The Impact of Air-conditioning on Residential Electricity Consumption across World Countries*

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Abstract

This paper provides the first global assessment of the energy implications of households' climate change adaptation through air-conditioning. We pool household survey data from 25 countries and employ a discrete-continuous choice econometric framework to simultaneously estimate the adoption and utilisation of air-conditioning. After identifying how individual drivers determine households' adaptation behaviours, we combine the estimated responses with socioeconomic, demographic, and, climate change scenarios available at a high spatial resolution to project future air-conditioning adoption and electricity demand, as well as the contribution of individual determinants. On average, we find that air-conditioning ownership increases households' electricity consumption by 34%, but the effect is highly heterogeneous, and it varies with weather conditions, income levels and across countries, revealing the importance of behaviors, practices, climate, and technologies. Compared to other socioeconomic, demographic, and climatic drivers of electricity demand, air-conditioning has the leading marginal effect, and it can account for a significant share of households' budget. We then show that, especially in developing and emerging countries, age, education, and urbanisation reinforce the positive, long-term effect of income and high temperatures on air-conditioning adoption and electricity demand for space cooling. The overall effect of socio-demographic, economic, and climatic drivers is a net increase in regional and global air-conditioning electricity by 2050, with a related social cost $128-175 billion due to the additional CO_2 emissions. Our findings highlight electricity expenditure for air-conditioning serves as an important benchmark for tracking a new dimension of energy poverty related to the need of space cooling. Moreover, our projections points at the emerging risk associated with this form of households' adaptation.

JEL Classification: D12, O13, Q41, Q5

Keywords: Adaptation; Air-conditioning; Electricity demand; Global survey data

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1 Introduction

Climate change is affecting a growing number of people (Pörtner et al., 2022; Dyer, 2022) and heat exposure is increasing in most places (Biardeau et al., 2020; Jay et al., 2021) as a result of co-occurring trends such as rising temperatures and inequalities, informal urbanization, and population aging (Carr et al., 2023). Air-conditioning is spreading quickly, often advertised as the only available adaptation action to cope with high temperatures (Turek-Hankins et al., 2021). Air-conditioning indeed provides protective effects as demonstrated by the significant reduction in morality (Barreca et al., 2016), by the ameliorative effects on learning outcomes (Park et al., 2020) and in mental health (Hua et al., 2022). However, its widespread usage carries important repercussions on households' expenditure and welfare (Mansur et al., 2008; Randazzo et al., 2020; Barreca et al., 2016), on economy-wide energy demand and electricity systems (Auffhammer and Mansur, 2014; Auffhammer et al., 2017), on air pollution, greenhouse gases (GHGs) emissions (Colelli et al., 2022), and climate policy (Rode et al., 2021). These repercussions, however, have only implicitly being quantified.

This paper provides the first global-scale, micro-founded empirical quantification of the actual electricity used for air-conditioning by applying a two-stage discrete-continuous framework that makes it possible to evaluate the long-term effects of climate change through household-level data. The paper uses a newly assembled global cross-sectional, multi-country database tracking households' expenditure patterns, energy behaviours in terms of electricity consumption and acquisition of air conditioners in 25 countries located in various continents, representing 62 percent of the world's population and accounting for 73% of the global electricity consumption to assess the current and future demand and expenditure for air-conditioning electricity in the residential sector.

As a guidance for the empirical analysis, we develop a simple adaptation model to frame two of the main adaptation strategies households can use to cope with extreme heat, namely air-conditioning adoption (extensive margin) and use (intensive margin), in the context of a household's welfare maximisation. Based on this framework, we then apply the discrete-continuous econometric model first developed by Dubin and McFadden (1984) to estimate the contribution of households' adaptation behaviours in the form of air-conditioning adoption and utilisation to electricity consumption. Our approach properly accounts for the correlation that exists between the two adaptation decisions, and it can identify the long-term effects of temperature on electricity consumption.

We find that on average households owning air-conditioning consume 34% more electricity consumption than those without the technology. This response is increasing but concave in temperature, with the effect reaching a peak at 67%. We document a significant heterogeneity across across income levels and across countries. We discuss how the different saturation with temperature, and the different marginal effect is suggestive of differences in practices, behaviours and technologies.

To situate our findings within the context of demand-side responses to climate mitigation, we compare the energy impact of air-conditioning to that of total income, age, gender, education, housing characteristics, home ownership, household size, and urbanisation through a descriptive meta-analysis of the standardised coefficients obtained from country-specific regressions. Factors such as education, gender, age, urbanisation, and housing quality have all been show to play a role in explaining energy use and expenditure patterns in both various high-income countries and in emerging economies such as India (Ameli and Brandt, 2015; Krishnamurthy and Kriström, 2015). Our evidence goes in this direction, but it also indicates that, when available, air-conditioning is the leading factor influencing residential electricity consumption. The rising attention to the social aspects of energy demand is also evident in the latest assessment report of the Intergovernmental Panel on Climate Change, which brings a novel focus on the social aspects of mitigation (Creutzig et al., 2022) and on the non-technical determinants of electricity demand in buildings (IPCC 2022).

Furthermore, we use our estimated coefficients to simulate for each household the amount of electricity used for running air-conditioning systems. We then transform this quantity into expenditure to test the impact of air-conditioning on households' budget. The results highlight a cooling-related dimension of energy poverty, with several poorer households owning air conditioners spending more than 5% of their budget on electricity for cooling. As we move along the income distribution, the burden decreases with high income households allocating less than 1% of their expenditure on air-conditioning use.

We then combine our estimates with projections of climatic, economic, and socio-demographic drivers to quantify future air-conditioning prevalence and space cooling electricity consumption in the residential sector. Residential space cooling demand would soar. The average household would increase its average annual demand for space cooling electricity from 1,979 kWh in 2020 to 2,100-2,300 kWh in 2050. On average, families in 2050 will almost reach the amount of electricity today used by the United States, about 2,515 kilowatt-hour per year. Yet, the economic burden on households will be highly diverse, as already today low-income families allocate to space cooling electricity expenditure between 10% and 0.6% of their budget. This is in sharp contrast with the much smaller share of richer families, which goes from 4% to 0.2%.

We conclude by providing back-to-the-envelope calculations of the potential repercussions for energy and climate policy of the surge in residential cooling demand. First, taking India as an example, we show that Indian electricity peak generation capacity should be expanded by 36% to 47% to satisfied peak electricity demand from future air-conditioning use. Second, we estimate that future residential air-conditioning demand would induce an increase in emissions by 692-948 $MtCO_2$ in 2050, generating a "Social Cost of Cooling" of 128-175 billion USD. Our findings so identify the potential emerging risks associated with this form of households' adaptation, and the potential interplay between mitigation and adaptation objectives.

Our paper contributes to the literature on how residential electricity consumption (Deschênes and Greenstone, 2011; Davis and Gertler, 2015; Auffhammer, 2022) responds to climate change by explicitly measuring the specific contribution of air-conditioning. Recent research has uncovered the determinants of the air-conditioning adoption decision in both emerging economies (Pavanello et al., 2021; Falchetta and Mistry, 2021) and developed countries (De Cian et al., 2019) with household-level micro data and, at the global scale, with country-level panel data (Andrijevic et al., 2021; Davis et al., 2021). Income is the leading driver in less affluent, hot areas (Davis and Gertler, 2015; Davis et al., 2021; Pavanello et al., 2021), whereas temperate, industrialised countries respond relatively more to thermal discomfort arising from more frequent hot days (De Cian et al., 2019). Yet, air-conditioning adoption patterns only partly correlate with actual use (Ara Begum et al., 2022), which in turn relates to socioeconomic conditions as well as to the actual real-feel temperature experiences. There is substantial evidence documenting the relationship between meteorological or climatic conditions and energy use (Auffhammer and Mansur, 2014; Deroubaix et al., 2021) for individual countries (Davis and Gertler, 2015; Zhang et al., 2020), multiple countries (Davis et al., 2021), cities (Romitti and Sue Wing, 2022), and even all world's regions (Van Ruijven et al., 2019). Yet, electricity consumption for specific end uses, such as cooking, space heating and cooling, is usually not metered, and it can only be estimated indirectly by using engineering (Bezerra et al., 2021) or econometric methods (Obringer et al., 2022). Two studies seek to empirically combine the intensive and extensive margin effects (Davis and Gertler, 2015; Auffhammer, 2022). Davis and Gertler (2015) stratifies electricity demand responses according to air-conditioning penetration in Mexico. The authors estimate the intensive margin in Mexican states with currently high levels of air-conditioning penetration. These response functions are used to project how households in the other Mexican states would behave if they were to reach the same level of air-conditioning penetration. There are two main drawbacks in their approach. First, there is no correction for sample selection of households that are more likely to own an air conditioner. Second, they use two different samples for the electricity demand and the computation of the average air-conditioning penetration rates. Our approach is able to overcome both these issues. Auffhammer (2022) only uses electricity demand observations of individual households. Here, the method consists of, initially, modelling demand regression with location-varying responses to contemporaneous temperature shocks, and subsequently modelling the responses' coefficients as a function of long-run zonal climate to estimate the long-run effects. Critically, this method is specific for the case when only household-level billing data are available, but the air-conditioning ownership is unknown. This is not the case for our work. Our two-stage discrete-continuous framework allows to obtain the long-term effects of temperature, when household-level data are available for both the intensive and extensive margin in a cross-sectional setting.

Another important novelty of this paper is the ability of our empirical strategy to identify not only the average marginal effect of air-conditioning on electricity demand, but also to characterise how utilisation is modulated by actual climatic conditions. The few existing econometric studies in the field have only quantifying the average effect of air-conditioning ownership on electricity demand (Randazzo et al., 2020). The quantification of the actual electricity consumed and of the related expenditure for space conditioning provides new inputs for updating the academic and policy discussion around the topic of energy poverty. Energy poverty has traditionally been defined in relation to the need to keep a house warm (Bradshaw and Hutton, 1983), and it has yet to conceptually include the notion of poverty arising from cooling needs.

The remainder of the paper is organised as follows. Section 2 presents our newly constructed dataset and some descriptive statistics. Section 3 provides the theoretical framework underlying our analysis. Section 4 shows our empirical approach. Results are discussed in Sections 5 and 6, and the concluding remarks in Section 7.

2 Data

2.1 Household survey data

We assemble a globally-relevant household micro-data database covering a large number of subnational administrative units from 25 countries.[1] Together, these countries represent 62 percent of the world's population and account for more than 70% of the global electricity consumption. Table 1 lists the countries included in the database, the macro-region of belonging, the year(s) when the interviews were carried out, and the number of households included in the final pooled database for each country. Overall, our data set includes 673,219 households.

For each survey we gather information on annual electricity expenditure and quantity consumed (when available), air-conditioning ownership, total household expenditure, and several socioeconomic and demographic variables. We limit our sample to the households that do not show missing values neither for air-conditioning nor for electricity use. This means that our analysis excludes households that did not have access to electricity at the survey year.

[1] See also Figure S2 for an account of the countries in our dataset.

When electricity quantity was not available in the survey, we augment the data set with information on average electricity prices to calculate electricity quantity implied by electricity expenditure. Electricity prices are either directly obtained dividing electricity consumption by quantity or collected at country or sub-national level from external sources.[2]

Similarly, the variable indicating whether a household lives in urban or in a rural area is not reported for all countries and - where reported - the definition of a urban household varies across countries. For these reasons, we also collect gridded data on urbanisation from Gao and Pesaresi (2021) to construct population-weighted shares at the sub-national level, and attribute this newly generated continuous variable for urbanisation to each household located in that corresponding sub-national region.

Table 1: Household survey microdata sources and details

Country	Year of wave analysed	Region	Primary source	N° Households
Canada	2011	North America	EPIC	481
United States of America	2003-2021	North America	AHS	69,144
Mexico	2018	Central America	INEGI	62,267
Brazil	2017 / 2018	Southern America	IBGE	46,945
Argentina	2017 / 2018	Southern America	ENGHO	19,871
Sweden	2011	Europe	EPIC	448
Switzerland	2011	Europe	EPIC	199
Netherlands	2011	Europe	EPIC	448
France	2011	Europe	EPIC	667
Germany	2019	Europe	SOEP	5,316
Spain	2011	Europe	EPIC	515
Italy	2019	Europe	HBS	17,244
Nigeria	2019	Africa	GHS	1,200
Ghana	2017	Africa	GLSS	6,812
Kenya	2015 / 2016	Africa	IHBS	5,863
Burkina Faso	2014	Africa	EMC	1,980
Niger	2014	Africa	ECVMA	858
Malawi	2019 / 2020	Africa	IHS	1,234
Tanzania	2017 / 2018	Africa	HBS	9,193
Pakistan	2018 / 2019	Central Asia	LSM-IHS	19,506
India	2019	Central Asia	CHPS	167,855
China	2014	Eastern Asia	CFPS	10,928
Japan	2011	Eastern Asia	EPIC	248
Indonesia	2017	Eastern Asia	SUSENAS	224,103
Australia	2011	Oceania	EPIC	527

2.2 Historical climate data

We describe the meteorological and climatic conditions influencing energy demand by using the degree-days methodology commonly applied in the energy sector (ASHRAE, 2009; Scott and Huang, 2008). Because the thermal comfort in buildings relates to both cooling and heating, the degree-days have been developed with the corresponding dual concepts of Cooling and Heating Degree Days (CDDs and HDDs). HDDs and CDDs are represented as temperature sums in degree Celsius day, and they are defined as the cumulative sum of days, within a year, with daily average temperature above (CDDs) or below (HDDs) the temperature threshold, T^* (Deroubaix et al., 2021):

$$CDD = \sum_{d=1}^{365} (\gamma_d)(T - T^*) \quad \text{and} \quad HDD = \sum_{d=1}^{365} (1 - \gamma_d)(T^* - T)$$

where γ_d is the binary multiplier.

[2]See Appendix for more information on how we assemble the data set.

CDDs and HDDs are computed for each grid cell, and then aggregated to the sub-national geographical unit. We construct meteorological CDDs and HDDs as the annual value calculated at the survey year. Climatic CDDs and HDDs are defined as the approximately 30-year average of the annual CDDs and HDDs across the period 1970-survey year. We obtain daily average dry-bulb temperature to calculate Cooling and Heating Degree Days (CDDs and HDDs) at each year and grid cell from the ECMWF's ERA-5 historical climate reanalysis data (Hersbach et al., 2020), covering the period 1970-2019, and having a spatial resolution of 0.25 arc-degrees. We adopt the temperature threshold of 18 °C.[3] Moreover, we also calculate CDDs and HDDs data from Global Land Data Assimilation System (GLDAS) (Beaudoing et al., 2020) to assess the robustness of our estimates. Household data are then merged with the resulting HDDs and CDDs at the most disaggregated geographical information available (e.g. provinces or districts), and all grid cells within each administrative unit are collapsed by taking a population-weighted average in order to represent temperature exposure for the average person within a sub-national administrative unit.

2.3 Descriptive Statistics

Table 2 describes the average households' characteristics for the global pooled dataset, while country-specific descriptive tables are found in Tables S2-S13 in the Appendix.

Table 2: Weighted Descriptive Statistics

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	2358.83	3799.80	253.56	650.99	1260.00	2424.24	5023.02
Air-conditioning (Yes = 1)	0.25	0.43					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	15.94	10.86	2.94	6.22	12.80	27.09	30.19
CDD (100s)	16.81	11.06	3.32	7.12	14.01	27.70	31.29
HDD (100s)	12.00	14.38	0.00	0.05	4.33	21.57	31.32
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	15733.86	33771.18	1313.22	3544.04	6545.82	14297.35	37928.57
Electricity Price ($2011 PPP / kWh)	0.19	0.14	0.10	0.12	0.15	0.24	0.33
Urbanisation Share	0.07	0.11	0.00	0.01	0.03	0.10	0.20
Home Ownership (Yes = 1)	0.82	0.38					
Household Size	3.91	2.25	2.00	2.00	4.00	5.00	6.00
No Education (Yes = 1)	0.28	0.45					
Primary Education (Yes = 1)	0.28	0.45					
Secondary Education (Yes = 1)	0.31	0.46					
Post Education (Yes = 1)	0.14	0.34					
Age of Household Head	34.94	25.55	0.00	0.00	39.00	55.00	66.00
Female Household Head (Yes = 1)	0.32	0.47	0.00	0.00	0.00	1.00	1.00
Observations				673219			

Notes: Descriptive statistics are computed survey weights.

Focusing on the two main dependent variables, across the pool of the 25 countries considered, on average, a household consume 2,359 kilowatt-hour (kWh) per year, whereas air-conditioning prevalence is around 25%. A high degree of heterogeneity in the distribution of both variables is observed across and within countries.

[3]We additionally construct cooling and heating degree days with temperature threshold of 24 and 15 °C respectively

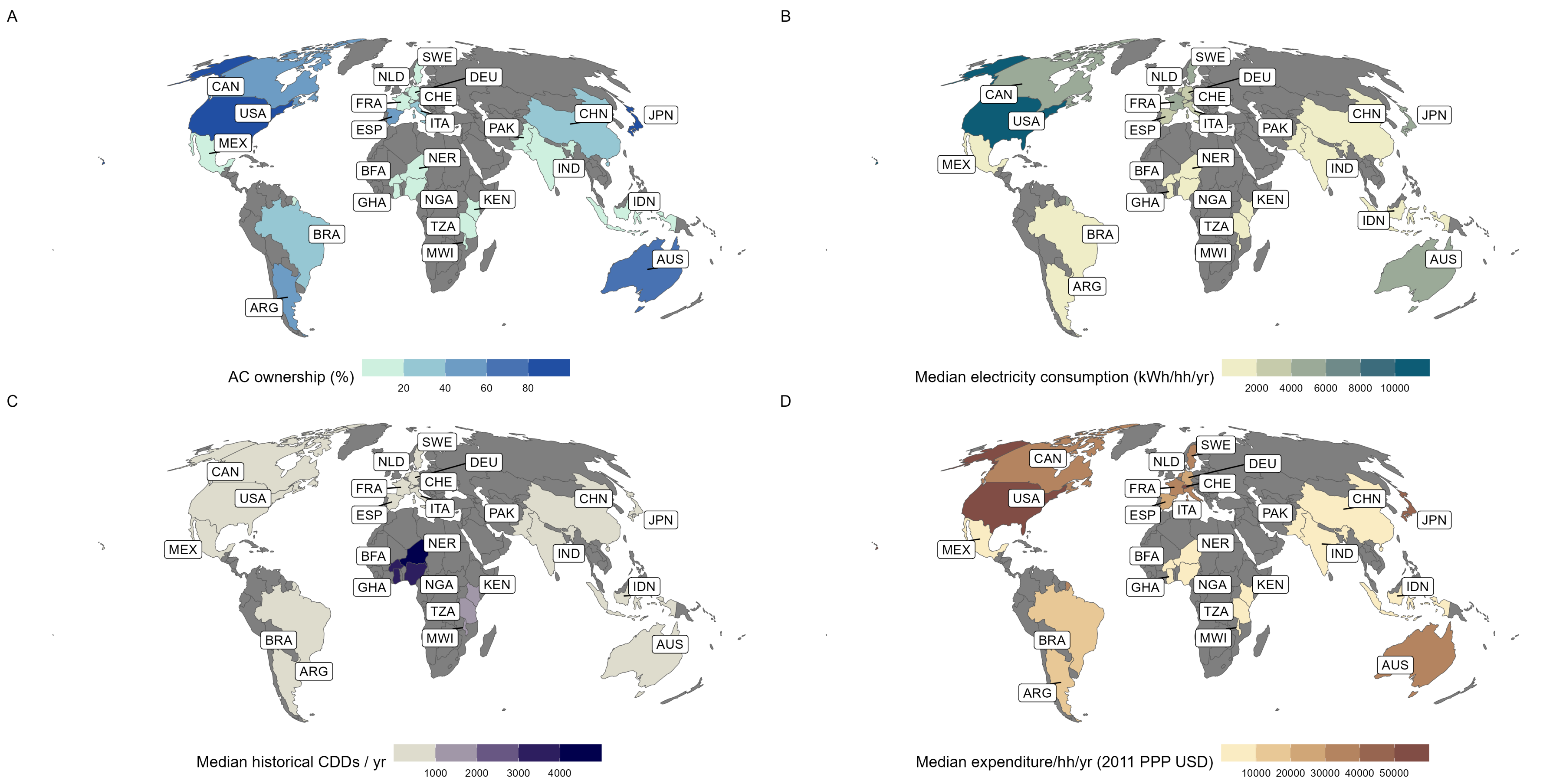

Figure 1: Panel A: Air-conditioning prevalence; Panel B: Median household electricity consumption; Panel C: Median historical CDDs; Panel D: Median household total expenditure, by country.

Figure 1 suggests that the between-country difference in cooling energy (Panels A and B) is mainly explained by the income level (approximated by the total expenditure shown in panel d). For instance, in the United States, the median household uses the highest amount of electricity and consumes about five times more than a median household in a developing country irrespective of a generally smaller household size. Crucially, areas with a warmer climate instead display lower levels of electricity demand and air-conditioning penetration. Indeed, the countries with the highest ownership of air-conditioning are United States, Japan and Australia, whereas the lower rates are reported in Africa and in South-East Asia. However, the within-difference across households in the same country is also important to explain the patterns in cooling energy, with the interaction between warm temperatures and income driving the adoption and use of air conditioners (Figure S1). Looking at the other determinants, most of the families own their dwelling (82%), and they usually consist of four members. Male heads of households are slightly predominant (68%), whereas their educational background is quite heterogeneous, with 31% having at least a secondary education degree.

3 Theoretical framework

To estimate the long-term temperature effects on household electricity consumption, we introduce a simple adaptation model. Here, households derive a long-run utility, u, from the consumption of a generic good, x, and from being in a situation of thermal comfort, T:

$$u = u(T, x) \tag{1}$$

where $\frac{\partial u}{\partial T} > 0$ and $\frac{\partial u}{\partial x} > 0$. Thermal comfort can be defined as a function of current climatic conditions c, and electricity quantity q, as changing energy habits is one of the main form of autonomous adaptation directly available to households:

$$T = f(c, q(c)) \tag{2}$$

Households then maximize their utility subject to Equation 2 and a budget constraint (Equation 3) defined over total income, y, generic expenditure on x, and adaptation costs $k(q(c))$:

$$x + k(q(c)) \leq y \tag{3}$$

While thermal discomfort can be defined as any deviation for a so called bliss point in which neither heating or cooling is required, here we focus on thermal comfort in situations of hotness relative to long-term expected climatic conditions. Since both thermal comfort and electricity quantity depends on c, we totally differentiate the production function of thermal comfort, and write:

$$\frac{dT}{dc} = \underbrace{\frac{\partial T}{\partial c}}_{\text{direct effect}} + \underbrace{\frac{\partial T}{\partial q}\frac{dq}{dc}}_{\text{role of cooling}}$$

The decomposition of the total derivative shows that (1) temperature changes directly impact thermal comfort, with $\frac{\partial T}{\partial c} < 0$; (2) adaptation intervenes as temperature increases demand for cooling, with $\frac{dq}{dc} > 0$, and so $\frac{\partial T}{\partial q}\frac{dq}{dc} > 0$.[4]

Thermal comfort is one the strongest driver of air-conditioning demand and use (Jay et al., 2021), and therefore we assume that households can effectively increase their thermal comfort through

[4] In line with Mansur et al. (2008), we assume that marginal adaptation costs are not affected by climate change. This means that (1) average electricity prices are not affected by climate change: $\partial p_q / \partial c = 0$; (2) the capital expenditures from purchasing air-conditioning in response to climate change are relatively small.

air-conditioning. A range of other cooling strategies exists, especially in countries that have always been coping with high temperature and humidity levels. In India, for example, fans are still preferred to air-conditioning and air coolers (Khosla and Bhardwaj, 2019). However, as soon as households cross certain income thresholds they seem to switch to air-conditioning (Pavanello et al., 2021). Moreover, the effectiveness of fans has being only marginally assessed (Malik et al., 2022). Here, we are interested in adaptation strategies that, from the household's perspective, entail an opportunity cost and pose an economic trade-off between thermal comfort and energy use. This implies that households maximise their utility with respect to a demand of electricity that is conditional on the ownership of air conditioning, a:

$$q = q(c) \rightarrow q = q(c \mid a)$$

where a indicates whether household owns at least an air-conditioner, and it is a function of long-term climatic conditions $\bar{c}$ and average energy efficiency of the appliances e:

$$a = a(\bar{c}, e)$$

Whereas the intensive margin q is a short-run response to temperature changes, the extensive margin a represents a long-run process. By solving the first order conditions of a household maximizing utility subject to the budget constraint, we obtain the equilibrium condition equalizing the marginal cost and the marginal benefit of adaptation:

$$\underbrace{\frac{\partial k(q^*(c \mid a))}{\partial q(c|a)}}_{\text{marginal cost of adaptation}} = \underbrace{MRS_{T,x}\frac{\partial f(c, q^*(c \mid a))}{\partial q(c \mid a)}}_{\text{marginal benefit of adaptation}} \tag{4}$$

Assuming a linear adaptation cost function in electricity price, p_e, and in the capital cost of air-conditioning, p_a, so that $k(q(c)) = p_e q(c) + p_a$, we can re-write the equilibrium condition as follows:

$$p_e = MRS_{T,x}\frac{\partial f(c, q^*(c \mid a))}{\partial q(c \mid a)} \tag{5}$$

where MRS is the marginal rate of substitution between thermal comfort and the generic good x, $\frac{\partial u/\partial T}{\partial u/\partial x}$.

Final conditional demand for electricity quantity q is then:

$$q^* = q(c, p_e, y \mid a(\bar{c}, e))) \tag{6}$$

Equation 6 implies that, in order to determine the long-term effects of climate change on a household's electricity consumption, we need to simultaneously identify the two margins of adaptation: 1) the effects of contemporaneous meteorological conditions c, and 2) the effect of long-term climate conditions $\bar{c}$ through air-conditioning adoption.

4 Empirical framework

Equation 6 implies that households simultaneously decide both the intensive margin, the change in electricity use for a given level of air-conditioning stock, and the extensive margin, the adjustment of the air-conditioning stock. We estimate the optimal conditional electricity demand by using a discrete-continuous choice model in which households simultaneously decided about air-conditioning adoption (a) and how much electricity to consume to operate it (q). We model the intensive margin, namely the demand for electricity, as follows:

$$\begin{aligned} Q_{ic} = \beta_0 + \beta_1 AC_{ic} + \beta_2 AC_{ic} \times f(CDD_{d(i)c}) + \beta_3 f(CDD_{d(i)c}) + \\ + \beta_4 Y_{ic} + \beta_5 P_{ic} + \beta_6 \mathbf{Z}_{ic} + \mu_c + \varepsilon_{ic} \end{aligned} \tag{7}$$

where Q_{ic} is the natural logarithm of electricity demand (in kWh) of household i in country c. AC_{ic} is a dummy variable taking value 1 if household i has an air conditioning installed in its dwelling, 0 otherwise. The function $f(CDD_{d(i)c})$ is a second-degree polynomial of the contemporaneous, annual CDDs experienced in the administrative area d in country c during the survey year, reflecting the nonlinear response of electricity to temperature (Davis and Gertler, 2015; Auffhammer, 2022). The interaction $AC_{ic} \times f(CDD_{d(i)c})$ tests whether air-conditioning amplifies electricity demand increases when heat exposure goes up or it occurs in warmer locations. We expect that the relationship to be concave, reflecting the limited operationability of air conditioners (a household cannot consume more than a certain amount of kWh) and the diminishing returns of adaptation to temperature once the bliss point of thermal comfort is achieved. The variables Y_{ic} and P_{ic} are respectively the natural logarithm of total household expenditure[5] and of average electricity prices in \$2011 PPP. We also include a vector $\mathbf{Z}_{ic}$ of household and housing characteristics.[6] We account for time-invariant, country-level, unobservable factors by including country-fixed effects μ_c. The error term ε_i captures the remaining unobserved variation.

The coefficients of air-conditioning are likely to be endogenous with respect to electricity demand, generating correlation between the error term, ε_i, and AC_{ic}. First, there may be simultaneity as electricity demand and air-conditioning ownership decisions are unlikely to be independent. Second, the two decisions share unobserved common determinants. For instance, the natural ventilation of a housing unit is likely correlated with both the adoption and the use of air conditioners.

These issues can addressed by estimating Equation 7 with a discrete-continuous approach, as in Davis and Kilian (2011) and Barreca et al. (2016), with the methodology first proposed by Dubin and McFadden (1984). This consists of a control function approach that allows the error terms in the indirect utility function underlying the decision to own or not own an air conditioner to be correlated with the error terms in the electricity demand equation. Specifically, we assume that (1) the errors in the air-conditioning ownership decision are independent and identically distributed extreme value type I, and (2) the error terms in the electricity demand equation are a function of the errors in the air-conditioning decision equation, essentially capturing the unobservable factors that influence air-conditioning and might affect electricity as well. We control for the correlation among the errors in two equations by including a correction term that is constructed with the predicted probabilities (π) from a first-stage, logit regression with air-conditioning as dependent variable:

$$\begin{aligned} AC_{ic} = \gamma_0 + \gamma_1 f(\overline{CDD}_{d(i)c}) + \gamma_2 Y_{ic} + \gamma_3 f(\overline{CDD}_{d(i)c}) \times Y_{ic} + \gamma_4 f(CDD_{d(i)c}) + \\ + \gamma_5 P_{ic} + \gamma_6 \mathbf{X}_{ic} + \gamma_7 \mathbf{Z}_{ic} + \mu_c + \eta_{ic} \end{aligned} \tag{8}$$

where $f(\overline{CDD}_{d(i)c})$ is a second-degree polynomial of the long-term CDDs experienced in administrative area d in country c across the period 1970-year before the survey. The vector $\mathbf{X}_{ic}$ contains interactions of electricity prices with $\overline{CDD}$, household size, and home ownership. Hence, our identification comes from a combination of the logit functional form and the exclusion from the second stage of the long-term CDDs and of the various interaction variables. The estimable demand equation then reads as follows:

$$\begin{aligned} Q_{ic} = \beta_0 + \beta_1 AC_{ic} + \beta_2 AC_{ic} \times f(CDD_{d(i)c}) + \beta_3 f(CDD_{d(i)c}) + \\ + \beta_4 Y_{ic} + \beta_5 P_{ic} + \beta_6 \mathbf{Z}_{ic} + \hat{\zeta}_{ic} + \mu_c + \varepsilon_{ic} \end{aligned} \tag{9}$$

[5] We use total expenditure as a proxy for income, which is not available for all household surveys.

[6] We include the socioeconomic and demographic variables that are available for all the countries. Particularly, we control for a second-degree polynomial of contemporaneous annual heating degree days, regional urbanisation, education level of the head, age of the head, gender of the head, household size and home ownership.

where $\hat{\zeta}_{ic}$ denotes the correction term, which defined as a function of the predicted probabilities, $\hat{\pi}$, from the first stage:

$$\hat{\zeta}_{ic} = \frac{\hat{\pi}_{ic} \ln \hat{\pi}_{ic}}{1 - \hat{\pi}_{ic}} + \ln \hat{\pi}_{ic}$$

The correction term is essentially approximating all factors in ε_{ic} that are correlated with AC_i (Wooldridge, 2015). In both first and second stage, we apply survey weights to make our results representative for the whole population.

Two main concerns remain for our empirical strategy. First, our average electricity prices are here likely to be endogenous. For some households, prices are computed by dividing electricity expenditure by quantity. This leads to the problem that the average price depends on the quantity consumed by the household, creating simultaneity, and so endogeneity in the demand equation. At the same time, for some countries we collect aggregate prices at either the sub-national- or the country-level, and measurement error can be another cause of endogeneity. In our empirical strategy we prefer not to address the endogeneity of prices. We use prices mainly as a control variable and we are not interested in price elasticities. Moreover, projections considering the role of prices would require either a methodology based on a general equilibrium approach or assumptions about future price regimes in all the countries (Auffhammer, 2022). We perform some robustness checks, such as excluding electricity prices or including interactions of electricity prices with income decile dummies. Second, our data do not provide any information about the efficiency level of air conditioners owned by households. By including income, we may control for richer households being more likely to adopt more efficient appliances.[7] However, consumers may face a trade-off between the adoption of more efficient cooling appliances — which can lower electricity consumption at constant output of cooling (technology effect) — and the increased willingness and ability to pay with more efficient appliances and higher income (rebound effect). If the technology effect prevails, the marginal effect of air-conditioning on electricity consumption decreases with income. If the rebound effect prevails, the marginal effect of air-conditioning on electricity might increases over time.

5 Results

We first estimate a global, pooled model across all countries to characterise the average relationship between air-conditioning, electricity demand, and the set of covariates. We uncover the role of income, climate, and of other socioeconomic and demographic characteristics. We then examine the heterogeneity of these effects across income levels and countries. Finally, we contextualise the role of air-conditioning as a driver of electricity demand with respect to the other determinants, and we explore the potential implications of owing air-conditioning on households' budget.

5.1 The effect of air-conditioning on residential electricity consumption

Table 3 shows the estimated impacts of air-conditioning ownership on a household's electricity consumption. We first estimate Equation 7 as a baseline for the analysis (Column 1-3). When air-conditioning is not considered as endogenous, we find that owning at least an air conditioner increases the electricity demand by 36-60%, ceteris paribus. However, as previously discussed, these estimates are likely to be biased.

In Column 3, we address air-conditioning's endogeneity. The correction term is always significant and negative (Table B1), suggesting that it is important to control for endogeneity and that

[7] Air-conditioning is not as spread as other technologies like refrigerators or washing machines. We may so expect high income households to adopt more energy efficient air-conditioning systems.

the OLS estimates are upward biased.[8] Compared to previous specification, we find a significant and slightly smaller effect of air-conditioning. Having the technology installed in the dwelling increases households' electricity consumption by 34%. In Column 4, we also add the interaction terms between air-conditioning and CDD. On the one hand, the coefficient of air-conditioning alone is not significant anymore, suggesting that, at zero CDDs, air-conditioning is not used and it does not affect electricity consumption. On the other hand, critically, we find that the effect of air-conditioning is increasing and concave in weather conditions (Figure 2). When households are exposed to warmer temperatures, the impact of air-conditioning reaches 67%.

Table 3: The Effect of Air-conditioning on Residential Electricity Consumption

	OLS (1)	OLS (2)	DMF (3)	DMF (4)
AC	0.601^{***}	0.363^{***}	0.336^{***}	-0.122^{**}
	(0.033)	(0.031)	(0.037)	(0.058)
AC $\times$ CDD				0.052^{***}
				(0.008)
AC $\times$ CDD^2				-0.001^{***}
				(0.000)
Controls	NO	YES	YES	YES
Correction Term	NO	NO	YES	YES
Country FE	YES	YES	YES	YES
R^2	0.651	0.721	0.721	0.725
Countries	25	25	25	25
Observations	673219	673219	673219	673219

Notes: Dependent variable: logarithm of electricity consumption (kWh) - (1), (2), (3) and (4) clustered standard errors at the ADM-1 level in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Regressions are conducted using survey weights. For DMF Columns the first stage is shown in Table B2 Columns 3-4. "Controls" include natural logarithm of electricity price, and weather and socio-economic and demographic variables.

The coefficients of the other covariates (Table B1) are in line with recent studies that have explored the determinants of electricity consumption across multiple countries (Randazzo et al., 2020; Pavanello et al., 2021). We find a positive effect of total household expenditure on electricity consumption. A 1% rise in total expenditure increases electricity consumption by 0.38% in our preferred specification. Contrary, contemporaneous weather conditions — CDD and HDD — do not have a significant effect once we introduce the interactions with air-conditioning. As for electricity prices we find an elasticity of -0.39, which is in the range of previous estimates.[9] However, as discussed, it has to be interpreted cautiously. Urbanisation share has a negative, but not significant. A negative sign of urbanisation is a common finding especially in developed countries (Randazzo et al., 2020).[10] However, the literature points at an opposite results in developing countries (Agrawal et al., 2019; Pavanello et al., 2021). This means that there are two competing mechanisms at play and, at the global level, and the former slightly prevails. Our findings also suggest that age and gender of the household head, household size, home ownership and education level are all positive determinants of residential electricity consumption.

[8] A reason for the positive bias that owners of air-conditioning appliances are positively selected.

[9] See Table 1 in Boogen et al. (2021) for a selected review.

[10] In developed countries urban households consume less electricity compared to rural households, who tend to own larger and less efficient dwelling and consumer more electricity.

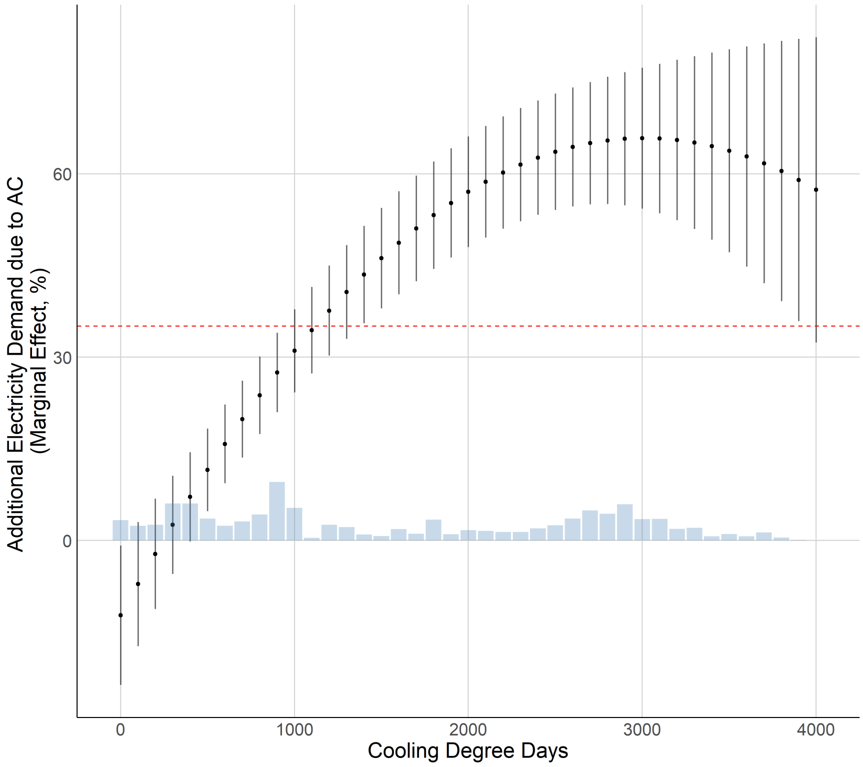

Figure 2: Marginal effects of air-conditioning ownership on household electricity consumption for different level of cooling degree days. Confidence intervals: statistical significance level at 95%. Red dashed line: pooled estimate (Table 3, Column 3). Background: distribution of population-weighted cooling degree days.

Table B2 report the estimates from the air-conditioning adoption's model. Column 1-2 show the results from a linear probability model (LPM), whereas Column 3-4 depicts the coefficients and marginal effects from the probit regression, that is our first-stage results. Again, our findings are consistent with the existing literature (De Cian et al., 2019; Randazzo et al., 2020; Pavanello et al., 2021; Davis and Gertler, 2015; Davis et al., 2021). We find that long-term climate conditions significantly shape air-conditioning ownership. The relationship between air-conditioning and concave, resembling a typical adoption curve. At the averages, a 100 degree days increase in the long-term average of CDD makes the probability of adopting the technology grow by 4.4 percentage points. This effect is increasing in expenditure, suggesting again the importance of the income-climate relationship. Expenditure indeed remains a key driver, as air-conditioning ownership increases by 0.02 to 0.09 percentage points when expenditure grows by 1%. Finally, regional urbanisation, household size, house ownership, household head age, education, and gender are all significant drivers of air-conditioning adoption.

5.2 Heterogeneity

The additional electricity needs that can be attributed to the ownership of air-conditioning vary significantly across income groups and countries. Our model detects whether a household owns at least an air-conditioning unit and how the intensity in usage varies with temperature. A higher intensive margin could mean that a household operates for more hours an air conditioners or that more units are being used depending on the indoor and outdoor temperature conditions.

To identify the heterogeneous effect of air-conditioning across income levels, we re-estimate our model globally but by using country-specific expenditure quintiles (Table B3). Panel A of Figure 3 shows that the total effect[11] of air-conditioning on electricity is greater for households in the second and in the fifth income quintiles. On average, air-conditioning owners in the third- and fourth-income quintiles add about 33 to 35% to their average annual electricity bill when operating this space cooling option, whereas households in the second and fifth quintiles would use 38-41% electricity more when operating their air conditioners. We speculate this evidence points at some efficiency gain, in terms of housing and appliances, as we move to middle income groups, which get outstripped when higher affluent levels are reached. Even though richer households are more likely to have more energy efficient appliances, they can also afford to use them longer and more frequently, leading so to higher level of consumption. We cannot really observe whether the increase in air-conditioning electricity with income also reflects the presence of the rebound effect, and whether households run their space cooling appliances more because they are more efficient.

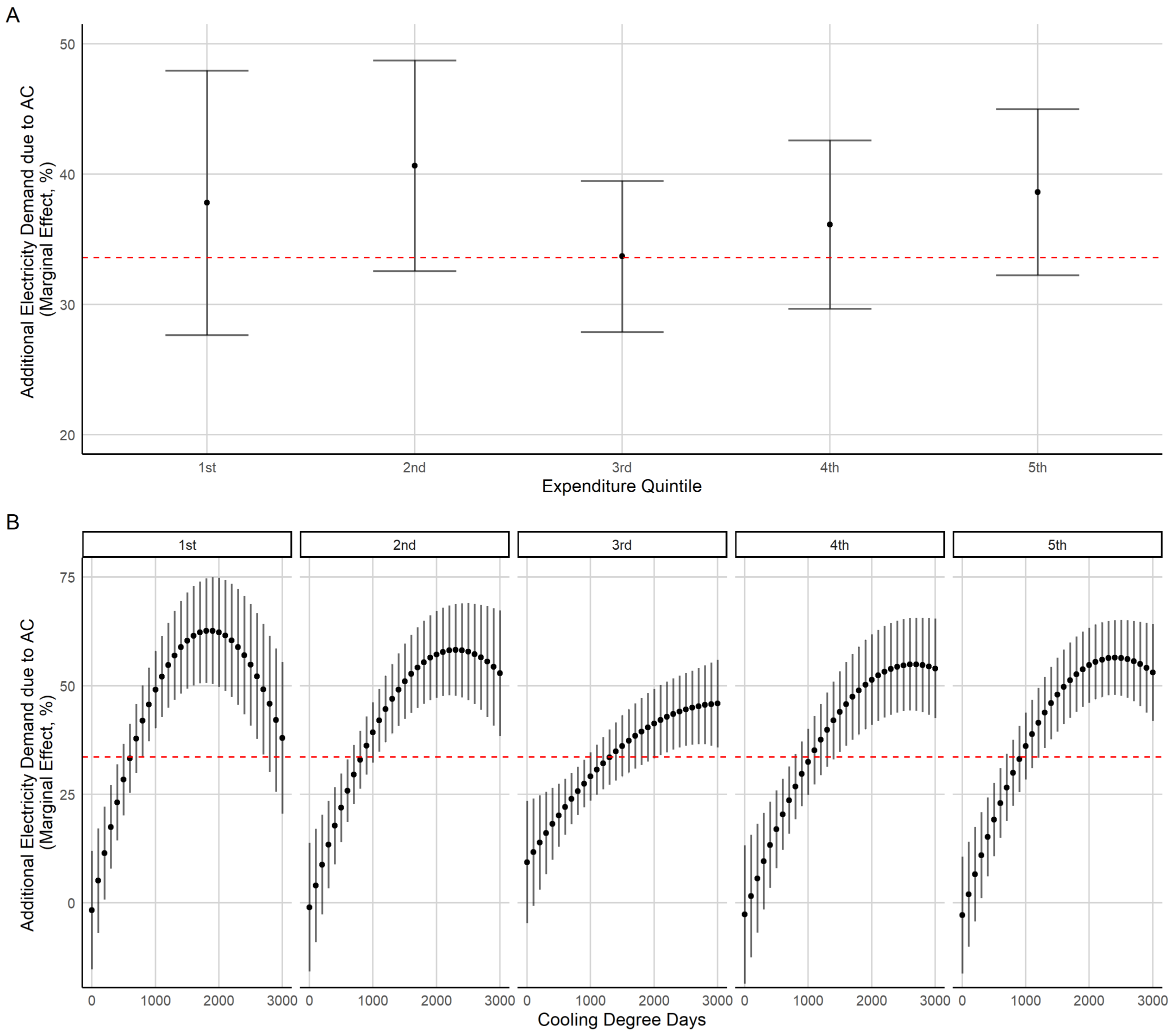

Figure 3: Marginal effects of air-conditioning ownership on household electricity consumption, by country-specific expenditure quintile: (A) Total effects; (B) Effects at different CDD levels. Confidence intervals: statistical significance level at 95%. Red dashed line: pooled estimate (Table 3, Column 3).

The inverse U-shaped relationship between air-conditioning electricity and income is also doc-

[11]With the expression "total effect" we mean that it is the sum of all the partial derivatives computed at the CDD mean value.

umented in Panel B of Figure 3, which depicts how, across the income distribution, households utilise air-conditioning when exposed to different temperatures. Families in the low-income quintiles reach a maximum level of air conditioning utilisation ealier compared to the richer quintiles, and air-conditioning capacity seems to saturate at about 1,800 CDDs. This is likely due to the fact poorer households have appliances with less cooling capacity (e.g. less efficient or also fewer air-conditioning units). Among wealthier families, air-conditioning use increases rapidly and it flattens at CDDs above 2,000. Middle income families in the third quintile do not even reach a maximum level or a plateau.

The differential shape of the response functions across income groups is indicative of variation in adaptive capacity of households. This means that they are those which can really respond when exposed to warm weather, whereas poorer households cannot handle electricity consumption with the same flexibility. We cannot really observe whether the increase in air-conditioning electricity with income reflects a greater use of more efficient appliances (e.g. rebound effect) or simply a greater number of air-conditioners, but it is reasonable to assume that richer families will be able to afford more efficient air conditioners and the number of air-conditioning units a households can have saturates quickly.

The tension between more efficient technologies and behaviours, on the one hand, and the large cooling needs, on the other hand, is also visible in the declining marginal effect of air-conditioning on electricity demand as we move from the hottest regions — located in Africa, India, and Indonesia —, to more temperate regions — such as Italy, Europe, Argentina, Australia, Canada, and Japan, and the United States (Figure 4)[12]. The coldest countries are also the more affluent ones, in which households, on average, can afford better technologies and therefore can achieve thermal comfort with less electricity. Higher income can also be associated with better housing conditions, such as walls and window insulation but also with more squared meters to cool down.

Air-conditioning increases average electricity expenditure between 80% in Africa, 10% in Italy, and 3% in non-European OECD countries. Countries seem to cluster into three groups. Africa and Indonesia in which electricity demand of the the average household with an air conditioner exceeds that of no-AC owners by more than 50%, a group of countries for which the additional contribution ranges between 25 and 50% and a third group of hot and cold countries for which the additional electricity for space cooling is below 25%.

[12]As of the low number of observations, countries from the EPIC survey are grouped in two groups: OECD-EU (France, Netherlands, Spain, Sweden and Switzerland) and OECD-NonEU (Australia, Canada and Japan). Differently from the global regression, the country-specific regressions include regional fixed-effects rather than country fixed-effects. When the most disaggregated administrative unit available in the country survey is ADM-2, we use ADM-1 units as fixed effects. When only ADM-1 areas are available, we construct macro-region variables to use as fixed-effect. Moreover, when available, we also add to the regression as a further control housing quality.

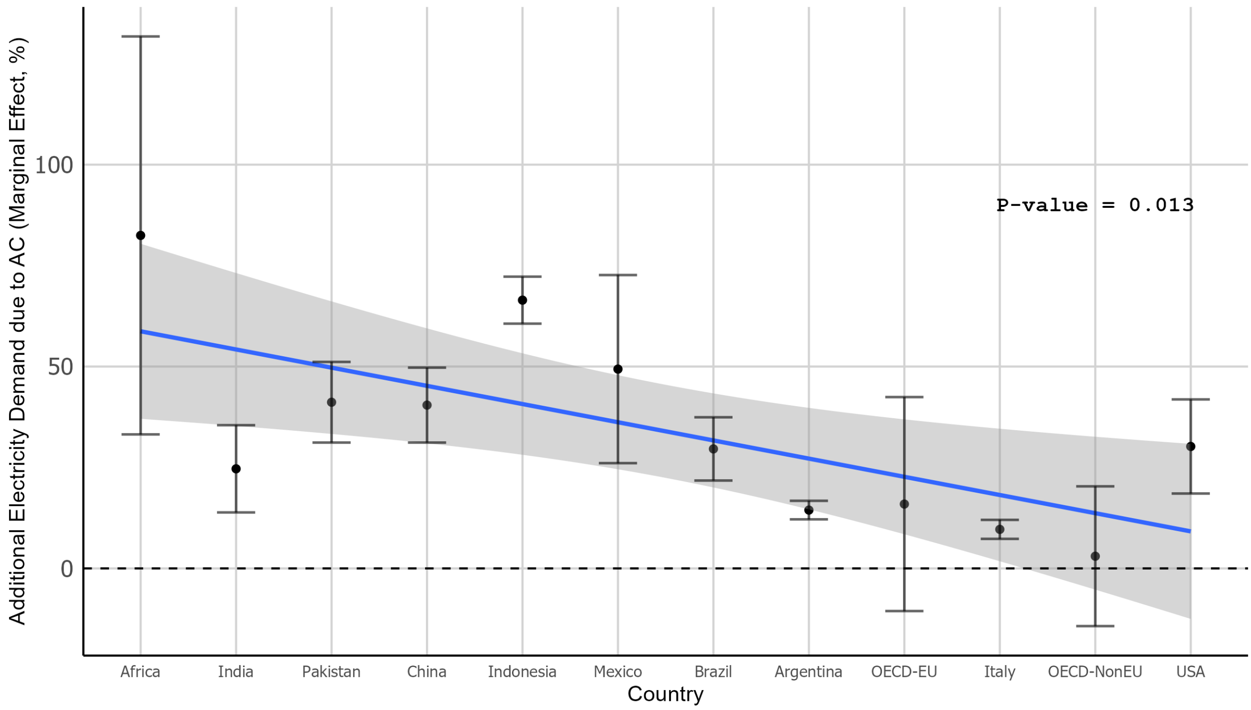

Figure 4: Marginal effects of air-conditioning ownership on electricity consumption by country. Estimates are obtained from country-specific models. Countries are ordered based on their total expenditure per capita. Confidence intervals depict statistical significance level at 95%. Black dashed line corresponds to the pooled estimate.

5.3 Air-conditioning and the role of other influencing factors

Air-conditioning emerges as a leading factor shaping households' final electricity use. Figure 5 compares the role of air-conditioning to that of other socioeconomic and demographic drivers, including total income, age, gender, education, housing characteristics, home ownership, household size, and urbanisation through a descriptive meta-analysis of the standardised coefficients obtained from country-specific regressions.

The ownership of air-conditioning is the single most important factor influencing a household electricity's consumption, with a median impact of above 30% (Figure 5), followed by total expenditure, housing quality,[13] and household size. Air-conditioning and housing tend to have a much smaller dispersion compared to socioeconomic factors, such as income or household size. Air-conditioning holds a prevailing role in both OECD and non-OECD countries (Figure B2), while other factors seem to have opposite effects depending on the region. Economic conditions has a median effect comparable to that of air-conditioning in non-OECD countries, whereas in OECD countries the effect is quite small. The sign of urbanisation is also region-specific. This finding is consistent with the previous literature, and it is likely associated with housing efficiency, size considerations as well as type and quality of urbanisation (Bhattacharjee and Reichard, 2011). For instance, Muratori (2014) finds that in the United States the average electricity consumption of rural households is about 50% larger than urban ones irrespective of similar household sizes. This is mostly owing to larger housing size and less efficient construction materials and appliances efficiency. Notably, the urbanisation rate of the United States stands at about 83%. Conversely, as highlighted by Agrawal et al. (2019), in a developing country like India — where the urbanisation rate stands at only about 35% —, the average electricity demand of rural households is half of the national average residential consumption. Overall,

[13]Housing quality is available only for African countries, Brazil, China, Indonesia, Mexico, and Pakistan.

these numbers suggest that economic development levels are determining an inverse-U shaped relationship between urbanisation and household electricity consumption, thus explaining the large range observed in the average marginal effects of the urban driver in Figure 5. The effect of education also exhibits a great dispersion across regions. In non-OECD countries, education levels are positively related to households' electricity consumption, while in OECD countries they have a negative impact. This might be explained by the fact that education is related to greater energy conservation awareness in OECD countries (Liu et al., 2022), while its correlation with income might be more prominent in developing countries. Regarding CDDs, the strong positive impact on air-conditioning electricity consumption in higher-income countries might be a signal of greater household expenditure capacity at the intensive margin of electricity consumption.

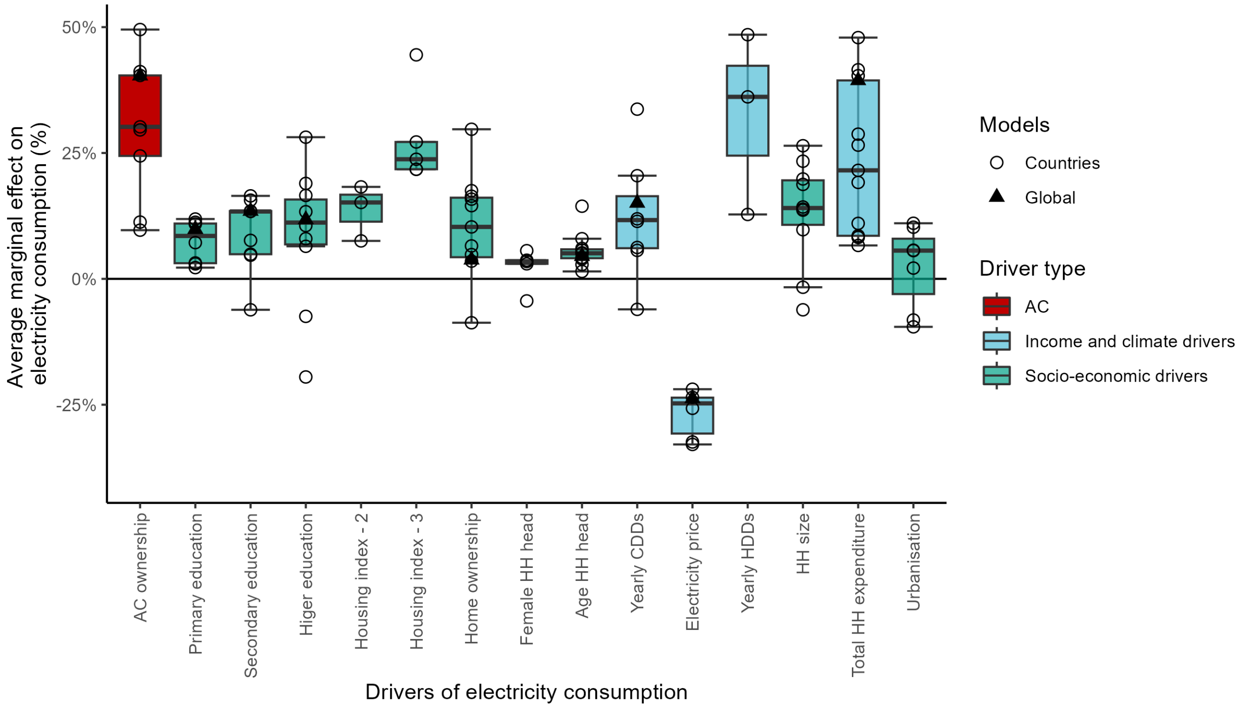

Figure 5: Boxplot of the marginal effects of the drivers of household electricity consumption. Estimates are based on country-specific average marginal effects calculated from standardised regression coefficient. Note: only coefficients with $p < 0.05$ are included.

5.4 Implications for household budget

When the electricity needs for cooling are translated into electricity expenditure, the utilisation of air-conditioning would set a higher burden on poorer households. Consider an Indonesian family, who on average allocates 2% of its total expenditure to electricity, and an American household, who on average allocates 24% of the budget to electricity. A 60% increase in electricity consumption for a Indonesian family is certainly more difficult to afford compared to the 15% increase for an American one.

To understand the budget implications for families of adopting air-conditioning, we use the expenditure share allocated to air-conditioning electricity as a pecuniary measure of cooling poverty. To do so, we first compute the amount of electricity quantity used for air-conditioning using the coefficients of air-conditioning from our main specification (Column 4 in Table 3), and, second, we multiply this quantity by electricity prices.

Figure 6 shows that, in emerging economies, such as Pakistan, Brazil, China, and India, poorer households — who adopted the cooling technology — allocate for air-conditioning alone about 5% or more of their total budget. In Pakistan, the median poorest household even spends 10% of their income on space cooling electricity. The budget share spent on total electricity and air-conditioning electricity is inversely related to a household's average income. This holds in all countries and regions analysed, albeit with more stark differences in some than others. In the United States, China, Brazil, India, Pakistan, the expenditure share spent by poorer households is more than twice the expenditure share spent by wealthier families on air-conditioning electricity. Such differences can be attributed to several factors, including but not limited to public subsidies on electricity prices, correlations in space between heat exposure and wealth distribution among households, technology efficiency, behaviours, and cultural norms.

Additionally, Figure B1 shows the fraction of a household's budget allocated to final residential electricity stratified by air-conditioning ownership, and the air-conditioning electricity share. Air-conditioning electricity accounts for a large share of total electricity expenditure. Families with air-conditioning tend to spend much more on electricity. In low-income households in developing countries, the median household with an air conditioner spends twice as much as any median household. In some countries and regions with currently low air-conditioning penetration levels — e.g. Africa, Brazil, Indonesia, India, Mexico, Pakistan —, air-conditioning electricity consumption by itself accounts for similar budget shares to the median total household electricity consumption. Conversely, in countries with already high relative air-conditioning penetration rates (such as Argentina, China, Italy, OECD regions, and the US), a significant difference is observed between the median values of air-conditioning electricity shares and total electricity shares. Importantly, in all countries the difference in the share of electricity expenditure between adopters and non-adopters of air-conditioning diminishes.

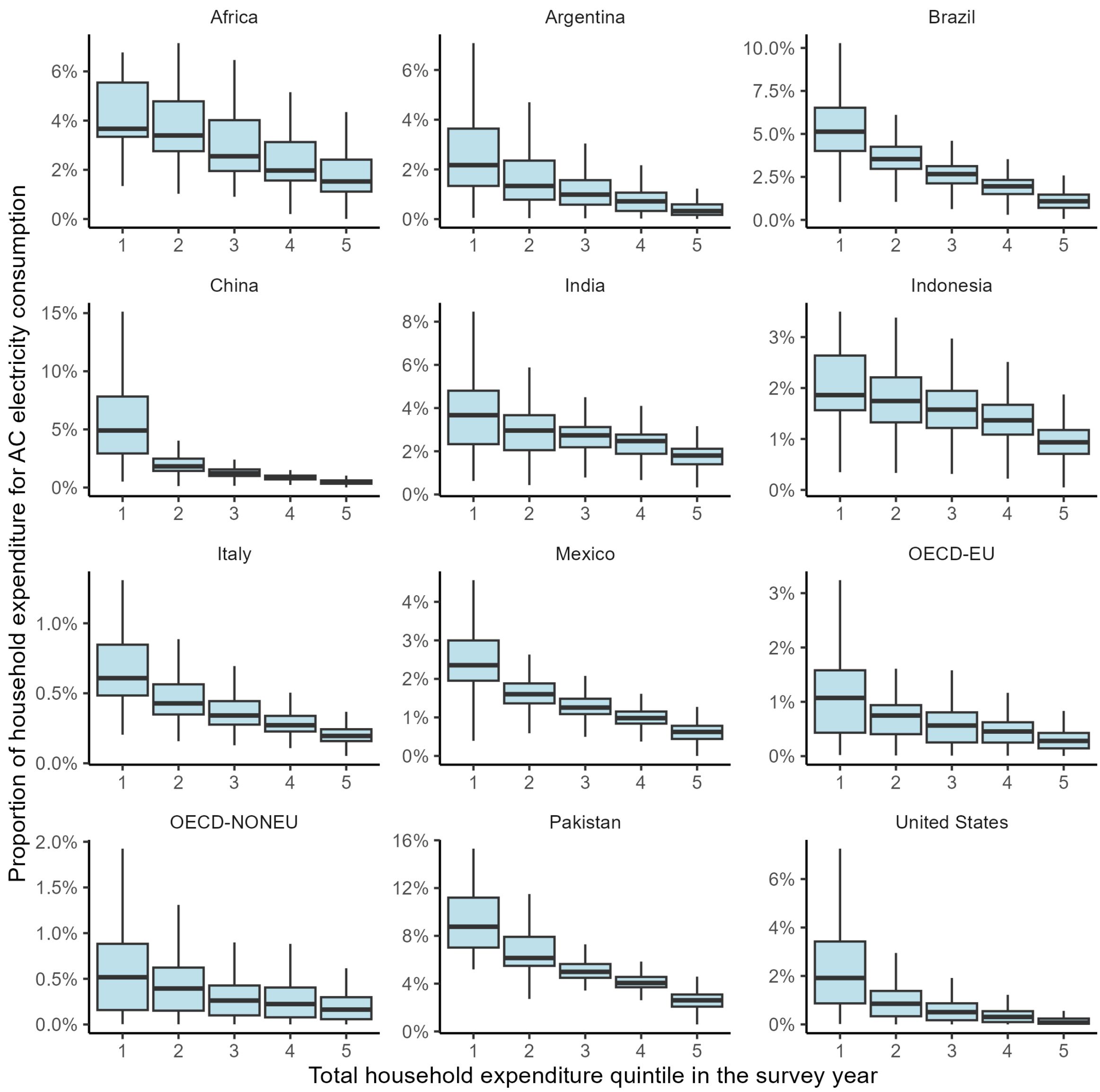

Figure 6: Distribution of estimated household electricity consumption for air-conditioning, stratified by quintile of total household electricity consumption in 2020. Note: only households owning air conditioning are included.

5.5 Robustness checks

We perform some robustness checks to further corroborate the baseline results of our analysis. In Columns (1)-(4), Table 4, we use more stringent fixed effects, replacing country dummies, with fixed-effects at, first, the most-disaggregated subnational level available for each country, and, second, at ADM-1 level. We find that our results remain consistent. Notice that with these specifications we lose few observations, as the logit distribution drops observations that perfectly predict 0 or 1 outcome. For this reason, we opt for using country fixed effects as the main specification.

Defining a threshold for CDD and HDD is usually arbitrary. We then re-estimate our discrete-continuous regressions, constructing these variables with alternative thresholds, particularly 24 and 15 °C for CDD and HDD respectively. We find similar effects to our main specification. However, once we interact the air-conditioning with CDD, the "alone" effect of CDD remains significant. This is likely due to the fact that CDD and HDD do not have a common threshold

(18 °C) anymore, and so there is an omitted category, that is the degree-days between 15 and 24, which correlates with the dummy of air-conditioning. Indeed, we find a strong correlation (-0.34) between air-conditioning ownership and this omitted category.

Because electricity prices are likely to be endogenous, we test whether their inclusion might have any influence on our results. First, in Columns (7)-(8) we drop electricity prices from both the first and second stage. Second, in Columns (7)-(8) we include an interaction between electricity prices and income deciles to test whether there is any heterogeneous effects of prices affecting our results. In all cases our estimates are very similar to the main specification.

Wooldridge (2015) suggests that in a control function approach the correction term can be modelled as any other variable. In another set of estimates (Columns (11)-(16)) we then test the robustness to changes in the functional form of the correction term. First, we include a squared term of θ. Second, we control for interactions of the correction term with contemporaneous CDD. The results remain consistent.

In Columns (17)-(18) we also estimate our demand equation using electricity consumption in level. The results show the same functional form for air-conditioning utilisation of our main specification.

We finally re-estimate our main specification without survey weights (Columns (19)-(20)). The estimates remain robust, but tend to overestimate air-conditioning's contribution.

Table 4: Robustness Checks

	Sub-national FE		ADM1-FE		CDD 24 - HDD 15		No Electricity Price		Price Interactions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AC	0.308^{***}	0.013	0.362^{***}	0.019	0.343^{***}	0.089^{**}	0.340^{***}	-0.126^{**}	0.333^{***}	-0.081
	(0.081)	(0.041)	(0.032)	(0.062)	(0.035)	(0.039)	(0.037)	(0.061)	(0.034)	(0.055)
AC × CDD		0.036^{***}		0.039^{***}		0.110^{***}		0.053^{***}		0.046^{***}
		(0.007)		(0.010)		(0.016)		(0.009)		(0.008)
AC × CDD^2		-0.001^{***}		-0.001^{**}		-0.005^{***}		-0.001^{***}		-0.001^{***}
		(0.000)		(0.000)		(0.001)		(0.000)		(0.000)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Correction Term	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES
Sub-national FE	YES	YES	NO	NO	NO	NO	NO	NO	NO	NO
ADM-1 FE	NO	NO	YES	YES	NO	NO	NO	NO	NO	NO
R^2	0.730	0.757	0.725	0.727	0.722	0.725	0.713	0.717	0.725	0.729
Countries	25	25	25	25	25	25	25	25	25	25
Observations	620463	620463	663199	663199	673215	673215	673215	673215	673215	673215
	Squared Correction		Interaction		Squared Interaction		Electricity in Level		Unweighted	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
AC	0.326^{***}	-0.162^{***}	0.322^{***}	-0.120^{**}	0.322^{***}	-0.120^{**}	1117.433^{***}	-868.276^{*}	0.434^{***}	-0.192^{*}
	(0.040)	(0.060)	(0.039)	(0.058)	(0.039)	(0.058)	(99.134)	(475.819)	(0.038)	(0.098)
AC × CDD		0.056^{***}		0.052^{***}		0.052^{***}		236.509^{***}		0.058^{***}
		(0.009)		(0.009)		(0.009)		(62.168)		(0.012)
AC × CDD^2		-0.001^{***}		-0.001^{***}		-0.001^{***}		-4.392^{***}		-0.001^{***}
		(0.000)		(0.000)		(0.000)		(1.508)		(0.000)
Correction Term	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Correction Term^2	YES	YES	NO	NO	NO	NO	NO	NO	NO	NO
Correction Term × CDD	NO	NO	YES	YES	YES	YES	NO	NO	NO	NO
Correction Term × f(CDD)	NO	NO	NO	NO	YES	YES	NO	NO	NO	NO
R^2	0.723	0.727	0.723	0.725	0.723	0.725	0.473	0.480	0.679	0.684
Observations	673215	673215	673215	673215	673215	673215	673215	673215	673215	673215
Countries	25	25	25	25	25	25	25	25	25	25

Notes: (1)-(20) std. errors clustered at the first sub-national (ADM1) level in parentheses in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Regressions (1)-(20) are conducted using survey weights. "Controls" include natural logarithm of electricity price, and weather and socio-economic and demographic variables. "Sub-national" means the most disaggregated geographical information available for each country.

6 Projections

We project future air-conditioning prevalence and residential space cooling electricity around 2050 by updating both the first and second stage of the empirical regressions with future values of climate (CDDs and HDDs), total expenditure, urbanisation, as well as the other socio-demographic characteristics, including education, age, and housing, when available. This is an important advancement compared to previous contributions, which generally only consider climate change and economic conditions (income). The joint estimation of the intensive and the extensive margin makes it possible to develop projections of future electricity for space cooling that account for the increased diffusion of air-conditioner as well as for the increased intensity in utilisation.

6.1 Method and data for projections

To project future air-conditioning adoption and electricity consumption, we collect projections data from various sources and for different scenarios. Table B4 summarises the evolution of the main drivers used in the projections of both extensive and intensive margin in 2020 and 2050 under two scenarios, the scenarios SSP245, a combination of SSP2 (Fricko et al., 2017) and RCP 4.5 implying an intermediate level of greenhouse gases and therefore of radiative forcing (4.5 W/m^2) and the scenario SSP585, a combination of SSP5 (Kriegler et al., 2017) and RCP 8.5 implying a high level of greenhouse gases and of radiative forcing (8.5 W/m^2).

Climate change projections are obtained from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6) data set (Rama Nemani / NASA, 2021) based on ScenarioMIP bias-corrected model runs. The native time resolution is daily and the spatial resolution is of 0.25 arc-degrees. We process both historical data from each model[14] to calculate pixel-wise median CDD and HDD values for the 1995-2014 historical period, and future projections for the 2041-2060 period along two scenarios, which, consistently with the CMIP6 logic, are based on SSP-RCP combinations (O'Neill et al., 2016).

Then, to project CDDs and HDDs for each scenario s and administrative unit i, we first calculate the difference between the CDDs/HDDs in year t in the historical average value for the historical CMIP6 period (1995-2014), i.e., for the example of CDDs, $\Delta_{ist} = \text{CDD}_{ist}^{cmip6} - \overline{\text{CDD}}_{ist}^{cmip6}$. Such difference is then added to the historical CDDs from GLDAS/ERA5 for each administrative unit i, yielding the projected CDDs/HDDs for each scenario s at each year t: $CDD_{ist} = \overline{\text{CDD}}_{ist} + \Delta_{ist}$. This procedure allows a cross-calibration between CDD/HDD data calculated from GLDAS/ERA5 and from CMIP6 climate models.

Projections of socio-economic and demographic characteristics build on gridded and national-scale projections. Yearly per capita GDP growth rates are computed from the gridded GDP projections for the SSPs of interest (Murakami et al., 2021). To achieve this, we extract GDP and population at the lowest administrative level that is provided with each country's survey, and then calculate administrative unit-level GDP per capita growth rates for each scenario and each future year between 2020 and 2050. Households located within a given administrative unit are then assumed to experience a growth in their total expenditure level equal to the average growth rate computed for that unit. In addition, SSPs-consistent gridded population growth rates (Jones and O'Neill, 2016) are used to project the growth in the number of households for each administrative unit in each country, and, similarly, SSP-consistent gridded urbanisation projections are used to update the urbanisation shares (Gao and Pesaresi, 2021).

[14] The dataset includes 32 models, from which 'hot models' (Hausfather et al., 2022) are filtered out.

Changes in household age, gender, and education levels across SSP scenarios are computed from country-wide stratified population projections (Samir and Lutz, 2017), though projecting these additional drivers poses some challenges, particularly in relation to binary and factor variables. While the age and gender share projections can directly be parsed to the corresponding survey variables, in the case of education levels, we assume shifts in the category of education of each household to match the growth rate in the education level-stratified population counts. In the case of housing, the historical improvements in the housing index are extrapolated into the future for countries where the variable is available.

Household survey weights, which ensure the national representativeness of the survey by attributing a specific relative importance to each surveyed household, are also updated for the future years, t, and scenarios, s. The survey weights of each household i ($W_{i,hist}$) is modified with the rate of change in population ($POPGR_{d,t,s}$) within the spatially finest administrative unit in which each surveyed household is located, d:

$$W_{i(d),t,s} = W_{i,hist} \times (1 + POPGR_{d,t,s})$$

This approach has the important drawback of not considering that the joint distribution of households' socio-economic characteristics will change. That is, a household will not change the type of households it will represent in the future, but it will only represent more/less households in the future.

Household-level projections uses the discrete-continuous global pool model specification (Column 4 in Table 3) to project the future prevalence of air-conditioning and future electricity consumption, including air-conditioning electricity. Future air-conditioning prevalence rates are predicted from the first stage logit regression after updating the values of CDDs, HDDs, total expenditure, age, education, urbanisation, and housing when available. The fitted equation from the first-stage logit model yields the future adoption probability for each household. A household is assumed to have air-conditioning in the future if the predicted probability exceeds the cutoff of 0.5. We then predict total households' electricity from the second stage regression after updating the values of CDDs, HDDs, total expenditure, age, education, urbanisation, housing when available for both sets of households with and without air-conditioning, where the number of households with air-conditioning is updated using the first stage logit regression results. Country-level, residential air-conditioning prevalence and electricity consumption is obtained by aggregating individual households with the adjusted survey weights.

6.2 Future projections of household air-conditioning electricity

The penetration of air-conditioning will increase significantly over the next thirty years. From the 2020 average of 26% in our pool of countries, it will reach 40-53% in 2050 under moderate and intense warming (Table 5). Country-specific results align with previous estimates (Pavanello et al., 2021; Davis et al., 2021). A significant use of air conditioners is expected in most high-income countries with warm regions such as Italy, United States and OECD-NonEU (Australia, Canada and Japan). Middle and lower-income countries that are expected to experience a faster growth in income will exhibit the largest relative increases in air-conditioning prevalence (e.g. China, India, Indonesia). Disparities remain, with particularly African countries (8-15%) and Pakistan (24-34%) not reaching a sufficient level of penetration to satisfy most households. Countries with colder climates (e.g. Sweden) or characterised by highly heterogeneous climate (Mexico) display more moderate growth rates of air-conditioning spread.

Air-conditioning diffusion explains only part of the future dynamics of electricity demand. Our empirical model shows that the intensity of air-conditioning usage is proportional to the exposure of households to CDDs, as well as to income availability and an array of additional socio-demographic factors. Moreover, the total cooling needs of a country are related to the size of its population. Consider, for example Italy and India. Projected air-conditioning penetration in 2020 in Italy is nearly the double of the prevalence rate projected in India. Yet, the estimated per capita electricity use for space cooling is much larger in India than in Italy, and so is the overall national demand. In 2020, residential electricity for space cooling in India is comparable to the total residential electricity in Italy (about 70 TWh).

As a result of a changing climate and economic and socio-demographic transformations, we project air-conditioning electricity use to increase, particularly in developing countries. For instance, in Indonesia the yearly electricity consumption driven by air conditioners would move from 12 TWh to 45-81 TWh. In India, per capita electricity demand for cooling would more than quadruplicate in the SSP2-RCP4.5 scenario, a figure consistent with previous projected trends Abhyankar et al. (2017). Overall, while not directly comparable due to the different geographical coverage, our pool projections of electricity use point at the same direction of the recent IEA's *The Future of Cooling* report (IEA, 2018).[15]

Finally, it is worth remarking that our projected change in the air-conditioning electricity expenditure reflects various underlining trends that influence both the extensive and the intensive margin. The literature has traditionally focused on drivers that are relatively easier to project, namely temperature and income variables, but Figure 5 shows that other socio-demographic drivers are equally important factors influencing both margins of adaptation. Figure B3 shows that projections based only on climate change and expenditure change in the future yield systematically lower air-conditioning penetration rates and utilisation levels of electricity consumption. Such pattern is observed both in the global pooled model (Panels A and B) as well as in the individual regions (Panels C and D). Furthermore, Figure B4 decomposes the role of the various factors influencing household electricity consumption in both the historical and future period. This plot suggests that on top of income and climate-related determinants, socio-demographic drivers and their transformations (e.g., age, gender, education) will play a major role in shaping future electricity demand in emerging economies.

[15] In the baseline scenario IEA estimates a threefold growth of global energy use for cooling in the residential sector by 2050.

Table 5: Projections of Residential Air-conditioning Adoption and Use

	AC penetration rate (%)			AC electricity (kWh/hh)			Total AC electricity (TWh)		
	2020	SSP2-4.5 (2050)	SSP5-8.5 (2050)	2020	SSP2-4.5 (2050)	SSP5-8.5 (2050)	2020	SSP2-4.5 (2050)	SSP5-8.5 (2050)
Country	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Pool	25.90	40.30	52.70	1979.30	2100.40	2293.80	532.10	1007.70	1381.50
Africa	3.50	7.60	15.00	344.00	378.40	379.20	0.80	3.20	5.40
Argentina	68.10	85.30	90.60	349.60	497.10	591.90	3.00	6.20	7.00
Brazil	34.60	54.50	71.90	1700.30	1760.50	1973.20	37.50	67.60	91.70
China	57.70	82.00	89.80	958.70	1370.80	1784.30	196.30	366.30	505.50
India	16.10	48.50	65.10	1382.90	1614.10	1839.90	72.50	322.90	439.50
Indonesia	15.70	46.30	72.90	1408.40	1657.20	1997.20	11.90	45.80	81.30
Italy	69.50	86.50	91.40	285.70	502.80	651.20	4.30	9.30	14.70
Mexico	28.10	45.40	57.80	630.70	785.70	803.10	5.80	13.80	15.20
OECD-EU	35.90	50.30	57.50	883.30	1161.50	1159.20	14.60	29.80	39.70
OECD-NonEU	94.20	97.80	98.70	985.60	1367.20	1831.20	52.40	76.70	122.00
Pakistan	14.90	24.30	33.50	1708.20	1847.20	1908.70	8.10	20.40	24.20
United States	94.90	97.80	98.60	2514.50	3230.10	3592.30	294.20	461.00	611.40

7 Discussion

7.1 Implications for household electricity expenditure

Projecting future changes in the budget shares allocate to air-conditioning electricity requires assumptions about the evolution of the entire income distribution, which we avoid. Contrary, Figure 7 shows the change in the distribution of households' air-conditioning electricity expenditure (in 2011 USD/hh/year) by country between 2020 and 2050, while keeping prices constant.[16] The dashed vertical lines in each panel summarise the variations in the mean air-conditioning electricity expenditures across years by country and scenario. This is possible thanks to the large across and within-country heterogeneity of our global household pooled database and the relative household-level future projections.

The flattening of the density peaks when shifting from 2020 (in red) to 2050 (in blue) suggests that air-conditioning becomes available to a larger number of people, including lower income households, which, therefore, contribute to counterbalancing the rightward shift in the mean air-conditioning electricity consumption. For example, in Pakistan and in Africa, households with spending levels below the country-level mean gain access to air-conditioning, only marginally increasing the national average irrespective of a strong growth in the absolute number of households using air-conditioning. Other countries are characterized by a more pronounced rightward shift, pointing at more households being located on high-expenditure levels and leading to a growth in the mean air-conditioning expenditure levels.

[16]Households that are not projected to have air conditioning in the future are excluded from the analysis

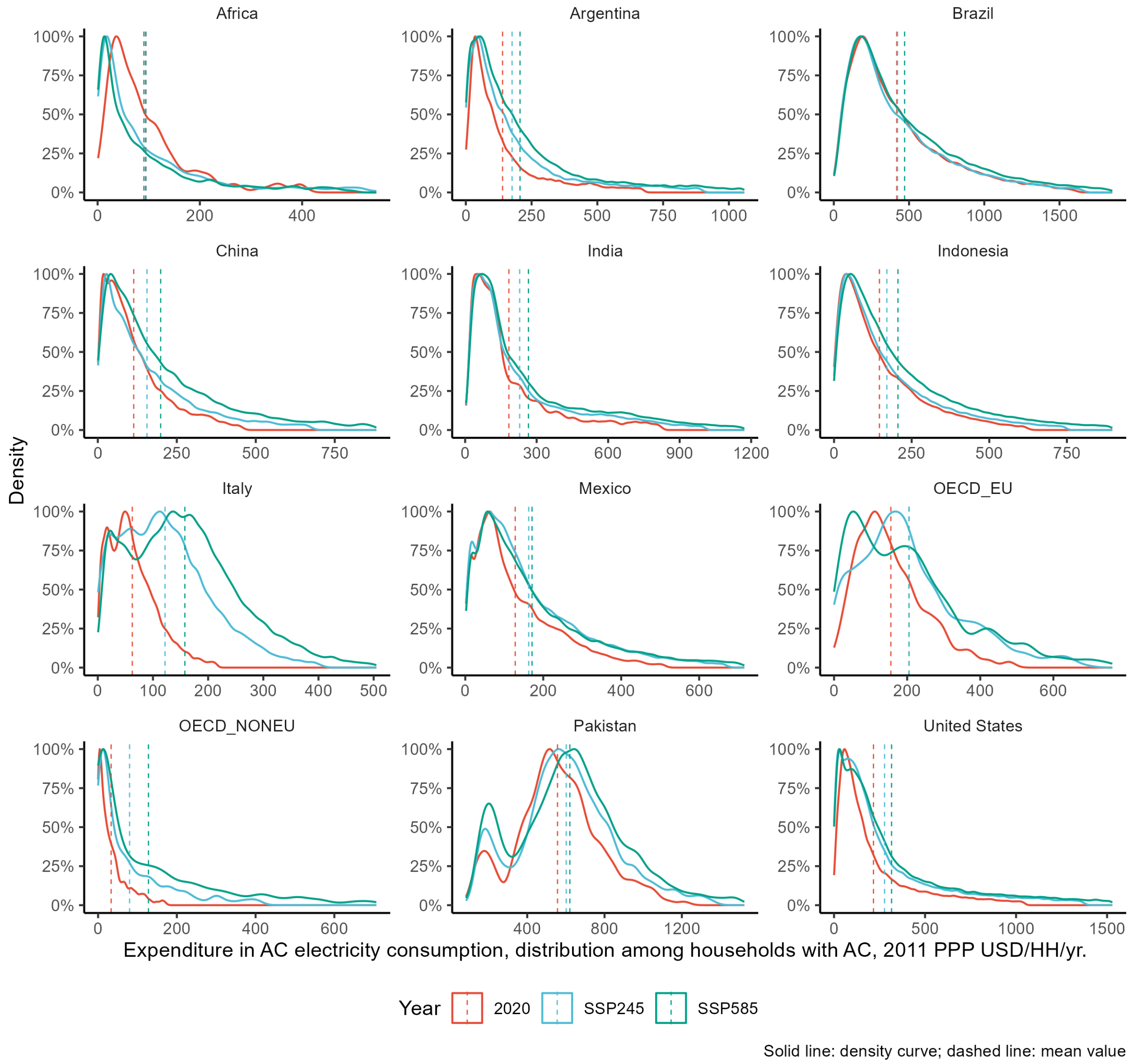

Figure 7: Distribution of households' expenditure for air-conditioning electricity driven by air-conditioning (2011 USD PPP/hh), by country/region and scenario.

7.2 Implications for electricity supply systems

Our estimates reveal that in the 25 countries considered in the analysis, air-conditioning electricity consumption will grow two to nearly three fold by 2050, reaching about 1,000-1,400 TWh/yr. To put this number into perspective, the figure is in the range of the current total final electricity consumption of India in 2020. It is therefore clear that — as also highlighted in previous studies (Colelli et al., 2022, 2023; Davis and Gertler, 2015) — this surge in energy use for adaptation will have very large implications for power systems planning (Sherman et al., 2022), their stability (Auffhammer et al., 2017), and the magnitude of the challenge for achieving global decarbonisation goals (Colelli et al., 2022).

To understand the implications of the surge in cooling demand for electricity supply, we provide a simple engineering back-to-the-envelope calculation for India, for which we estimate the total yearly electricity consumption for air-conditioning to grow from 70 TWh/yr. to 325-440 TWh/yr. in 2050. We assume (i) homogeneous utilisation of air-conditioning throughout months of the year,[17] (ii) an average run time of about six hours (Ramapragada et al., 2022), and (iii) a homogeneous distribution of use in this period and in each hour of the day. We so estimate that an increase in the range of 150-200 GW in peak generation capacity - or, combined generation and storage capacity - would be implied as necessary to satisfy the increased hourly peak electricity demand from air-conditioning.[18] Interestingly, if we instead assume a distribution of use with higher intensity in certain periods of the year (Colelli et al., 2023) — in India half of air-conditioning electricity consumption is concentrated in the summer season (Ramapragada et al., 2022) —, and that in these months air conditioners would be used an average of 12 hours per day, we obtain peak generation capacity increases in the same range[19]. These are very significant findings, considering that the current installed capacity of India stands at about 420 GW in year 2023, and they have important repercussions for planning a power system with both sufficient capacity, stability, and flexibility to accommodate such surge in peak demand.

To mitigate these impacts, policies and investments into more efficient cooling appliances are also crucial (IEA, 2018; Ramapragada et al., 2022). The adoption of energy-efficient cooling appliances has indeed been the focus of international agreements, such as the Kigali Cooling Efficiency Program (K-CEP) and the Clean Cooling Collaborative, which aim at channelling funds to provide universal access to efficient cooling.

7.3 Implications for emissions and climate policy

The surge in energy use for air-conditioning will imply further challenges for decarbonisation goals as a consequence of energy-related CO_2 emissions. According to our estimates (Table B5), the estimated growth in air-conditioning electricity consumption in the 25 countries considered in the analysis may imply a growth in CO_2 emissions by between 692 and 948 $MtCO_2$ — starting from the current estimate of 365 $MtCO_2$ —, a figure corresponding to more than the total national CO_2 emissions of France. Most of these emissions would come from developing countries like China, India, and Indonesia, where the adoption of air-conditioning would indeed skyrocket.

To understand the social cost of such potential growth in CO_2 emissions as a consequence of increased cooling use, we take as a reference the central value of the social cost of carbon of 185 USD/tCO_2 from Rennert et al. (2022). We so estimate that this would translate into a ”Social Cost of Cooling” of 128-175 billion USD. in 2050.

As a consequence, to mitigate the global impacts of cooling, in parallel of efficiency gains, a rapid decarbonisation of the global power sector is crucial, in particular in countries with a current or projected high intensity of air-conditioning usage and a high carbon intensity of the national electricity system. Relevant examples include China, India, and Indonesia (highly reliant on coal), but also high-income countries such as the USA.

It should be noted that if one follows the finding of Rode et al. (2021), such surge in global cooling energy use — and so CO_2 emissions and thus social cost — would be counterbalanced by decreases in global heating energy use. Yet, the high spatial and social unbalance in the source of emissions causing impacts and the ultimate impacts of emissions (Gazzotti et al., 2021), provides a reason to believe that adverse impacts might still strongly hamper the most vulnerable social groups in highly exposed regions.

[17] This is a conservative assumption.

[18] Calculation example: 325 TWh/year. / 12 (homogeneous AC use across months of the year) / 30 (days in a month) / 6 (average AC utilisation hours per day) = 150 GW

[19] Calculation example: 325 TWh/year. / 2 (half of yearly consumption concentrated in three peak demand months) / 90 (days in three months) / 12 (average AC utilisation hours per day) = 150 GW

8 Conclusion

This paper presents the first global assessment of current patterns of both intensive and extensive margin of adaptation through household air-conditioning uptake and utilisation. To estimate the long-term effects of temperature on electricity consumption we use a discrete-continuous choice econometric framework applied to a newly constructed household-level, multi-country micro data set. We also project potential implications of future cooling uptake and electricity consumption to around 2050 under an array of last generation socio-economic and climate change scenarios, considering a broad array of grid-cell level and country-level drivers projections at the household level.

Compared to previous assessments, our household-level analysis allows disentangling the different sources of heterogeneity determining a large range of variability on the impact of air-conditioning ownership on household electricity consumption, such as at changing heat exposure and affluence levels, but also through the mediating role of drivers such as education, age, and urbanisation. In turn, this analysis provides important hints on the importance of behaviors, practices, and technologies.

Overall, we find that on average, air conditioning ownership increases households' electricity consumption by 34%. The interplay between growing air-conditioning adoption, climate change, disposable income, and socio-demographic drivers will induce global households' electricity consumption to soar. When contextualising the impact of space cooling with respect to other socio-economic, demographic, and climatic drivers, air-conditioning stands out as a leading determinant of electricity demand (when available).

These findings have important implications as they shed light on the interaction between micro and household-level factors and global trends in shaping current and future implications of adaptation on households' expenditure and welfare, environmental pollution and greenhouse gas emissions, and point at unforeseen challenges that need to be seriously addressed by policy. In addition, they reveal the current and future patterns of climate adaptation inequalities in different world regions and social groups.

Moreover, we demonstrate that air-conditioning penetration and related electricity consumption will soar as a result of a changing climate, socio-economic growth and transformation, and global demographic growth. This will have important implications for both infrastructure planning and environmental policy, but also for energy poverty and equity, as less affluent households will face an increasing economic burden as a share of their income for thermal comfort adaptation.

To conclude, it is worth highlighting some limitations of our work that should be further explored in future research. First, Dubin and McFadden (1984)'s methodology mainly relies on the assumption that error term in the underlying random utility model are distributed as a generalized extreme value (GEV) distribution. Since the selection term is constructed from the predicted probabilities, the more the first-stage model is accurate, the better it also performs in the second stage. Second, our results come from cross-sectional estimates. Even though we correct for air-conditioning's endogeneity, some bias may still be present. However, whereas micro-panel data would be the ideal setting, household expenditure and energy surveys are currently mostly cross-section. This highly limits the data that can be used for multi-country micro analysis. Last but not least, our data lacks information about energy efficiency, and so technological level of air conditioners. Thus, our projections assume that technologies would remain the same for the next thirty years. This is a strong assumption as we may expect there will be technological improvements in the future. Future works should aim at identifying the role of innovation in future patterns of air-conditioning uptake and utilisation.

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Author contributions

G.F., F.P., E.D.C. designed the analysis. G.F. and F.P. gathered, processed, and harmonized household data. G.F. and F.P. performed the analysis. All authors contributed to analysis of the results and the writing of the paper.

Competing interests

The authors declare no competing interests.

Data and materials availability

The replication code, instruction for accessing the input data, and output data generated in this study will be made available in a Github repository upon publication of the manuscript.

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A Data description

Our data set consider three categories of drivers of electricity consumption:

1. **Air-conditioning ownership (AC)**: it is a binary variables expressing whether at the interview date of the survey a household owns at least an air-conditioning unit, either a window/room or a centralised air-conditioning system.

2. **Climate and income** are the core determinants of air-conditioning uptake and utilisation that have been used traditionally by the literature. We measure them using households' total expenditure as a proxy for income conditions, and the Cooling and Heating Degree Days experienced in the administrative area where the household resides.

3. **Socio-demographic drivers**: they include households' characteristics such as education, age, and gender of the household head, home ownership, housing quality (when available), household size, urbanisation level in the administrative area where the household resides.

The remainder of this section describes in more detail the micro data variables considered in our dataset.

- **Total expenditure (in natural logarithm)**: household total expenditure (or household income, depending on the country-specific questionnaire) refers to the sum of all expenditures (durable goods, services, etc.) faced by the household in the survey year. It is the key variable identifying the economic status of the household. The unit is harmonised to 2011 PPP USD: first, to convert from local currency unit to USD we multiply total expenditure by the survey year-specific World Bank's PPP conversion factor for private consumption (LCU per international USD) (World Bank indicator *PA.NUS.PRVT.PP*)[20]; second, to obtain the variable in 2011 USD PPP we adjust the variable for inflation by using the US Bureau of Labor Statistics CPI inflation calculator[21].

- **Electricity consumption (in natural logarithm)**: household electricity consumption is - depending on the country-specific questionnaire - either directly available or inferred through information on electricity expenditure. In the latter case, electricity expenditure information is divided by either national or sub-national or household-specific residential retail prices data matching the survey year of each country.

- **Urbanisation**: since in declared urban status of the household was not available for all countries, we extract gridded population-weighted urbanisation rates data from Gao and Pesaresi (2021) for the smallest administrative unit available at each survey country and parse it to households. This way, we generate an additional continuous variable for urbanisation expressing the share of population-weighted area within the administrative unit of belonging to the household that is classified as urban.

- **Age and gender of household head**: each surveyed household in each country identifies a unique member of the household who is classified as the household head. Information on the age and gender of the person in charge are processed and included in the database as a continuous and categorical variable, respectively.

- **Education level category of household head**: depending on the country-specific questionnaire, education levels are generally reported in a set of different categories, or as the number of years of education received. To harmonise the variable, a standard categorisation of education levels is proposed considering the four following levels: (i) No/lower

[20] https://data.worldbank.org/indicator/PA.NUS.PRVT.PP

[21] https://data.bls.gov/cgi-bin/cpicalc.pl

than primary education; (ii) primary education; (iii) secondary education; (iv) tertiary or superior education level. The categorisation is then applied to all countries, resulting in a harmonised categorical variable.

- **Household size**: numerical variable describing the number of people living inside the household.
- **Home ownership status**: a categorical variable describing whether the household is owning or renting (or other forms of arrangement) the home where it lives.
- **Housing quality index**: the housing quality index is a three-category variable introduced for low and lower-middle income countries only. Albeit heterogeneous across countries, it seeks to capture different characteristics of the dwelling based on country-specific questionnaire information on walls and roof materials and quality; water supply infrastructure; and type of toilet service available. A value of 1 describes a household with building materials such as dung and mud and lack of toilet inside the household; a value of 2 identifies a dwelling built with more solid and insulating materials; while a value of 3 describes a home built with bricks and having piped water and a toilet facility. The housing quality index variable thus serves as a proxy of the type of household and is additional to other socio-economic variable. As it is not available for all countries, we include these variable only in country-specific regression.
- **Electricity prices**: we gather residential electricity prices information from different sources, and at different scales (national, sub-national, household-level). As for total expenditure, electricity prices are also converted in 2011 USD PPP.

B Additional results

Table B1: The Effect of Air-conditioning on Residential Electricity Consumption

	OLS (1)	OLS (2)	DMF (3)	DMF (4)
AC	0.601***	0.363***	0.336***	−0.122**
	(0.033)	(0.031)	(0.037)	(0.058)
AC × CDD				0.052***
				(0.008)
AC × CDD^2				−0.001***
				(0.000)
CDD		0.025**	0.024**	0.017
		(0.010)	(0.011)	(0.011)
CDD^2		−0.000*	−0.000*	−0.000
		(0.000)	(0.000)	(0.000)
HDD		0.001	0.000	0.006
		(0.008)	(0.008)	(0.007)
HDD^2		−0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)
Log(Exp)		0.372***	0.371***	0.368***
		(0.031)	(0.031)	(0.031)
Log(P)		−0.388***	−0.391***	−0.392***
		(0.084)	(0.085)	(0.085)
Urbanisation (%)		−0.182	−0.177	−0.134
		(0.152)	(0.149)	(0.140)
House Ownership (Yes = 1)		0.033**	0.034**	0.038***
		(0.014)	(0.015)	(0.014)
Household Size		0.024*	0.024*	0.025*
		(0.013)	(0.013)	(0.013)
Primary Edu.		0.111***	0.106***	0.098***
		(0.015)	(0.015)	(0.014)
Secondary Edu.		0.153***	0.147***	0.134***
		(0.020)	(0.020)	(0.020)
Post Edu.		0.155***	0.147***	0.117***
		(0.028)	(0.028)	(0.027)
Age (Head)		0.002***	0.002***	0.002***
		(0.001)	(0.001)	(0.001)
Female (Yes = 1)		0.015*	0.015*	0.016*
		(0.009)	(0.009)	(0.008)
$\hat{\zeta}$			−0.036**	−0.022*
			(0.014)	(0.012)
Country FE	YES	YES	YES	YES
R^2	0.651	0.721	0.721	0.725
Countries	25	25	25	25
Observations	673215	673215	673215	673215

Notes: (1), (2), (3) and (4) clustered standard errors at the ADM-1 level in parentheses in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Regressions are conducted using survey weights. For DMF Columns the first stage is shown in Table B2 Columns 3-4.

Table B2: Logit Regression for Air-conditioning Ownership

	LPM		Logit	
			Coefficients	M. Effects
	(1)	(2)	(3)	(4)
$\overline{\text{CDD}}$	0.096**	0.033	0.596*	0.057*
	(0.039)	(0.040)	(0.334)	(0.032)
$\overline{\text{CDD}}^2$	−0.002**	−0.000	−0.021**	−0.002**
	(0.001)	(0.001)	(0.009)	(0.001)
$\overline{\text{CDD}} \times$ Log(Exp)		0.008***	0.038	0.004
		(0.003)	(0.024)	(0.001)
$\overline{\text{CDD}}^2 \times$ Log(Exp)		−0.000**	0.001	0.000
		(0.000)	(0.001)	(0.000)
CDD	−0.058*	−0.067*	−0.461*	−0.044*
	(0.035)	(0.035)	(0.251)	(0.024)
CDD^2	0.001	0.001	0.002	0.000
	(0.001)	(0.001)	(0.005)	(0.001)
$\overline{\text{CDD}} \times$ Log(P)	−0.005	−0.005	0.034	−0.003
	(0.006)	(0.006)	(0.059)	(0.006)
$\overline{\text{CDD}}^2 \times$ Log(P)	0.000	0.000	−0.002	−0.000
	(0.000)	(0.000)	(0.002)	(0.000)
Log(Exp)	0.090***	0.032**	0.225*	0.022*
	(0.007)	(0.016)	(0.132)	(0.013)
Log(P)	0.062	0.056	−0.040	−0.004
	(0.057)	(0.056)	(0.431)	(0.041)
Log(P) × Household Size	0.000	0.000	−0.049	−0.005
	(0.004)	(0.004)	(0.045)	(0.004)
Log(P) × House Ownership	0.039***	0.036***	0.152	0.015
	(0.014)	(0.014)	(0.117)	(0.011)
Urbanisation (%)	0.328***	0.341***	2.902***	0.280***
	(0.100)	(0.099)	(0.640)	(0.060)
House Ownership (Yes = 1)	0.105***	0.101***	0.663***	0.059***
	(0.020)	(0.019)	(0.177)	(0.015)
Household Size	−0.004	−0.004	−0.146**	−0.014**
	(0.005)	(0.005)	(0.065)	(0.006)
Primary Edu.	0.048***	0.045***	0.670***	0.058***
	(0.009)	(0.009)	(0.064)	(0.006)
Secondary Edu.	0.118***	0.114***	1.156***	0.110***
	(0.014)	(0.014)	(0.088)	(0.008)
Post Edu.	0.196***	0.193***	1.795***	0.180***
	(0.016)	(0.016)	(0.107)	(0.012)
Age (Head)	0.000**	0.000**	0.007***	0.001***
	(0.000)	(0.000)	(0.001)	(0.00)
Female (Yes = 1)	−0.005	−0.004	−0.134***	−0.013***
	(0.004)	(0.004)	(0.036)	(0.004)
Country FE	YES	YES	YES	YES
Countries	25	25	25	25
Observations	673215	673215	673215	673215

Notes: Dependent variable is air-conditioning (0,1). Clustered standard errors at the ADM-1 level in parentheses. Column (4) shows the average marginal effects (AMEs) from the logit regression. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Regressions are conducted using survey weights.

Table B3: The Effect of Air-conditioning on Electricity Quantity — Income Quintile

	1st Quintile (1)	2nd Quintile (2)	3rd Quintile (3)	4th Quintile (4)	5th Quintile (5)
AC	-0.017	-0.010	0.094	-0.027	-0.028
	(0.069)	(0.076)	(0.072)	(0.081)	(0.069)
AC $\times$ CDD	0.069^{***}	0.051^{***}	0.024^{**}	0.043^{***}	0.049^{***}
	(0.011)	(0.011)	(0.010)	(0.011)	(0.009)
AC $\times$ CDD^2	-0.002^{***}	-0.001^{***}	-0.000	-0.001^{***}	-0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Controls	YES	YES	YES	YES	YES
Correction Term	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES
R^2	0.714	0.738	0.747	0.728	0.677
Countries	21	25	23	25	25
Observations	131411	135075	133874	134717	134000

Notes: Clustered standard errors at the ADM1 level in parentheses. Regressions are conducted using survey weights. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. "Controls" include natural logarithm of electricity price, and weather and socio-economic and demographic variables.

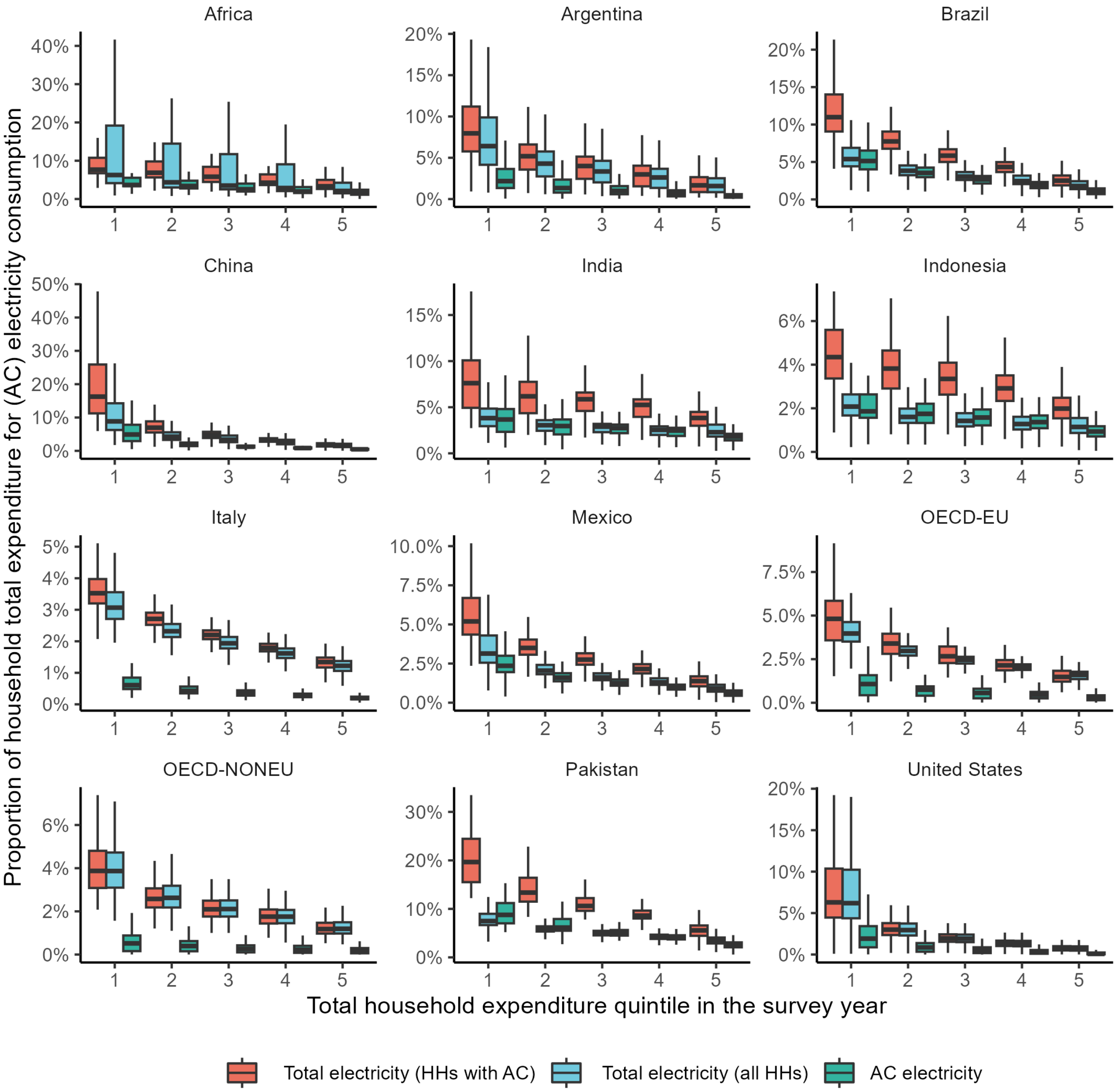

Figure B1: Distribution of estimated household (air-conditioning) electricity consumption, stratified by quintile of total household electricity consumption in 2020.

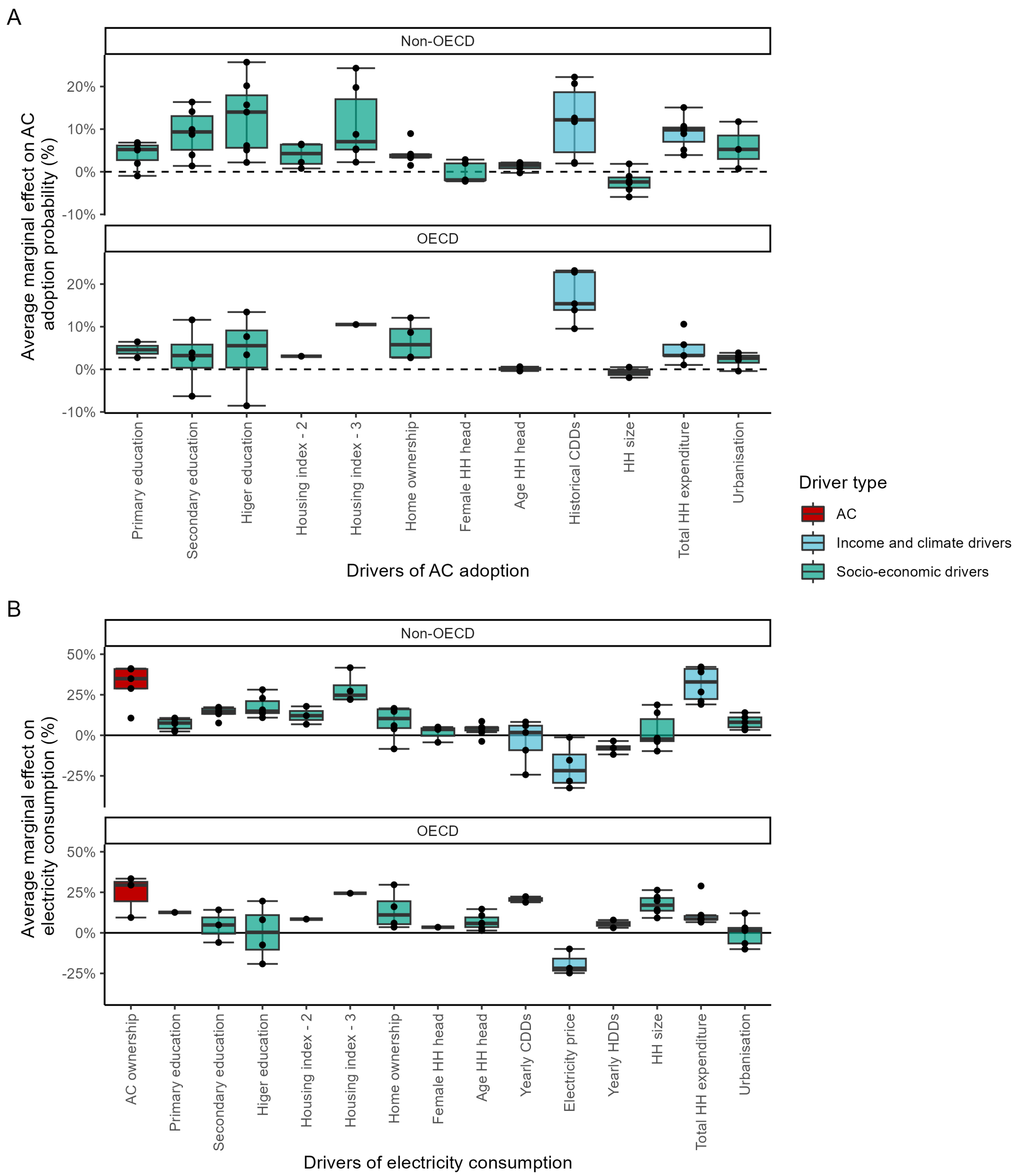

Figure B2: Boxplot of the marginal effects of the drivers of (A) household air-conditioning ownership and (B) household electricity consumption, divided into OECD and non-OECD countries. Estimates are based on country-specific average marginal effects calculated from standardised regression coefficients. Note: only coefficients with $p < 0.05$ are included.

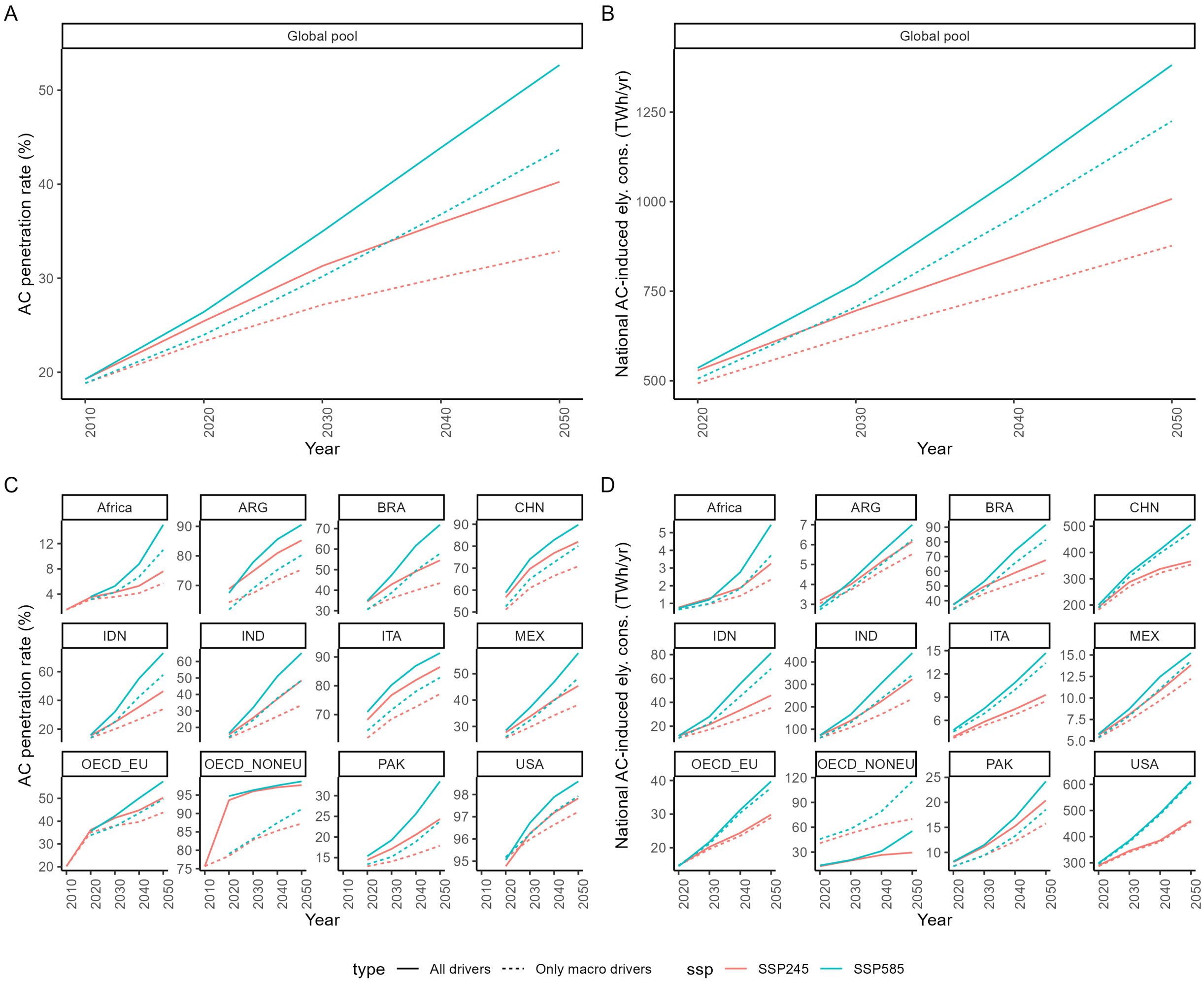

Figure B3: Comparison of future (A,C) air-conditioning penetration and (B,D) total electricity consumption for cooling (TWh/yr) when projecting all drivers (bold line) or only climate and income (dashed line). Note: projections are based on the global households pool model.

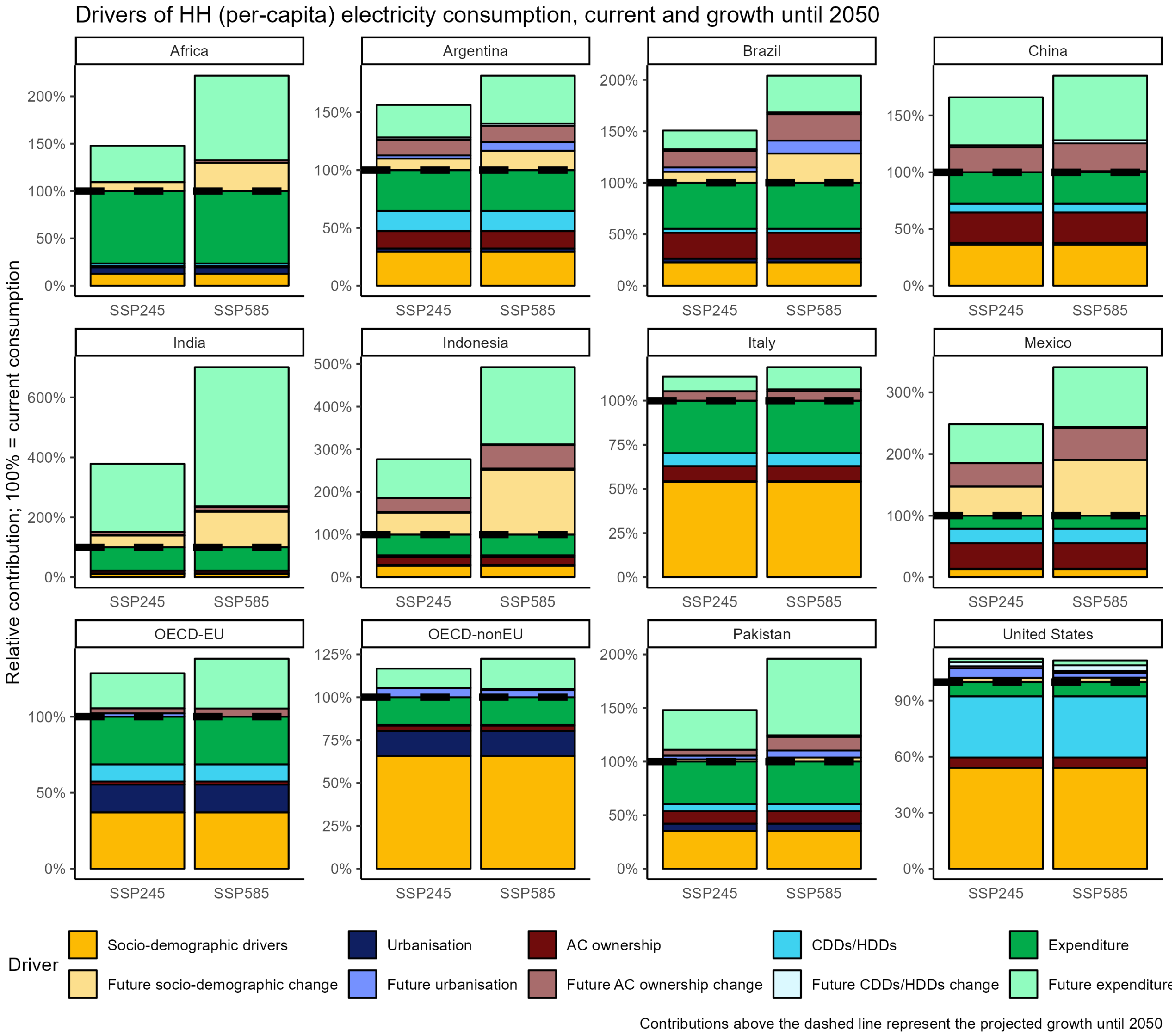

Figure B4: Decomposition analysis of average (per household) historical and future electricity demand. Facets group countries and regions. Each facet shows to socio-economic/climate change scenario combination (SSPs). Colours describe the determinants of current (up to 100%) and future projected (above 100%) electricity consumption, inclusive of changes in air-conditioning intensive and extensive margins. The total value on the y-axis represents consumption growth in year 2050 compared to baseline. Note: projections are based on country/region-specific models.

Table B4: Evolution of AC adoption and utilisation drivers (population-weighted mean value) used for household-level projections, by country/region.

		CDD	HDD	Expenditure	Age	Edu	Housing index	Urban
Country	Scenario	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Africa	Current	781.58	5.10	975.49	46.72	0.68	1.53	0.05
	SSP2, 2050	1044.41	1.93	3530.40	47.64	1.72	2.34	0.03
	SSP5, 2050	1192.91	1.45	7112.50	47.58	1.72	2.34	0.05
Argentina	Current	194.79	567.38	16 428.81	51.40	1.54	2.94	0.07
	SSP2, 2050	538.26	271.47	41 628.02	53.79	2.72	3.00	0.09
	SSP5, 2050	563.60	262.47	60 891.98	52.82	2.73	3.00	0.14
Brazil	Current	506.69	18.43	13 598.31	50.37	1.52	2.77	0.05
	SSP2, 2050	786.28	9.58	25 846.24	53.47	2.64	2.99	0.07
	SSP5, 2050	979.74	7.93	45 060.97	52.48	2.65	2.99	0.09
China	Current	177.94	1947.28	5292.69	47.79	1.27	2.60	0.08
	SSP2, 2050	240.60	1658.77	39 070.21	50.61	2.50	2.97	0.16
	SSP5, 2050	298.20	1500.97	67 782.94	49.93	2.50	2.97	0.18
Germany	Current	2.50	2464.79	26 217.15	44.58	2.02		0.15
	SSP2, 2050	19.76	2250.18	53 814.01	46.34	2.91		0.21
	SSP5, 2050	26.27	2066.22	67 190.90	46.17	2.91		0.25
India	Current	1035.63	126.39	5397.26	46.87	1.36		0.05
	SSP2, 2050	1015.52	115.18	17 656.35	49.74	2.43		0.05
	SSP5, 2050	1190.18	102.89	31 764.76	48.70	2.43		0.06
Indonesia	Current	676.93	0.69	7532.69	46.79	1.47	2.76	0.05
	SSP2, 2050	891.76	0.00	30 377.00	49.76	2.58	3.00	0.10
	SSP5, 2050	1031.67	0.00	77 282.24	48.95	2.58	3.00	0.13
Italy	Current	32.68	1654.54	30 078.02	56.68	1.61		0.10
	SSP2, 2050	84.68	4.92	48 178.26	59.03	2.68		0.15
	SSP5, 2050	113.26	0.00	60 394.15	58.62	2.67		0.18
Mexico	Current	359.65	139.59	8807.44	49.37	1.59	2.88	0.08
	SSP2, 2050	486.88	42.22	31 681.76	52.30	2.63	3.00	0.11
	SSP5, 2050	566.25	40.78	54 089.87	51.45	2.63	3.00	0.12
OECD-EU	Current	21.45	1945.93	31 281.15	45.04	2.09		0.23
	SSP2, 2050	54.75	1499.23	52 649.87	46.39	2.88		0.14
	SSP5, 2050	66.63	1398.91	62 837.04	46.12	2.89		0.17
OECD-NonEU	Current	45.52	1957.53	36 970.23	46.03	2.04		0.34
	SSP2, 2050	135.80	979.38	78 778.68	47.15	2.93		0.27
	SSP5, 2050	164.59	848.43	119 115.84	46.99	2.94		0.29
Pakistan	Current	1336.06	241.27	7902.02	46.25	1.07	2.12	0.03
	SSP2, 2050	1878.83	107.90	13 124.18	48.90	2.12	2.90	0.05
	SSP5, 2050	1953.75	81.64	19 056.90	47.57	2.11	2.90	0.06
United States	Current	190.28	1562.99	49 283.27	52.31	2.32		0.26
	SSP2, 2050	325.49	1562.28	66 269.82	53.87	2.95		0.21
	SSP5, 2050	358.17	1533.52	77 524.95	53.78	2.95		0.25

Table B5: CO_2 emissions from air-conditioning electricity use

	2020	SSP2-4.5 (2050)	SSP5-8.5 (2050)
Country	Mean	Mean	Mean
Pool	365.20	691.60	948.10
Africa	0.70	2.50	4.20
Argentina	1.40	3.20	3.60
Brazil	16.70	34.30	46.90
China	159.60	267.90	318.30
India	63.80	225.10	306.20
Indonesia	9.10	21.70	38.90
Italy	2.20	5.40	8.60
Mexico	2.70	5.70	6.30
OECD-EU	7.30	17.50	23.30
OECD-NonEU	26.50	38.70	61.70
Pakistan	7.10	13.90	17.00
United States	171.30	229.00	304.10

Supplementary Materials

Table S1: Weighted Descriptive Statistics — Africa

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	294.56	620.06	25.86	47.21	108.58	310.79	690.65
Air-conditioning (Yes = 1)	0.02	0.14					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	23.08	10.96	2.97	20.16	27.67	29.94	32.47
CDD (100s)	24.58	10.98	4.75	21.79	29.08	31.46	33.70
HDD (100s)	0.07	0.28	0.00	0.00	0.00	0.00	0.01
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	4055.90	5367.09	748.82	1105.92	1859.65	5040.49	10151.82
Electricity Price ($2011 PPP / kWh)	0.27	0.06	0.23	0.24	0.24	0.34	0.34
Urbanisation Share	0.03	0.04	0.00	0.01	0.02	0.03	0.08
Home Ownership (Yes = 1)	0.52	0.50					
Household Size	6.28	4.08	2.00	4.00	6.00	8.00	11.00
No Education (Yes = 1)	0.10	0.30					
Primary Education (Yes = 1)	0.33	0.47					
Secondary Education (Yes = 1)	0.44	0.50					
Post Education (Yes = 1)	0.12	0.33					
Age of Household Head	47.52	21.82	30.00	36.00	45.00	57.00	67.00
Female Household Head (Yes = 1)	0.21	0.41					

Notes: Descriptive statistics are computed survey weights.

Table S2: Weighted Descriptive Statistics — Argentina

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	2433.76	4398.94	239.56	484.62	1087.77	2582.62	5733.21
Air-conditioning (Yes = 1)	0.46	0.50					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	7.28	2.95	5.07	6.21	6.21	7.44	9.52
CDD (100s)	8.43	3.14	5.85	7.26	7.26	8.98	10.26
HDD (100s)	0.07	0.28	0.00	0.00	0.00	0.00	0.01
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	25682.37	22100.51	7333.79	11654.01	19648.50	32602.36	50299.60
Electricity Price ($2011 PPP / kWh)	0.82	0.77	0.13	0.29	0.88	0.88	1.69
Urbanisation Share	0.12	0.13	0.00	0.01	0.16	0.16	0.16
Home Ownership (Yes = 1)	0.70	0.46					
Household Size	3.18	1.75	1.00	2.00	3.00	4.00	5.00
No Education (Yes = 1)	0.09	0.29					
Primary Education (Yes = 1)	0.37	0.48					
Secondary Education (Yes = 1)	0.34	0.47					
Post Education (Yes = 1)	0.20	0.40					
Age of Household Head	51.12	16.37	30.00	38.00	50.00	64.00	73.00
Female Household Head (Yes = 1)	0.43	0.49					

Notes: Descriptive statistics are computed survey weights.

Table S3: Weighted Descriptive Statistics — Brazil

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	2090.27	1484.72	756.00	1140.00	1740.00	2604.00	3780.00
Air-conditioning (Yes = 1)	0.19	0.40					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	17.76	8.17	7.00	12.21	13.89	25.40	30.28
CDD (100s)	19.37	8.24	8.06	14.68	16.04	26.21	31.98
HDD (100s)	0.89	1.19	0.00	0.00	0.46	1.08	2.31
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	23587.53	32498.58	5457.50	8774.37	15081.70	26918.83	48577.91
Electricity Price ($2011 PPP / kWh)	0.28	0.09	0.19	0.23	0.27	0.31	0.36
Urbanisation Share	0.07	0.07	0.01	0.01	0.03	0.17	0.17
Home Ownership (Yes = 1)	0.74	0.44					
Household Size	3.01	1.47	1.00	2.00	3.00	4.00	5.00
No Education (Yes = 1)	0.07	0.26					
Primary Education (Yes = 1)	0.40	0.49					
Secondary Education (Yes = 1)	0.36	0.48					
Post Education (Yes = 1)	0.18	0.38					
Age of Household Head	50.46	15.68	30.00	38.00	50.00	62.00	72.00
Female Household Head (Yes = 1)	0.42	0.49					

Notes: Descriptive statistics are computed survey weights.

Table S4: Weighted Descriptive Statistics — China

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	2148.61	2678.63	590.16	969.70	1481.48	2424.24	4232.80
Air-conditioning (Yes = 1)	0.36	0.48					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	8.24	3.89	2.97	4.76	8.47	10.38	11.87
CDD (100s)	8.69	4.07	3.86	4.98	9.11	10.43	13.52
HDD (100s)	24.99	13.28	13.49	16.98	21.66	29.38	41.40
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	8654.19	13511.67	1191.45	2859.47	5957.23	10723.02	16680.25
Electricity Price ($2011 PPP / kWh)	0.12	0.01	0.11	0.12	0.12	0.13	0.14
Urbanisation Share	0.07	0.07	0.01	0.02	0.04	0.09	0.14
Home Ownership (Yes = 1)	0.87	0.33					
Household Size	3.78	1.80	2.00	2.00	4.00	5.00	6.00
No Education (Yes = 1)	0.28	0.45					
Primary Education (Yes = 1)	0.23	0.42					
Secondary Education (Yes = 1)	0.42	0.49					
Post Education (Yes = 1)	0.07	0.26					
Age of Household Head	47.89	16.71	25.00	35.00	48.00	60.00	70.00
Female Household Head (Yes = 1)	0.49	0.50					

Notes: Descriptive statistics are computed survey weights.

Table S5: Weighted Descriptive Statistics — Germany

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	2415.17	1296.08	1166.94	1539.47	2070.75	2942.21	4134.37
Air-conditioning (Yes = 1)	0.01	0.11					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	1.13	0.22	0.88	0.96	1.04	1.24	1.52
CDD (100s)	2.32	0.57	1.70	2.02	2.11	2.53	3.42
HDD (100s)	28.15	1.11	26.85	27.42	27.81	28.72	29.96
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	29099.72	18545.79	11719.93	16435.71	25285.71	37928.57	50571.43
Electricity Price ($2011 PPP / kWh)	0.31	0.01	0.30	0.31	0.31	0.32	0.33
Urbanisation Share	0.14	0.06	0.08	0.10	0.13	0.23	0.23
Home Ownership (Yes = 1)	1.00	0.00					
Household Size	1.79	1.12	1.00	1.00	1.00	2.00	3.00
No Education (Yes = 1)	0.00	0.00					
Primary Education (Yes = 1)	0.20	0.40					
Secondary Education (Yes = 1)	0.58	0.49					
Post Education (Yes = 1)	0.22	0.41					
Age of Household Head	50.42	20.87	23.75	31.00	52.00	67.00	79.00
Female Household Head (Yes = 1)	0.66	0.47					

Notes: Descriptive statistics are computed survey weights.

Table S6: Weighted Descriptive Statistics — Indonesia

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	1324.28	1443.93	357.60	578.40	960.00	1596.00	2522.40
Air-conditioning (Yes = 1)	0.07	0.25					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	23.90	5.74	15.80	20.57	25.03	28.59	29.90
CDD (100s)	24.91	5.74	16.71	21.37	25.93	29.65	31.20
HDD (100s)	0.03	0.44	0.00	0.00	0.00	0.00	0.00
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	9842.66	9005.16	3323.36	4917.03	7491.50	11729.88	18166.15
Electricity Price ($2011 PPP / kWh)	0.15	0.15	0.07	0.08	0.12	0.18	0.25
Urbanisation Share	0.80	0.40	0.00	0.01	0.06	0.11	0.20
Home Ownership (Yes = 1)	1.00	0.00					
Household Size	3.86	1.58	2.00	3.00	4.00	5.00	6.00
No Education (Yes = 1)	0.15	0.36					
Primary Education (Yes = 1)	0.33	0.47					
Secondary Education (Yes = 1)	0.40	0.49					
Post Education (Yes = 1)	0.12	0.32					
Age of Household Head	45.94	12.39	30.00	37.00	45.00	54.00	63.00
Female Household Head (Yes = 1)	0.10	0.30					

Notes: Descriptive statistics are computed survey weights.

Table S7: Weighted Descriptive Statistics — India

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	1167.36	882.68	397.79	623.37	959.32	1434.62	2122.88
Air-conditioning (Yes = 1)	0.07	0.25					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	27.64	5.13	22.17	25.67	27.95	30.31	33.87
CDD (100s)	28.40	5.22	22.81	26.32	28.64	31.08	34.74
HDD (100s)	1.51	4.25	0.00	0.00	0.36	1.59	3.68
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	5301.87	2904.82	2385.18	3457.20	4781.11	6439.58	8695.825
Electricity Price ($2011 PPP / kWh)	0.15	0.05	0.08	0.11	0.16	0.19	0.21
Urbanisation Share	0.02	0.05	0.00	0.00	0.01	0.02	0.07
Home Ownership (Yes = 1)	1.00	0.05					
Household Size	4.05	1.63	2.00	3.00	4.00	5.00	6.00
No Education (Yes = 1)	0.53	0.50					
Primary Education (Yes = 1)	0.29	0.45					
Secondary Education (Yes = 1)	0.08	0.28					
Post Education (Yes = 1)	0.10	0.30					
Age of Household Head	45.94	12.39	30.00	37.00	45.00	54.00	63.00
Female Household Head (Yes = 1)	0.12	0.33					

Notes: Descriptive statistics are computed survey weights.

Table S8: Weighted Descriptive Statistics — Italy

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	2763.90	1551.01	1370.63	1774.26	2375.02	3339.28	4542.93
Air-conditioning (Yes = 1)	0.43	0.49					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	4.41	1.39	2.73	3.65	4.25	5.17	5.45
CDD (100s)	6.24	1.62	4.34	5.55	6.05	7.32	7.69
HDD (100s)	20.49	5.26	16.14	16.33	20.54	23.27	25.80
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	36481.53	22754.50	14458.31	20603.46	30889.67	46113.30	65731.10
Electricity Price ($2011 PPP / kWh)	0.25	0.00	0.25	0.25	0.25	0.25	0.25
Urbanisation Share	0.07	0.05	0.05	0.07	0.15	0.15	
Home Ownership (Yes = 1)	0.73	0.44					
Household Size	2.30	1.23	1.00	1.00	2.00	3.00	4.00
No Education (Yes = 1)	0.03	0.17					
Primary Education (Yes = 1)	0.48	0.50					
Secondary Education (Yes = 1)	0.34	0.47					
Post Education (Yes = 1)	0.15	0.36					
Age of Household Head	55.73	12.61	50.00	50.00	50.00	70.00	70.00
Female Household Head (Yes = 1)	0.36	0.48					

Notes: Descriptive statistics are computed survey weights.

Table S9: Weighted Descriptive Statistics — Mexico

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	1020.00	1811.33	176.62	298.84	505.91	963.77	2087.03
Air-conditioning (Yes = 1)	0.15	0.36					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	9.66	10.06	0.25	0.53	5.53	18.37	25.57
CDD (100s)	10.75	10.89	0.30	0.76	6.48	19.94	28.14
HDD (100s)	5.92	5.39	0.01	0.87	4.74	10.73	11.96
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	12820.30	3606.75	5902.63	9589.12	15476.91	25013.37	
Electricity Price ($2011 PPP / kWh)	0.27	0.04	0.23	0.25	0.30	0.30	0.30
Urbanisation Share	0.10	0.17	0.00	0.01	0.03	0.08	0.50
Home Ownership (Yes = 1)	0.70	0.46					
Household Size	3.68	1.81	2.00	2.00	4.00	5.00	6.00
No Education (Yes = 1)	0.22	0.42					
Primary Education (Yes = 1)	0.20	0.40					
Secondary Education (Yes = 1)	0.25	0.44					
Post Education (Yes = 1)	0.32	0.47					
Age of Household Head	49.48	15.68	30.00	38.00	48.00	60.00	72.00
Female Household Head (Yes = 1)	0.28	0.45					

Notes: Descriptive statistics are computed survey weights.

Table S10: Weighted Descriptive Statistics — OECD-EU

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	5055.94	4652.77	1588.72	2400.00	3814.09	6356.81	9535.22
Air-conditioning (Yes = 1)	0.26	0.44					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	2.63	2.51	0.50	0.80	1.39	4.16	6.94
CDD (100s)	2.96	3.12	0.36	0.65	1.33	4.91	8.23
HDD (100s)	21.76	7.20	13.36	17.15	21.91	25.48	30.74
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	34064.92	17367.73	14135.19	20405.94	31820.01	44234.54	59740.24
Electricity Price ($2011 PPP / kWh)	0.19	0.08	0.13	0.15	0.15	0.24	0.24
Urbanisation Share	0.14	0.16	0.02	0.03	0.08	0.21	0.51
Home Ownership (Yes = 1)	0.70	0.46					
Household Size	2.75	1.15	1.00	2.00	3.00	4.00	4.00
Primary Education (Yes = 1)	0.21	0.40					
Secondary Education (Yes = 1)	0.51	0.50					
Post Education (Yes = 1)	0.28	0.45					
Age of Household Head	45.02	13.34	26.00	34.00	45.00	57.00	63.00
Female Household Head (Yes = 1)	0.46	0.50					

Notes: Descriptive statistics are computed survey weights.

Table S11: Weighted Descriptive Statistics — OECD-Non EU

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	5675.61	5759.40	1810.98	2889.90	4531.95	6708.44	9929.03
Air-conditioning (Yes = 1)	0.76	0.43					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	4.75	2.91	0.94	2.33	5.09	6.98	7.814
CDD (100s)	5.25	3.04	0.97	2.58	5.44	7.80	8.39
HDD (100s)	26.69	13.49	10.62	17.79	22.05	38.56	44.69
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	47058.09	27508.71	16241.84	26211.27	41219.45	59798.27	74837.71
Electricity Price ($2011 PPP / kWh)	0.20	0.08	0.17	0.18	0.19	0.21	0.21
Urbanisation Share	0.22	0.19	0.01	0.05	0.19	0.34	0.43
Home Ownership (Yes = 1)	0.65	0.48					
Household Size	2.80	1.49	1.00	2.00	2.00	4.00	6.00
Primary Education (Yes = 1)	0.18	0.39					
Secondary Education (Yes = 1)	0.54	0.50					
Post Education (Yes = 1)	0.28	0.45					
Age of Household Head	45.65	12.28	28.00	37.00	46.00	55.00	62.00
Female Household Head (Yes = 1)	0.47	0.50					

Notes: Descriptive statistics are computed survey weights.

Table S12: Weighted Descriptive Statistics — Pakistan

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	1791.21	2091.39	381.21	667.11	1238.92	2096.64	3526.16
Air-conditioning (Yes = 1)	0.09	0.28					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	26.15	7.32	17.10	22.94	26.73	31.63	33.50
CDD (100s)	27.54	7.46	18.66	24.11	29.39	32.67	35.02
HDD (100s)	4.82	7.00	0.29	1.91	3.25	4.34	7.52
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	9665.84	7436.78	3906.88	5398.02	7761.23	11584.50	17033.55
Electricity Price ($2011 PPP / kWh)	0.33	0.00	0.33	0.33	0.33	0.33	0.33
Urbanisation Share	0.03	0.04	0.00	0.00	0.01	0.03	0.07
Home Ownership (Yes = 1)	0.84	0.37					
Household Size	6.24	3.04	3.00	4.00	6.00	8.00	10.00
No Education (Yes = 1)	0.40	0.49					
Primary Education (Yes = 1)	0.27	0.45					
Secondary Education (Yes = 1)	0.22	0.41					
Post Education (Yes = 1)	0.11	0.31					
Age of Household Head	46.39	13.46	30.00	36.00	45.00	55.00	65.00
Female Household Head (Yes = 1)	0.10	0.31					

Notes: Descriptive statistics are computed survey weights.

Table S13: Weighted Descriptive Statistics — United States

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	11288.91	8077.64	3653.89	5757.37	9241.43	14604.46	21419.88
Air-conditioning (Yes = 1)	0.94	0.25					
Climate and weather							
$\overline{\text{CDD}}$ (100s)	8.11	4.94	3.51	5.08	6.55	11.37	16.34
CDD (100s)	8.90	5.41	3.64	4.41	7.04	12.89	17.62
HDD (100s)	22.36	11.38	6.83	12.61	25.53	29.24	35.71
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	85926.55	104692.42	14112.00	30240.00	59628.00	105840.00	172200.00
Electricity Price ($2011 PPP / kWh)	0.12	0.03	0.10	0.10	0.11	0.12	0.19
Urbanisation Share	0.28	0.16	0.08	0.15	0.25	0.49	0.50
Home Ownership (Yes = 1)	0.64	0.48					
Household Size	2.55	1.47	1.00	1.00	2.00	3.00	5.00
Primary Education (Yes = 1)	0.09	0.29					
Secondary Education (Yes = 1)	0.49	0.50					
Post Education (Yes = 1)	0.42	0.49					
Age of Household Head	51.38	16.48	30.00	38.00	51.00	64.00	74.00
Female Household Head (Yes = 1)	0.48	0.50					

Notes: Descriptive statistics are computed survey weights.

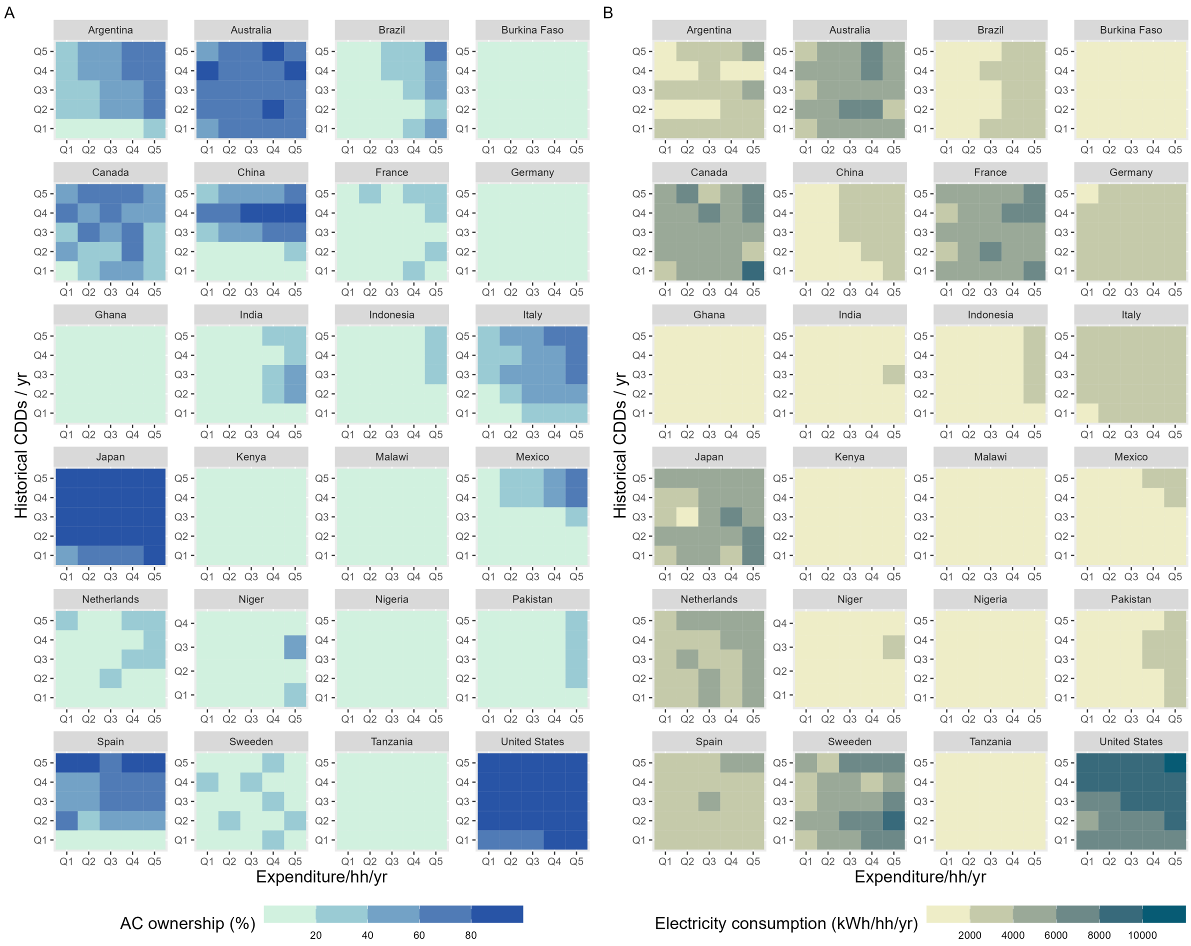

Figure S1: Heat maps of (A) AC ownership and (B) household electricity consumption, by country. Each facet maps the average level of the two variables at each expenditure and CDDs quintiles intersection in each country. N.B.: expenditure and CDDs quintiles are specific to each country.

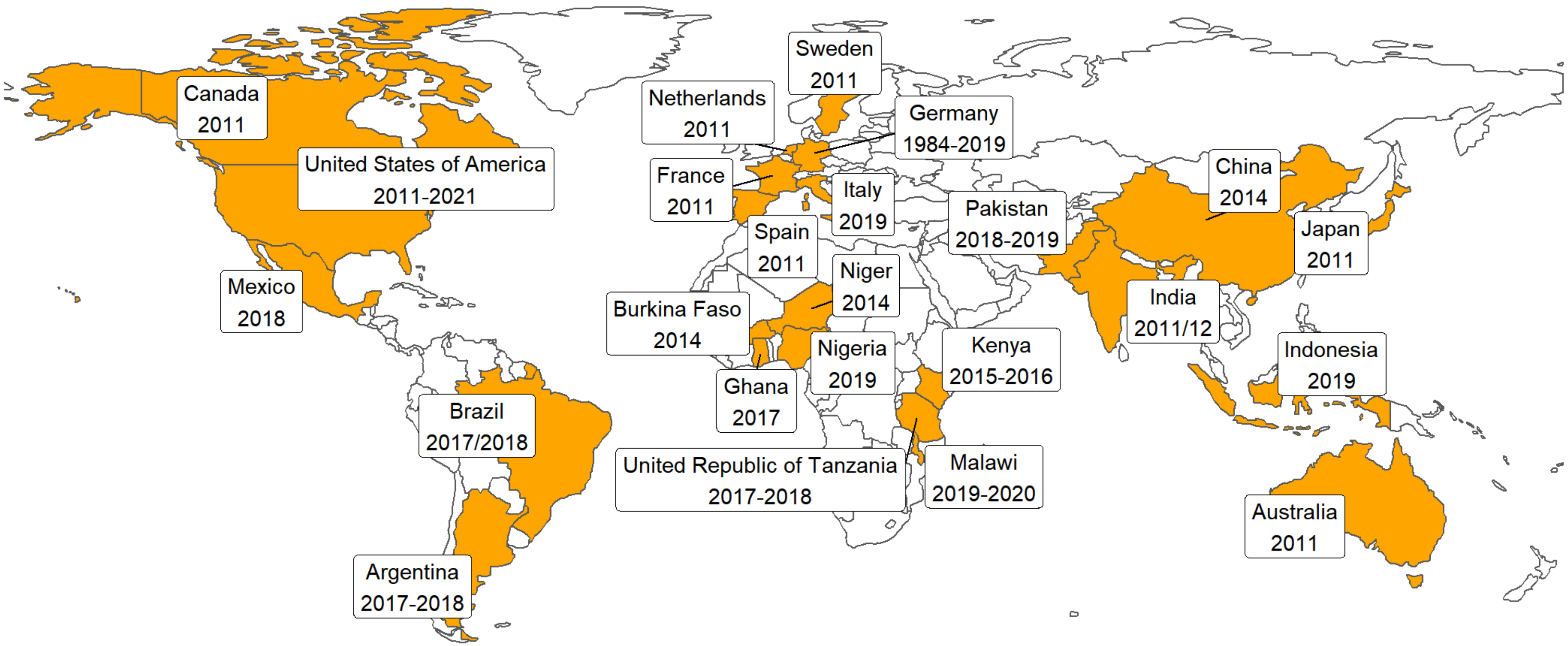

Figure S2: Country coverage

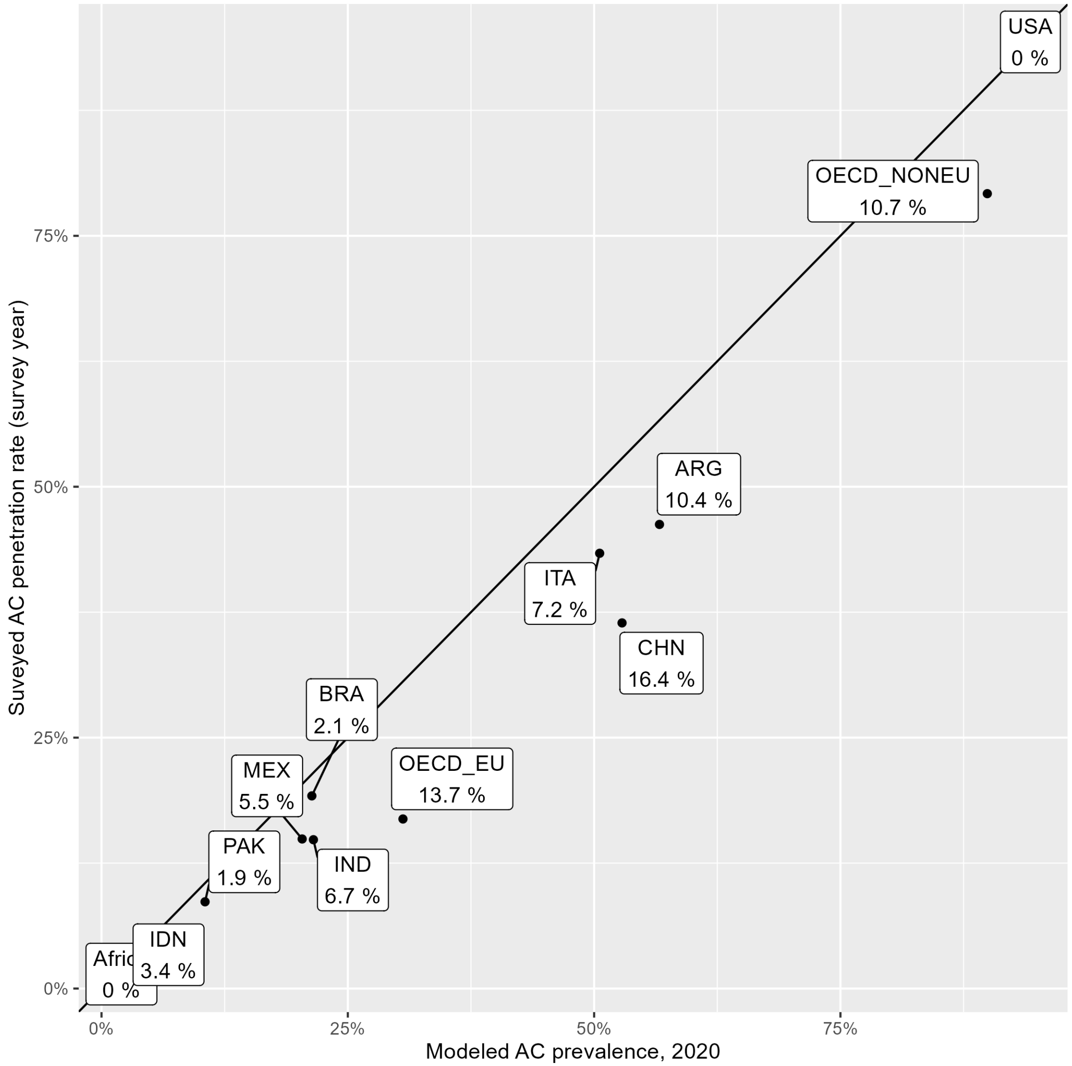

Figure S3: Bias in AC prevalence between survey data (pre-2020) and first projection timestep (2020).

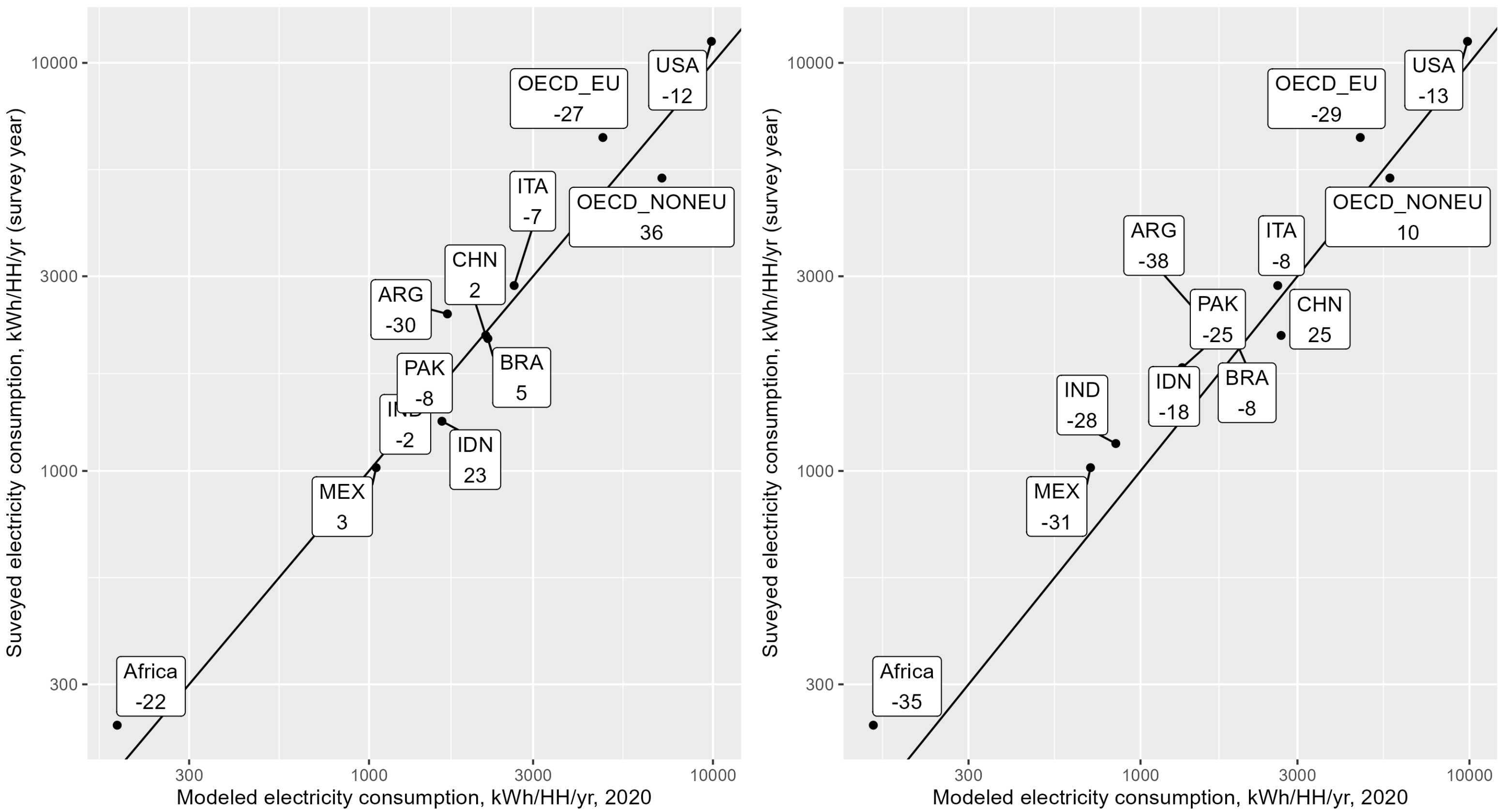

Figure S4: Bias in total household electricity consumption between survey data (pre-2020) and first projection timestep (2020).