electricity expenditure at the upper and lower estreme values of 1%. After accounting for the missing values in our relevant variables we conduct the analysis for 3711 geocoded households.

Table 1 presents the variables used in the empirical analysis by country. The prices of electricity calculated within the sample are in line with the official statistics, with the exception of Australia, which shows a relatively larger price. Electricity prices are computed as average prices, $P_i = E_i/Q_i$ following the practice of household-level studies that typically lack information on energy prices (see Fell et al. 2014, Alberini and Filippini 2011 for a discussion).[14] Given that energy prices are often not reported, studies on residential energy demand using household survey data often rely on imputed prices and quantities (Fell et. al 2014). For example, Branch's (1993) study on the Consumer Expenditure Survey for the US uses state-level average electricity prices as household prices. Also, Alberini et al. (2011) uses the average price of a given utility by state. The literature (e.g. Alberini et. al 2011, Fell et al 2014 and Krishnamurthy and Kriström, 2015) supports the view that households' consumption decisions respond to average not marginal prices. In fact, even if marginal prices varies with the quantity consumed and can vary by season to season they are costly to determine as it seems improbable that households keep track of the variation of marginal prices or they know marginal prices when consumption decisions are made. Instead, average prices are easily calculated by the electric bills. Moreover, consumers are more likely to devote a certain share of their income to electricity consumption. However, the use of average prices as a independent variable in a specification in which quantity or expenditure on electricity is the dependent variable is not without drawback. In fact, average prices are measured with errors and can create endogeneity problems. Krishnamurthy and Kriström 2015 who use our same survey and similar specification show that in the case of the double-log demand function the bias coming from the prices is not large enough to take away the results (see Krishnamurthy and Kriström 's paper for more details).

The adoption of air conditioning ranges from almost 90% in Japan to only 5% in Switzerland. Switzerland is the country with less homeowners (39%) and households living in urban areas (34%) while 82% of households in Spain own their primary residence. Above 70% of households in Australia and Japan live in urban areas. Our data seems to suggest that those countries with higher concentration of households in urban areas are also the countries with deeper air conditioning adoption. Countries with the highest urbanization rates (Australia and Japan) have also the highest value of CDDs, the variable that most strongly correlates with AC ownership. Yet, Canada provide a counter example, showing relatively high AC adoption rates (48%) despite the relatively low CDDs value.

Efficient windows and thermal insulation indicate whether a household has implemented any of those

[14] Actual consumption and expenditure are used to derive prices. For those households who do not provide consumption we construct the prices using the average price in the country given the stability of price at the country level.

two investment types, which influence electricity demand and help to give a better picture of the household standards of living.[15] The Netherlands and Australia are the countries with a higher percentage of household who have invested in improving thermal insulation (62% and 58%, respectively) and the efficiency of windows. On the one hand, improved thermal insulation can reduce cooling and heating needs. On the other hand, overheating due to more heat being trapped inside of the building might require a more frequent use of air conditioning (Jakubcionis and Carlsson, 2017). Overall, the effect of improving the thermal insulation of windows and walls on final electricity demand can be ambiguous, and being influenced also by the location (urban versus rural) as well as by the type of heating system, whether it is based on electricity or not.

Residential electricity demand depends also on household characteristics and behaviour. A unique feature of the OECD EPIC survey is that it reports a number of attitudinal variables that specifically relate to the use of energy and concerns for the environment. Of particular interest in this context is the energy behaviour index, which summarizes the energy-saving behaviours of a household in a score between 0 and 10. The higher the score, the more frequent the household implements behaviours such as switching off the lights or cutting down heating or air conditioning to save energy consumption. From the energy behaviour index we construct a dummy variable equal to one for those showing a saving behaviour above the mean.[16] Spanish households are those with a more energy saving orientation (75%) while surprisingly Swedish people seem to be paying less attention to simple, domestic, energy-saving practices (15%). Household size ranges from 2.4 in Canada to 2.9 in Spain and the years of post-secondary education of the household head from 2.4 in Sweden to 4.6 in Japan. Among the different countries under analysis differences exist in the reported annual household income with Switzerland leading the group of households with an average high income level followed by Japan and Australia. Finally, our variables capturing cold and hot climate show that Japan and Australia are the countries with a higher level of CDDs while Canada, Sweden and Switzerland, as expected, are those with the higher values of HDDs.

[15]We are aware that several energy appliances can affect electricity consumption such as refrigerator, washing mashine, television. These are very widely used appliances. Almost all households in OECD countries own them and therefore we do not have enough variability needed to perform the analysis.

[16]The mean in our sample is 7.32.

Table 2: Descriptive statistics by country

Variables	Australia	Canada	France	Japan	Netherlands	Spain	Sweden	Switzerland	Total
Electricity expenditure	1048.6	1032.0	837.0	1090.1	1133.9	858.6	1374.5	815.1	1018.0
	(625.4)	(665.2)	(463.1)	(883.2)	(717.5)	(789.6)	(1125.9)	(621.3)	(764.6)
Electricity use (KWh)	5834.0	10178.9	6902.1	4986.5	3775.6	3974.1	11736.8	5073.5	7026.8
	(7025.0)	(9056.2)	(5088.7)	(3453.0)	(2349.0)	(3826.8)	(8921.6)	(5698.7)	(7009.8)
Aircondit	0.728	0.483	0.133	0.90	0.116	0.536	0.189	0.051	0.40
	(0.445)	(0.500)	(0.340)	(0.300)	(0.321)	(0.499)	(0.392)	(0.221)	(0.491)
Electricity price (euro/kWh)	1.450	0.290	0.186	0.234	0.306	0.553	0.185	0.162	0.470
	(1.557)	(0.309)	(0.152)	(0.111)	(0.178)	(0.597)	(0.164)	(0.0226)	(0.806)
Import AC 1990-2000	0.195	0.938	0.357	0.250	0.199	0.433	0.0972	0.0647	0.356
	-	-	-	-	-	-	-	-	(0.265)
CDDs 1986-2010 (18°C)	597.9	129.3	195.2	691.8	56.22	558.5	22.13	96.60	307.62
	(438.5)	(101.2)	(133.3)	(249.2)	(17.85)	(317.2)	(11.86)	(54.65)	(342.25)
CDDs 1986-2010 (22°C)	156.0	13.88	29.62	259.9	3.060	191.0	0.461	7.192	84.73
	(174.7)	(32.30)	(36.10)	(125.2)	(2.097)	(154.3)	(0.675)	(5.482)	(136.19)
CDDs 1986-2010 (23°C)	96.11	6.846	15.66	184.9	1.154	132.9	0.138	2.972	55.86
	(124.6)	(23.98)	(21.29)	(96.59)	(1.018)	(118.6)	(0.244)	(2.476)	(98.36)
CDDs 1986-2010 (24°C)	54.08	3.323	7.558	122.7	0.368	87.32	0.0312	1.075	34.64
	(83.44)	(17.45)	(11.33)	(70.29)	(0.450)	(87.03)	(0.0616)	(1.000)	(67.27)
CDDs 1986-2010 (25°C)	27.75	1.618	3.302	73.58	0.0932	53.62	0.00683	0.318	19.94
	(51.69)	(12.19)	(5.434)	(47.05)	(0.164)	(60.23)	(0.0136)	(0.339)	(42.96)
HDDs 1986-2010 (18°C)	1041.6	4439.2	2396.4	2148.7	2834.8	1704.4	4184.2	3294.1	2660.8
	(632.2)	(911.9)	(442.5)	(745.9)	(86.41)	(913.3)	(514.0)	(705.4)	(1344.49)
Home owner	0.653	0.708	0.641	0.594	0.751	0.820	0.644	0.397	0.676
	(0.476)	(0.455)	(0.480)	(0.492)	(0.433)	(0.384)	(0.479)	(0.491)	(0.468)
Household size	3.234	2.818	2.401	2.425	2.771	2.497	2.400	2.567	2.654
	(1.319)	(0.957)	(0.729)	(0.950)	(0.835)	(0.739)	(0.678)	(0.794)	(0.952)
N. of other appliances	6.794	7.184	6.194	6.019	6.964	6.159	6.520	6.237	6.531
	(2.703)	(2.634)	(2.532)	(2.503)	(2.538)	(2.629)	(2.639)	(2.604)	(2.633)
Effic. windows	0.0292	0.0203	0.0193	0.00937	0.0156	0.0168	0.0175	0	0.0181
	(0.169)	(0.141)	(0.138)	(0.0965)	(0.124)	(0.129)	(0.131)	-	(0.133)
Thermal insulation	0.588	0.433	0.520	0.247	0.616	0.344	0.376	0.418	0.454
	(0.493)	(0.496)	(0.500)	(0.432)	(0.487)	(0.475)	(0.485)	(0.494)	(0.498)
Urban area	0.775	0.669	0.449	0.700	0.465	0.619	0.537	0.340	0.587
	(0.418)	(0.471)	(0.498)	(0.459)	(0.499)	(0.486)	(0.499)	(0.475)	(0.493)
HH size	2.820	2.438	2.701	3.013	2.618	2.973	2.452	2.598	2.707
	(1.475)	(1.158)	(1.153)	(1.607)	(1.142)	(1.097)	(1.157)	(1.329)	(1.268)
Share of members under18	0.164	0.127	0.173	0.130	0.154	0.163	0.173	0.160	0.157
	(0.228)	(0.210)	(0.235)	(0.211)	(0.234)	(0.219)	(0.238)	(0.225)	(0.226)
Age of the hh head	45.21	47.25	45.19	45.81	46.46	43.76	44.73	44.51	45.36
	(13.40)	(13.05)	(13.28)	(10.95)	(12.56)	(12.35)	(13.17)	(12.45)	(12.84)
Gender of the hh head (male)	0.521	0.526	0.530	0.547	0.584	0.547	0.566	0.593	0.545
	(0.500)	(0.500)	(0.499)	(0.499)	(0.493)	(0.498)	(0.496)	(0.493)	(0.498)
HH head's years of post-educ	3.390	3.188	2.759	4.800	4.587	3.814	2.476	2.933	3.422
	(3.500)	(2.938)	(2.399)	(4.088)	(3.163)	(2.986)	(2.497)	(2.724)	(3.116)
Annual hh income	48683.2	42912.8	38617.4	52422.7	40287.7	30706.4	42190.3	63863.0	42633.1
	(27096.7)	(26302.3)	(17377.0)	(30656.7)	(16536.7)	(16712.8)	(18133.6)	(30144.0)	(23877.6)
Energy saving behaviour	8.001	7.234	8.044	7.241	7.086	8.356	5.512	6.781	7.429
	(1.595)	(1.650)	(1.545)	(1.856)	(1.728)	(1.458)	(1.800)	(1.875)	(1.864)
Observations	582	544	675	320	385	596	458	194	3754

Notes: Standard deviation in parenthesis. Descriptive statistics derived by a trimmed model for which the upper and lower 1% of observations on expenditure of electricity are dropped. CDDs and HDDs are computed over thresholds of 18, 22, 23, 24, 25°C. Prices and annual income are in Euros. Income level refers to the average annual income after tax.

5 Results

The regression results from our preferred specifications are reported in Table 2 in which columns (1) and (2) show respectively the probit coefficients and marginal effects on adopting air conditioning. Remaining columns present the estimates for the electricity expenditure equatiton without accounting for the potential endogeneity of air conditioning (Column 3), using a Control Function approach (Column 4) and using a more flexible Control Function approach allowing for correlated random coefficients (Column 5).

Our estimates suggest that indeed air conditioning is endogenous and the Control Function approach should be preferred. Although the bias produced by the OLS model is quite small, not accounting for the endogeneity of AC leads to an overestimation of the marginal impact of climatic conditions on electricity expenditure. The OLS regression indicates that CDDs has an additional influence on electricity expenditure beside the AC channel, whereas this effect goes away in the CF specification. Instead, we can ignore the random coefficienct on air conditioning given that the interaction term between IMR and aircondit is not statistically significant, as shown in column (5), suggesting that air conditioning heterogeneity across individuals is not an issue in our analysis. Home characteristics and location as well as household socio-economic characteristics seems to absorb the majority of heterogenenity in our sample.

Our results show that air conditioning significantly affects households' electricity demand, along with other electricity-using durables (number of other appliances), shifting the electricity demand equation to the right. Households that have acquired AC, on average spend about 9.9% more on electricity, an impact comparable to a 10% increase in income. This result is also very close to what found by Barreca et al. (2016) for the US. Using electricity quantity data they find that households with AC consume 11% more of annual electricity. To put our numbers into perspective, a Standard Deviation (SD) increase in AC (0.49) compared to the mean value (0.4) would increase electricity expenditure by 4.5%, which is similar to the additional electricity expenditure that would be induced by a SD increase in income and number of appliances (of about 4.5% and 3.6%, respectively).

A key role in the implementation of the CF approach is played by the exclusion restriction, which is identified in the past AC imports interacted with latitude. Past AC imports affect the probability of air conditioning adoption by 3% at the level of significance of 1%. An F-statistics larger than 10 (12.17) supports the relevance of our exclusion restriction. Table A.1 shows that the exclusion restriction holds across three different variations of the main model in which Japan is excluded (model 2), other forms of investments that can be influenced by CDDs are included (model 3), we combine model 2 and 3. A specification without Japan is considered because during the 90s this country was among the top 5 air conditioner machine exporters, though its export share over world exports of AC machines declined from 25% in 1990 to 6% in 2010, when China took the lead with a 32% share. Climatic conditions might influence other investment decisions related to thermal comfort, and we tested whether the exclusion restriction holds when including thermal insulation and efficient windows. Estimates from the IV regressions show that our results are robust to the different specifications.

An important determinant of the decision to adopt air conditioning and consequently of the use of electricity is the exposure to warmer climatic conditions. Long-term CDD averages, a proxy for long-term climatic conditions, are positively related with the AC adoption decision. Marginal effects suggest that a 1% increase in long term average CDDs raises the probability of adopting air conditioning by 0.04%. A 100% increase in CDDs, which is comparable to 1 SD increase, would raise the AC share by 4%. For comparison consider that the mean and the SD values of CDDs in the sample is 308 and that moving from the average climate of France (mean CDDs equal to 195) to that of Spain (mean CDDs equal to 558) would imply a percentage increase in past CDDs of 111%. In the CF approach, the CDDs effect on electricity expenditure seems to be absorbed by AC, while HDDs continue to have an impact, capturing the heating signal of those households using electricity also for heating.

Price of electricity does not affect the decision of adopting air conditioning but it does have an impact on electricity expenditure. A one percent increase in price reduces expenditure by -0.86%, suggesting that the demand of electricity is unelastic changing less then the variation of price, as found in previous studies (i.e. Alberini et al. 2011). A SD increase in electricity prices over the mean value would reduce electricity expenditure by about 9%, an impact comparable in size to that of AC.

Household and house characteristics are important determinants of AC adoption and expenditure decisions. Income affects electricity expenditure. One percent increase in income raises the demand of air conditioning by 4% and the expenditure of electricity by 10%. These elasticities are significant at 5% and 1% level. As found also in Krishnamurthy and Kriström (2015), both household size and home size are positively associated with energy expenditure, but those variables do not affect the adoption of air conditioning. On the one hand, electricity usage increases with the age of the respondent. As argued by Fell. et all. (2014), the age of the respondent may be an indicator of the presence of older individual in the household who may spend more time at home, due to reduced working hours, therefore consuming more electricity. Younger member spend more time outside the house (e.g school, activities) and consume less electricity. As the share of young members below 18 years old increases the adoption of air contitioning goes up by 16%. Households members under 18 would be still in education and the household decision to adopt air conditioning may be due to the fact that their children need a cooling enviroment to study. More in general, air conditioning adoption represents a household strategy to protect minors from the exposure to hot weather (Deschenes and Greenstone 2011). Gender and education of the household head affect air conditioning adoption with a different sign. Households with a male head are 5% more likely to have air conditioning while on the other hand, households led by a male head spend 7% less on electricity suggesting that men pay more attention, on average, on household consumption and expenditure. As the head's years of posteducation increases households are 0.5% less likely to invest in air conditioning. The latter finding could be related to the fact that more educated individuals are more aware of the impact of energy on the enviroment and may try to reduce the use of appliances. The impact of education on quantity of electricity disappears when we adopt the control function model even if the sign of the coefficient remains negative. A very similar pattern is found for the energy behaviour index. Households who are more concern about the enviroment tend to adopt a saving behaviour are less likely to adopt an air conditioners and to spend less on electricity, but the statistical evidence is weak, as the coefficient of the energy saving behaviour variable is not statistically significant (p-value of 0.131 in the adoption equation and 0.2 in the electricity expenditure equation).

When we turn our attention to the home characteristics and location, we find that living in an urban area increases the probability of having AC by 9%. CDDs are higher in urban locations due to the heat-island effect, and households respond with a higher investment in cooling systems. The same variable, living in an urban location, is associated with a lower expenditure on electricity. Access to more efficient appliances or better insulation might help cut consumption. Households with a higher number of appliances tend to have a higher propensity towards AC adoption, which might indicate that households used to higher standards of comfort are also more likely to adopt AC.

Table 3: Estimates for the adoption and expenditure decisions

	Air conditioning		Expenditure on Electricity		
VARIABLES	Probit coeff	Probit mfx	OLS	CF	CF(crc)
Past AC imports * latitude	0.0857***	0.0325***			
	(0.025)	(0.009)			
CDDs 1986-2010	0.0011***	0.0004***	0.0001**	-0.0000	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HDDs 1986-2010	0.0001	0.0000	0.0001*	0.0000**	0.0000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log(price of electricity)	0.0098	0.0037	0.1381***	0.1396***	0.1395***
	(0.040)	(0.015)	(0.023)	(0.024)	(0.024)
Home owner	0.1985***	0.0743***	0.1201***	0.0740**	0.0726**
	(0.060)	(0.022)	(0.024)	(0.031)	(0.032)
Home size	-0.0281	-0.0107	0.0600***	0.0637***	0.0641***
	(0.031)	(0.012)	(0.013)	(0.014)	(0.014)
N. of other appliances	0.1286***	0.0488***	0.0403***	0.0134	0.0123
	(0.012)	(0.005)	(0.005)	(0.010)	(0.010)
Urban area	0.2383***	0.0896***	-0.1937***	-0.2461***	-0.2484***
	(0.052)	(0.020)	(0.023)	(0.029)	(0.029)
Household size	-0.1015***	-0.0385***	0.1047***	0.1259***	0.1267***
	(0.029)	(0.011)	(0.011)	(0.016)	(0.016)
Share of members under 18	0.4444***	0.1685***	-0.0049	-0.1050	-0.1098
	(0.132)	(0.050)	(0.059)	(0.073)	(0.074)
Age of the hh head	-0.0010	-0.0004	0.0051***	0.0053***	0.0053***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Sex of the hh head (male)	0.1391***	0.0526***	-0.0397*	-0.0721***	-0.0735***
	(0.052)	(0.020)	(0.021)	(0.025)	(0.025)
Head's years of post-secondary school	-0.0153**	-0.0058**	-0.0064*	-0.0037	-0.0036
	(0.008)	(0.003)	(0.003)	(0.004)	(0.004)
Log(income)	0.1120**	0.0425**	0.1227***	0.1001***	0.0990***
	(0.056)	(0.021)	(0.022)	(0.025)	(0.025)
Energy saving behaviour	-0.0254*	-0.0096*	-0.0140**	-0.0079	-0.0077
	(0.014)	(0.005)	(0.006)	(0.008)	(0.008)
AC			0.0990***	0.0889***	0.1142**
			(0.025)	(0.024)	(0.051)
IMR				-0.3519***	-0.3572***
				(0.096)	(0.097)
IMR*AC					-0.0270
					(0.049)
Constant	-2.46***		4.51***	5.43***	5.46***
	(0.648)		(0.246)	(0.336)	(0.338)
Country FE	Yes		Yes	Yes	Yes
F-test 1st stage			12.17		
P-value joint			0.00		
Observations	3,711	3,711	3,711	3,711	3,711
R-squared			0.255		

Notes: Robust standard errors in parentheses adjusted for 1086 clusters (districts). *** p<0.01, ** p<0.05, * p<0.1. Reported results are based on a trimmed model in which the upper and lower 1% of electricity expenditure observations are dropped. Average electricity prices are constructed as the ratio between quantity and expenditure. Households not reporting the quantity of electricity are imputed country-level average prices. Country controls include Australia, Canada, France, Japan, Netherlands, Spain, Sweden and Switzerland. Price elasticity is computed as $\beta_p = \tilde{\beta}_p - 1$ is -0.86. F-test for the relevance of our exclusion restriction comes from the IV-regression.

The typical thermal comfort standards used in the calculation of CDDs have been developed for for commercial settings in the UK and USA, and use a low base temperature of 18–22°C, which previous studies suggest could result in exaggerated estimates of energy demand (Azevedo et al. 2015). The descriptive statistics in Table 2 indeed show that the mean occurrence of CDDs drops significantly when a 25°C threhsold is considered as opposed to 18, from a mean value of 308 to 20 degree days. Yet, the actual impact on AC adoption and electricity expenditure depends on the interaction between exposure (number of CDDs) and sensitivity (estimated coefficients).

Table 4 shows the impact of CDDs when different temperature thresholds are used to calcuate CDDs. As we move towards higher thresholds, from 18°C up to 25°C, the marginal effect of one additional degree day on the adoption decision increases significantly. The extent of the intensive margin goes up as well (third and fourth columns), but once endogeneity is properly controlled for, the impact of CDDs on electricity expenditure is only indirect. The variation in the estimated coefficient of AC across different CDD thresholds is limited, suggesting that the biggest impact of using a different temperature cutoff is on the adoption decision.

Table 4: Estimates with different CDDs thresholds

	Air conditioning		Expenditure on electricity	
VARIABLES	Probit coeff.	Probit mfx	OLS	CF
CDDs 1986-2010 (18°C)	0.0011***	0.0004***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
HDD 1986-2010 (18°C)	0.0001	0.000	0.0001***	-0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
AC			0.0990***	0.0889***
			(0.025)	(0.024)
CDD 1986-2010 (22°C)	0.0026***	0.0010***	0.0004***	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)
HDD 1986-2010 (18°C)	0.0000	0.0000	0.0001*	0.0000**
	(0.000)	(0.000)	(0.000)	(0.000)
AC			0.0920***	0.0879***
			(0.030)	(0.024)
CDD 1986-2010 (23°C)	0.0034***	0.0013***	0.0005***	-0.0001
	(0.001)	(0.000)	(0.000)	(0.000)
HDD 1986-2010 (18°C)	0.0000	0.0000	0.0001*	0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)
AC			0.0922***	0.0886***
			(0.030)	(0.024)
CDD1986-2010 (24°C)	0.0045***	0.0017***	0.0007***	-0.0001
	(0.001)	(0.000)	(0.000)	(0.000)
HDD 1986-2010 (18°C)	-0.0000	-0.0000	0.0001*	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
AC			0.0924***	0.0896***
			(0.030)	(0.024)
CDD 1986-2010 (25°C)	0.0062***	0.0024***	0.0011***	-0.0001
	(0.002)	(0.001)	(0.000)	(0.000)
HDD 1986-2010 (18°C)	-0.0001	-0.0000	0.0000*	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
AC			0.0930***	0.0909***
			(0.030)	(0.024)

Notes: Robust standard errors in parentheses adjusted for 1086 clusters (districts). *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Reported results are based on a trimmed model in which the upper and lower 1% of electricity expenditure observations are dropped. Average electricity prices are constructed as the ratio between quantity and expenditure. Households not reporting the quantity of electricity are imputed country-level average prices. The relevance of our exclusion restriction holds across the different CDD threshold-specifications. Country controls include Australia, Canada, France, Japan, Netherlands, Spain, Sweden and Switzerland. The table summarizes the estimation results using different thresholds to compute CDDs.

6 Discussion and conclusions

Empirically-based measures of price, income, and climate elasticities are important inputs into the analysis of climate and energy policies, as well as for projecting future energy trends. Air conditiong is emerging as potentially a critical driver of future electricity demand, although much of the debate and also much of the most recent empirical analyses has been mostly addressing either major users, the US, or emerging tropical countries, such as India and Mexico. The focus on countries with good data availability (the US), and more recently on emerging economies has left a research gap concerning AC and electricity demand in European and other OECD countries. In this paper we address this gap, contributing to expand the empirical evidence on how air conditioning adoption influences household-level electricity expenditure in relation to demographic characteristics, socio-economic conditions, and climate conditions using a cross-sectional dataset of geo-coded households across eight different OECD countries.

AC significantly affects electricity expenditure. In terms of magnitude, a standard deviation increase in the AC share has an impact that is comparable to that of a standard deviation increase in income, in the number of other electricity-using appliances, or in electricity prices, though with opposite sign. We also show that the main effect of Cooling Degree Days on electricity expenditure is modulated by the AC utilization, and that once AC is correctly specified in the electricity expenditure equation, long-term climate conditions influence electricity expenditure only indirectly, through the effect on air conditioner acquisition. In other words, there do not seem to be other major mechanims beside space cooling through which climatic conditions influence electricity use. Heating Degree Days (HDDs) remain a significant driver of electricity expenditure, as they capture the heating signal. In addition to income and climate, air conditioning adoption is also influenced by a rich set of determinants, such as location in urban areas, presence of minors in the family, household size, gender, sex, education, behavioural attiudes towards the environments, some of which also affect expenditure patterns.

Our results suggest that climate change, by increasing the frequency of CDDs, could lead to wider AC adoption and therefore to a larger share of household income being allocated to electricity consumption. Whether improved AC efficiency will partly compensate the increase in energy expenditure remains to be studied. Still, in a context of increasing electricity prices due to electrification pushed by ambitious climate policies especially in European and industrialized countries, energy poverty could occur for two reasons. People might not be able to afford technologies such as AC, leading to disutility costs. At a given income level, electricity expenditure might increase. As an illustrative example, we compute the proportion of households whose share of electricity expenditure in income is more than twice the median share in our sample of OECD countries.[17] In order to isolate what would be the impact of

[17] This is one possible indicator of energy poverty. For a list of energy poverty indicators, see `https://www.energypoverty.eu/indicators-data`.

climate change on energy poverty, we only consider a change in CDDs due to high and moderate warming, as in the Representative Concentration Pathway scenarios (van Vuuren et al. 2014) RCP4.5 (moderate warming) and 8.5 (higher warming), keeping everything else, including income, constant to the 2011 level. Climate projections are from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP), which provides bias-corrected daily maximum and minimum temperatures on a 0.25deg x 0.25deg grid simulated by 21 Earth System Models participating in the global Climate Model Intercomparison Project round 5 (CMIP5). We use the multi-model median increase in CDDs between 2021 and 2060 compared to 1986-2005. Around year 2040, CDDs would increase between 162 and 247%, on average, under moderate and vigorous warming, respectively, for a total average of 121 and 161 additional CDDs. AC adoption would increase from about 30%, on average, to 33%, with larger increases in cold countries such as Sweden (from 16% to 22%). On average, these higher adoption rates translate into higher electricity expenditure, between 12% (in France) and 73% (in Sweden). The number of households that actually has an expenditure share above twice the median value, which is about 2% of annual average income, is about 17%. Assuming income does not change and considering only the climate shocks, the number of energy poor households would double under high warming, increasing from an average of 86 to 138 households. Addressing the broader distributional and macroeconomic implications requires a general equilibrium approach that goes beyond the partial equilibrium analysis of this paper, but which could use the estimated marginal effects as inputs.

Our study is not without caveats. The availability of geocoded data made it possible to have an heterogeneous sample with respect to several dimensions both within and across countries. Yet, it should be acknowledged that data reported on electricity expenditure and consumption are not always reliable, an issue that is partly mitigated by trimming the sample, at the cost of reducing the sample size. Moreover, our dataset goes back to 2011. Having a new wave of the same survey for a more recent year would enable major advacements on this topic. Another potential issue is the endogeneity of average prices, which can be related to measurement errors and simultaneity. Here we focus on the endogeneity of air conditioning, our variable of interest, and show to what extent our estimated elasticities might be biased (Alberini et al. 2011). Our climatic indicators are CDDs and HDDs, but since they are computed as annual average of number of days with temperature below or above a thresholds, they miss the inter-annual variability in the extremes, which more and more drive decisions related to air conditioning adoption. Future work will explore the role of extreme event indices and extend the analysis to non-OECD countries. Although we control for a rich set of covariates, and the Control Function approach makes it also possible to include correlated random coefficients, future work will examine the research question addressed by this paper using household-level panel data.

7 References

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A Appendix

Table A.1: IV Estimates for the expenditure on electricity

	Expenditure on electricity			
	(1)	(2)	(3)	(4)
AC	1.2201***	1.2932***	1.2265***	1.3006***
	(0.386)	(0.428)	(0.386)	(0.428)
CDDs 1986-2010	-0.0002	-0.0002	-0.0002	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)
HDDs 1986-2010	0.0000	0.0000	0.0000	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
Log (price of electricity)	0.1372***	0.1252***	0.1382***	0.1264***
	(0.026)	(0.026)	(0.026)	(0.026)
Home owner	0.0701**	0.0469	0.0698**	0.0476
	(0.033)	(0.037)	(0.034)	(0.038)
Home size	0.0676***	0.0682***	0.0672***	0.0679***
	(0.017)	(0.018)	(0.017)	(0.018)
N. of other appliances	0.0025	-0.0008	0.0033	0.0001
	(0.015)	(0.017)	(0.014)	(0.017)
Effic. windows			-0.1693*	-0.1819*
			(0.102)	(0.110)
Thermal insulation			0.0014	-0.0027
			(0.027)	(0.030)
Urban area	-0.2659***	-0.2841***	-0.2645***	-0.2829***
	(0.039)	(0.043)	(0.039)	(0.043)
Household size	0.1329***	0.1305***	0.1332***	0.1306***
	(0.018)	(0.021)	(0.018)	(0.021)
Share of members under 18	-0.1348	-0.1546	-0.1346	-0.1534
	(0.085)	(0.097)	(0.085)	(0.097)
Age of the hh head	0.0056***	0.0051***	0.0055***	0.0050***
	(0.001)	(0.001)	(0.001)	(0.001)
Sex of the hh head (male)	-0.0791***	-0.0868***	-0.0793***	-0.0866***
	(0.029)	(0.032)	(0.029)	(0.032)
Head's years of post-secondary school	-0.0029	-0.0048	-0.0026	-0.0044
	(0.004)	(0.005)	(0.004)	(0.005)
Log (income)	0.0891***	0.0899***	0.0889***	0.0897**
	(0.032)	(0.035)	(0.032)	(0.035)
Energy saving behaviour	-0.0076	-0.0010	-0.0072	-0.0005
	(0.008)	(0.008)	(0.008)	(0.008)
Constant	4.4653***	4.4682***	4.4622***	4.4662***
	(0.307)	(0.340)	(0.310)	(0.343)
Country FE	Yes	Yes	Yes	Yes
F-test 1st stage	12.17	9.84	12.25	9.90
P-value joint	0.005	0.001	0.000	0.001
Observations	3,711	3,398	3,710	3,397

Notes: Robust standard errors in parentheses adjusted for 1086 clusters (districts). *** p<0.01, ** p<0.05, * p<0.1. Reported results are based on a trimmed model in which the upper and lower 1% observations of electricity expenditure are dropped. Country controls include Australia, Canada, France, Japan, The Netherlands, Spain, Sweden and Switzerland. Column (1) is our baseline specification. Column (2) excludes Japan. Column (3) includes house investments in thermal comfort. Column (4) includes house investments in thermal comfort excluding Japan. Estimates of our endogenous variable AC are not interpretable in the IV framework given the binary nature of AC. Our interpretation is limited to the sign and level of significance.