Economic Modelling 90 (2020) 273–287

Contents lists available at ScienceDirect

Economic Modelling

journal homepage: www.journals.elsevier.com/economic-modelling

Air conditioning and electricity expenditure: The role of climate in temperate countries☆

Teresa Randazzo*, Enrica De Cian, Malcolm N. Mistry

Dept. of Economics, Ca' Foscari University of Venice, Centro Euro-Mediterraneo, Sui Cambiamenti Climatici, Italy

ARTICLE INFO

JEL classification:
N5
O13
Q1
Q54

Keywords:
Control function
Climate
Adaptation
Energy demand

ABSTRACT

This paper investigates how households adopt and use air conditioning to adapt to climate change and increasingly high temperatures, which pose a threat to the health of vulnerable populations. The analysis examines conditions in eight temperate, industrialized countries (Australia, Canada, France, Japan, the Netherlands, Spain, Sweden, and Switzerland). The identification strategy exploits cross-country and cross-household variations by matching geocoded households with climate data. Our findings suggest that households respond to excess heat by purchasing and using air conditioners, leading to increased electricity consumption. Households on average spend 35%–42% more on electricity when they adopt air conditioning. Through an illustrative analysis, we show that climate change and the growing demand for air conditioning are likely to exacerbate energy poverty. The number of energy poor who spend a high share of income on electricity increases, and households in the lowest income quantile are the most negatively affected.

1. Introduction

The threat of global warming is one of the most urgent issues facing humanity today. Climate change and climate variability affect nearly all sectors, including agriculture, forestry, energy, tourism, and recreation industries. These widespread impacts have spurred research in many different fields. In particular, there is a recent and growing economics literature focusing on the implications of climate change on residential demand for electricity throughout the world.

Households respond to uncomfortably hot climate conditions by adopting cooling devices that contribute to maintaining thermal comfort at home, and protecting vulnerable members from the risk of mortality and other health issues. Moreover, protective behaviour in response to warmer temperatures might lead people to allocate more time to indoor activities. When indoors, people can use air conditioning (AC), which can mitigate the effect of extreme temperature, counteracting the potential health impacts of heat (Graff Zivin and Neidell, 2014). Deschênes and Greenstone (2011) show that mortality risk is higher at the extremes of cold and hot temperatures, and that infants and the elderly are the most sensitive to extreme temperatures. AC increases households' probability of survival on hot days, reducing mortality risks (Barreca et al., 2016). Therefore, in a changing climate, space cooling becomes an energy service of growing significance in two key respects. Use of air conditioning grows in importance by potentially protecting people from ill health effects of high temperatures, and, at the same time, air conditioning potentially drives future electricity demand to respond to increasing temperatures.

The use of energy for space cooling is growing faster than for use of any other energy service in buildings. Between 1990 and 2016, global demand for "cooling" energy more than tripled. Today, cooling of buildings accounts for about 20% of the total electricity use worldwide (IEA, 2018). From 1990 to 2016, annual sales of air conditioners nearly quadrupled to 135 million units. Figures from the residential sector alone underscore the trend. China leads the world, with 41 million residential units registered, followed by 16 million in the US, and roughly 9 million in both Japan and Europe (IEA, 2018). In many Euro-

☆ This paper has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme under grant agreement No 756194 (ENERGYA). The authors would like to thank Irene Mammi, Francesco Vona, two anonymous referees and the Editors for very helpful comments and suggestions.The dataset used for this study – the 2011 Environmental Policy and Individual Behaviour Change Survey (EPIC) – is available from the OECD upon request. The analysis was performed using Stata 15.0 and R 3.5.0. The code is available to bona fide researchers from the authors upon request. The views expressed in the paper are those of the authors.

* Corresponding author. Ca' Foscari University, Cannaregio 873/b, 30121, Venezia, Italy.
E-mail addresses: teresa.randazzo@unive.it (T. Randazzo), enrica.decian@unive.it (E. De Cian), malcolm.mistry@unive.it (M.N. Mistry).

https://doi.org/10.1016/j.econmod.2020.05.001
Received 3 June 2019; Received in revised form 24 April 2020; Accepted 2 May 2020
Available online 11 May 2020

pean countries the adoption rate and use of air conditioning remain low, even in relatively warm countries, such as Spain.[1] However, penetration of air conditioning is expected to increase. The combination of more frequent high-temperature events and increasing standards of living leads more and more people to buy and use AC to keep themselves cool. In temperate countries, electricity consumption is rising rapidly, especially during the summer months. Even in countries located at mid-latitudes, the frequency of days with very high average temperature is rising, and therefore the demand for space cooling is also rising (Mora et al., 2017). Unprecedented heatwaves hit Paris in 2003 and Moscow in 2010, for example.[2] In Moscow, people responded by purchasing any available air conditioner , rapidly depleting stocks (Kahn, 2016).

A recent literature has begun to examine the implications of the adoption of air conditioning on residential demand for electricity. However, the majority of studies look at two essential components – the matter of how climate affects the adoption of air conditioning, and how the adoption of air conditioning affects electricity demand – as two separate decisions, ignoring that these matters are inextricably connected. Electricity demand depends on the electric appliances people want to power, and the extent to which they use them. Household decisions about whether to purchase an appliance, and how intensively to use it share unobservable common determinants. These can lead to biased and inconsistent estimates of price, income, and temperature elasticities (Dubin and McFadden, 1984). Because these empirical estimates are often used to inform future energy policies, quantifying the extent of the potential bias is extremely important. The limited availability of data on AC use and electricity consumption has thus far enabled scholars to examine such joint decisions and their economic implications in the US only (Barreca et al., 2016). Extending such empirical evidence to other countries has proven to be challenging. Our paper addresses this gap.

This paper contributes to expanding the empirical evidence on how the adoption of air conditioning relates to climatic conditions, and how the use of that appliance influences households' electricity expenditures. We examine the situation in eight industrialized countries that span different latitudes: Australia, Canada, France, Japan, the Netherlands, Spain, Sweden, and Switzerland. So far as we are aware, previous empirical analyses investigating the adoption and use of air conditioning by households in relation to climate have focused primarily on the US market. For the rest of the world, the evidence is scarce, largely due to data limitations. Our paper uses a unique cross-sectional dataset of geocoded households. This allows us to exploit the cross-country and the cross-household variation as an identification strategy. Thus, we are able to disentangle the roles of demographics, house characteristics, and socioeconomic conditions from the role of climate in decisions regarding the adoption and utilization of air conditioning. Our sample consists of 3615 geocoded households interviewed in 2011 (Kriström and Krishnamurthy, 2014; OECD, 2014).

To the best of our knowledge, this paper represents a first attempt to address the endogeneity of air conditioning uptake and use in a rigorous way, and to quantify its size outside of the context of the US. The only other paper of which we are aware that addresses similar issues is Barreca et al. (2016), who use the discrete-continuous model of Dubin and McFadden (1984) to estimate consumer surplus stemming from the decline in hot day-related fatalities as a result of the introduction of residential air conditioning in the US.

We test for the potential endogeneity of air conditioning use by using an instrumental variable strategy to account for the non-random choice of purchasing air conditioners. Given the non-linearity of the potentially endogenous variable we then use a control function (CF) approach (Wooldridge, 2015), with past imports of air conditioners serving as an exclusion restriction. When the endogeneity of air conditioning is taken into account, we find that warm climatic conditions do not influence electricity expenditures per se. Our findings show that AC adoption is endogenous, and that the resulting bias can lead to a significant underestimation of its impact on electricity expenditures. Households with AC on average spend 35%–42% more on electricity than those that do not own AC; our findings contrast sharply with the estimates suggesting increased electricity usage of 5%–10%, when assuming that AC is exogenous. Our work also shows that air conditioning is the main mechanism that increases households' electricity use and expenditures.

In this paper, we also discuss some of the potential aggregate, macroeconomic implications of the demand for space cooling by simulating, *ceteris paribus*, the implications of climate-induced air conditioning adoption and use on energy poverty. In Europe and other developed countries, the concept of energy poverty is mostly linked to the issue of affordability. Even in the developed world, a significant fraction of population is not able to pay for energy services adequately. If climate change makes indoor cooling an essential good for the health and safety of a growing number of people, sustainable solutions will urgently be needed (Phoumin and Kimura, 2019).

The remainder of the paper is organized as follows: Section 2 frames our analysis within the most recent and related literatures. Section 3 describes the data used for the analysis. Section 4 provides the empirical framework. Section 5 discusses results and implications. Section 6 concludes.

2. Literature review

Studies on residential electricity demand using household-level data have been conducted for many decades, as reviewed by Fell et al. (2014) and Miller and Alberini (2016). The main objective of those studies was to estimate energy price and income elasticities for informing policy analysis. Most of the studies focus on the US (Reiss and White, 2005; Alberini et al., 2011; Fell et al., 2014; Miller and Alberini, 2016), though a few empirical analyses surface for other countries or regions (Nesbakken, 1999 [Norway]; Bernard et al., 2011 [Quebec]; Gans et al., 2013 [Ireland]; Pourazarma and Cooray, 2013 [Iran]). Multi-country cross-sectional studies are comparatively rare. Krishnamurthy and Kriström (2015) offer what we believe to be the lone example, characterizing the heterogeneity in price and income elasticities across countries in Australia, Canada, Chile, France, Israel, Japan, South Korea, the Netherlands, Spain, Sweden, Switzerland. A large number of studies find that electricity price and income elasticities are smaller than one, and, therefore, electricity consumption is not very sensitive to changes in price and income (Filippini, 1999; Narayan and Smyth, 2005; Pourazarma and Cooray, 2013). This implies that electricity consumption is not easily discouraged, and that other factors, beside income and prices, explain electricity demand. Some studies suggest that temperature and other meteorological conditions play a role. For example, Henley and Perison (1998) show that consumers' responses to higher electricity prices are conditional on temperature levels. A growing literature supports the relevance of climate variables in determining energy consumption, suggesting that electricity demand is very sensitive to meteorological conditions (Pourazarma and Cooray, 2013; Auffhammer and Mansur, 2014).

Evidence shows that weather and climate conditions affect energy demand, the choice of fuel, and the adoption of energy appliances. Using cross-sectional data, Mansur et al. (2008) investigate adaptation to climate change through fuel choice and consumption in the US energy sector. They conclude that households experiencing colder winters tend to use more natural gas; by contrast, the main source of energy for households located warmer regions is electricity. The relationship between climate and electricity consumption as a means of adaptation has been investigated using panel data, which have the advantage of addressing the potential bias due to unobserved time-invariant heterogeneity that characterizes cross-sectional approaches.

[1] Authors' calculations based on data available from https://www.enerdata.net/.

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

Eskeland and Mideksa (2010) conduct a study for 31 European countries, strengthening the evidence regarding the relevance of climate variables in determining electricity use; they predict a reduction in heating demand in Northern Europe, and an increase in cooling demand in Southern Europe.

Deschênes and Greenstone (2011) and Auffhammer and Aroonruengsawat (2011) also adopt the panel data approach. Both rely on random fluctuations in weather to identify climate effects on electricity consumption. Using annual, state-level data on residential electricity consumption in the US, Deschênes and Greenstone (2011) find a U-shaped response function in which electricity consumption is higher on very cold and hot days. Estimating California's residential electricity consumption using panel-micro data, Auffhammer and Aroonruengsawat (2011) conclude that the effect of temperature on electricity consumption varies greatly across climate zones. Moreover, the authors' simulation results suggest much larger effects of climate change on electricity consumption than has been suggested by previous studies using more aggregate data (e.g. Deschênes and Greenstone, 2011). A limitation of their work, however, is that the dataset used does not allow for the control of household composition and characteristics.

Larger effects of temperature on energy demand also surface in studies using panel data and dynamic models. The idea is that behavioural adjustments and changes in appliance efficiency take place over time, leading to a persistent effect of weather shocks. De Cian and Sue Wing (2017) show that long-run elasticities of energy demand to temperature tend to be larger than the short-run elasticities, especially in response to high temperature levels. This finding suggests that the adoption of more appliances can amplify the impacts on energy demand, especially for electricity. The main limitation of panel approach based on macro studies is the inability to explicitly control for appliance ownership rates, which are not consistently available across countries over time.

Thus far the literature has not explicitly accounted for the amplification effect due to the adoption of appliances for space heating and cooling in response to changes in climatic conditions. One of the major mechanisms for adaptation to climate change is the adoption of devices that help to control for indoor temperatures in the face of rising outdoor temperatures. Electricity is used in combination with energy appliances in order to produce energy services, which are the sources of actual utility for people. Yet, only a few studies have developed empirical estimates that take into account the relationship between the demand for durables and their use. The two decisions – whether to purchase energy durables, and whether to put these durables to use – are interrelated. Advancing understanding of these issues requires joint analysis because unobserved factors can affect both choices – leading to the potential of biased estimates (Dubin and McFadden, 1984; Vaage, 2000). In their pioneering study, Dubin and McFadden (1984) suggest the use of instrumental variable methods to address the basic idea: that households make a joint decision regarding whether to purchase an AC unit and how often to use it.

Branch (1993) treats AC ownership as exogenous, and includes an AC ownership dummy and its interaction with climate variables in the demand equation; the results show that, during the summer months in New York City, for example, households with AC spend 294% more on electricity than those without AC. In the same spirit, Depaula and Mendelsohn (2010) estimate the short-run and long-run effects of climate on residential electricity use in Brazil. They conclude that having AC increases electricity expenditures by 23%–33%, and that climate-induced changes in electricity expenditures can reach levels that approximate the welfare damages of increased temperature.

Asadoorian et al. (2008) follow a two-stage procedure. They first estimate the demand of a set of durables, including AC; and then regress residential electricity demand conditional on the first-stage choices, including the predicted ownership rates obtained from the first-stage. They show that having AC shifts electricity demand upwards, among both rural and urban families in China. Davis and Gertler (2015) use a sequential approach to, first, predict future AC adoption rates for Mexico, and, second, to estimate the response function of electricity demand to temperature using only those regions with historically comparable AC ownership rates. The authors attribute the difference between the average response function for Mexican households and the response function of those regions with high AC ownership to the penetration of new AC, but without including a sample-selection correction term. They highlight that omitting the first-stage adoption decision significantly underestimates the impacts of climate change on future electricity demand in Mexico.

Barreca et al. (2016) apply the model by Dubin and McFadden (1984) in a rigorous way. Estimating the gain in consumer surplus associated with the adoption of residential AC, they find that AC adoption increases average household electricity consumption by 11%, and that the AC penetration rate is associated with a consumer surplus of $5 billion to $10 billion annually. Their study emphasizes the important role of new technologies, such as AC, in helping households to adapt changes in climate conditions, and, therefore, to minimize potential adverse consequences on the welfare of an entire country and its citizens. The increasing demand for cooling as an adaptation mechanism to climate change motivates our work to understand both the determinants and the effects of AC adoption on electricity consumption in a group of countries that have not previously been the subject of such research.

3. Data

Our dataset combines i) the 2011 Environmental Policy and Individual Behaviour Change survey (EPIC; OECD, 2014), which collects data for 12,200 households; and ii) long-term averages (1986–2010) of gridded annual Cooling (CDDs) and Heating (HDDs) Degree-Days assembled by using a high-spatial resolution dataset of global-gridded degree-days (Mistry, 2019). Stratification and quota sampling on a set of key variables[3] are used for collecting the data at the country-level (see Annex B in OECD (2014) for more detail). Of the 11 countries covered in the EPIC survey, we retained Australia, Canada, France, Japan, the Netherlands, Spain, Sweden and Switzerland – the countries for which the location of each family had been geocoded, adding an additional source of cross-sectoral heterogeneity within each country.[4]

CDDs and HDDs[5] are measurements commonly used in the energy demand literature to capture the typical intensity and duration of hot and cold climates, and the corresponding cooling and heating requirements (Mistry, 2019; Atalla et al., 2018). Utilizing annual CDDs and HDDs, we compute the corresponding long-term averages for the 1986–2010 period as a proxy for past, long-term climatic conditions,[6]

[3] Quotas were set for age, gender, region and income. For Switzerland, the proportions of French and German speakers were used rather than region. When quotas were filled, further respondents with those characteristics were not accepted. For each country, post-stratification weights were constructed based on official statistics on age and employment status.

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

[5] They have been calculated using the daily temperature (°C) data aggregated from the three hourly, global surface-gridded temperature fields (0.25° × 0.25° resolution, approximately 27 × 27 km at the equator) obtained from the Global Land Data Assimilation System (GLDAS) (Rodell et al., 2004).

[6] The survey and climate data were merged by using the R-software package rgdal and the DIVA-GIS shapefile provided by the Database of Global Administrative Areas (GDAM) https://gadm.org/. We have used the *extract* function of the R *raster* package (Hijmans and van Etten, 2014) to extract historical CDDs/HDDs for each OECD participant through geolocation. The CDDs/HDDs grid cells are retained and assigned to each household only where the OECD spatial points fall over them. Each grid cell and each household are then assigned to the region that overlaps with the largest share of the grid cell. Note that the grid cells close to water have missing values, because GLDAS data do not report data close to water bodies. These households have therefore been dropped.

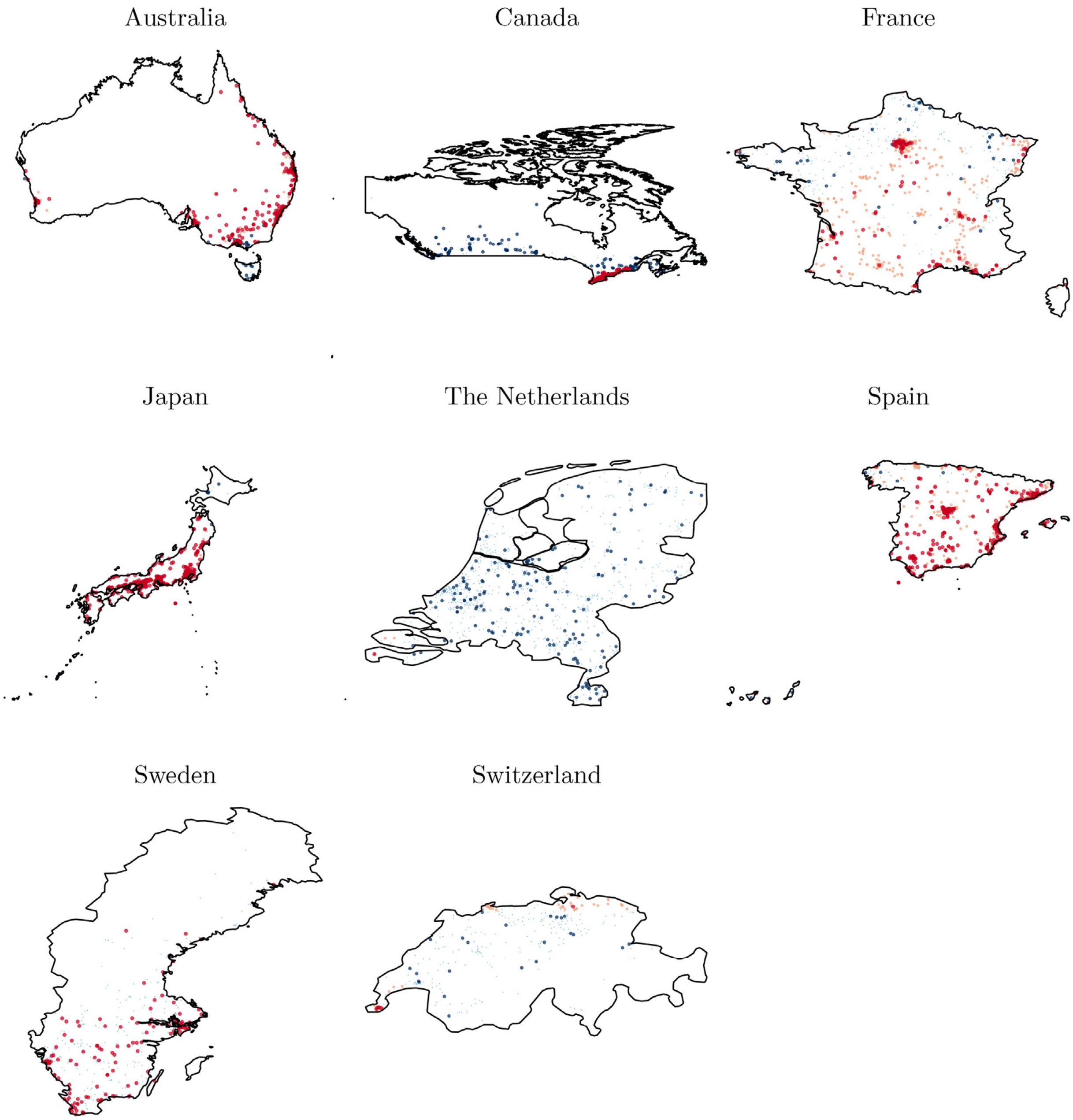


Fig. 1. CDDs 18 °C (1986–2010) and AC ownership (EPIC Survey, 2011). Red dots indicate households with high CDDs and with AC. Light red indicates high CDDs, no AC. Blue indicates low CDDs, with AC. Light Blue indicates low CDDs, no AC. High and low CDD levels are defined relative to the sample median of 160 annual degree days across the eight countries. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

in line with the practice of using long-term climatic conditions in cross-sectional studies (e.g. see Mansur et al., 2008). Because the calculation of CDDs and HDDs is sensitive to the chosen balance point temperature, we test different thresholds between 18 °C and 25 °C. Although 18 °C is the most frequently used temperature threshold in the literature (Sailor and Pavlova, 2003; Deschênes and Greenstone, 2011; Rapson, 2014), recent studies have started to explore different thresholds (Mastrucci et al., 2019). Increasing the temperature threshold at which AC can be turned on is also part of the policy strategies aimed at reducing energy consumption of several countries, such as Japan and India.

Fig. 1 plots the spatial distribution of households' ownership of air conditioners along with the long-term average of CDDs and HDDs. Red dots identify households that are exposed to high CDDs and own an air conditioner. Clusters generally coincide with major urban centres or with the southern regions of countries. A number of households, especially in France and Spain, highlighted in light red, did not own air conditioners as of 2011, despite being exposed to relatively warm climatic conditions. The map also shows the households that have air conditioners, but for which CDDs exposure is below the sample median (blue dots). The smaller, lighter blue dots are the households that do not have air conditioners, and have a relatively low exposure to CDDs. The map provides a way to visualize the large climate variability within countries and across households, as well as the tendency for urban centres to register higher temperatures due to "heat island" effects.

While time-series data of residential AC ownership rates are not available for the countries analysed here, import statistics suggest that cooling needs have been increasing in these countries. Fig. 2 shows the value over time for AC imports for the product category 71,912 according to the Standard International Trade Classification SITC Rev.1 obtained from the United Nations Comtrade Database. We clearly see that, starting from the 1990s, the imports of air conditioners have substantially increased in each country, responding to the emerging demand for such devices. Thus, AC imports indeed provide a good proxy for the demand for air conditioning (see Section 4.1).

The OECD survey collects a number of energy-related variables including yearly electricity expenditures and consumption (in kilowatt-hour, kWh), along with households' socio-demographic and behavioural characteristics. Only a small subset of households report information on the average annual quantity of electricity consumed in kWh.[7] Because data on annual electricity bills are available for a larger group of households, we follow methodologies used by Hunt and Ryan (2015) and Krishnamurthy and Kriström (2015), using electricity expenditures instead of quantity as our variable of interest when estimating the energy demand equation. After accounting for the missing values in our relevant variables, we conduct the analysis for 3615 geocoded households.

Table 1 presents the descriptive statistics of the survey variables used in the empirical analysis by country. The adoption of AC ranges widely, from almost 91% in Japan to only 5% in Switzerland. Switzerland has the smallest proportion of homeowners (38%) and households living in urban areas (34%). By contrast, Spain has the highest level of homeownership (80%), and Australia and Japan have the highest proportion of residents in urban areas (above 70% of households). Our data seem to suggest that those countries with a higher concentration of households in urban areas also have both a deeper penetration of AC and relatively high values of annual CDDs, the variable that most strongly correlates with AC ownership. Indeed, our variables capturing hot and cold climate show that Japan and Australia are the countries with a higher level of CDDs; Canada, Sweden and Switzerland, as expected, are those with the higher values of HDDs.

The presence of efficient windows and thermal insulation suggest whether a household has undertaken investments that influence electricity demand. Moreover, their presence – or absence – helps to better characterize the living standards of households.[8] The Netherlands and Australia are the countries with the highest percentage of households with improved thermal insulation (59% in each country). The Netherlands and France have the highest percentage of households with efficient windows, 79% and 65%, respectively.

Household size in our sample ranges from 2.4 members in Canada to 2.9 in Spain. The years of post-secondary education for the household head ranges from 2.4 in Sweden to 4.7 in Japan. Differences also exist in reported annual household income, with average household income levels highest in Switzerland, followed by Japan and Australia.

Residential electricity demand also depends upon households' 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 consumption of energy, and to concerns for the environment. Of particular interest in this context is the energy behaviour index, which summarizes the energy-saving behaviours of a household on a score between zero and ten. The higher the score, the more frequent the household implements behaviours such as switching off lights, or cutting down heating or AC use to save on energy consumption. From the energy behavioural index, we construct a dummy variable equal to one for those showing a saving behaviours above the mean. Spanish households exhibit the highest level of energy saving behaviours, while, surprisingly, Swedes seem to pay less attention to simple, domestic, energy-saving practices.

[7] In our selected sample only 1402 households provide this information, which represents 18.8% of the sample.

[8] We are aware that several energy appliances such as refrigerators, washing machines, and televisions can affect electricity consumption. These are very widely used appliances in the countries analysed. Because almost all households in our sample own them, we do not have enough variability within the dataset to include them in the analysis.

4. Methodology

People use sources of energy to power durable goods that they use for cooking, lighting, space heating and cooling. Here we focus on AC appliances and the cooling they provide. Together, AC and electricity are used to adjust a home's interior temperature, and to obtain a desired level of thermal comfort. We model the demand for electricity as a function of household characteristics and climatic conditions. Our empirical model uses electricity expenditures instead of electricity quantity as the dependent variable because electricity expenditure information is available for a larger number of households. In our sample, 56.7% of respondents include their electricity expenditures, compared to the 18.8% that report information on the quantity of electricity consumed. As shown in Krishnamurthy and Kriström (2015) and in Hunt and Ryan (2015), energy demand equations can be estimated in terms of quantity or expenditure. Equation (1) models electricity expenditures (Y) for household i as a function of a set of covariates $\boldsymbol{X}_i$ and AC_i, our variable of interest, as follows:

$$Y_i = \boldsymbol{X}_i\boldsymbol{\beta} + \gamma\, AC_i + \epsilon_i \tag{1}$$

The matrix $\boldsymbol{X}_i$ includes our climate variables, CDDs and HDDs, representing cooling and heating degree days, respectively[9]; household-specific control variables, such as household income, the presence of other electricity-using appliances, house characteristics (size, type, insulation), household size, household location in urban areas; and head of household-specific characteristics, such as education, age, sex, and attitudes towards energy efficient behaviours. The term ϵ_i represents the disturbance term.

The main challenge in estimating Equation (1) with cross-sectional data is that the explanatory variables do not capture unobserved heterogeneity.

Even after controlling for a large number of household characteristics, unobservable heterogeneity that could be correlated with our covariates could remain. Dubin and McFadden (1984) suggest that the demand for energy-using appliances and demand for electricity are related and share common, unobserved determinants. Because AC is an example of an energy-using durable good in our specific equation, we suspect that this variable might be endogenous.

As an example, individual body characteristics that affect the balance point for thermal comfort could simultaneously affect the decision about whether to adopt AC, as well as the actual quantity of electricity consumed. Moreover, the adoption of AC is a small investment that might be affected by household's risk aversion, a characteristic that may not be perfectly observable and could cause an omitted variable bias. Our strategy for addressing the endogeneity of the variable AC_i, is based on an instrumental variable approach.

While a two-step approach based on instrumental variables (two-stage least squares [2SLS] regression analysis) and a two-stage residual inclusion method (control function [*CF*] analysis) produce identical estimates in a linear case, the equivalence does not hold in a non-linear setting. When the endogenous variable is modelled in a non-linear framework, the *CF* method is more efficient than the 2SLS method. Moreover, the *CF* produces a test of endogeneity, the heteroskedasticity-robust Hausman test based on the null hypothesis that our variable of interest (AC_i) is exogenous (Terza et al., 2008; Wooldridge, 2015).

4.1. Exclusion restriction

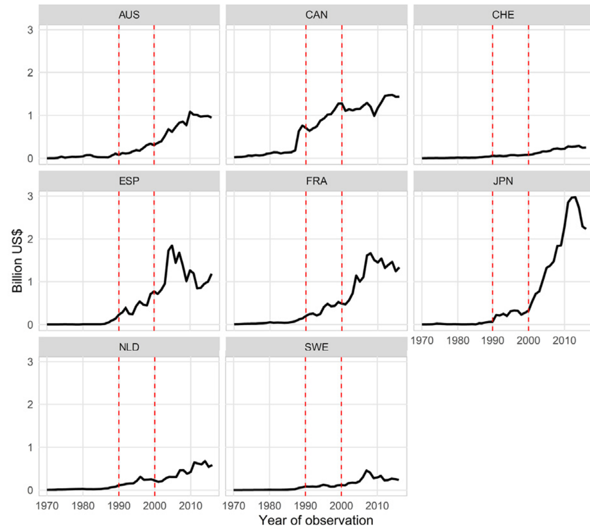
For an instrumental variable strategy to be valid, the instrument has to be strongly correlated with the potential endogenous variable (AC_i) and must have no direct effect on the outcome of interest (Y_i). Because our dataset is a cross section, we do not have information on past AC

[9] As discussed under Data in Section 3.

Table 1
Descriptive statistics by country.

Variables	Australia	Canada	France	Japan	The Netherlands	Spain	Sweden	Switzerland	Total
Electricity expenditure in euros	1162.4	1120.5	862.1	1146.8	1156.6	994.5	1411.6	843.1	1049.5
	(1027.7)	(1045.7)	(599.4)	(1310.0)	(795.7)	(2058.4)	(1254.7)	(741.6)	(1303.1)
AC (yes = 1)	0.746	0.483	0.137	0.910	0.112	0.539	0.195	0.0515	0.522
	(0.436)	(0.500)	(0.344)	(0.286)	(0.315)	(0.499)	(0.396)	(0.222)	(0.500)
Import AC 1990–2000 ($ mn)	195.3	937.6	356.6	249.6	199.1	433.1	97.22	64.66	380.6
	(0)	(1.14e-13)	(5.69e-14)	(0)	(0)	(0)	(0)	(0)	(222.5)
CDDs 1986–2010 (18 °C)	581.7	133.9	194.8	702.3	55.52	551.2	22.08	94.49	419.1
	(411.9)	(110.0)	(133.5)	(235.1)	(17.27)	(315.3)	(11.85)	(54.19)	(338.8)
CDDs 1986–2010 (22 °C)	145.9	15.31	29.55	264.6	2.972	187.1	0.461	6.929	132.1
	(158.1)	(38.32)	(36.22)	(117.5)	(2.010)	(152.4)	(0.675)	(5.391)	(148.1)
CDDs 1986–2010 (23 °C)	88.12	7.816	15.62	188.1	1.111	129.9	0.138	2.838	90.33
	(110.5)	(28.80)	(21.39)	(90.78)	(0.975)	(116.9)	(0.245)	(2.427)	(109.4)
CDDs 1986–2010 (24 °C)	48.20	3.966	7.539	124.6	0.350	84.99	0.0314	1.013	57.99
	(72.07)	(21.09)	(11.41)	(66.19)	(0.431)	(85.56)	(0.0617)	(0.975)	(76.08)
CDDs 1986–2010 (25 °C)	23.84	2.033	3.293	74.42	0.0868	51.95	0.00688	0.296	34.14
	(43.37)	(14.77)	(5.481)	(44.41)	(0.156)	(59.07)	(0.0136)	(0.330)	(48.89)
HDDs 1986–2010 (18 °C)	1034.3	4388.6	2399.8	2105.5	2835.4	1712.2	4180.5	3308.6	2395.7
	(616.7)	(879.5)	(446.0)	(701.0)	(86.32)	(906.6)	(511.0)	(709.1)	(1148.9)
Home owner (yes = 1)	0.677	0.739	0.642	0.589	0.750	0.804	0.657	0.389	0.674
	(0.468)	(0.440)	(0.480)	(0.493)	(0.434)	(0.397)	(0.475)	(0.489)	(0.469)
Home size (m^2)	162.4	126.1	100.9	97.11	128.9	109.1	100.2	112.5	110.1
	(112.8)	(62.13)	(44.70)	(54.83)	(63.39)	(54.19)	(41.64)	(56.07)	(62.32)
N. of other appliances (#)	6.912	7.323	6.171	6.062	6.933	6.185	6.519	6.320	6.373
	(2.803)	(2.777)	(2.484)	(2.571)	(2.668)	(2.738)	(2.685)	(2.747)	(2.667)
Effic. windows (yes = 1)	0.150	0.555	0.658	0.219	0.791	0.608	0.447	0.466	0.468
	(0.358)	(0.497)	(0.475)	(0.414)	(0.407)	(0.489)	(0.498)	(0.500)	(0.499)
Thermal insulation (yes = 1)	0.608	0.465	0.514	0.242	0.590	0.343	0.378	0.432	0.402
	(0.489)	(0.499)	(0.500)	(0.429)	(0.492)	(0.475)	(0.486)	(0.497)	(0.490)
Urban area (yes = 1)	0.809	0.680	0.453	0.725	0.474	0.614	0.542	0.345	0.618
	(0.394)	(0.467)	(0.498)	(0.447)	(0.500)	(0.487)	(0.499)	(0.477)	(0.486)
HH size (#)	2.900	2.426	2.679	2.852	2.627	2.923	2.414	2.603	2.751
	(1.416)	(1.153)	(1.145)	(1.561)	(1.145)	(1.089)	(1.143)	(1.304)	(1.300)
Share of members under 18	0.160	0.123	0.168	0.104	0.159	0.144	0.159	0.161	0.139
	(0.227)	(0.207)	(0.235)	(0.197)	(0.233)	(0.211)	(0.230)	(0.227)	(0.217)
Age of the HH head	43.24	46.67	45.37	47.02	43.83	45.32	44.63	41.33	45.71
	(14.48)	(13.85)	(13.98)	(11.81)	(13.35)	(13.60)	(14.15)	(11.58)	(13.35)
Gender of the HH head (male = 1)	0.590	0.518	0.525	0.570	0.580	0.535	0.550	0.611	0.547
	(0.492)	(0.500)	(0.500)	(0.496)	(0.494)	(0.499)	(0.498)	(0.489)	(0.498)
HH head's years of post-educ	3.602	3.280	2.745	4.718	4.693	3.708	2.435	2.984	3.683
	(3.503)	(2.861)	(2.363)	(4.010)	(3.084)	(2.980)	(2.440)	(2.823)	(3.289)
Annual HH income in euros	51964.8	45406.3	38452.4	52284.4	40778.5	29741.8	42462.8	64311.7	43030.9
	(27550.2)	(26885.8)	(17141.5)	(30787.0)	(16643.3)	(16428.2)	(18041.0)	(30993.8)	(25350.8)
Energy saving behaviour (yes = 1)	8.039	7.197	8.058	7.204	7.048	8.373	5.507	6.818	7.644
	(1.615)	(1.636)	(1.547)	(1.914)	(1.734)	(1.436)	(1.788)	(1.870)	(1.787)
Observations	457	518	688	311	382	597	466	196	3615

Notes: Standard Deviations (SDs) are shown in parentheses. Post-stratified weights provided by the survey are used to compute all descriptive statistics. CDDs are computed with the thresholds of 18 °C, 22 °C, 23 °C, 24 °C, 25 °C. HDDs utilize the threshold of 18 °C. Annual income refers to the average annual income after taxes.



Notes: Data were downloaded from `https://comtrade.un.org/data/` on 24 January 2019. Red lines mark the 1990-2000 period, which is used to define the exclusion restriction.

Fig. 2. Value of AC imports in selected OECD countries. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

adoption at the same resolution of our data. We identify our instrumental variable in the past average value of imports of air conditioners. The past average value of air conditioner imports serves as a good proxy for demand for air conditioning, in light of the fact that most of the countries included in the analysis are, in fact, importers of such devices.

Trade data are the only source available[10] to serve as a proxy for the demand for air conditioners because production and demand data are not available at the global scale. We use the 1990–2000 time frame to avoid contemporaneous correlation between the AC imports and electricity consumption. The use of a 10-year time window is motivated by the average lifetime of air conditioners. As shown in Fig. 2 Section 3, starting from the 1990s all countries in our sample exhibit a constant increasing trend in air conditioner imports. Data on past levels of air conditioner imports are available only at the country level.

Because imports of air conditioners are not uniform across the subnational regions of each country, we weight AC country-level imports by the share of past CDDs[11] of each subnational region in each country. We further redistribute the resulting regional imports to the geocoded households within each region by using the distance from the equator measured by the latitude of each household available in our dataset. We interact the weighted regional imports with the latitude of households. This procedure makes it possible to create variability at the same spatial resolution of our data (geocoded points), which we exploit as an identification strategy. If past imports of air conditioners are correlated with adoption of air conditioning, there is no reason to believe that they directly influence the contemporaneous demand for electricity through other mechanisms different from the availability of air conditioning.

4.2. Control function approach

The adoption of AC, our endogenous variable, is modelled by using a latent-variable approach:

$$AC_i = 1[\boldsymbol{X}_i\boldsymbol{\delta} + \theta\, IMP_i + \mu_i > 0] \tag{2}$$

where $1[.]$ is the binary indicator function. Equation (2) is estimated by using a probit model, and the error term $\mu_i \sim$ Normal (0, 1) is uncorrelated with all the explanatory variables in the equation. In the CF set-up, Equation (2) represents our reduced form equation. It expresses the endogenous variable AC_i, as a function of all exogenous variables included in the matrix $\boldsymbol{X}_i$ plus the exclusion restriction, IMP_i, identified in the weighted past AC imports discussed in Section 4.1.

Key assumptions are the relevance of the exclusion restriction in Equation (2), and its orthogonality with electricity demand in Equation (1), namely $E(IMP_i, \epsilon_i) = 0$. We implement the CF following Wooldridge (2015) who shows how the two-stage residual inclusion can be used even when the endogenous variable is not linear.

Because of the endogeneity of AC_i, the structural error ϵ_i and the reduced form error μ_i are correlated. In a linear framework, the CF shows that the correlation can be captured by using a linear relationship:

$$\epsilon_i = \eta\mu_i + e_i \tag{3}$$

$$E(\mu_i e_i) = 0 \tag{4}$$

Wooldridge defines $\eta = E(\mu_i\, \epsilon_i)/E(\mu_i{}^2)$ as the population regression coefficient. Based on the assumption that ϵ_i and μ_i are uncorrelated with the explanatory variables included in the matrix $\boldsymbol{X}_i$, a valid estimation equation can be obtained by substituting Equation (3) in (1):

$$Y_i = \boldsymbol{X}_i\beta + \gamma\, AC_i + \eta\mu_i + e_i \tag{5}$$

where e_i is the new error term uncorrelated with all right-hand-side variables, including AC_i. Instead, μ_i is estimated from the reduced form equation (the first-stage regression), and when added to the structural equation, it controls for the endogeneity of AC_i, thus making it appropriately exogenous.

In a linear framework, the CF variable is simply the raw residuals of the reduced form equation. When the reduced form is estimated by using a probit model, Wooldridge (2015) shows that the CF variable, μ_i, is the generalized error. Given the conditional expectation:

$$E(Y_i|\boldsymbol{X}_i,\, AC_i) = \boldsymbol{X}_i\beta + \gamma\, AC_i + \eta\, [AC_i\, \lambda(\boldsymbol{Z}_i\, \boldsymbol{\delta}) - (1 - AC_i)\lambda(-\boldsymbol{Z}_i\boldsymbol{\delta})] \tag{6}$$

where the matrix $\boldsymbol{Z}_i$ includes all the variables in $\boldsymbol{X}_i$ and the exclusion restriction IMP_i, and $\lambda(.) = \varphi(.)/\Phi(.)$ represents the inverse Mills ratio. The generalized residual, computed after the first-stage probit model, is

[10] Our import data are from UN Comtrade, https://comtrade.un.org/data/.

[11] We use the average annual CDDs in the 1986–2000 period.

expressed in the following way:

$$\widehat{\mu}_{\mathrm{i}} = \mathrm{AC}_i \lambda(\boldsymbol{Z}_i \widehat{\boldsymbol{\delta}}_{\mathrm{i}}) - (1 - \mathrm{AC}_i) \lambda(-\boldsymbol{Z}_i \widehat{\boldsymbol{\delta}}_{\mathrm{i}}) \tag{7}$$

Y_i is therefore estimated on $\boldsymbol{X}_i$, AC_i and $\widehat{\mu}_i$. A simple test of the null hypothesis that AC_i is exogenous is given by the heteroskedasticity - robust t statistics on $\widehat{\mu}_i$ (Wooldridge, 2015).

5. Results

5.1. Empirical results

As discussed in Section 4.2, the control function strategy is implemented in two stages. We first estimate the reduced form in Equation (2) for the probability of adopting AC by using past import of air conditioners as an exclusion restriction. In the second stage, we estimate expenditure of electricity, expressed in a natural logarithm,[12] including the residuals from the first stage in the outcome equation together with the full set of controls, as in Equation (5).

Table 2 reports regression results. Columns 1 and 2 present the first stage in which we report the probit coefficients and the marginal effects of adopting AC. The remaining columns present the second stage for electricity expenditures. Column 3 shows the OLS estimates for households' electricity expenditures without accounting for the potential endogeneity of AC.

The CF approach makes it possible to quantify the bias induced by the potential endogeneity through the coefficient of the residuals, $\widehat{\mu}_i$. We first compute the raw residuals by estimating AC with a linear probability model (LPM) (Column 4), and then use generalized residuals after a probit model (Column 5). Our preferred specification uses the generalized residuals after a probit model, as suggested by Wooldridge (2015), and discussed in Section 4. Moreover, the CF makes it possible to compute a test of exogeneity. The heteroskedasticity-robust Hausman test for exogeneity is rejected, suggesting that AC is endogenous.

A key role in implementing the CF approach is played by the exclusion restriction, which is identified in the past AC imports weighted by the regional CDDs and interacted with latitude. Past levels of imports significantly increase the probability of adopting AC; the F-test on the relevance of the IV, which is greater than 10, confirms that past imports are a significant and reliable predictor of adopting AC. Table A.2 shows that the exclusion restriction holds across different specifications. In the first specification, we exclude Japan (columns 1–2) as a major exporter of air conditioners during the 1990s (though its export share of air conditioners declined from 25% in 1990 to 6% in 2010, when China took the lead with a 32% share). The second specification considers other forms of investments related to thermal comfort that can be influenced by CDDs (columns 3–4), such as thermal insulation and efficient windows. Finally, we combine the first two specifications (columns 5–6).

Our results suggest that climatic conditions affect electricity expenditures by inducing more households to adopt air conditioning. From the first stage we can conclude that a one-standard-deviation (one-SD) increase in CDDs, which in our sample is 338, increases the adoption probability by 13.5 percentage points.[13] An increase in log income by one unit increases the probability of adopting air conditioning by 5 percentage points (i.e., a 172% increase in income from the mean of 43,031, equivalent to a three-SD increase, will increase the probability of ACs being adopted by 5 percentage points [or 1 SD corresponds to 4/3 = 1.6 percentage points]). Conducting a similar analysis for Mexico, Davis and Gertler (2015) find that climate and income contribute to increase the probability of adopting air conditioning by 7–12 percentage points and 8 percentage points, respectively. Our results, referring to industrialized countries, point to a relatively larger role of climate, as also suggested by US studies (Biddle, 2008; Rapson, 2014).

Our findings show that adoption of AC shifts expenditure by 35%–42%, depending on the specification adopted.[14] There is a lot of variability across countries in the amount of electricity demanded for space cooling, which normally reaches its peak over summertime. Previous research has shown that in locations where the "summer" season lasts for most of the year, demand for cooling accounts for 50% or more of total electricity demand (IEA, 2018).

In a related US study, Barreca et al. (2016) find that households with AC consume 11% more electricity annually. Using a sample of 11 OECD countries from the same EPIC survey, Krishnamurthy and Kriström (2015) find that using electricity as an energy source for heating and cooling increases electricity demand from 22% to 36%. Work in Brazil by Depaula and Mendelsohn (2010) finds similar impacts ranging from 23% to 33%. Moreover, the actual impact of AC on electricity expenditures also depends on technical parameters, such as efficiency and type of the air conditioner itself. These parameters vary both across and within countries and households (IEA, 2018).

Finally, since the marginal effect of AC is estimated as a percentage shift in expenditure, it also depends on the overall amount of electricity consumed. Indeed, when estimating the same two equations for countries with low (high) average electricity expenditures, we find a larger (smaller) marginal effects.[15]

While air conditioning has a rather strong impact on electricity expenditures, CDDs do not influence electricity expenditures once the endogeneity of AC is properly accounted for. Only the OLS regression indicates that CDDs have an additional influence on electricity expenditures in addition to the AC channel, whereas this effect vanishes when the CF strategy is implemented. The effect of CDDs on electricity expenditures is absorbed by AC, while HDDs continue to have an impact, capturing the heating signal of those households that also use electricity for heating.

Indeed, other studies suggest that other forms of self-protection or adaptation to high temperature could also influence electricity consumption. Temperature might affect the allocation of leisure time between indoor and outdoor activities, influencing electricity consumptions through other channels such as cooking, showering, and watching television (Graff Zivin and Neidell, 2014).

Average annual income also influences electricity expenditures, though the elasticity is small, in line with the empirical evidence that suggests declining elasticities of key energy services once income reaches certain thresholds (Fouquet, 2014). Electricity demand is not very sensitive to variations in income and prices, suggesting little room for discouraging residential electricity consumption (Filippini, 1999).

The rest of Table 2 presents the impact of other households' characteristics on the two related energy decisions, showing their relevance as determinants of AC adoption and electricity expenditures. All explanatory variables have the expected sign. For example, as also found in Krishnamurthy and Kriström (2015), both household and home size are positively associated with energy expenditures, but those variables do not affect the adoption of AC. Filippini (1999) also concludes that a large family consumes more electricity given a certain stock of appliances in the household. Electricity usage increases with the age of the respondent. As argued by Fell et al. (2014), this may be an indicator of the presence of older individuals in the household who may spend more time at home due to reduced work hours, and who, therefore, consume more electricity. A larger share of younger members below the age of 18 has a positive effect on the adoption of AC, bringing evi-

[12] The functional form in logarithm is chosen to reduce the problem of heteroskedasticity investigated with a Breusch-Pagan test (Verbeek, 2017).

[13] A one-unit increase in CDDs raises the probability of adoption by 0.04 percentage points; that is, an increase in CDDs of 100 raises the probability of adoption by 4 percentage points.

[14] Table A.1 presents weighted estimates using the post-stratified weights provided by the survey, and shows a 35% impact of AC on electricity expenditures.

[15] Results are available upon request.

Table 2
Estimates for AC adoption and decision on electricity expenditure.

	First stage		Second stage		
	AIR CONDITIONING		EXP ON ELECTRICITY		
				Control function	
VARIABLES	coeff.	mfx	OLS	LPM Res	Probit Gen Res
AC Imports 1990–2000 × Lat	0.0167***	0.0063***			
	(0.004)	(0.001)			
CDDs 1986–2010 (18 °C)	0.0011***	0.0004***	0.0002*	−0.0002	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HDDs 1986–2010 (18 °C)	0.0001	0.0000	0.0001*	0.0000*	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Home owner	0.2221***	0.0820***	0.0652**	0.0156	0.0501
	(0.063)	(0.023)	(0.029)	(0.036)	(0.030)
Home size	−0.0005	−0.0002	0.0010***	0.0012***	0.0011***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of other appliances	0.1289***	0.0484***	0.0484***	0.0130	0.0376***
	(0.012)	(0.004)	(0.007)	(0.014)	(0.009)
Urban area	0.2267***	0.0844***	−0.2076***	−0.2684***	−0.2262***
	(0.052)	(0.019)	(0.028)	(0.038)	(0.030)
HH size	−0.1161***	−0.0436***	0.1157***	0.1456***	0.1248***
	(0.029)	(0.011)	(0.013)	(0.018)	(0.014)
Share of members under18	0.4708***	0.1768***	−0.0664	−0.1888**	−0.1038
	(0.138)	(0.052)	(0.067)	(0.085)	(0.074)
Age of the HH head	−0.0017	−0.0007	0.0049***	0.0056***	0.0051***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Gender of the HH head (male)	0.1340**	0.0502***	−0.0595**	−0.0922***	−0.0695***
	(0.052)	(0.019)	(0.024)	(0.030)	(0.025)
HH head's years of post-educ	−0.0143	−0.0054	−0.0063	−0.0034	−0.0054
	(0.009)	(0.003)	(0.005)	(0.005)	(0.005)
Log annual HH income	0.1392**	0.0523**	0.1231***	0.0798**	0.1099***
	(0.059)	(0.022)	(0.028)	(0.033)	(0.027)
Energy saving behaviour	−0.0247*	−0.0093*	−0.0162**	−0.0110	−0.0146*
	(0.015)	(0.005)	(0.008)	(0.009)	(0.008)
Country	yes	yes	yes	yes	yes
AC			0.0984***	1.1372***	0.4157***
			(0.032)	(0.322)	(0.157)
First stage residuals				−1.0528***	−0.1880**
				(0.325)	(0.092)
Constant	−1.9892***		4.4348***	4.7870***	4.5424***
	(0.632)		(0.303)	(0.347)	(0.286)
F-test 1st stage				20.99	17.42
Prob > F				0.000	0.000
Heterosk. robust Hausman test				10.99	4.00
				0.000	0.045
R-squared			0.197	0.1954	0.1978
Observations	3615	3615	3615	3615	3615

Notes: Robust standard errors are shown in parentheses, and are adjusted for 1056 clusters (districts). **p < 0.01, **p < 0.05, *p < 0.1. Country controls include Australia, Canada, France, Japan, the Netherlands, Spain, Sweden and Switzerland. The first-stage residuals in column (4) are linear residuals ("Res") computed after a Linear Probability Model "LPM". In column (5) we calculate the generalized residuals ("Gen Res") after the probit model.

dence to its role as a strategy to protect minors from exposure to hot weather, as suggested by studies conducted in the US (Deschênes and Greenstone, 2011). At the same time, households with a larger share of young members consume less electricity, reflecting the different habits of persons of different ages, but also possibly pointing to the role of credit constraints.

Gender and education of the household head affect AC adoption with a different sign. Households with a male head are more likely to have AC but, at the same time, they spend 6% less on electricity, suggesting that men pay more attention, on average, to consumption and expenditure. Turning to education, as the head's years of post-education increases, households are 0.5 percentage points less likely to invest in AC, suggesting that more educated individuals may be more aware of the impact of energy on the environment, and may try to reduce the use of those appliances. A very similar pattern is found for the energy behaviour index. Households that are more accustomed to adopting energy-saving behaviours are less likely to adopt AC. The coefficient relating the energy-saving attitude to electricity expenditures is negative, as expected, but it is not statistically significant. The role of preferences is also indirectly captured by the appliance number variable. Households with a higher number of appliances tend to have a higher propensity to adopt AC – which may be an indication that households used to higher standards of comfort are also more likely to adopt AC.

With respect to the role of home characteristics and location, we find that, on the one hand, living in an urban area increases the probability of having AC by 9 percentage points, a sizable effect compared to the role of income and climate. In fact, CDDs are higher in urban locations due to the "heat island" effects, and households respond with a higher investment in cooling systems. On the other hand, the same variable, that of living in an urban location, is associated with a lower expenditure on electricity. This is may be due to the fact that more efficient buildings and appliances, which help saving energy, are concentrated in urban areas.

Table 3 shows the impact of CDDs when different temperature thresholds are used to calculate them. The typical thermal comfort standards used in calculating CDDs have been developed for commercial settings in the UK and the US, and use a low base temperature of 18 °C–22 °C, which previous studies suggest could result in exagger-

Table 3
Estimates with different CDD thresholds.

	First stage		Second stage	
	AIR CONDITIONING		EXP ON ELECTRICITY	
				Control Function
VARIABLES	Probit coeff.	Probit mfx	OLS	Probit (Gen Res)
CDDs 1986–2010 (18 °C)	0.0011***	0.0004***	0.0002**	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
HDDs 1986–2010 (18 °C)	0.0001	0.0000	0.0001*	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
AC			0.0984***	0.4157***
			(0.032)	(0.157)
CDDs 1986–2010 (22 °C)	0.0022***	0.0008***	0.0004***	0.0002
	(0.000)	(0.000)	(0.000)	(0.000)
HDDs 1986–2010 (18 °C)	0.0000	0.0000	0.0001*	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
AC			0.0826***	0.4029***
			(0.031)	(0.151)
CDDs 1986–2010 (23 °C)	0.0029***	0.0011***	0.0006***	0.0003
	(0.001)	(0.000)	(0.000)	(0.000)
HDDs 1986–2010 (18 °C)	0.0000	0.0000	0.0001*	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
AC			0.0827***	0.4050***
			(0.031)	(0.151)
CDDs 1986–2010 (24 °C)	0.0039***	0.0015***	0.0008***	0.0004
	(0.001)	(0.000)	(0.000)	(0.000)
HDDs 1986–2010 (18 °C)	−0.0000	−0.0000	0.0001*	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
AC			0.0827***	0.4096***
			(0.031)	(0.151)
CDDs 1986–2010 (25 °C)	0.0053***	0.0020***	0.0012***	0.0007
	(0.001)	(0.001)	(0.000)	(0.000)
HDDs 1986–2010 (18 °C)	−0.0000	−0.0000	0.0000*	0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
AC			0.0830***	0.4167***
			(0.031)	(0.152)

Notes: Robust standard errors are shown in parentheses, and are adjusted for 1056 clusters (districts). ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. The relevance of our exclusion restriction holds across the different CDD threshold-specifications. Country controls include Australia, Canada, France, Japan, the Netherlands, Spain, Sweden and Switzerland. Column (4) present the Control Function approach using generalized residuals ("Gen Res") after the probit model. The table summarizes the estimation results using different thresholds to compute CDDs. For conciseness, the remaining controls are omitted from the table.

ated estimates of energy demand (Azevedo et al., 2015). The descriptive statistics in Table 1 actually show that the mean occurrence of CDDs drops significantly when a 25 °C threshold is considered, as opposed to 18 °C, from a mean value of 419 to 34° days.

As we move towards higher thresholds, from 18 °C up to 25 °C, the marginal effect of one additional cooling degree day on the adoption decision increases significantly, by almost 10 times. Varying the thermal comfort set point influences the marginal effect of CDDs on electricity expenditures, which rises, but, as found in the main specification, the coefficient is statistically significant only when the OLS approach is used. When using the CF approach, the estimated coefficient of the AC variable does not vary across the different CDD thresholds, suggesting that the biggest impact of using a different temperature cut-off is on the first-stage, adoption decision.

5.2. Implications

Empirical results in Section 5.1 show that an increase in CDDs leads to a wider adoption of air conditioners, and that households with air conditioners on average spend yearly between 35% and 42% more on electricity compared to families that do not own such appliances. Considering that climate change will increase the number of extremely hot days (Russo et al., 2014), in this section we briefly explore the potential implications of climate-induced AC adoption on energy poverty, *ceteris paribus*. Energy itself is not recognized as one of the basic needs, but it is needed to provide basic services for sheltering, health and education (Pachauri et al., 2004). Despite consistent progress in providing wider access to electricity, 840 million people have no such access (World Bank, 2019). Energy poverty is not an issue only in developing countries (see Pachauri et al., 2004; Pourazarma and Cooray, 2013). In the US about one-third of households struggle to pay energy bills (IEA, 2018), and in Europe, the population affected by fuel poverty ranges from 9.7% to 15.11%, depending on the member state (BPIE, 2014). Here we only present an illustrative exercise aimed at showing the economic significance of the potential distributional impacts of climate change through energy consumption.[16]

In order to isolate the impact of global warming through AC adoption, we limit ourselves to considering a change in CDDs, keeping all other determinants constant to the 2011 level. This is a first-order assessment that accounts for neither income nor substitution effects. Considering the role of prices would require a different methodology based on a general equilibrium approach. The projected change in future annual CDDs is computed by utilizing average daily minimum and maximum temperatures from the US National Aeronautics and Space Administration (NASA) Earth Exchange Global Daily Down-

[16] Further exploration of wider ramifications is left for future research. The literature on energy poverty has offered a broad set of indicators. Addressing the broader distributional and macroeconomic implications requires a general equilibrium approach that goes beyond the partial equilibrium analysis of this paper.

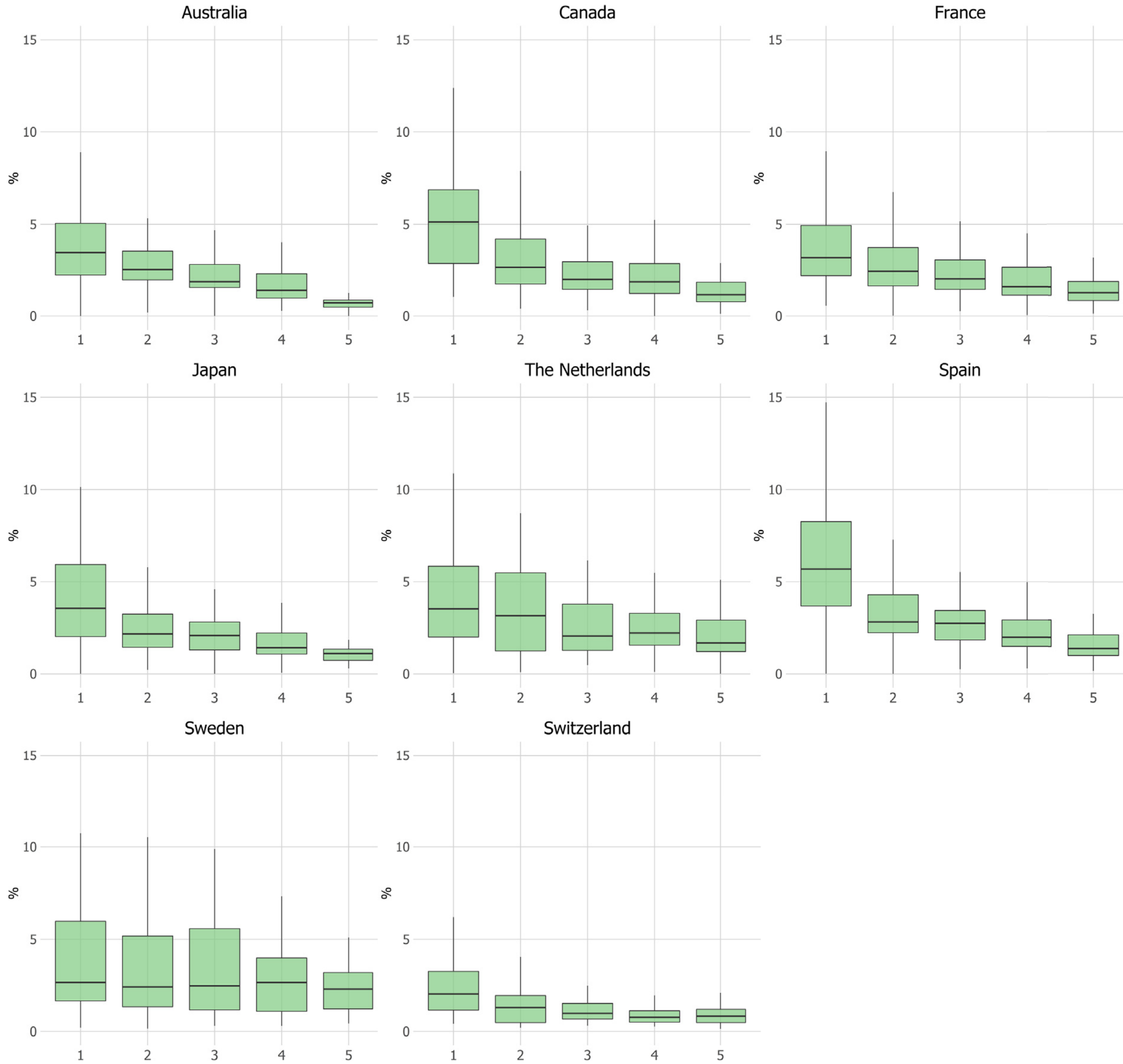


Fig. 3. Share of income spent on electricity (%) across the eight countries within each income quintile as reported in the EPIC Survey (OECD, 2014).

scaled climate Projections (NEX-GDDP).[17] We use the multi-model median increase in annual CDDs between 2021 and 2060 compared to 1986–2005 period. The simulations are from the higher warming scenario, the Representative Concentration Pathway scenario RCP8.5 (van Vuuren et al., 2011), which gives a global average temperature increase of 2 °C around the year 2040. We obtain the predicted AC adoption rates under current and future CDDs, and subsequently compute the induced change in electricity expenditures. We next use the electricity expenditures under current and future climate conditions to calculate a standard indicator of energy poverty – that is, the number of households with annual electricity expenditures exceeding 5% of household income (Faiella and Lavecchia, 2019).[18]

The distribution of electricity expenditure shares across income groups already provides information on the extent of vertical (across income groups) and horizontal (within income groups) equity (Pizer and Sexton, 2019). Fig. 3 shows a declining share of households' electricity spending across income quintiles, with the exception of Sweden. Spain and Canada show the largest gaps between low- and high-income households, with poor households spending on average 5% of their income on electricity, compared to the 1% figure for high-income households. All countries in our sample include households that spend more than 5% of household income on electricity. In Canada and Spain, a significant fraction of households spends more than 10% of their income on electricity.

Countries exhibit a different degree of horizontal inequality, as illustrated by the dispersion of the boxplots within each income group. Within-income dispersion is largest for the first decile in Spain, Canada and, the Netherlands, and it tends to decline when moving towards higher-income classes.

[17] The data includes bias-corrected daily maximum and minimum temperatures on a 0.25°gridded resolution, simulated by 21 Earth System Models participating in the global Climate Model Intercomparison Project round 5 (CMIP5). Data source: https://cds.nccs.nasa.gov/nex-gddp.

[18] There is a broad literature on how to measure energy poverty. For the purpose of this investigation, we focus on one simple indicator.

Table 4
Share of households spending more that 5% of income on electricity.

	Current climate	Future climate
Australia	11.5	13
Canada	20.4	21.1
Switzerland	5.1	5.1
Spain	18.5	19
France	8	8.4
Japan	12.8	12.5
The Netherlands	18.1	18.4
Sweden	24.2	24.5

Under the RCP8.5 climate scenario considered in this exercise, the number of annual CDDs around year 2040 will increase – from as few as 49 additional degree-days in Sweden, to as many as 302 additional degree-days in France. Warming induces more households to adopt air conditioning universally among the countries in our study. Increase in the adoption of air conditioning ranges from about 3% in Japan to 35% in France. Increased adoption rates translate into higher annual electricity expenditures, with additional costs per household ranging from 7 additional euros in Sweden and the Netherlands, to 38 additional euros in Spain. On average, each household spends at least 20 euros more per year on electricity in Australia, Canada, and Spain across all income deciles, whereas the impact of climate change is more limited in Switzerland, the Netherlands, Sweden, and Japan. Climate impacts tend to be regressive, and the increase in the share of electricity spending is relatively larger among the lowest quintiles. With climate change, the number of energy poor households that spend more than 5% of their income on electricity rises, though the effect is moderate. The share of energy poor varies between 24.2% in Sweden and 5.1% in Switzerland. The extent of the increase in the population of the energy poor varies from country to country, as shown in Table 4. The share of energy poor increases the most in Australia, from 11.5% to 13%, and in Canada, from 20.4% to 21.1%

6. Conclusions

This paper uses a unique dataset to examine to what extent climatic conditions influence households' electricity expenditures in eight developed, temperate economies (Australia, Canada, France, Japan, the Netherlands, Spain, Sweden, and Switzerland). We use a cross-sectional dataset of geolocated households in these eight countries, which are characterized by different climatic conditions, which we proxy by cooling degree days (CDDs) and heating degree days (HDDs).

We show that CDDs affects electricity expenditures primarily by inducing households to purchase and then use air conditioners. Once the endogeneity of air conditioning is controlled for in the electricity expenditure equation, warm climatic conditions influence electricity expenditures only indirectly, through the acquisition of air conditioners. There do not seem to be other mechanisms through which a hot climate influences electricity consumption. Instead, cold climatic conditions, measured by HDDs, remain a significant driver of electricity expenditures, capturing the heating signal for those households that use electricity for space heating.

Evidence shows that space cooling consistently affects the demand of electricity, and that extremely high temperature levels drive demand. Such high-temperature extremes will intensify with global warming. Thus, the situation requires policy interventions – particularly because air conditioning may evolve into a new health "need" for vulnerable populations in places that face an increasing number of days with ever hotter temperatures. Space cooling can put enormous pressure on electricity systems, and drive up emissions. National policy agendas should thus prioritize increasing the supply of electricity from renewable sources, incentivising both supply and demand of more efficient appliances, and improving the energy performance of buildings.

Our results suggest that climate change, by increasing the number of CDDs, could lead to a wider adoption of air conditioning, and therefore could lead households to spend a larger share of their income for electricity. The emerging role of cooling as a new, basic need – even in countries that traditionally have not "needed" such appliances – could exacerbate energy poverty. Families might not be able to purchase the most efficient appliances, due to overall costs and credit constraints. They might need to divert a larger share of their income to satisfy the demand for cooling, and away from other types of expenditures, such as food and education, that contribute to increase welfare. An illustrative simulation exercise based on our empirical estimates shows that climate-induced increase in electricity expenditures tend to be regressive and could increase energy poverty because households within the lowest income quintiles are more strongly affected.

Our study is not without caveats. The availability of geocoded data made it possible to have a heterogeneous sample with respect to several attributes both within and across countries. Yet, it should be acknowledged that the data reported on electricity expenditures and consumption are not always reliable, an issue that we address by showing that our results are robust to using a trimmed sample. Energy prices, as well as appliance prices, are important variables affecting both adoption and utilization decisions. While the survey used and the cross-country nature of the analysis make it difficult to include these controls, we exploit the cross-country dimension of the survey and include country fixed effects to control for country-specific factors. We note that our climate indicators (CDDs and HDDs) are computed as an annual average number of days with temperatures above or below a threshold. Thus, they do not capture the inter-annual variability in the extremes, which could also potentially drive decisions related to the adoption and use of air conditioning. Future work is needed to explore the role of climate extreme indices, and to extend the analysis to OECD and non-OECD countries.

Declaration of competing interest

None.

A. Appendix

Table A.1
Estimates for AC adoption and decision on electricity expenditure

	First stage		Second stage		
	AIR CONDITIONING		EXP ON ELECTRICITY		
				Control function	
VARIABLES	coeff.	mfx	OLS	LPM Res	Probit Gen Res
Import AC 1990–2000 × Lat	0.0188***	0.0074***			
	(0.005)	(0.002)			
CDDs 1986–2010 (18 °C)	0.0014***	0.0006***	0.0003***	−0.0002	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HDDs 1986–2010 (18 °C)	0.0000	0.0000	0.0001*	0.0001*	0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Home owner	0.1353	0.0536	0.0346	0.0116	0.0279
	(0.082)	(0.033)	(0.049)	(0.060)	(0.056)
Home size	−0.0011*	−0.0004*	0.0008	0.0010**	0.0008**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
N. of other appliances	0.1361***	0.0538***	0.0492***	0.0177	0.0400***
	(0.016)	(0.006)	(0.009)	(0.015)	(0.013)
Urban area	0.2833***	0.1120***	−0.2111***	−0.2755***	−0.2300***
	(0.062)	(0.024)	(0.042)	(0.048)	(0.045)
HH size	−0.1199***	−0.0474***	0.1118***	0.1373***	0.1193***
	(0.036)	(0.014)	(0.017)	(0.021)	(0.020)
Share of members under18	0.5494***	0.2171***	−0.0588	−0.1786*	−0.0939
	(0.163)	(0.064)	(0.079)	(0.096)	(0.087)
Age of the HH head	0.0000	0.0000	0.0052***	0.0055***	0.0053***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Gender of the HH head (male)	0.1057	0.0418	−0.0863**	−0.1087**	−0.0929**
	(0.065)	(0.026)	(0.036)	(0.046)	(0.043)
HH head's years of post-educ	−0.0122	−0.0048	−0.0011	0.0007	−0.0006
	(0.013)	(0.005)	(0.009)	(0.010)	(0.009)
Log annual HH income	0.2193***	0.0867***	0.1527***	0.0975*	0.1365***
	(0.068)	(0.027)	(0.048)	(0.052)	(0.045)
Energy saving behaviour	−0.0226	−0.0089	−0.0386***	−0.0333***	−0.0370***
	(0.019)	(0.007)	(0.011)	(0.011)	(0.010)
Country	yes	yes	yes	yes	yes
AC			0.0525	1.0582***	0.3475*
			(0.041)	(0.313)	(0.192)
First stage residuals				−1.0217***	−0.1751+">+
				(0.317)	(0.109)
Constant	−2.9920***		4.2562***	4.6513***	4.3721***
	(0.736)		(0.464)	(0.503)	(0.449)
F-test 1st stage				20.54	14.96
Prob > F				0.000	0.000
Heterosk. robust Hausman test				10.41	2.57
Prob > χ^2				0.001	0.108
Observations	3615	3615	3615	3615	3615
R-squared			0.169	0.171	0.169

Notes: Robust standard errors are shown in parentheses, and are adjusted for 1056 clusters (districts). **p < 0.01, **p < 0.05, *p < 0.1, +">+p < 0.11. Post-stratified weights provided by the survey are used to compute the regressions. Country controls include Australia, Canada, France, Japan, the Netherlands, Spain, Sweden and Switzerland. The first-stage residuals in column (4) are linear residuals ("Res") computed after a Linear Probability Model ("LPM"). In column (5) we calculate the generalized residuals ("Gen Res") after the probit model.

Table A.2
Robust Estimates for the expenditure on electricity

VARIABLES	Second stage: EXP ON ELECTRICITY					
	LPM Res	Probit Gen Res	LPM Res	Probit Gen Res	LPM Res	Probit Gen Res
AC	1.1900***	0.4613***	1.1478***	0.4188**	1.2001***	0.4616***
	(0.364)	(0.175)	(0.316)	(0.163)	(0.365)	(0.176)
CDDs 1986–2010 (18 °C)	−0.0002*	0.0000	−0.0002*	0.0000	−0.0003*	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HDDs 1986–2010 (18 °C)	0.0000	0.0000**	0.0000*	0.0001**	0.0000	0.0000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Home owner	0.0058	0.0456	0.0210	0.0550*	0.0117	0.0513
	(0.040)	(0.032)	(0.039)	(0.032)	(0.040)	(0.032)
Home size	0.0013***	0.0012***	0.0012***	0.0011***	0.0013***	0.0012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N. of other appliances	0.0106	0.0365***	0.0130	0.0378***	0.0106	0.0369***
	(0.016)	(0.010)	(0.013)	(0.009)	(0.016)	(0.010)
Effic. windows			−0.0113	−0.0083	0.0088	0.0112
			(0.038)	(0.034)	(0.035)	(0.029)
Thermal insulation			−0.0163	−0.0155	−0.0341	−0.0329
			(0.034)	(0.030)	(0.035)	(0.029)
Urban area	−0.2789***	−0.2338***	−0.2701***	−0.2274***	−0.2820***	−0.2361***
	(0.039)	(0.028)	(0.035)	(0.029)	(0.039)	(0.028)
HH size	0.1432***	0.1216***	0.1458***	0.1248***	0.1430***	0.1210***
	(0.023)	(0.017)	(0.018)	(0.015)	(0.023)	(0.017)
Share of members under18	−0.1997*	−0.1122	−0.1901**	−0.1042	−0.1997*	−0.1109
	(0.105)	(0.081)	(0.089)	(0.075)	(0.105)	(0.081)
Age of the HH head	0.0051***	0.0046***	0.0056***	0.0052***	0.0051***	0.0046***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender of the HH head (male)	−0.0861***	−0.0605**	−0.0924***	−0.0695***	−0.0866***	−0.0607**
	(0.032)	(0.026)	(0.030)	(0.026)	(0.032)	(0.026)
HH head's years of post-educ	−0.0074	−0.0090*	−0.0033	−0.0054	−0.0073	−0.0090*
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)
Log annual HH income	0.0671*	0.0937***	0.0806**	0.1107***	0.0677**	0.0945***
	(0.034)	(0.027)	(0.035)	(0.028)	(0.034)	(0.027)
Energy saving behaviour	−0.0047	−0.0085	−0.0102	−0.0140*	−0.0039	−0.0078
	(0.010)	(0.009)	(0.009)	(0.008)	(0.011)	(0.009)
First stage residuals	−1.1031***	−0.2140**	−1.0634***	−0.1898**	−1.1133***	−0.2142**
	(0.363)	(0.103)	(0.318)	(0.094)	(0.364)	(0.103)
Constant	5.0095***	4.7449***	4.7792***	4.5337***	5.0045***	4.7375***
	(0.366)	(0.296)	(0.366)	(0.298)	(0.367)	(0.296)
F-test 1st stage	20.44	17.44	20.86	17.35	20.32	17.34
Prob > F	0.002	0.000	0.000	0.000	0.000	0.000
Heterosk. robust Hausman test	9.25	4.35	11.15	4.11	9.34	4.33
Prob > χ^2	0.002	0.037	0.000	0.042	0.002	0.037
R-squared	0.2125	0.2095	0.2005	0.1979	0.2129	0.2099
Observations	3304	3304	3615	3615	3304	3304

Notes: Robust standard errors are shown in parentheses, and are adjusted for 1046 clusters (districts). ***p < 0.01, **p < 0.05, *p < 0.1. Country controls include Australia, Canada, France, Japan, the Netherlands, Spain, Sweden and Switzerland. Columns (1–2) exclude Japan. Columns (3–4) include house investments in thermal comfort. Columns (5–6) include house investments in thermal comfort, excluding Japan. The first-stage residuals ("Res") in columns (1), (3) and (5) are linear, computed after a Linear Probability Model ("LPM"). In column (2), (4) and (6) we calculate the generalized residuals ("Gen Res") after the probit model.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.econmod.2020.05.001.

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