Journal of Environmental Economics and Management 131 (2025) 103122

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

The impact of air conditioning on residential electricity consumption across world countries[☆]

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ARTICLE INFO

Dataset link: https://github.com/FPavanello/acglobal

JEL classification:
D12
O13
Q41
Q5

Keywords:
Adaptation
Air conditioning
Electricity demand
Global survey data

ABSTRACT

We provide a first globally-relevant assessment of the electricity consumption consequences of households' adaptation to ambient heat through air conditioning (AC). We use household survey data from 25 countries within a discrete-continuous choice empirical framework to model households' joint air conditioning adoption and utilization decisions, and combine the estimated responses with scenarios of socioeconomic, demographic, and climatic change to project air conditioning prevalence and cooling electricity demand circa mid-century. We find that air conditioning ownership increases households' electricity consumption by 36%, on average, but the effect is heterogeneous, varying with weather conditions, income and country contexts, revealing the importance of behaviors, practices, climate, and technologies. Compared to the other drivers of electricity consumption, air conditioning has the leading marginal effect, also accounting for a significant share of household budgets. By 2050, the overall effect is a net increase in global yearly residential cooling electricity to 976–1393 TWh, with an additional 670–956 Mt of CO_2 emissions, and associated social costs of \$124–177 billion. Our findings highlight cooling energy expenditure as an emerging indicator of energy poverty as the climate warms, and provide an initial quantification of the economic and environmental risks associated with air conditioning as an adaptation to climate change.

☆ We are grateful to Lorenza Campagnolo, Francesco Pietro Colelli, Marinella Davide, Malcolm Mistry, Anastasios Xepapadeas, and Guglielmo Zappalá for valuable feedbacks and comments. We also thank attendees at the 2nd ERC-ENERGYA Workshop, the 11th IAERE Conference, 10th SISC Annual Conference, 28th EAERE Conference, LSE Environment Week, and seminar participants at Centro Euro-Mediterraneo sui Cambiamenti Climatici. This research was supported by the ENERGYA project, funded by the European Research Council (ERC), under the European Union's Horizon 2020 research and innovation program, through grant agreement No. 756194. Enrica De Cian also acknowledges financial support from the DIGITA (PRIN) project, CUP: H73C20000090001. The views expressed here are those of the authors. The authors are solely responsible for any errors in the manuscript. The authors declare they have no financial or personal relationships with any person or organization that could inappropriately influence or bias in any way the following manuscript.

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https://doi.org/10.1016/j.jeem.2025.103122
Received 14 February 2024

Available online 4 February 2025

1. Introduction

The impacts of climate change are already being felt across the world (Pörtner et al., 2022; Dyer, 2022). There are widespread increases in detrimental exposure to extreme heat (Biardeau et al., 2020; Jay et al., 2021) as a consequence of rising temperatures, growing economic inequality, expanding informal urbanization, and population aging (Carr et al., 2023). Air conditioning (AC), a major large-scale adaptation option used to shield individuals from heat exposures, is also increasing globally (Turek-Hankins et al., 2021). Air conditioning's protective benefits include significant reductions in morality (Barreca et al., 2016), as well as ameliorative effects on learning (Park et al., 2020) and mental health outcomes (Hua et al., 2022). However, widespread use of air conditioning has important repercussions on households' expenditure and welfare (Mansur et al., 2008; Randazzo et al., 2020; Barreca et al., 2016), economy-wide energy demand and electricity systems (Auffhammer and Mansur, 2014; Auffhammer et al., 2017), emissions of greenhouse gases (GHGs) and other air pollutants (Colelli et al., 2022), and climate change mitigation policy (Rode et al., 2021). The latter consequences are only just beginning to be systematically quantified.

To our knowledge, this paper provides the first near-global scale, micro-founded empirical quantification of the electricity use associated with air conditioning. Our analysis employs a two-stage discrete-continuous framework that facilitates evaluation of the long-run effects of climate warming. We assemble a cross-sectional database of household air conditioning ownership and patterns of electricity consumption and expenditure across 25 countries that account for 62% of the world's population and 73% of global electricity consumption, which we use to assess the current and future demand for residential cooling electricity and its sources of heterogeneity.

As a guidance for the empirical analysis, we develop a simple adaptation model to frame the main adaptation strategies that welfare-maximizing households can pursue to cope with extreme heat: the extensive-margin adjustment of purchasing cooling appliances, namely air conditioning units, and the intensive-margin adjustment of consuming the quantity of energy that determines the level of utilization of these durables (Auffhammer and Mansur, 2014). This discrete-continuous setting motivates our use of the econometric framework developed by Dubin and McFadden (1984) to estimate households' adaptation behavior through adoption of air conditioning and its subsequent utilization for cooling via electricity consumption. Our approach accounts for the correlation between the two adaptation margins, and identifies the long-run impact of temperature on electricity consumption.

We find that AC-owning households consume, on average, 36% more electricity than those without the technology. This response is increasing and concave in temperature, reaching a peak of 57%. However, there is considerable heterogeneity in responses across income levels and countries, which is suggestive of differences in practices, behaviors, and technologies. Factors such as education, gender, age, urbanization, and housing quality all play a role in explaining patterns of energy use and expenditure in both high-income and emerging economies (Ameli and Brandt, 2015; Krishnamurthy and Kriström, 2015). To shed further light on this phenomenon, we first compare electricity demand's response to air conditioning with its responses to income and other socio-economic and demographic drivers through a descriptive meta-analysis of the standardized coefficients obtained from country-specific regressions. Our results broadly corroborate prior findings, but highlight the fact that when air conditioning is available, it exerts the largest influence on residential electricity consumption. Second, we compare air conditioning utilization to those of other electrical appliances, *e.g.* refrigerators. Interestingly, air conditioners appear as the only appliance whose utilization responds to warm temperatures.

Our fitted empirical model allows for the computation of household-level quantity of electricity used to operate air conditioning. By multiplying our estimates with statistics on electricity prices, we are able to highlight a previously underappreciated aspect of energy poverty, namely 'cooling poverty', which affects low-income households who own air conditioners. Our findings indicate that this burden is regressive, with expenditure shares decreasing along the income distribution. High-income households allocate between 0.2% to 2.5% of their expenditure on air conditioning use, while the poorest households may spend up to 8% of their budget on electricity for cooling.

In light of the increasing prevalence of residential solar energy, we investigate the potential mitigating effects of solar power generation on the electricity demand for cooling. Our findings show that households in areas with higher-than-sample-median photovoltaic (PV) power generation are associated with 25% less electricity for cooling than those in lower-PV regions, though the estimates lack precision. Moreover, the interaction between the actual amount of PV generation and electricity prices suggests a possible moderating effect of decentralized power generation on households' electricity consumption.

Looking ahead to the next decades, the combination of our estimates with future projections of climatic, economic, and socio-demographic drivers shows that increases in population, per-capita income, and temperatures are associated with a significant expansion in residential air conditioning adoption and related electricity demand by mid-century. The average household's annual cooling electricity consumption rises from 1610 kWh in 2020 to 1869–2069 kWh by 2050, depending on the socio-demographic and climate change scenario considered. This is almost on par with today's cooling electricity use of the average household in the United States, 2680 kWh.

We conclude our analysis with a back-to-the-envelope assessment of the potential implications of surging residential cooling electricity demand for energy and climate policy. Taking India as an example, we estimate that satisfying the cooling-driven increase in peak electricity demand may require a 18% to 29% expansion of generation capacity. Worldwide, similar induced expansion of electric power production are associated with GHG emission increases of 670–956 $MtCO_2$ in 2050, generating a "social cost of residential cooling energy" of $124–177 billion, based on recent estimates for the social cost of carbon. This result underscores trade-offs between adaptation and mitigation as a key challenge that will accompany households' adjustment to heat exposures (Colelli et al., 2023b).

Our analysis makes three primary contributions to the existing literature. First, we contribute to the literature on how energy consumption responds to climate change (Deschênes and Greenstone, 2011; Davis and Gertler, 2015; Auffhammer, 2022) by explicitly accounting for the specific role of air conditioning in electricity demand amplification. Recent research has uncovered the determinants of the air conditioning adoption decision, regionally (Romitti et al., 2022), in both emerging (Pavanello et al., 2021; Falchetta and Mistry, 2021) and developed (De Cian et al., 2019) economies, as well as globally (Andrijevic et al., 2021; Davis et al., 2021; Falchetta et al., 2024). Income is the leading driver in less affluent, hot areas (Davis and Gertler, 2015; Davis et al., 2021; Pavanello et al., 2021), whereas temperate, industrialized countries are relatively more responsive to thermal discomfort arising from more frequent hot days (De Cian et al., 2019). Air conditioning adoption and use are imperfectly correlated (Ara Begum et al., 2022), reflecting the moderating effects of socioeconomic conditions as well as individuals' and households' heterogeneous lived experiences adapting to extreme high temperature exposures. The response of energy use to weather and climatic conditions (Auffhammer and Mansur, 2014; Deroubaix et al., 2021) is well documented for individual (Davis and Gertler, 2015; Zhang et al., 2020), multiple (Davis et al., 2021) countries, regions (Romitti et al., 2022), cities (Romitti and Sue Wing, 2022), and even globally (Van Ruijven et al., 2019). Yet, electricity consumption for specific end uses, such as cooking or space conditioning, is not metered and can only be indirectly inferred using engineering (Bezerra et al., 2021) or econometric methods (Obringer et al., 2022).

A key challenge is to consistently characterize households' correlated adjustments along the extensive margin of air conditioning adoption and the intensive margin of cooling electricity consumption. Prior studies have addressed this issue in different ways, each with its own advantages and limitations. Davis and Gertler (2015) stratify electricity demand responses in Mexico according to air conditioning prevalence, estimating the intensive margin in Mexican states with current high levels of air conditioning penetration. The resulting 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. This approach suffers from two key shortcomings: lack of a correction for sample selection bias associated with households' differential likelihood of air conditioning ownership, and the use of different samples to estimate air conditioning penetration and electricity demand. Randazzo et al. (2020) apply a control function approach to empirically model the long-term effects of temperature in a cross-sectional data set where intensive- and extensive-margin adjustments are observed for the same households across eight developed, temperate countries. However, they only the estimate average marginal effect of air conditioning on electricity demand without characterizing the moderating effects of weather conditions on utilization. The latter is the focus of Auffhammer (2022), who uses a two-step approach to model household electricity demands in large dataset of utility bills for the state of California. In the first stage, demand is modeled using locationally-varying responses to contemporaneous temperature shocks, and in the second-stage the resulting response coefficients are modeled as a function of long-run climate variables to capture the climate response. However, unlike Davis and Gertler (2015), household-level billing information is not matched to either household- or location-specific estimates of air conditioning prevalence, leaving the precise role of cooling implicit.

These studies are limited in geographic scope. The key question is the extent to which their results reflect extensive- and intensive-margin responses that are globally valid, and, symmetrically, whether differences across these studies might reflect methodological variation or more fundamental moderation of responses by climatic, socioeconomic and demographic conditions. The answer has enormous implications for how, as economies and household incomes grow, and warm-season temperatures rise with climate change, private adaptation could expand—with increasing unintended consequences for energy consumption, GHG emissions, and social inequality. Refining Randazzo et al.'s (2020) two-stage empirical model, we expand its application to a broad slate of world regions, including many developing and emerging areas, exploiting survey microdata that record air conditioning ownership and electricity use in the same households. This broader application allows us to capture a more comprehensive and nuanced view of air-conditioning demand globally, thus providing critical insights into how adaptation behaviors may evolve in different contexts.

Second, our results characterize the distributional implications of cooling electricity consumption, and contribute to updating the definition of energy poverty—a concept that has traditionally been associated with the inability to keep a home warm at reasonable cost (Bradshaw and Hutton, 1983) while neglecting excessive expenditure arising from cooling needs. We define cooling poverty through an expenditure-based approach (Boardman, 1991) and provide a first multi-country, comparative assessment of the distributional implications of using air conditioning, contributing to the emerging literature looking into summer poverty. Summer poverty considers the inability of households to keep a house cool in summer times due low-income, high costs, and inefficient housing stock (Sanchez-Guevara et al., 2019). To date, existing assessments have been limited to local case studies, and cross-country comparisons have yet to be conducted. Our analysis considers actual air conditioning expenditure, whereas other (Pavanello et al., 2021; Mastrucci et al., 2019) look at the *potential* for cooling poverty by intersecting the lack of air conditioning with exposure to high ambient temperatures.

Finally, our paper contributes to the literature on the interaction between mitigation and adaptation in the residential energy sector. First, our results provide suggestive evidence that PV systems have the potential to reduce the burden of air conditioning usage on electricity consumption and expenditure, enhancing energy security and affordability for households. To the best of our knowledge, the only other study addressing this interplay is that of Colelli et al. (2023a). In the context of an Italian province, the paper shows that, when equipped with solar PV households extract 68% less electricity compared to the extraction before the installation of the PV technology. Moreover, they are less responsive to warm temperatures, and less exposed to price shocks. Second, we present an initial quantification of the social cost of CO_2 emissions driven by increased electricity use for cooling. Our estimates complement recent assessments of the contribution of warming-induced energy expenditures to the social cost of carbon (SCC) (Rode et al., 2021). However, our analysis specifically focuses on the residential electricity sector, providing a targeted perspective on the sectoral impacts of climate change on energy demand and associated emissions.

Table 1
Household survey microdata sources and details.

Country	Year of wave analyzed	Region	Primary source	N° Households
Canada	2011	North America	EPIC	481
United States of America	2003–2021	North America	AHS	85,236
Mexico	2018	Central America	INEGI	62,267
Brazil	2017/2018	Southern America	IBGE	49,734
Argentina	2017/2018	Southern America	ENGHO	19,870
Sweden	2011	Europe	EPIC	448
Switzerland	2011	Europe	EPIC	199
Netherlands	2011	Europe	EPIC	447
France	2011	Europe	EPIC	667
Germany	2019	Europe	SOEP	5,299
Spain	2011	Europe	EPIC	515
Italy	2019	Europe	HBS	17,244
Nigeria	2019	Africa	GHS	1,597
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	1,142
Tanzania	2017/2018	Africa	HBS	9,193
Pakistan	2018/2019	Central Asia	LSM-IHS	19,506
India	2019	Central Asia	CHPS	167,238
China	2014	Eastern Asia	CFPS	11,245
Japan	2011	Eastern Asia	EPIC	247
Indonesia	2017	Eastern Asia	SUSENAS	224,103
Australia	2011	Oceania	EPIC	527
Total				692,718

The remainder of the paper is organized as follows. Section 2 presents our newly constructed data set 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-dataset covering a large number of sub-national administrative units from 25 countries. Together, these countries represent 62% 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 years when the interviews were carried out, and the number of households included in the final pooled database for each country. Overall, our dataset includes 692,718 households.

From each survey we gather information on annual expenditure on and, where available, consumption of electricity, ownership of any kind of air conditioning, total household expenditure,[1] and a range of socio-economic and demographic variables. We restrict our sample to households without missing data for either air conditioning or electricity use. This choice effectively excludes households without access to electricity in the year they were surveyed. We also collect information on the ownership of other basic electrical appliances, such as refrigerators, televisions, computers and washing machines. However, broad appliance ownership is not recorded for all countries.[2]

In instances where electricity consumption was not reported, we augment the survey with information on average electricity prices to impute the implied annual electricity consumption quantities.[3] Electricity prices are either directly obtained dividing electricity consumption by quantity or collected at country or sub-national level from external sources.

Similarly, indicators of households' location in a urban or rural area were not reported for all countries, and, where they were recorded, the definition of urban varied across countries. To address this inconsistency we use gridded data on urbanization from Gao and Pesaresi (2021) to construct the population-weighted urban fractions for each sub-national region, a continuous indicator which we assigned to the households residing in each region.[4]

[1] When it is not available we collect information on total household income. We prefer total household expenditure because it is a more reliable measure of spending power in less developed countries (Davis et al., 2021).

[2] We exclude some appliances such as oven or microwave since they are available only for very few countries.

[3] See Supplementary information for additional information on electricity prices.

[4] See Supplementary information for additional information on how we assemble the data set.

2.2. Historical meteorological data

We describe the weather and climatic conditions using the degree-day metric common in energy studies (ASHRAE, 2009; Scott and Huang, 2008). We use cooling and heating degree days (CDDs and HDDs, respectively), computed as the sum over the year of deviations of average daily temperatures above (CDDs) or below (HDDs) a 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.

Our raw temperature data come from two sources. Our primary source is the ERA5 historical climate reanalysis dataset of hourly dry-bulb temperatures on a global 0.25° grid over the period 1970–2019 (Hersbach et al., 2020). We adopt the temperature threshold of 18 °C.[5] We compute CDDs and HDDs at each grid cell, and then aggregate the results to the sub-national geographical unit of the surveys using population weights for the corresponding survey years. Climatic CDDs and HDDs are computed as the average of annual CDDs and HDDs over the 30-year period prior to each survey year. Finally, we merge household data with the resulting HDD and CDD series at the finest geographic scale available (*i.e.*, provinces or districts) to construct representative household-level ambient short- and long-run meteorological exposures.

2.3. Additional data

We also gather additional data from various sources and combine them with our household-level dataset. We use these information for auxiliary analyses.

Solar PV potential output. We collect spatial data on PV power potential from the Global Solar Atlas.[6] PV power potential (also called *PVOUT*) represents the potential amount of power generated per unit of the installed PV capacity over the long-term, and it is measured in kilowatthours per installed kilowatt-peak of the system capacity (kWh/kW peak). We then compute the average PV potential at the smallest administrative unit available in each country.

PV generating capacity. We also obtain spatial data on solar PV generating capacity from the Global Inventory of Utility-Scale Solar Energy Installations (Kruitwagen et al., 2021).[7] This is the first global inventory of commercial, industrial, and utility scale solar energy stations. It identifies about 70,000 facilities around the world, and it has information on the capacity installed in MWp. This dataset covers solar energy stations between June 2016 to October 2018. Based on the installation year attribute of the PV data set, we only consider the capacity that was installed before the year in which the household survey was conducted in each region. We use these filtered data entries to compute the cumulative PV generating capacity installed in each administrative unit before the household survey year. When survey year is after 2018 we use information up to 2018 to compute capacity. This information allows us to build a proxy of the differences in current installed PV generating capacity across countries.

2.4. Descriptive statistics

Table 2 describes the average households' characteristics for the global pooled dataset.[8] Focusing on the two main dependent variables, across the pool of the 25 countries considered, on average, a household consume 2439 kilowatt-hour (kWh) per year, whereas air conditioning prevalence is around 26%. A high degree of heterogeneity in the distribution of both variables is observed across and within countries. Critically, other electrical appliances like refrigerators and televisions are three times more widespread than air conditioning in the sample. This suggests a potential hierarchy on which appliances are firstly adopted by households.

Fig. 1 suggests that the between-country difference in cooling energy (Panels A and B) is highly 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 (Fig. A.1). 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.

[5] In addition, to assess the robustness of our results we construct CDDs and HDDs using temperature thresholds of 24 and 15 °C respectively.

[6] Data are downloaded from https://globalsolaratlas.info/global-pv-potential-study.

[7] Data are available for download here: https://resourcewatch.org/.

[8] Country/region-specific descriptive tables are reported in the Supplementary information.

Table 2
Descriptive statistics.

	Mean	SD	10th	25th	Median	75th	90th
Outcome							
Electricity Quantity (kWh)	2439.24	3942.46	258.57	663.13	1287.55	2474.23	5278.37
Air Conditioning (Yes = 1)	0.26	0.44					
Climate and weather							
$\overline{\text{CDD}}$ (100 s)	15.88	10.79	2.89	6.21	12.89	26.92	30.04
CDD (100 s)	16.78	11.00	3.33	7.26	14.68	27.68	31.29
HDD (100 s)	11.31	13.53	0.00	0.05	4.46	19.15	29.45
Socio-economic and demographic							
Total Expenditure ($2011 PPP)	16 358.92	35 464.50	1324.27	3557.33	6628.43	14 635.63	39 995.22
Electricity Price ($2011 PPP/kWh)	0.19	0.14	0.10	0.12	0.15	0.23	0.33
Urbanization Share	0.08	0.12	0.00	0.01	0.03	0.10	0.23
Home Ownership (Yes = 1)	0.82	0.38					
Household Size	3.91	2.27	2.00	2.00	4.00	5.00	6.00
No Education (Yes = 1)	0.27	0.44					
Primary Education (Yes = 1)	0.28	0.45					
Secondary Education (Yes = 1)	0.31	0.46					
Post Education (Yes = 1)	0.14	0.35					
Age of Household Head	48.82	15.18	29.00	38.00	48.00	59.00	69.00
Female Household Head (Yes = 1)	0.32	0.47					
Other electrical appliances							
Refrigerator (Yes = 1)	0.71	0.45					
Television (Yes = 1)	0.85	0.36					
Computer (Yes = 1)	0.43	0.49					
Washing Machine (Yes = 1)	0.53	0.50					
Observations				692718			

Notes: Descriptive statistics are computed survey weights.

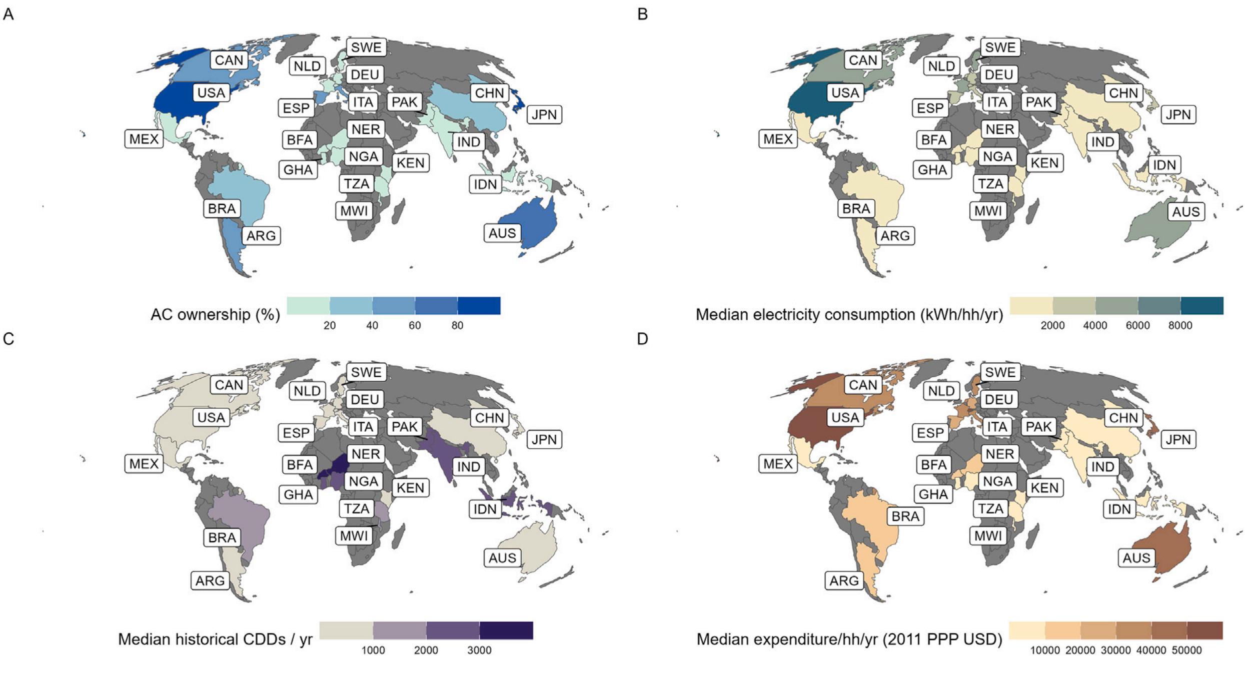

Fig. 1. Panel A: Air conditioning prevalence; Panel B: Median household electricity consumption; Panel C: Median historical CDDs; Panel D: Median household total expenditure, by country.

3. Theoretical framework

To guide our investigation, we develop a simple model of households' joint decision to adjust along the intensive and extensive margins. Consider a representative household who derives long-run utility, u, from the consumption of a generic good, x—which we treat as the numeraire—, and thermal comfort, $\mathcal{T}$:

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

where $u_{\mathcal{T}}, u_x > 0$. Thermal comfort is a function of current ambient conditions, c, and electricity consumption, q, as adjusting energy use is one of the main adaptations under the household's direct control:

$$\mathcal{T} = f(c, q(c); \boldsymbol{z}) \tag{2}$$

In general, thermal comfort declines with positive or negative deviations from a "bliss point", or ideal ambient indoor temperature at which space conditioning is unnecessary. The latter is not directly observed but is modulated by various characteristics of the household, $\boldsymbol{z}$. For clarity and analytical tractability we focus on situations of ambient excess heat. Hence, we can define q as cooling electricity consumption. Treating c as synonymous with high temperature anomalies suggests that $f_c < 0$ and $f_q \geq 0$, while consuming additional energy for cooling in order to moderate excess indoor temperatures implies $q_c > 0$.

Households maximize utility subject to Eq. (2) and a budget constraint (Eq. (3)) defined over income, y, generic expenditure and adaptation costs, $k(q(c))$:

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

with $k_q > 0$. The solution to the household's utility maximization problem is the optimal level of cooling energy consumption, q^*. Given the dependence of both thermal comfort and electricity consumption on climate, totally differentiation of the thermal comfort production function yields:

$$\frac{d\mathcal{T}}{dc} = \underbrace{\frac{\partial \mathcal{T}}{\partial c}}_{\text{Direct discomfort } <0} + \underbrace{\frac{\partial \mathcal{T}^*}{\partial q} \cdot \frac{dq^*}{dc}}_{\text{Cooling adaptation } >0}$$

indicating that high temperatures directly reduce thermal comfort but can be wholly or partially offset by induced increases in cooling electricity consumption.[9]

Provision of thermal comfort is one the strongest drivers of air-conditioning demand and use (Jay et al., 2021). Accordingly, we focus on air conditioning as the technology that households adopt to effectively maintain their thermal comfort. Other cooling strategies exist, especially in countries with hot and humid climates. In India, for example, fans are still preferred to air-conditioning units and evaporative coolers (Khosla and Bhardwaj, 2019). However, the cooling effectiveness of fans is comparatively low (Malik et al., 2022), and above certain income thresholds air conditioning appears to be the technology of choice (Pavanello et al., 2021). The household's cooling electricity demand is thus conditional on the availability of air conditioning, a:

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

In turn, air conditioning ownership is a function of the expected climate at the household's location, $\overline{c}$, and the cooling efficiency of air-conditioning capital—*i.e.*, the average transformation efficiency of energy into thermal comfort in that weather conditions—, η, in addition to the households income and other characteristics:

$$a = a(\overline{c}, \eta, y, \boldsymbol{z})$$

The household adjusts along the intensive margin in response to short-run temperature fluctuations, and along the extensive margin in response to long-run changes in the expected climate. The first order conditions of the household's problem yield the equilibrium condition equalizing the cost and benefit of cooling energy consumption at the margin:

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

where $MRS_{\mathcal{T},x}$ denotes the marginal rate of substitution between thermal comfort and the numeraire. In the simplest case of adaptation costs that are linear in electricity prices, p_q, and air-conditioning capital costs, p_a, such that:

$$k(q(c)) = p_q q(c) + p_a$$

That is, the left-hand side of Eq. (4) reduces to p_q, yielding the conditional demand function electricity

$$q^* = q(c, p_q, y, \boldsymbol{z} \mid a(\overline{c}, \eta, y, \boldsymbol{z})) \tag{5}$$

Thus, to determine the long-term effects of climate change on electricity consumption, we need to simultaneously identify the two margins of adaptation by empirically distinguishing the direct effect of contemporaneous meteorological conditions, c, on energy demand conditional on air conditioning ownership, from the indirect effect of long-term climate, $\overline{c}$, on the decision to adopt air conditioning.

[9] In line with Mansur et al. (2008), we assume that marginal adaptation costs, *e.g.*, electricity prices and capital costs of cooling appliances such as air-conditioning units, are invariant to climate change.

4. Empirical framework

Following Eq. (5), we estimate the optimal conditional electricity demand using a discrete-continuous econometric framework in which each household, h, simultaneously chooses whether to adopt air conditioning, and, conditional on their decision, the level of utilization of air-conditioning capital by choosing how much cooling electricity to consume. Our basic model of the latter intensive-margin electricity demand adjustment is:

$$\begin{aligned} Q_h = {} & \beta_1 AC_h + \beta_2 AC_h \times f(CDD_{i(h)}) + \beta_3 f(CDD_{i(h)}) \\ & + \beta_4 Y_h + \beta_5 P_h + \chi' \mathbf{Z}_h + \nu_{\mathcal{A}(h)} + \varepsilon_h \end{aligned} \tag{6}$$

in which Q is the natural logarithm of electricity consumption (in kWh) and AC is a dummy variable that equals 1 if a household has an air conditioning installed in its dwelling, and 0 otherwise. The function $f(CDD_{i(h)})$ is a second-degree polynomial of the contemporaneous annual CDDs experienced in the most disaggregated administrative area available for each country, i, during the survey year, reflecting the nonlinear response of electricity to temperature (Davis and Gertler, 2015; Auffhammer, 2022). The interaction $AC \times f(CDD)$ tests whether air conditioning amplifies electricity demand increases when heat exposure goes up or it occurs in warmer locations. We expect a concave relationship, reflecting the unobserved capacities of households' air-conditioning units and associated latent upper bounds on cooling electricity use, and sharply diminishing returns to additional electricity consumption once the desired thermal comfort level has been achieved. The variables Y and P are respectively the natural logarithms of total household expenditure and electricity prices ($2011 PPP). We also include a vector $\mathbf{Z}$ of demographic and housing characteristics.[10] Finally, we account for time-invariant unobservable factors (*e.g.* preferences) by including fixed effects, $\nu_{\mathcal{A}(h)}$, defined at the level-1 subnational administrative divisions (ADM-1) inhabited by each household.[11] The error term, ε, is clustered at the ADM-1 level, and captures the residual unobserved variation in the outcome.

Air conditioning is likely endogenous to electricity demand, generating correlation between the error term, ε_h, and AC_h. Not only there is simultaneity as households' air conditioning adoption and utilization decisions are not independent, the two decisions also likely 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 conditioning. These issues can addressed by estimating Eq. (6) with a discrete-continuous choice approach, as in Mansur et al. (2008), Davis and Kilian (2011) and Barreca et al. (2016), using the methodology proposed by Dubin and McFadden (1984). This consists of a control function approach that allows the error term in the indirect utility function underlying the decision to adopt air conditioning to be correlated with the error term in the electricity demand equation. Specifically, we make two assumptions: (i) the errors in the air conditioning ownership decision are independent and identically distributed extreme value type I, and (ii) the electricity demand equation's errors are a function of the air conditioning decision equation's errors, essentially capturing the unobservable factors that influence air conditioning prevalence and might affect electricity consumption as well. We control for the correlation among the errors by including a (selection) correction term that is constructed from the predicted probabilities from a first-stage logistic regression with air conditioning as the outcome variable:

$$\begin{aligned} AC_h = {} & \gamma_1 f(\overline{CDD}_{i(h)}) + \gamma_2 Y_h + \gamma_3 f(\overline{CDD}_{i(h)}) \times Y_h + \gamma_4 f(CDD_{i(h)}) \\ & + \gamma_5 P_h + \gamma_6 \mathbf{X}_h + \boldsymbol{\psi}' \mathbf{Z}_h + \mu_{\mathcal{A}(h)} + u_h \end{aligned} \tag{7}$$

where $f(\overline{CDD})$ is a second-degree polynomial of long-run CDDs in the most disaggregated available administrative area. The vector $\mathbf{X}$ 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 demand equation we estimate then becomes:

$$\begin{aligned} Q_h = {} & \beta_1 AC_h + \beta_2 AC_h \times f(CDD_{i(h)}) + \beta_3 f(CDD_{i(h)}) \\ & + \beta_4 Y_h + \beta_5 P_h + \chi' \mathbf{Z}_h + \lambda \zeta_h + \nu_{\mathcal{A}(h)} + \varepsilon_h \end{aligned} \tag{8}$$

where ζ is a correction term that is a function of first-stage predicted probabilities, $\hat{\pi}_h$,

$$\zeta_h = \begin{cases} \frac{(1-\hat{\pi}_h)\ln(1-\hat{\pi}_h)}{\hat{\pi}_h} + \ln \hat{\pi}_h & \text{if } AC_h = 1 \\ \frac{\hat{\pi}_h \ln \hat{\pi}_h}{1-\hat{\pi}_h} + \ln(1-\hat{\pi}_h) & \text{Otherwise} \end{cases} \tag{9}$$

The correction term approximates the components of ε_h that are correlated with AC_h (Wooldridge, 2015). As well, we estimate the first and second stage using survey weights to ensure that our results are representative of the populations in the surveys.

Our fitted empirical model enables us to estimate the electricity associated with the utilization of air conditioning for cooling. Cooling electricity (Q^{AC}) is imputed using a counterfactual calculation of the difference in the level of predicted consumption with and without air conditioning for the subset of AC-owning households in our sample, $h(AC_h = 1)$:

$$Q^{AC}_{h(AC_h=1)} = \exp(\hat{Q}_{h(AC_h=1)} | AC = 1) - \exp(\hat{Q}_{h(AC_h=1)} | AC = 0) \tag{10}$$

[10] 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 urbanization, education level of the head, age of the head, gender of the head, household size and home ownership.

[11] Cross-country comparisons of expenditure, prices, and other survey variables are not straightforward, since data are collected in different countries and from different agencies. By including ADM-1 level fixed effects, we reduce to some degree these concerns about measurement error.

This calculation facilitates projections of future cooling electricity consumption in response to shifts in socio-economic and demographic drivers (due to economic development) and in temperature (due to warming). The key difference is that in the future, households that are predicted to have access to air conditioning expand beyond the AC-owning subset in the sample (see Appendix A.1 for details).

Our empirical strategy is subject to two main caveats. First, average electricity prices in the second stage are likely to be endogenous. For some surveys we compute prices by considering the ratio of observed electricity expenditures and the reported level of consumption, a procedure that introduces simultaneity (division bias) between P and Q in Eq. (8) (Borjas, 1980). For most countries we collect aggregate data at either the sub-national- or the country-level from various sources. On one hand, the fact that households respond to average rather than marginal electricity prices (Ito, 2014) is reassuring but, on the other hand, this procedure likely introduces measurement error. Taken together, these issues are sufficiently challenging that we are unable to address them fully. We argue that this should not be cause for concern because prices serve the role of controls, and price elasticities of demand are not the focus of this study. Furthermore, prices play no role in our mid-century projections: to be able to consider them we would need general equilibrium simulations of electricity market conditions or assumptions about future price regimes in disparate regions (Auffhammer, 2022). Nonetheless, we do perform some robustness checks, such as excluding electricity prices, including interactions of electricity prices with income decile dummies, and instrumenting electricity prices.

Second, our survey data sets are uninformative about either the energy efficiency or the capacity of households' air-conditioning units, which jointly determine the parameter η in our theoretical model. Including income as an explanatory variable potentially controls for the likelihood that richer households purchase appliances that are simultaneously of higher capacity and more energy efficient. Penetration of air conditioning is indeed not as widespread as that of other technologies such as refrigerators or washing machines, and it is relatively concentrated among high-income households, especially in developing economies. We therefore note that the ultimate impact remains ambiguous. On one hand, more efficient cooling appliances require less electricity to produce a given amount of cooling. On the other hand, richer households are likely to have higher willingness and/or ability to pay for air-conditioning units with larger cooling capacities and higher total electricity consumption. Depending on whether the first or the second effect dominates, the marginal effect of air conditioning on electricity consumption may decrease or increase with income, respectively.

5. Results

We first present the results of our global, pooled model across all countries, characterizing the average relationship between air conditioning, electricity demand, and their income, climatic, and socioeconomic and demographic drivers. Next, we examine the heterogeneity of air conditioning effects across different income levels and countries. In addition, we contextualize the role of air conditioning as a key driver of electricity demand relative to other determinants, including other electrical appliances. Finally, we use the climate, household, and geography-specific estimated model parameters with scenarios of the drivers to project air conditioning prevalence and cooling electricity consumption circa 2050.

5.1. The effect of air conditioning on residential electricity consumption

Baseline. Table 3 shows the estimated impacts of air conditioning ownership on household electricity consumption. We first estimate Eq. (6) as a baseline for the analysis (columns 1–3). When ignoring the potential endogeneity of air conditioning, we find that owning at least one air conditioner is associated with an increase in the electricity demand by 38%–60%, ceteris paribus. However, as previously discussed, these estimates are likely to be biased.

In column 3, we highlight the result of addressing endogeneity via our two-step approach. The correction term is always significant and negative (Table A.1), suggesting that it is important to control for endogeneity and that the OLS estimates are upward biased. A reason for the positive bias is that owners of air-conditioning units are positively selected. Compared to the previous specification, the effect of air conditioning is still significant but smaller in magnitude. Having the technology installed in one's dwelling increases electricity consumption by 36%. In column 4, we also add interactions between AC and CDD. At zero CDDs, the appliance is not used. Above this threshold, the effect of air conditioning is increasing and concave in cooling degree days (Fig. 2), amplifying residential electricity consumption by up to 57%.

Our results align with previous estimates. Randazzo et al. (2020) find that air conditioning increases electricity expenditure by 35% in eight OECD countries, while DePaula and Mendelsohn (2010) find an effect size of 23%–33% in Brazil. Finally, model simulations from IEA (2018) indicate cooling demand can account for 50% or more of total electricity demand in countries with a long summer period. The coefficients of the other covariates (Table A.1) 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 0.32% in our preferred specification. Contemporaneous weather conditions—CDD and HDD—also have significant positive effects, even when we introduce the interactions with air conditioning. On one hand, the uninteracted terms of CDD likely indicate the use of lightning and other appliances as households tend to spend more time at home when it is hot outside. On the other hand, the effect of HDD likely capture the use of electric heating systems. Regarding electricity prices, we find an elasticity of −0.41, which is in the range of previous estimates,[12] though this result should be interpreted with caution in light of the aforementioned

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

Table 3
The effect of air conditioning on residential electricity consumption.

	OLS (1)	OLS (2)	DMF (3)	DMF (4)
AC	0.597***	0.377***	0.361***	0.028
	(0.032)	(0.029)	(0.031)	(0.062)
AC × CDD				0.038***
				(0.010)
AC × CDD^2				−0.001**
				(0.000)
Controls	NO	YES	YES	YES
Correction Term	NO	NO	YES	YES
ADM-1 FE	YES	YES	YES	YES
R^2	0.670	0.729	0.729	0.731
Mean Outcome (kWh)	2495.943	2495.943	2495.943	2495.943
Countries	25	25	25	25
Observations	682 727	682 727	682 727	682 727

Notes: Dependent variable: logarithm of electricity consumption (kWh). Full results are available in Table A.1. For DMF Columns the first stage is shown in Table A.2, columns 3–4. "Controls" include natural logarithm of electricity price, and weather and socio-economic and demographic variables. Regressions are conducted using survey weights. Standard errors are clustered at the ADM1 level; *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

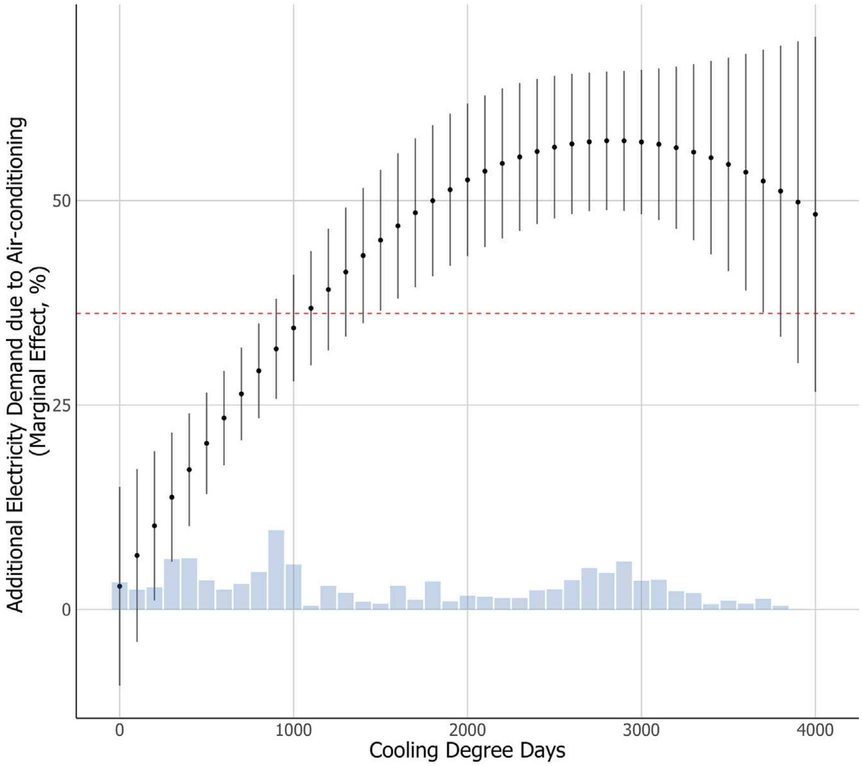

Fig. 2. Marginal effects of air conditioning ownership on household electricity consumption for different level of cooling degree days. Confidence intervals: statistical significance level at 95%. Red dashed line: pooled estimate (Table 3, column 3). Background: distribution of population-weighted cooling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

endogeneity and measurement error concerns. Urbanization share has a positive, but not significant effect. While a negative effect of urbanization is a common finding especially in developed countries (Randazzo et al., 2020),[13] the literature points at an opposite results in developing countries (Agrawal et al., 2019; Pavanello et al., 2021). Of two competing mechanisms, we find that the latter slightly prevails at the global level. 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.

[13] 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.

Table A.2 reports estimates from the air conditioning ownership model. Columns 1–2 show the results from a linear probability model (LPM), whereas columns 3–4 depicts the coefficients and marginal effects from the logit 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 long-term CDDs is concave, reminiscent of a classical S-shaped adoption curve. A 100-degree day increase in the long-term average of CDD makes the probability of adopting the technology grow by 3.1–5.5 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 0.08 percentage points when expenditure grows by 1%. Finally, regional urbanization, household size, house ownership, household head age, education, and gender are all significant drivers of adoption.

Robustness checks. Robustness checks further corroborate our baseline results. In columns 1–4, Table A.3, we test for alternative fixed effects, replacing ADM-1 dummies, with fixed effects at, first, the most disaggregated sub-national level available for each country, and, second, at the country level. We find that our results remain consistent. Notice that with the former we lose more observations, as the logit regression drops observations that perfectly predict 0 or 1 outcome.

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 (Table A.3, columns 5–6). We find similar effects to our main specification. However, even interacting air conditioning ownership with CDDs, the main coefficient on air conditioning remains significant. This is likely due to the fact that in this specification CDDs and HDDs no longer share a common temperature threshold, resulting in an omitted category of moderate temperature exposure—*i.e.*, degree days between 15 and 24 °C—which ends up being correlated with the air conditioning dummy.[14]

Because electricity prices are likely to be endogenous, we test whether their inclusion might influence on our results. First, in columns 7–8, we drop electricity prices from both the first and second stage. Second, in columns 9–10, 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. In additional regressions, we also directly control for the endogeneity of prices using an instrumental variable (IV) approach. Table A.4 reports the 2SLS results. In columns 2–3, we instrument electricity prices in the demand equation using either ADM-1 or country fixed effects.[15] This strategy is inspired by Davis and Kilian (2011) and Barreca et al. (2016), who address potential measurement error by instrumenting electricity prices with US census region dummies that capture geographic variation in the costs of generating the electricity consumed by households.[16] We find that price elasticity increases in absolute value once we correct for endogeneity, suggesting that in our baseline estimates we are likely underestimating households' responsiveness. Contrary, the effect of air conditioning remains unchanged.

Wooldridge (2015) suggests that in a control function approach the correction term can be modeled as any other variable. In another set of estimates (Table A.3, columns 11–14), we then test the robustness to changes in the functional form of the correction term. First, we include a squared term of the correction term, and, second, we control for its interactions with contemporaneous CDD. The results are similar to our main estimates. We also test for winsorizing (columns 15–16) and trimming (columns 17–18) the sample at the 5th and 95th percentiles. Again, the results are basically the same. Finally, we re-estimate our main specification without survey weights (Table A.3, columns 19–20). Our main findings remain robust.[17]

5.2. Heterogeneity

The additional electricity demand attributable to air conditioning ownership varies significantly across income groups and countries. We model whether a household owns one or more air-conditioning units, and how the intensity of utilization of those appliances varies with temperature. A larger intensive margin response could indicate the presence of more units, higher capacity units, and/or operation of those appliances over longer periods at a given ambient temperature.

Across levels of income. To identify the heterogeneous effect of air conditioning across income levels, we estimate our model using a global response function with country-specific expenditure quintiles (Table A.5). Panel A of Fig. 3 shows that the total effect of air conditioning on electricity consumption—*i.e.*, the sum of partial derivatives computed at the CDD mean value—is slightly larger for households in the first, second and in the fifth income quintiles. On average, utilization air conditioning owning households in the third- and fourth-income quintiles add about 34 to 35% to their average annual electricity consumption, whereas households in the first, second and fifth quintiles use 38%–40% electricity. However, these average effects are not statistically different from one other. We speculate this may be attributable to improved characteristics of buildings and appliances as we move from the lowest to the middle income groups, an effect that is compensated by patterns of air conditioning adoption and use when households become

[14] We find a correlation coefficient of −0.32 between air conditioning ownership and this omitted category.

[15] Note that this means that we exclude them from both the air conditioning and the electricity equation.

[16] In Supplementary information we also instrument prices using the fuel-specific shares of electricity generation at the ADM-1 level obtained from the Global Power Plant data base. In both cases we notice that instrumenting electricity prices leads to larger elasticity to prices. However, the fuel-specific shares appears as a weak instrument once we control for unobserved confounders at the ADM1-level. Hence, 2SLS estimates obtained using these instruments should be only taken as suggestive of how measurement error is affecting our price elasticity.

[17] In Supplementary information we provide further robustness checks. For instance, we estimate our demand equation using electricity consumption in level. The results show the same functional form for air conditioning utilization of our main specification once we take accounts of outliers.

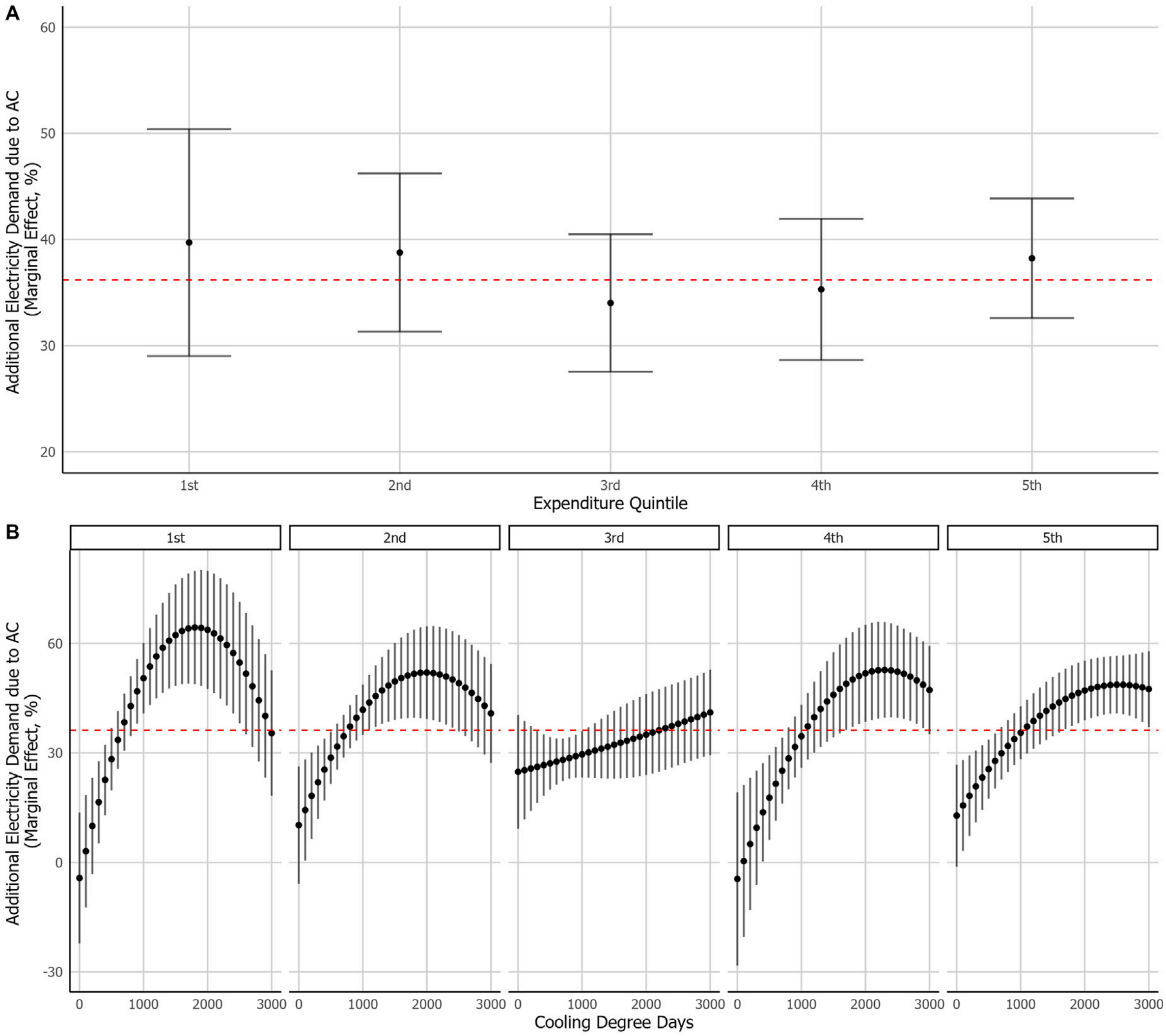

Fig. 3. Marginal effects of air conditioning ownership on household electricity consumption, by country-specific expenditure quintile: (A) Total effects; (B) Effects at different CDD levels. Confidence intervals: statistical significance level at 95%. Red dashed line: pooled estimate (Table 3, column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

more affluent. Richer households can afford to adopt higher quality air conditioners that are both efficient and expensive, but they may also purchase larger capacity appliances, additional air-conditioning units, and operate them for longer periods and more frequently, with the net effect of higher consumption. Lack of data prevents us from empirically disentangling these contending influences. Critically, looking at these estimates in relative terms hides the striking differences in levels among income groups. AC-owning households in the poorest quintile consume, on average, 679 kWh annually for cooling. However, consumption rises to more than 800 kWh for each household in the second and third quintiles, reaching 1033 and 1436 kWh for the richest households.

Fig. 3 Panel B illustrates how patterns of air conditioning utilization respond to temperature across the income distribution. With the exception of middle incomes, the relationship between cooling electricity and income generally follows an inverse U-shape, with low-income households attaining maximum utilization at smaller heat exposures than their high-income counterparts, whose utilization saturates at about 1800 CDDs. A likely reason is that poor households can afford fewer and/or smaller-capacity units. Variation across income groups in the shape of the response functions is thus suggestive of inequality in households' adaptive capacity. When exposed to ambient high temperature extremes, rich households are able to shield themselves through large increases in spending on cooling electricity, whereas poorer households may not have the same flexibility to ramp up electricity consumption in ways that translate into cooling.

Across countries. Tension between more efficient technologies and adaptive behaviors, on one hand, and large cooling demands, on the other, is also evident in Fig. 4. This illustrates the declining marginal effect of air conditioning ownership on cooling electricity consumption as we move from the poorest regions (India, Indonesia, Sub-Saharan Africa) to more developed regions

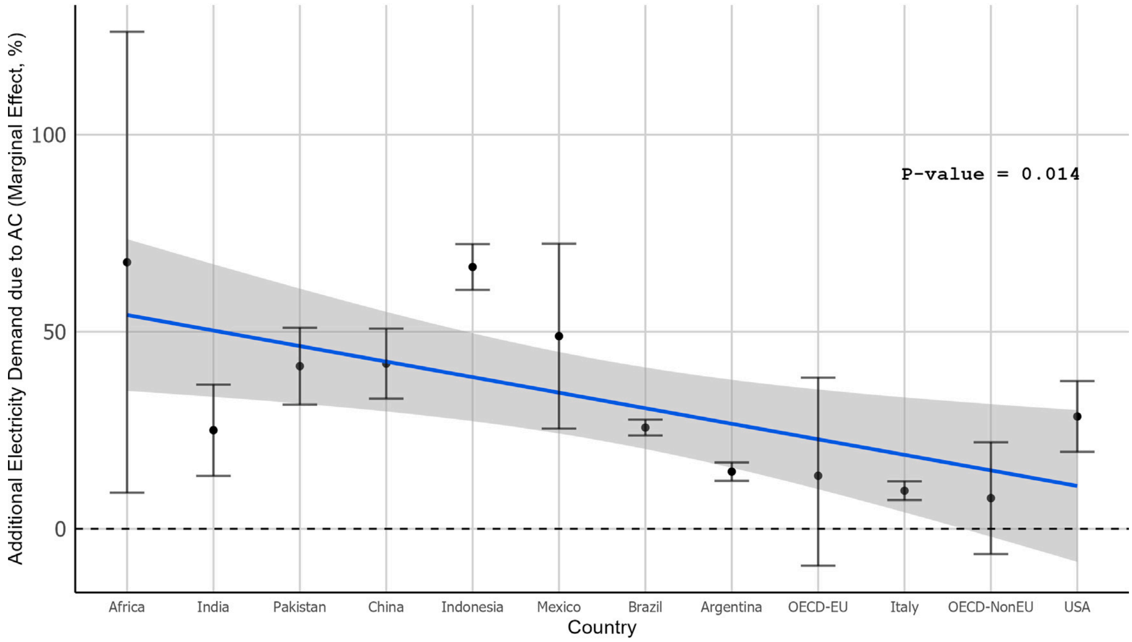

Fig. 4. Marginal effects of air conditioning ownership on electricity consumption by country. Estimates are obtained from country-specific models. Countries are ordered based on their total expenditure per capita. Confidence intervals depict statistical significance level at 95%.

(Northern Europe, Argentina, Australia, Canada, Japan, USA).[18] As countries with cooler climates also tend to be more affluent, their households, on average, can afford better technologies and therefore can achieve thermal comfort with less electricity. Higher income can also be associated with higher-quality housing—building envelopes with better thermal performance—but larger per-household residential spaces and associated cooling demand.

Air conditioning increases average electricity consumption by about 68% in Africa, 10% in Italy, and 7% in non-European OECD countries. Countries tend to fall into three clusters: Africa and Indonesia, where average cooling electricity consumption of AC-owning households is 50% larger than that of households without air conditioning, and two additional groups for which AC-driven amplification of electricity use are 25%–50% (India, Pakistan, China, Mexico, Brazil, USA) and < 25% (Argentina, OECD-EU, Italy, OECD-nonEU), respectively.

5.3. Air conditioning and the role of other influencing factors

Social and demographic characteristics. Our results suggest that air conditioning is the leading factor influencing households' consumption of electricity. Fig. 5 compares the magnitude and sign of air conditioning's effect to those of other socioeconomic and demographic drivers. To do so, we employ a descriptive meta-analysis of the standardized coefficients obtained from country-specific regressions.

Air conditioning ownership emerges as the single most important individual factor with a median impact of about 27% across the country-specific model coefficients, followed by total expenditure, electricity prices, housing quality, household head's education, and household size. Heating degree days are also relevant, but they only matter in a few high latitude countries. 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 (Fig. A.2), 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 urbanization 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

[18] To obtain Fig. 4 we run country/region-specific regression. 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-Non EU (Australia, Canada and Japan). Similarly, we also group African countries in an unique region. In the country-specific regressions 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 effects. Region-specific regressions employ country-level fixed effects. Moreover, where available, we also include an index of housing quality as a further control. The coefficient for Germany has been averaged with the coefficient for EU countries in the EPIC survey using total population as a weight. Germany's very low rate of air conditioning ownership (1%) leads to coefficient of counterintuitive sign that is not significant. In the Supplementary information we show the same graph including Germany, as well as robustness tests using different groupings of countries. The pattern of results remains the same as described in the text.

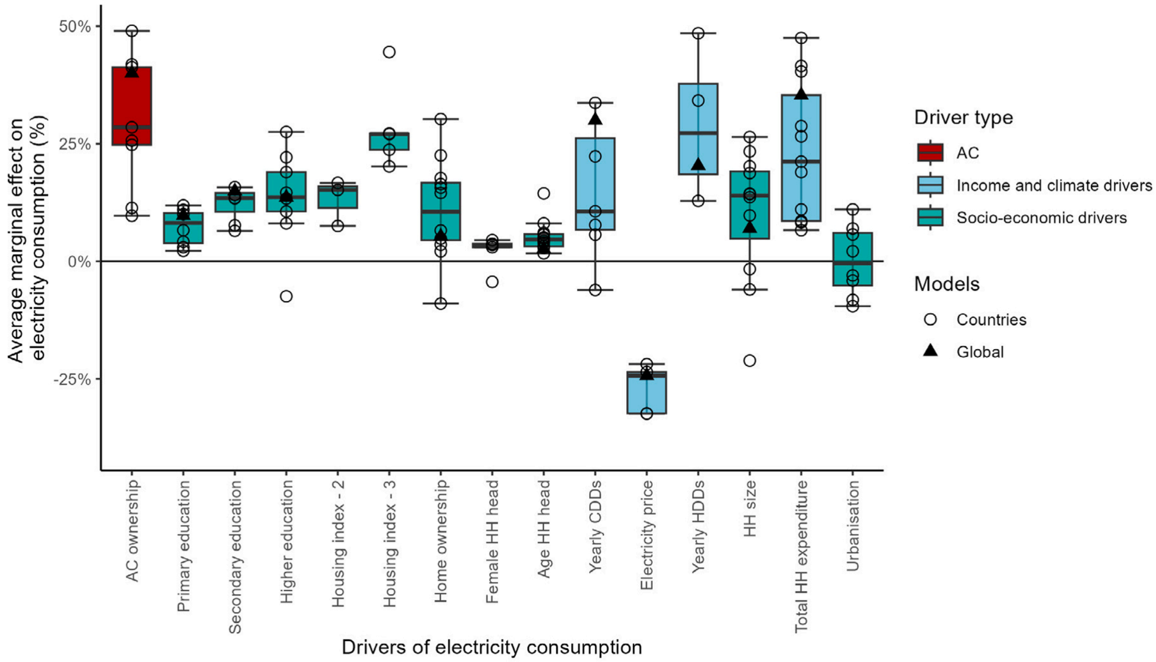

Fig. 5. Boxplot of the marginal effects of the drivers of household electricity consumption. Estimates are based on country-specific average marginal effects calculated from standardized regression coefficients.
Note: only coefficients with $p < 0.05$ are included.

quality of urbanization (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 urbanization rate of the United States stood at about 83% in 2023, according to the United Nations Population Division. Conversely, as highlighted by Agrawal et al. (2019), in a developing country like India—where the urbanization rate stands at about 36%—, the average electricity demand of rural households is half of the national average residential consumption. Overall, these numbers suggest that economic development levels are determining an inverse-U shaped relationship between urbanization and household electricity consumption, thus explaining the large range observed in the average marginal effects of the urban driver in Fig. 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.

Other electrical appliances. To further contextualize the importance of air conditioning, we compare its effect on electricity consumption with that of other appliances: refrigerators, televisions, computers and washing machines. Appendix Tables A.6–A.9 report the results of adding each of these appliances to our main specification, with and without interactions with contemporaneous CDDs. Controlling for other electrical appliances does not significantly alter our estimates. The average effect of refrigerators is similar, if not larger in magnitude, to that of air conditioning, indicating their importance for residential electricity consumption—and energy poverty, given their high investment and operational costs. However, refrigerators' attributable electricity consumption does not significantly increase with temperature as does air conditioning.[19] Overall, the presence of these other appliances increases average residential electricity demand, but not its sensitivity to temperature. In a global warming context this result has important policy implications, as we go on to demonstrate.

5.4. Mid-century projections of air conditioning prevalence and utilization

In an advance over prior empirical climate impact studies, we project future air conditioning prevalence and residential space cooling electricity around 2050 by combining our fitted first and second stage regressions (Table 3, column 4) with estimates of

[19] Such an interaction occurs only for washing machines, but its effect is small, and noisy.

Table 4
Projections of residential air conditioning adoption and use.

	AC penetr.rate (%)			Per cap. AC electr. (avg. kWh/hh/yr)			Total AC electr. (TWh)		
	2020	SSP245 (2050)	SSP585 (2050)	2020	SSP245 (2050)	SSP585 (2050)	2020	SSP245 (2050)	SSP585 (2050)
Country	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean	Mean
Pooled	27.5	40.7	54.6	1610.0	1869.4	2069.4	494.5	975.8	1392.6
Africa	5.6	9.1	14.9	386.8	323.9	248.8	1.3	3.3	3.5
Argentina	65.4	84.1	90.0	517.3	716.8	855.5	4.3	8.8	10.1
Brazil	24.0	45.4	65.0	1316.9	1413.2	1636.2	20.2	45.5	69.1
China	48.0	73.2	82.5	985.7	1441.6	1764.6	167.2	342.6	457.9
Indonesia	10.6	34.7	59.3	1063.6	1335.3	1644.1	6.1	27.6	54.4
India	9.0	32.7	52.0	1230.8	1419.6	1545.0	36.1	191.3	294.8
Italy	58.7	81.7	88.3	516.7	705.2	834.0	6.6	12.3	18.2
Mexico	22.0	34.5	43.9	915.0	1058.8	1126.6	6.5	14.1	16.2
OECD-EU	37.5	50.0	56.5	851.6	1197.3	1278.2	14.7	30.6	43.1
OECD-NonEU	81.8	88.0	89.8	801.6	1370.1	1921.5	35.4	65.2	109.4
Pakistan	16.9	30.3	40.3	1371.1	1436.4	1446.1	7.4	19.7	22.1
United States	92.8	97.0	97.9	2677.2	3319.1	3690.6	305.9	468.9	622.5

future climate and weather (long-run and contemporaneous CDDs and HDDs), income (a proxy for total expenditure), urbanization, and demographic characteristics (including education and age of household head) under different scenarios. Our joint estimation of the interacting intensive and extensive margins facilitates projections of electricity use for space cooling that account for climate-driven increases in the diffusion of air conditioning in conjunction with weather-driven increases in utilization intensity.

As detailed in the Appendix, we collect data on changes in temperature exposures from global climate model (GCM) simulations, and changes in income, population and demographic variables from various sources, for two shared socioeconomic pathway (SSP) scenarios, the moderate-warming SSP 245 and high-warming SSP585 pathways (O'Neill et al., 2016; Fricko et al., 2017; Kriegler et al., 2017). Table A.10 summarizes the evolution of the main drivers used in the projections of both extensive and intensive margin.

We find that air conditioning ownership will grow significantly over the next thirty years, increasing from the sample average of 28% in 2020 to 41%–55% in 2050 under moderate and intense warming, respectively (Table 4). Country-specific results align with previous estimates (Pavanello et al., 2021; Davis et al., 2021). Substantial air conditioning utilization is expected in most high-income countries with warm regions such as Italy, United States and Non-EU OECD (Australia, Canada and Japan). Middle and lower-income countries projected to experience faster income growth will exhibit the largest relative increases in air conditioning penetration (*e.g.* China, India, Indonesia). However, prevailing disparities are likely to persist: air conditioning penetration in African countries (9%–15%) and Pakistan (30%–40%) in particular falls short of 50% households, suggesting that substantial numbers of people will remain without access to cooling. Countries with cool climates (*e.g.* northern Europe) or substantial climatic heterogeneity (*e.g.*, Mexico) see rates of increase of air conditioning that are more moderate.

Diffusion of air conditioning only partly explains future cooling electricity demand growth. The intensity of air conditioning utilization is proportional to households' CDD exposure, income availability and demographic characteristics. Moreover, countries' aggregate cooling needs are determined by the size of their populations. Consider, for example, Italy and India. While Italy's projected 2050 air conditioning prevalence in is nearly the double that of India, both the population and the estimated per capita electricity use for space cooling in India are much larger, leading to higher overall national demand.

Coincident temperature, economic and demographic trends lead to increases in cooling electricity consumption that are likely to be concentrated in developing countries. For instance, Indonesia's annual cooling electricity consumption would grow from 6.1 TWh to 28–54 TWh, while India could expect a five-fold increase in a SSP 245 scenario—consistently with previous projections, *e.g.*, Abhyankar et al. (2017). Although not directly comparable due to differences in geographical coverage, our projections point in the same direction as, and are of comparable magnitude to, the IEA's *Future of Cooling* report (IEA, 2018).[20]

Finally, it is worth noting that projected changes in cooling electricity expenditures reflect trends that simultaneously influence adjustments at the extensive and intensive margins. The focus of prior studies has been on exploiting trends in drivers for which projections that the integrated assessment literature has made readily available (temperature, income, population). However, Fig. 5 shows that other socio-demographic drivers substantially influence both margins of adaptation. Indeed, projections based only on future changes in temperature and expenditures yield systematically lower air conditioning penetration rates and cooling electricity consumption levels (Fig. A.4)—a pattern that is consistent across the global pooled model (panels A and B) as well as individual regions (panels C and D). Fig. A.5 decomposes the influence of the various factors on household electricity consumption in both current and future periods, confirming the important role of socio-demographic drivers in shaping future electricity demand in emerging economies.

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

6. Discussion

In this section, we examine the potential consequences of households' adaptation to rising temperatures through increased air conditioning use. First, we assess the impact on household electricity expenditures, addressing both immediate budgetary effects and projected future costs. In doing so, we identify an often-overlooked aspect of energy poverty: 'cooling poverty'. Furthermore, we investigate the role of renewable energy, particularly solar power, in enhancing energy security and making cooling more affordable for households. Second, we present a back-of-the-envelope calculation to estimate the potential strain on electricity supply systems driven by the rise in cooling demand. Finally, we consider the broader climate policy implications by quantifying the additional CO_2 emissions associated with this demand surge and estimating the resulting social costs of these emissions.

6.1. Implications for household expenditures

Current period. When cooling electricity consumption is translated into additional expenditure, the cost burden incurred by air conditioning utilization is larger for poor households. For example, an average Indonesian household allocates 1.6% of its expenditure to electricity purchases, while the corresponding figure for an average American household is 3.5%. A more than 66% increase in electricity consumption for the Indonesian household is certainly more difficult to afford compared to the 29% increase for the American one. As a monetary measure of cooling poverty, to highlight the budgetary implications for AC-owning households, we examine the cost of electricity associated with the operation of air conditioning as share of total household expenditure. We predict cooling electricity quantities using our fitted main empirical specification (Table 3, column 4) and multiply the result by our estimated electricity prices. Fig. 6 shows that, in emerging economies such as Pakistan and China, poor households who own air-conditioning units allocate more than 5% of their total expenditure to cooling, with shares above 3% among the lowest quintile found also in Africa, Argentina, India, and Mexico. The budgetary consequences of AC-driven electricity demand amplification are regressive. Expenditure shares of both total and cooling-related electricity both decline with household income, a pattern holds across countries and regions, albeit with steeper declines in some areas. In the United States, China, Brazil, India, Pakistan, poor households' cooling electricity expenditure share is more than twice as large as that of their rich counterparts.

Fig. A.3 illustrates the electricity share of total expenditure, stratifying households by air conditioning ownership. Cooling electricity accounts for a large share of total electricity expenditure, and households with air conditioning tend to spend much more on electricity. In low-income households in developing countries, the median household with air conditioning spends twice as much as the median household. In low air-conditioning penetration areas (*e.g.* Africa, Brazil, Indonesia, India, Mexico, Pakistan), cooling electricity's fraction of expenditure can be as large as the total electricity expenditure share of the median household. Conversely, in high air conditioning penetration areas (*e.g.*, Argentina, China, Italy, 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 as income grows.

Future residential electricity expenditures. Our projections of future electricity use highlight a critical question: as the climate warms, will growth in the demand for cooling translate into increasing pressure on household budgets? Unfortunately, a definitive answer is elusive. To quantify the fraction of total expenditure that households will allocate to power consumption, it is necessary to make assumptions about the future distribution of incomes and the positions of the surveyed households within it, as well as residential electricity prices in the future. Elaborating these factors in a consistent fashion requires an integrated assessment research framework that is well beyond the scope of the present study. Our fallback is the more straightforward approach of a simple *ceteris paribus* calculation of the expenditure burden associated with changes in electricity consumption, holding constant the prices and household incomes at the levels prevailing today.

First, Fig. 7 shows the shifts in the region-specific distributions of cooling electricity expenditure (in \$2011 PPP) between 2020 and 2050 with constant prices.[21] Dashed vertical lines indicate the mean cooling electricity expenditures in the different scenarios. This is possible thanks to the large within- and across-country heterogeneity of our pooled data set and household-level future projections. The flattening of the density peaks when shifting from 2020 (gray) to 2050 (orange and red) reflects increasing air conditioning penetration, including rising ownership among low-income households, which counterbalances the rightward shift in the mean air conditioning electricity consumption. Most countries' distributions exhibit pronounced rightward shifts, indicating rising air conditioning adoption concentrated among relatively high-expenditure households, whose increased electricity consumption drives growth in mean cooling electricity expenditures.

As a complementary exercise, we calculate how the foregoing shifts translate to *ceteris paribus* changes in households' cooling electricity share of total expenditure, when both electricity prices and total expenditure are held constant at current levels. The result, shown in Fig. A.6, is increased pressure on household budgets in all countries and regions assessed, in conjunction with a widening of the distribution of expenditure shares. In China, India and Pakistan, households above the 75th percentile of the expenditure distribution could spend more than 5% of their budget on cooling. Nevertheless, it bears emphasizing that the precise future implications depend on the "horse race" among three factors that the present analysis is unable to completely capture: in addition to the growth in air conditioning penetration and cooling electricity consumption with warming-driven temperature increases, the effects of demographic and economic development trends on the future distribution of households' total expenditures, and shifts in electricity generation technologies and the structure of energy markets that determine future residential power prices.

[21] Households that we project do not own air conditioning in the future are excluded from the analysis in Fig. 7.

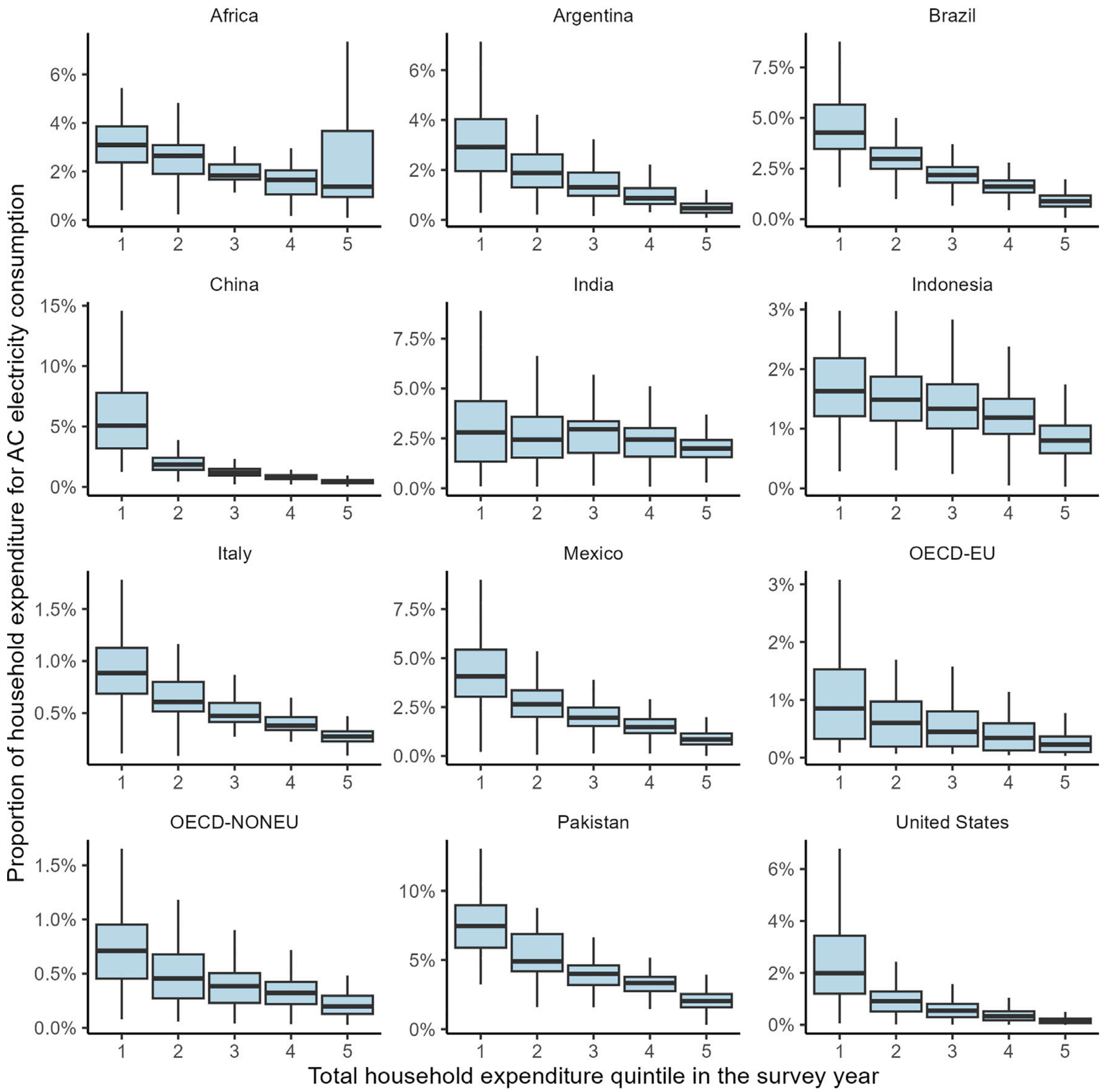

Fig. 6. Distribution of estimated household electricity consumption for air conditioning, stratified by quintile of total household electricity consumption in 2020. Note: only households owning air conditioning are included.

Potential mitigating effects of solar power generation. Renewable electricity generation has the potential to moderate both the consumption and cost of the additional electricity associated with operating air conditioners. In developing countries where populations face limited access to power grids, unreliable power supplies, and/or high electricity prices, alternative power generation technologies such as PV have the potential to make air conditioning technologically and economically feasible (Falchetta and Mistry, 2021). Our study setting provides an opportunity to quantify this potential. To do so, we augment our baseline regression with a measure of potential solar electricity generation at the sub-national level, and interact the latter with both air conditioning ownership and electricity prices. Our measure is constructed as the product of PV generation potential and installed solar power capacity, which proxies for the kWh of PV electricity generated in the sub-national area assuming a typical utility-scale PV system.[22] This calculation reflects the fact that many high-insolation areas with large solar generation potential currently have low installed generation

[22] PV electricity generation (kWh) = PV potential output (kWh/kW peak) × (PV installed capacity (MW peak) × 1000).

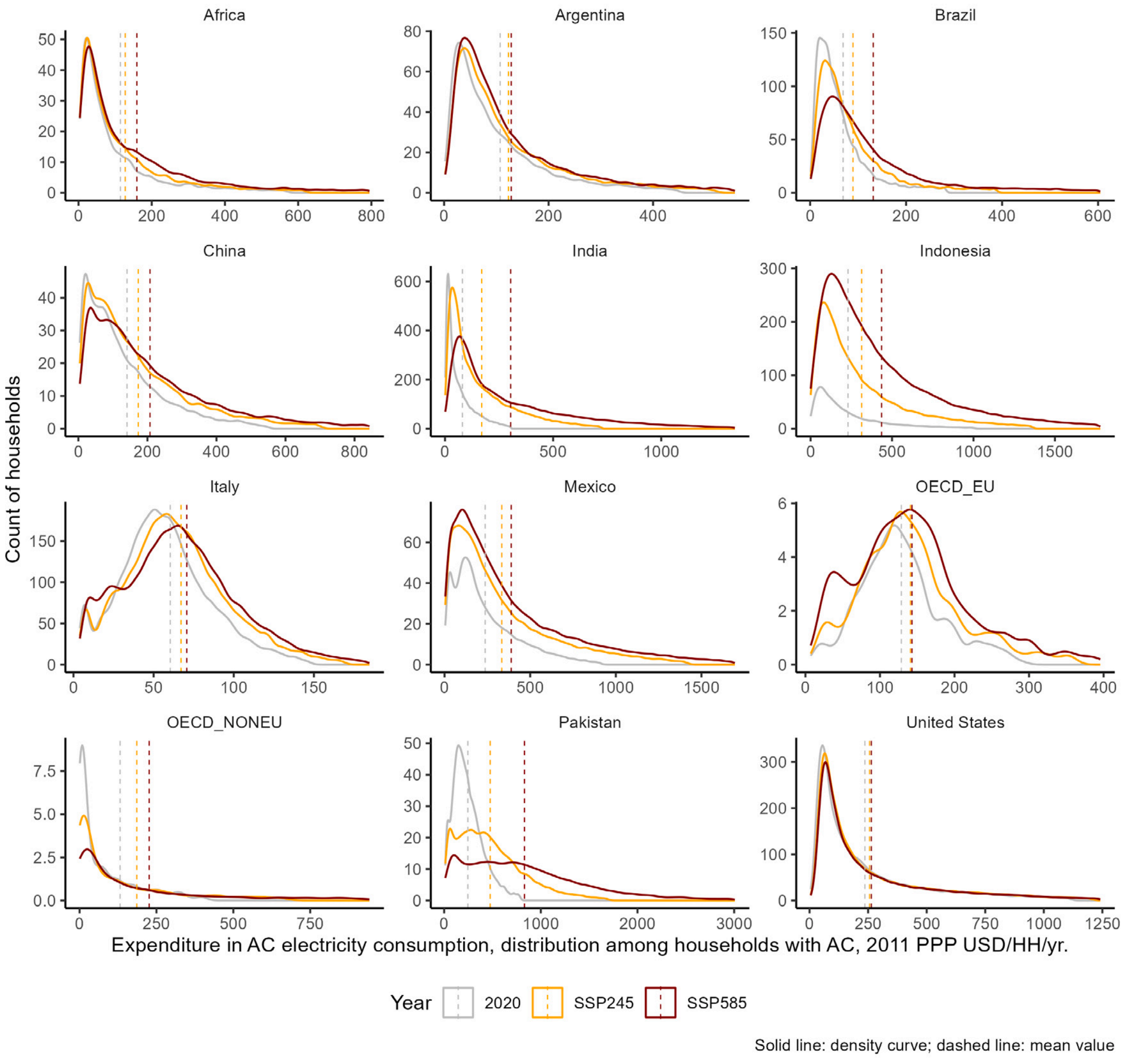

Fig. 7. Distribution of households' expenditure for air conditioning electricity (2011 USD PPP), by country/region and scenario.

capacity (*e.g.*, African countries), while comparatively low-potential areas have a high installed capacity (*e.g.*, Germany). To facilitate interpretation, we specify our covariate as a "high PV generation" dummy variable that identifies locations with higher-than-median generation potential, which is positively correlated with the adoption of air conditioning (Table A.14).

Table 5 reports our results. Compared to their lower-than-median counterparts, households in areas with higher-than-median PV generation are associated, on average, with 25% less cooling electricity—*i.e.*, 0.112/0.456. This finding is in line with recent results that demonstrate that PV adoption reduces households' electricity consumption responses to high temperatures in Italy (Colelli et al., 2023a).[23] The coefficient on the interaction between greater-than-median PV generation and electricity prices is negative but not significant. However, the weakly significant coefficient on the interaction between electricity prices and continuous measures of PV capacity or generation (Tables A.12 and A.13) suggests that residential electricity demand tends to be more price-elastic in high

[23] In the Appendix, the effect of the interaction between the potential output measure and air conditioning is negative but not significantly different from zero (Table A.11). We obtain similar results interacting air conditioning with PV capacity, as well as with a continuous measure of PV generation (Tables A.12 and A.13). These latter interactions become highly significant when we relax assumptions about unobserved heterogeneity at the country level (see Supplementary information).

Table 5
The role of solar power generation in residential electricity demand.

	DMF (1)	DMF (2)	DMF (3)
AC	0.361***	0.456***	0.361***
	(0.031)	(0.053)	(0.031)
𝟙(PV Gen. > Median)	0.005	0.014	−0.080
	(0.022)	(0.023)	(0.093)
AC × 𝟙(PV Gen. > Median)		−0.112*	
		(0.059)	
Log(P)	−0.392***	−0.396***	−0.376***
	(0.040)	(0.039)	(0.035)
Log(P) × 𝟙(PV Gen. > Median)			−0.045
			(0.043)
Controls	YES	YES	YES
Correction Term	YES	YES	YES
ADM-1 FE	YES	YES	YES
R^2	0.729	0.730	0.730
Mean Outcome (kWh)	2495.943	2495.943	2495.943
Countries	25	25	25
Observations	682 727	682 727	682 727

Notes: Dependent variable: logarithm of electricity consumption (kWh). "Controls" include weather and socio-economic and demographic variables. Regressions are conducted using survey weights. Standard errors are clustered at the ADM-1 level in parentheses; $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

solar generation regions. We speculate that, to the extent that our proxy variable reflects households being more likely to operate their own rooftop PV systems, this result could indicate substitution of own-supplied PV generation for mains electricity supply during daylight hours. Supply-switching is consistent with Colelli et al.'s (2023a) finding that PV adoption reduces exposure to electricity price shocks and increases the price-responsiveness of electricity demand, particularly during warm seasons with more daylight hours. Notwithstanding these indications of PV generation's potential to reduce the burden associated with air conditioning utilization, and mitigate the energy security and affordability challenges facing adapting households, the precise mechanisms are unclear, and will likely remain so pending the availability of household-level data on distributed generation.

6.2. Implications for electricity supply systems

Our estimates reveal that, across our sample of 25 countries, cooling electricity consumption will grow by a factor of two to three by 2050, reaching about 1000–1400 TWh per year—in line with India's total final electricity consumption in 2020. As previously highlighted (Colelli et al., 2022, 2023b; Davis and Gertler, 2015), this surge in electricity consumption for climate adaptation has enormous implications for generation and transmission capacity planning (Sherman et al., 2022), operational stability of electricity grids (Auffhammer et al., 2017), and the costs of achieving global decarbonization goals (Colelli et al., 2022).

We illustrate implications for electricity supplies using a simple back-of-the-envelope engineering calculation for India. Conservatively assuming constant utilization over the course of a six-hour average daily air conditioning run time (Ramapragada et al., 2022), and constant average utilization of air conditioning over months of the year, annual cooling electricity consumption will grow from nearly 40 TWh to about 200–300 TWh per year in 2050. The latter corresponds to a 75–120 GW increase in peak supply (generation and/or storage capacity) to satisfy AC-driven amplification in hourly peak electricity demand.[24]

Considering that India's current installed capacity is about 420 GW, accommodating an average 1% per year rise in peak capacity demand—on top of general increases due to population and income growth—will have important repercussions for power system planning and operations. The ultimate effects of peak demand amplification on the power grid will depend on how the additional electricity will be generated (Colelli et al., 2023a). The previous section's results suggest that future penetration of distributed PV generation could be an important moderator of both peak and total electricity system load. Additionally, policies and investments to improve the efficiency of the installed base of cooling appliances are likely to be an important complementary demand-side strategy (IEA, 2018; Ramapragada et al., 2022). The efficacy of the latter will depend on technological progress in manufacturing low-cost, high-efficiency air conditioning units, as well as the diffusion of regulations to implement and strengthen minimum energy performance standards for cooling appliances—especially in developing countries.[25]

Notwithstanding, projected increases in global cooling electricity use are likely to be at least partially offset by declines in the consumption of electricity and multiple fossil fuels for heating as cool-season temperatures rise in the future (Van Ruijven et al.,

[24] 260 TWh higher annual cooling electricity consumption $\times 1,000 \div$ (365 days $\times$ 6 hours/day) = 119 GW. We obtain the same result under alternative assumptions that half of cooling electricity consumption is concentrated in summer months with an average utilization of 12 h per day (Colelli et al., 2023b; Ramapragada et al., 2022).

[25] Clean Cooling Collaborative (2024). Mid-Program Impact Report (2022–2024): Setting a Course for Efficient, Climate-Friendly Cooling for All. https://www.cleancoolingcollaborative.org/wp-content/uploads/2024/08/CCC_Mid-Program-Impact-Report.pdf.

2019; Rode et al., 2021). This compensating effect will moderate total additional electricity consumption in temperate countries, but not in the tropics (Romitti and Sue Wing, 2022), and is unlikely to attenuate the pressure on generation and transmission capacity as cooling adaptation shifts peak power demand to the hottest days of the year.

6.3. Implications for emissions and climate policy

The projected surge in cooling electricity demand suggests that climate adaptation could increase power generation-related CO_2 emissions, posing a challenge for achieving decarbonization goals (Colelli et al., 2023b). We estimate that electricity demand amplification could increase CO_2 emissions from 339 Mt today to 670–956 Mt by mid-century (Table A.15), an amount exceeding France's current national emissions. The bulk of these additional emissions would come from developing countries such as China, India, and Indonesia that are projected to experience rapid increases in air conditioning adoption. To quantify the associated "social cost of residential cooling energy", we use the central value of the social cost of carbon of 185 $/tCO_2$ (Rennert et al., 2022), which translates into a total cost of $124-177 billion in 2050.

Effective mitigation of emissions from cooling will be key, in addition to improvements in end-use appliance efficiency, rapid decarbonization of the power sector—especially in countries with high current or projected air conditioning utilization and fossil fuel-intensive electricity generation systems (*e.g.*, China, India, Indonesia and USA). While previous studies provided evidence for the moderating effects of warming winter temperatures on electricity demand amplification, likely resulting in an offset of aggregate power consumption (Rode et al., 2021), this counterbalancing is only likely to be observed in temperate countries. Contrary, regions in warmer climates—and, coincidentally, also low income—will likely experience a net increase in temperature-related energy use. Altogether, this implies that the bulk of the twin burdens of the pecuniary costs of expanding electricity supplies, and the social costs of the additional CO_2 emitted in the process, will fall most heavily on populations with the least capacity to adapt (Gazzotti et al., 2021).

7. Conclusion

This paper has provided a global-scale assessment of households' adaptation to excessive heat through coordinated extensive-margin adoption of air conditioning and intensive-margin utilization of air conditioning via consumption of electricity for cooling. We estimate the long-run effects of temperature on electricity consumption with a discrete-continuous choice econometric framework applied to a novel dataset of household survey microdata pooled across 25 countries. We also project the potential household-level implications of future cooling uptake and electricity consumption circa 2050 under multiple socioeconomic and climate change scenarios, considering a broad array of drivers at national and sub-national scales.

Our main finding is that air conditioning ownership is a leading determinant of residential electricity demand, associated with an average increase of 36% in household electricity consumption. We also shed light on the considerable variation in this response, providing insight into the mediating effects of key drivers—weather, income, education, age, and urbanization. Future shifts in income, social and demographic drivers, and co-occurring climate warming will induce large increases in air conditioning adoption and concomitant amplification of electricity consumption for cooling by 2050. This phenomenon will likely be associated with multiple underappreciated policy challenges. On the supply side, the need to expand electric power generation and transmission capacity to meet this higher demand will have important implications for infrastructure planning, growth in global GHG emissions, and potential trade-offs between mitigating, and adapting to, climate change. We provide suggestive indications that distributed solar generation could partially alleviate this trade-off through supply switching at the household level. On the demand side, we demonstrate that electricity expenditure burden of cooling is regressive, revealing current and future patterns of climate adaptation inequalities within and across regions. Although the total number of households without air conditioning will decline, leading to a general increase in heat adaptation capacity, especially in developing countries a substantial fraction of households that adopt air conditioning will be low income, and will face significant expenditure burdens to attain thermal comfort, raising the specter of "cooling poverty".

To conclude, we briefly discuss some limitations of our work that future research can address. A first caveat is that our results are based on cross-sectional estimates. While we correct for the endogeneity of air conditioning, potential omitted variable bias remains a concern, especially in our second-stage regression which is unable to fully exploit quasi-random variation in weather realization. Unfortunately little can be done to address this issue: although micro-panel data would be ideal, household expenditure surveys that record both air conditioning and energy use are almost universally cross-sectional, which constrains the data available for multi-country analysis. As additional survey waves, or new longitudinal micro datasets, become available across the world, the ability to exploit the associated temporal variation has the potential to strengthen our inference about the relative importance of climate, weather, economic, demographic and contextual influences on air conditioning adoption and utilization. Undertaking these refinements is high on our research agenda.

Second, price elasticity increases in absolute value once we correct for endogeneity, suggesting that in the baseline we are likely underestimating households' responsiveness to prices. Even though our projections hold prices constant, the value of elasticity still has implications for how changes in prices—a potential policy target—could affect future cooling electricity consumption, GHG emissions, and expenditure burden and heat adaptation differentials across households in different income groups.

Last but not least, our dataset entirely lacks information on the energy efficiency and cooling capacity of the air conditioning units owned by households. Consequently, embedded in our projections is the implicit assumption that the level of cooling technology will remain static into the future, although in the coming decades there will almost surely be technological progress in air conditioning, and differential uptake by households. A key challenge for future research is quantifying innovation in air conditioning, and implications for future patterns of adoption and utilization for cooling.

CRediT authorship contribution statement

Enrica De Cian: Writing – review & editing, Writing – original draft, Conceptualization. **Giacomo Falchetta:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Filippo Pavanello:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yasmin Romitti:** Writing – review & editing, Data curation. **Ian Sue Wing:** Writing – review & editing, Conceptualization.

Declaration of competing interest

The authors declare no known interests related to their submitted manuscript.

Appendix A

A.1. Method and data for projections

For each scenario we obtain downscaled and bias-corrected daily temperatures on a 0.25° grid simulated by global climate models (GCMs) under the Coupled Model Intercomparison Project, Phase VI experiment from the NASA Earth Exchange Global Daily Downscaled Projections, NEX-GDDP CMIP6 data set (Thrasher et al., 2022).[26] We extract daily temperature series for 14 GCMs, and use them to calculate grid cell-wise annual CDDs and HDDs for the 1995–2014 historical epoch and the 2041–2060 mid-century epoch under the two SSP scenarios. The results are then spatially aggregated to match the finest levels of geographic disaggregation in the household surveys.

To project CDDs and HDDs for each GCM, g, administrative unit, i, and climate scenario, s, we first calculate the difference between the future CDDs/HDDs in year t (2041–2060) and the historical average value for the historical period of the CMIP6 experiment (1995–2014). E.g., for CDDs:

$$\Delta_{gis} = \mathbb{E}_t \left[CDD_{gist}^{CMIP6} - \overline{CDD}_{gis}^{CMIP6} \right]$$

The resulting mean shift, or "climate delta", is then added to the ERA5 historical CDDs at the corresponding administrative unit, yielding projected future CDD and HDD exposures under different GCM-scenario combinations for each household in our survey dataset, *e.g.*:

$$\widetilde{CDD}_{gis} = CDD_i + \Delta_{gis}, \quad \widetilde{\overline{CDD}}_{gis} = \overline{CDD}_i + \Delta_{gis}$$

Future household socioeconomic and demographic characteristics are imputed based on gridded and national-scale projections. Annual per capita GDP growth rates are computed from the gridded projections of real GDP and population consistent with the SSP scenarios (Murakami et al., 2021; Gao, 2020). We extract GDP and population at finest levels of geographic disaggregation in the surveys and calculate scenario- and location-specific growth rates of GDP per capita 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. Gridded population growth rates consistent with the SSP scenarios (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, gridded projections of urbanization by SSP are used to update the urban shares (Gao and Pesaresi, 2021).

Changes in household age, gender, and education levels across SSP scenarios are computed from country-level demographic projections (Samir and Lutz, 2017). Projecting these drivers poses a challenge, especially in the case of binary and multi-level factor variables. Projected age and sex shares consistent with the SSPs were calculated and mapped directly to the corresponding survey variables. For education levels, we assumed that the level of educational attainment of each head-of-household in the sample shifts in such a way as to match the growth of the encompassing national population corresponding to each education level. For housing quality indicators, historical trends in the housing indices are extrapolated into the future for countries with multiple survey waves available and where these variables are available.

We project future air conditioning prevalence and cooling electricity consumption across countries exploiting the fitted discrete-continuous global model specification (Column 4 in Table 3). On the other hand, the country-specific models are used to conduct decomposition and density analysis of historical and projected household electricity demand, as presented in Fig. 7 and Fig. A.5. To predict future air conditioning prevalence we use the fitted first-stage regression updated with future values of climatic CDDs and HDDs, expenditure, age, education, urbanization, and housing quality (indicated below using a tilde). This procedure yields a predicted household-level probability of air conditioning, and a household is assumed to own air conditioning if the probability exceeds or is equal to 50%. To predict future cooling electricity consumption we use the second stage regression updated with future values of contemporaneous CDDs and HDDs, expenditure, age, education, urbanization, and housing quality (where available), for households that are predicted to both own and lack air conditioning. The algorithm uses Eqs. (7)–(10) as follows:

[26] NEX-GDDP CMIP6 includes data for 32 GCMs, from which we exclude "hot" models that exhibit anomalously large equilibrium climate sensitivities and transient climate responses (Hausfather et al., 2022).

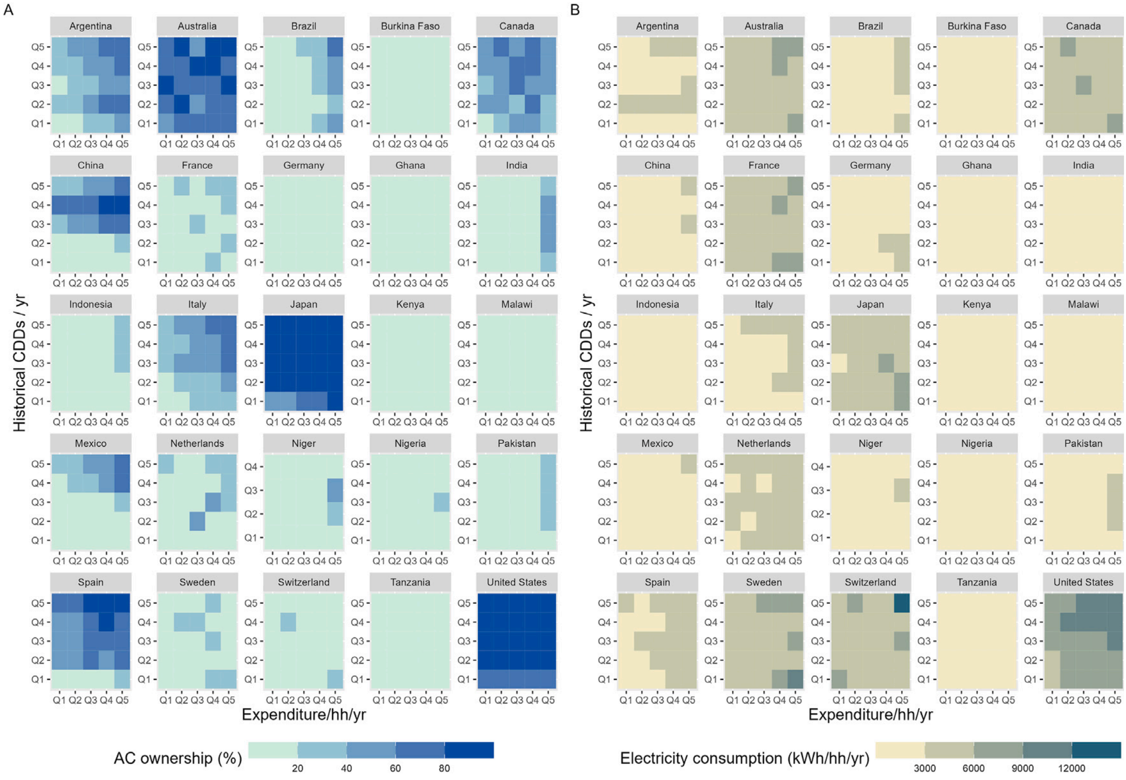

Fig. A.1. Heat maps of (A) AC ownership and (B) household electricity consumption, by country. Each facet maps the average level of the two variables at each expenditure and CDDs quintiles intersection in each country. N.B.: expenditure and CDDs quintiles are specific to each country.

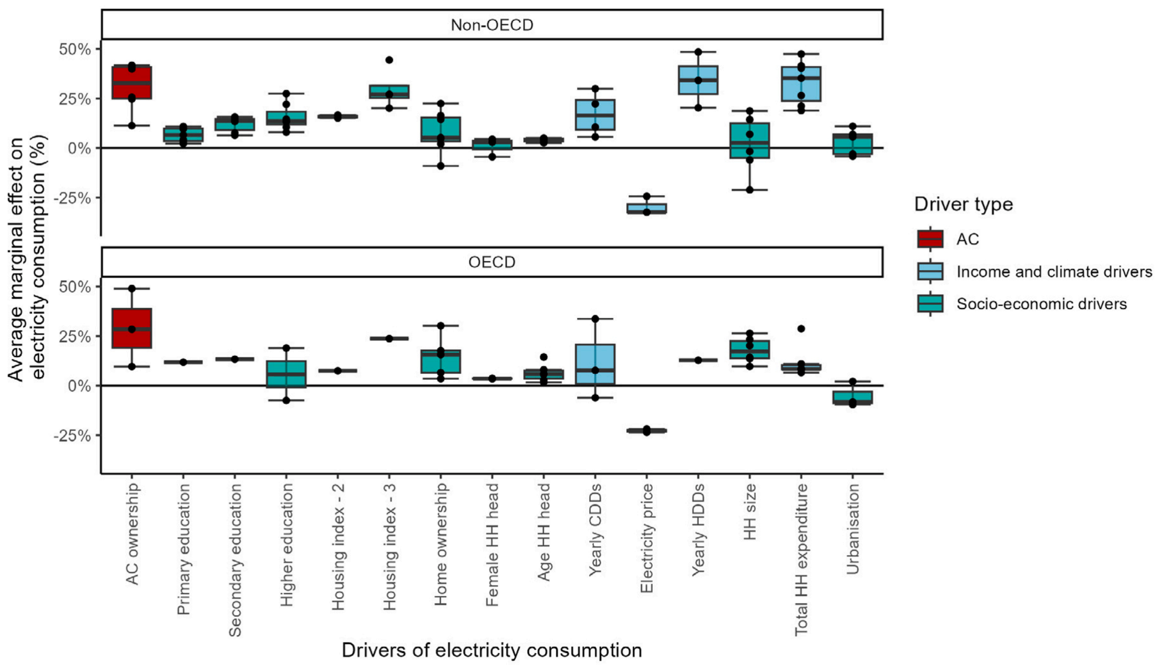

Fig. A.2. Boxplot of the marginal effects of the drivers of household electricity consumption, divided into OECD and non-OECD countries. Estimates are based on country-specific average marginal effects calculated from standardized regression coefficients.
Note: only coefficients with $p < 0.05$ are included.

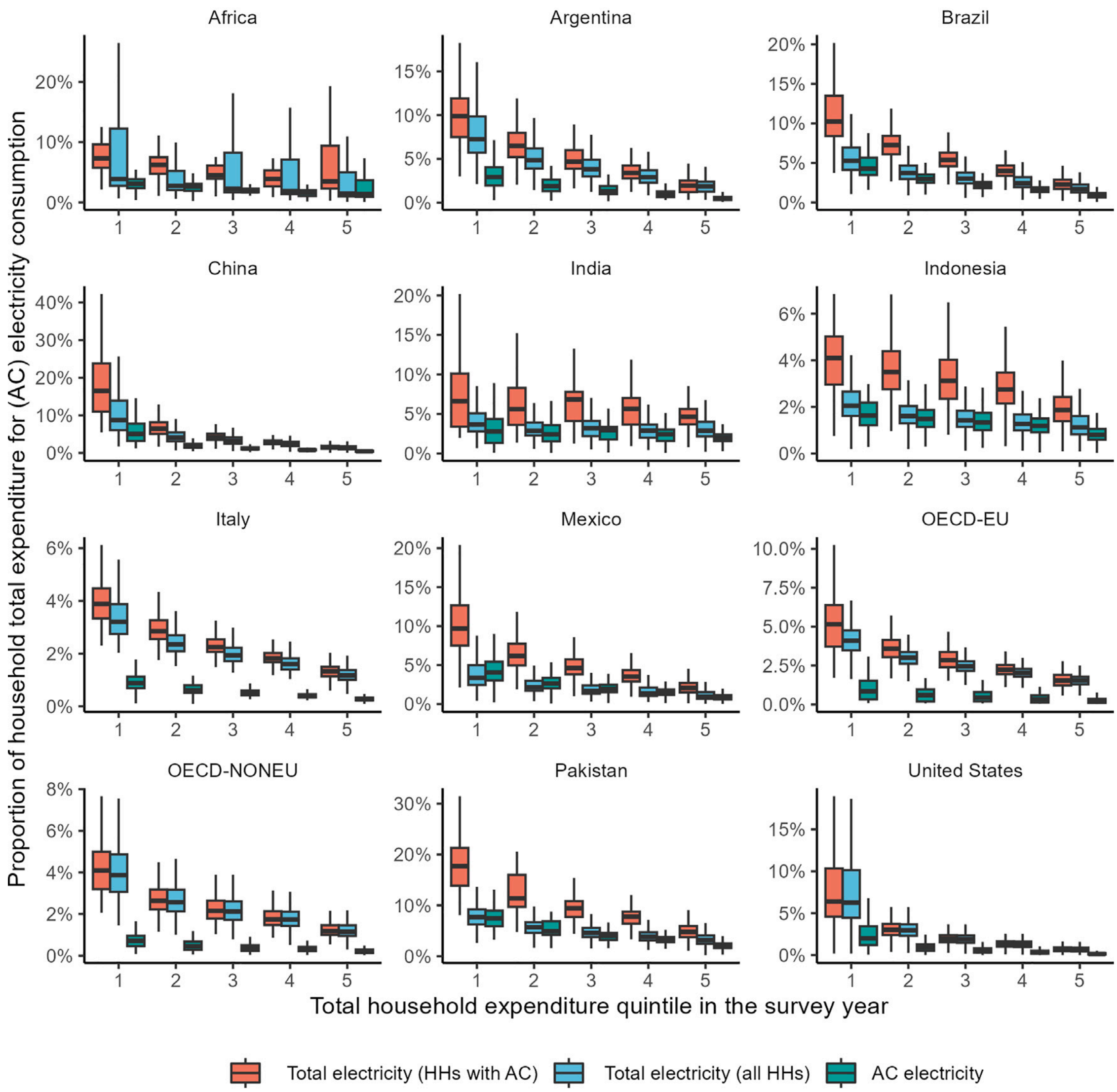

Fig. A.3. Distribution of estimated household (air conditioning) electricity consumption, stratified by quintile of total household electricity consumption in 2020.

First, we estimate the predicted probability of air conditioning ownership for a given household in a given future year and scenario based on:

$$\begin{aligned}\widetilde{\pi}_h &= \widehat{\gamma}_1 f(\widetilde{\overline{CDD}}_{i(h)}) + \widehat{\gamma}_2 \widetilde{Y}_h + \widehat{\gamma}_3 f(\widetilde{\overline{CDD}}_{i(h)}) \times \widetilde{Y}_h + \widehat{\gamma}_4 f(\widetilde{CDD}_{i(h)}) \\ &\quad + \widehat{\gamma}_5 P_h + \widehat{\gamma}_6 \widetilde{\mathbf{X}}_h + \widehat{\boldsymbol{\psi}}' \widetilde{\mathbf{Z}}_h + \widehat{\mu}_{A(h)}\end{aligned}$$

Then, we transform the predicted probability back into a binary variable of expected air conditioning ownership using a probability of 0.5 as a threshold:

$$\widetilde{AC}_h = 0 + 1 \times (\widetilde{\pi}_h \geq 0.5)$$

We also update the correction term based on the predicted probability:

$$\widetilde{\zeta}_h = \begin{cases} \frac{(1-\widetilde{\pi}_h)\ln(1-\widetilde{\pi}_h)}{\widetilde{\pi}_h} + \ln \widetilde{\pi}_h & \text{if } \widetilde{AC}_h = 1 \\ \frac{\widetilde{\pi}_h \ln \widetilde{\pi}_h}{1-\widetilde{\pi}_h} + \ln(1-\widetilde{\pi}_h) & \text{Otherwise} \end{cases}$$

We proceed estimating the quantity of electricity consumed by each given household in a given future year and scenario based on estimating two times the following equation. The first estimate is a function of the predicted, binary-transformed air conditioning

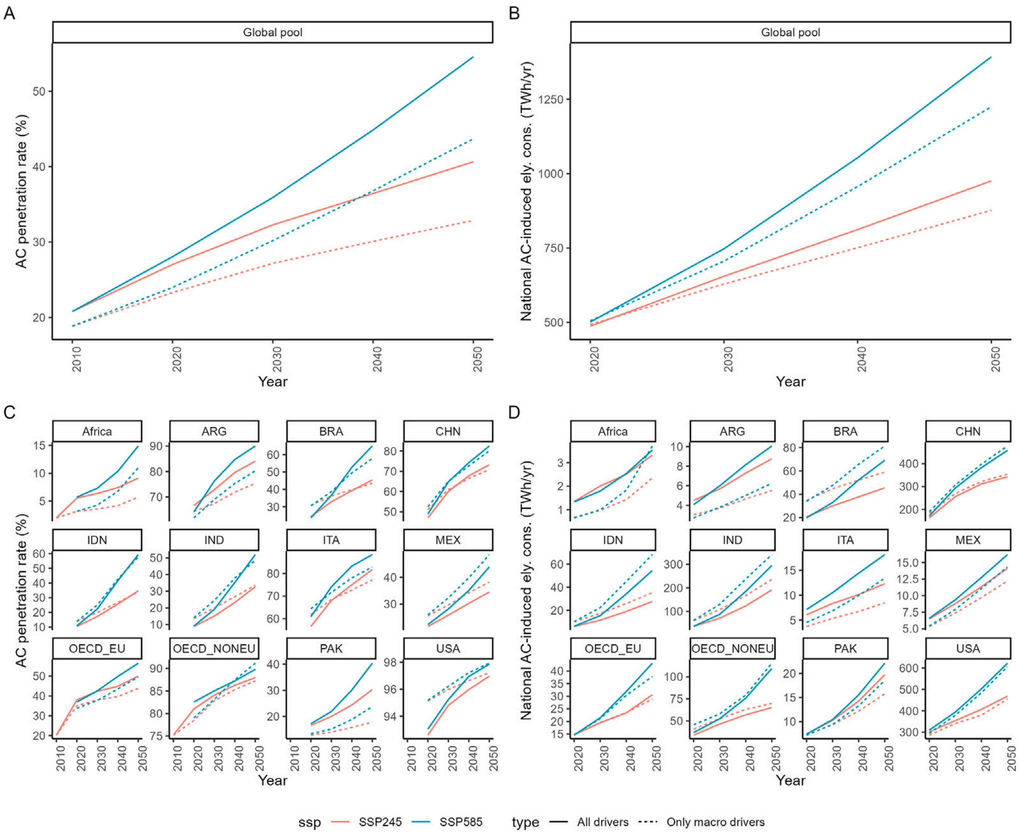

Fig. A.4. Comparison of future (A ,C) air conditioning penetration and (B, D) total electricity consumption for cooling (TWh) when projecting all drivers (bold line) or only climate and income (dashed line).

status, as well as of the other drivers, while in the second estimate an assumption of no AC ownership is imposed:

$$\widetilde{Q}_h = \widehat{\beta}_1 \widetilde{AC}_h + \widehat{\beta}_2 \widetilde{AC}_h \times f(\widetilde{CDD}_{i(h)}) + \widehat{\beta}_3 f(\widetilde{CDD}_{i(h)}) \\ + \widehat{\beta}_4 \widetilde{Y}_h + \widehat{\beta}_5 P_h + \widehat{\chi}' \widetilde{\mathbf{Z}}_h + \widehat{\lambda} \widetilde{\zeta}_h + \widehat{\nu}_{\mathcal{A}(h)}$$

Hence, we conclude subtracting the two conditional predictions, after taking their exponential, to obtain the estimated quantity of electricity consumed for air conditioning:

$$\widetilde{Q}^{AC}_{h(\widetilde{AC}_h=1)} = \exp(\widetilde{Q}_{h(\widetilde{AC}_h=1)} | \widetilde{AC} = 1) - \exp(\widetilde{Q}_{h(\widetilde{AC}_h=1)} | \widetilde{AC} = 0)$$

To scale up household-level results to national and global cooling electricity consumption projections, household weights, W_h, which ensure that each survey is representative of the population of its encompassing country, also updated for future periods and scenarios. Each weight is scaled according to the 2020–2050 rate of change of the population, Γ_{is}, in the most disaggregated administrative unit in which the household resides:

$$\widetilde{W}_h = W_h \times (1 + \Gamma_{i(h)s})$$

This approach has the important drawback that it does not consider potential changes in the joint distribution of households' socio-economic characteristics. In particular, we do not predict how a given household's characteristics could shift, causing it to change the type of households it might represent in the future. We only project whether it might represent a larger or smaller number of the type of households that it currently represents.

A.2. Additional tables and figures

See Table A.1 to Table A.15, and Fig. A.1 to A.6.

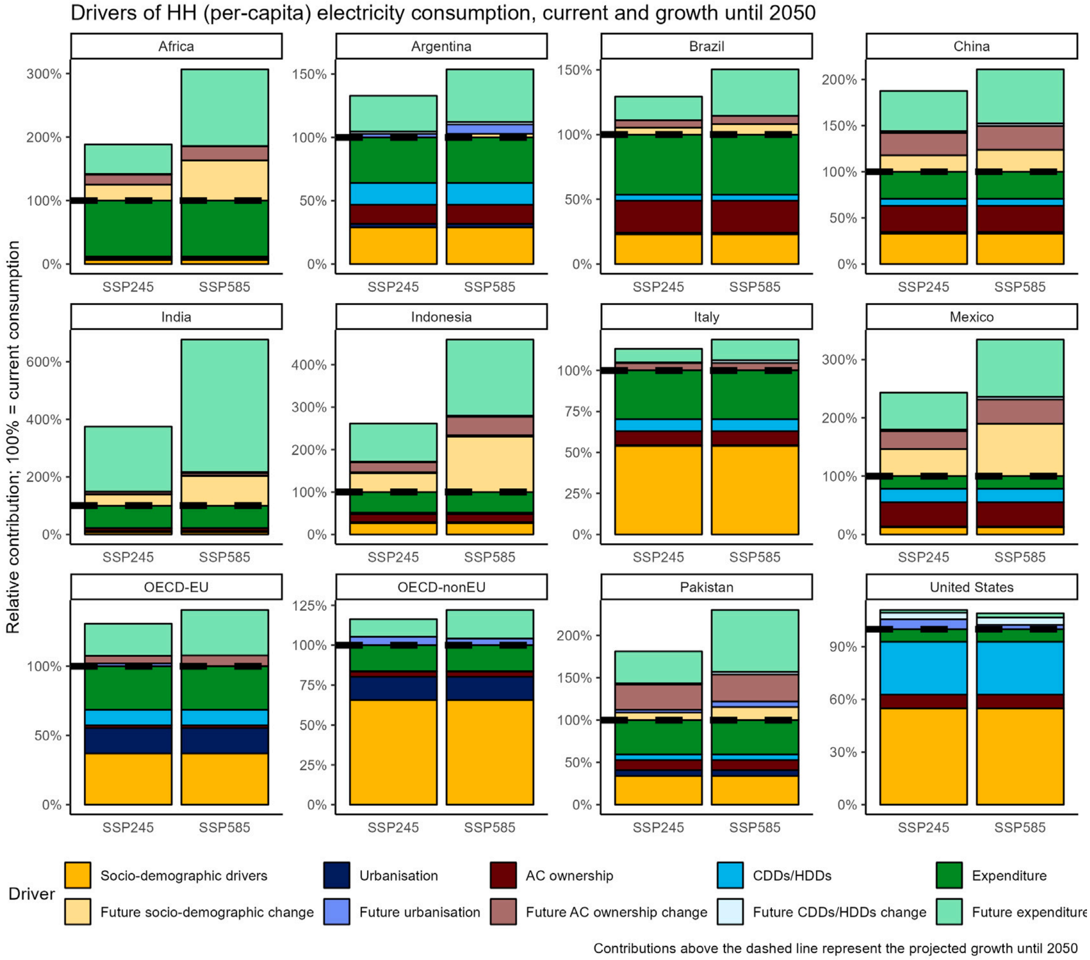

Fig. A.5. Decomposition analysis of average (per household) historical and future electricity demand. Facets group countries and regions. Each facet shows to socio-economic/climate change scenario combination (SSPs). Colors describe the determinants of current (up to 100%) and future projected (above 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.

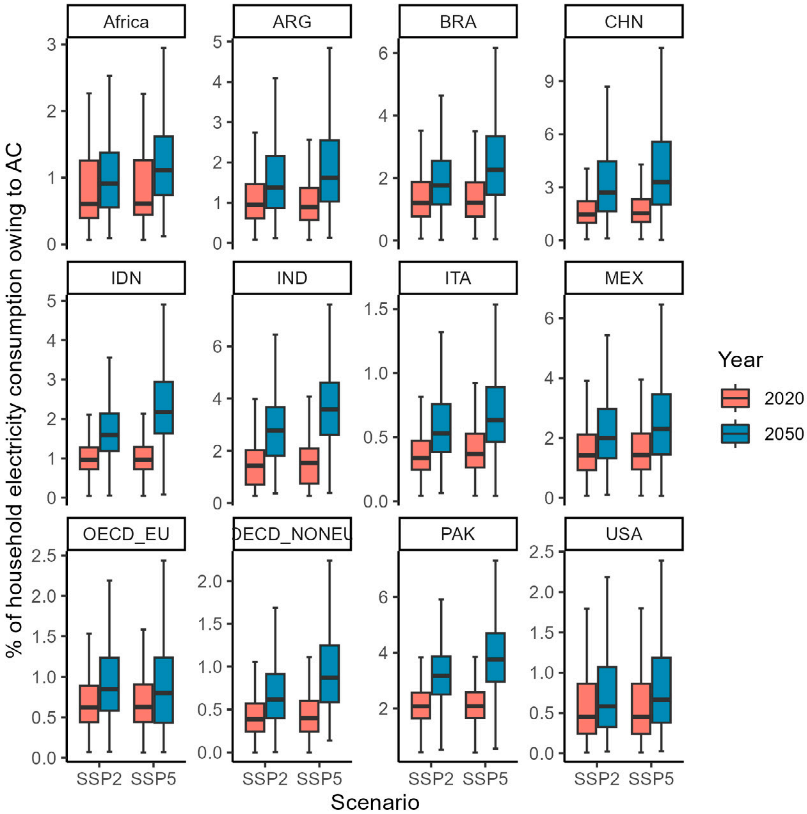

Fig. A.6. Ceteris paribus analysis of the change in the proportion of households' expenditure for air conditioning electricity as a share of total expenditure, by country/region and scenario.

Table A.1
The effect of air-conditioning on residential electricity consumption — Full Table.

	OLS (1)	OLS (2)	DMF (3)	DMF (4)
AC	0.597***	0.377***	0.361***	0.028
	(0.032)	(0.029)	(0.031)	(0.062)
AC × CDD				0.038***
				(0.010)
AC × CDD^2				−0.001**
				(0.000)
CDD		0.055***	0.054***	0.046***
		(0.013)	(0.013)	(0.013)
CDD^2		−0.001***	−0.001***	−0.001**
		(0.000)	(0.000)	(0.000)
HDD		0.029**	0.029**	0.027*
		(0.014)	(0.014)	(0.014)
HDD^2		−0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)
Log(Exp)		0.322***	0.322***	0.320***
		(0.028)	(0.028)	(0.029)
Log(P)		−0.387***	−0.392***	−0.405***
		(0.039)	(0.040)	(0.040)
Urbanization (%)		0.168	0.163	0.109
		(0.238)	(0.235)	(0.231)
House Ownership (Yes = 1)		0.049***	0.049***	0.053***
		(0.014)	(0.014)	(0.014)
Household Size		0.036***	0.036***	0.037***
		(0.013)	(0.013)	(0.013)
Primary Edu.		0.104***	0.101***	0.097***
		(0.014)	(0.014)	(0.014)
Secondary Edu.		0.160***	0.156***	0.149***
		(0.019)	(0.019)	(0.019)
Post Edu.		0.159***	0.154***	0.136***
		(0.024)	(0.024)	(0.024)
Age (Head)		0.002***	0.002***	0.002***
		(0.001)	(0.001)	(0.001)
Female (Yes = 1)		0.008	0.008	0.009
		(0.008)	(0.008)	(0.008)
$\hat{\zeta}$			−0.025**	−0.016*
			(0.010)	(0.009)
ADM-1 FE	YES	YES	YES	YES
R^2	0.670	0.729	0.729	0.731
Mean Outcome (kWh)	2495.943	2495.943	2495.943	2495.943
Countries	25	25	25	25
Observations	682 727	682 727	682 727	682 727

Notes: Dependent variable: logarithm of electricity consumption (kWh). For DMF Columns the first stage is shown in Table A.2 Columns 3–4. Regressions are conducted using survey weights. Standard errors are clustered at the ADM1 level; $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table A.2
Logit regression for air-conditioning ownership.

	LPM		Logit	
			Coefficients	M. Effects
	(1)	(2)	(3)	(4)
$\overline{\text{CDD}}$	0.059*	−0.040	0.818*	0.073
	(0.033)	(0.035)	(0.449)	(0.056)
$\overline{\text{CDD}}^2$	−0.001	0.002**	−0.021**	−0.002
	(0.001)	(0.001)	(0.010)	(0.001)
$\overline{\text{CDD}}$ × Log(Exp)		0.010***	0.020	0.002
		(0.002)	(0.024)	(0.002)
$\overline{\text{CDD}}^2$ × Log(Exp)		−0.000***	0.001	0.000
		(0.000)	(0.001)	(0.000)
CDD	−0.006	−0.009	−0.249	−0.022
	(0.028)	(0.028)	(0.321)	(0.030)
CDD^2	−0.000	−0.000	−0.003	−0.000
	(0.000)	(0.000)	(0.005)	(0.001)
HDD	0.014***	0.014***	0.185***	0.017*
	(0.005)	(0.005)	(0.059)	(0.001)
HDD^2	−0.000**	−0.000***	−0.002***	−0.000*
	(0.000)	(0.000)	(0.001)	(0.000)
$\overline{\text{CDD}}$ × Log(P)	0.008**	0.005	0.134***	0.012**
	(0.003)	(0.003)	(0.032)	(0.005)
$\overline{\text{CDD}}^2$ × Log(P)	−0.000*	−0.000	−0.003***	−0.000**
	(0.000)	(0.000)	(0.001)	(0.000)
Log(Exp)	0.077***	0.006	0.354***	0.032
	(0.008)	(0.014)	(0.132)	(0.021)
Log(P)	−0.023	−0.012	−0.077	−0.007
	(0.037)	(0.037)	(0.293)	(0.027)
Log(P) × Household Size	−0.008***	−0.009***	−0.127***	−0.011**
	(0.003)	(0.003)	(0.042)	(0.005)
Log(P) × House Ownership	0.022**	0.020*	0.113	0.010
	(0.010)	(0.011)	(0.102)	(0.009)
Urbanization (%)	0.186***	0.181***	1.668***	0.150**
	(0.067)	(0.063)	(0.483)	(0.071)
House Ownership (Yes = 1)	0.074***	0.074***	0.604***	0.052**
	(0.014)	(0.015)	(0.144)	(0.020)
Household Size	−0.017***	−0.018***	−0.264***	−0.024**
	(0.004)	(0.005)	(0.072)	(0.010)
Primary Edu.	0.043***	0.041***	0.680***	0.057**
	(0.008)	(0.008)	(0.076)	(0.025)
Secondary Edu.	0.105***	0.102***	1.156***	0.100***
	(0.012)	(0.012)	(0.104)	(0.039)
Post Edu.	0.177***	0.175***	1.836***	0.180***
	(0.014)	(0.014)	(0.127)	(0.056)
Age (Head)	0.001***	0.001***	0.010***	0.001**
	(0.000)	(0.000)	(0.002)	(0.000)
Female (Yes = 1)	−0.003	−0.003	−0.116***	−0.010**
	(0.004)	(0.004)	(0.037)	(0.005)
ADM-1 FE	YES	YES	YES	YES
Mean Outcome	0.263	0.263	0.263	0.263
Countries	25	25	25	25
Observations	692 718	692 718	682 727	682 727

Notes: Dependent variable is air-conditioning (0,1). Column (4) shows the average marginal effects (AMEs) from the logit regression. Regressions are conducted using survey weights. Standard errors are clustered at the ADM1 level; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.3
Robustness checks.

	Subnational FE		Country FE		CDD 24 - HDD 15		No Electricity Price		Price Interactions	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AC	0.315***	0.008	0.335***	0.026	0.362***	0.165***	0.358***	0.033	0.358***	0.061
	(0.024)	(0.040)	(0.033)	(0.063)	(0.031)	(0.037)	(0.032)	(0.062)	(0.029)	(0.062)
AC × CDD		0.038***		0.038***		0.086***		0.039***		0.034***
		(0.007)		(0.010)		(0.019)		(0.010)		(0.010)
AC × CDD^2		−0.001***		−0.001**		−0.004***		−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	YES	YES	NO	NO	NO	NO	NO	NO
Sub-national FE	YES	YES	NO	NO	NO	NO	NO	NO	NO	NO
ADM-1 FE	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES
R^2	0.728	0.729	0.723	0.756	0.730	0.731	0.726	0.728	0.733	0.734
Mean Outcome (kWh)	2695.744	2695.744	2439.238	2439.238	2495.943	2495.943	2495.943	2495.943	2495.943	2495.943
Countries	25	25	25	25	25	25	25	25	25	25
Observations	639 793	639 793	692 718	692 718	682 727	682 727	682 727	682 727	682 727	682 727
	Squared Correction		Interaction		Winsorized Sample		Trimmed Sample		Unweighted	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
AC	0.358***	0.024	0.348***	0.015	0.435***	−0.030	0.343***	0.011	0.367***	−0.031
	(0.032)	(0.063)	(0.034)	(0.061)	(0.034)	(0.072)	(0.029)	(0.059)	(0.026)	(0.057)
AC × CDD		0.039***		0.042***		0.059***		0.040***		0.034***
		(0.010)		(0.010)		(0.012)		(0.009)		(0.007)
AC × CDD^2		−0.001***		−0.001***		−0.001***		−0.001***		−0.001***
		(0.000)		(0.000)		(0.000)		(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
ADM-1 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 × f(CDD)	NO	NO	YES	YES	NO	NO	NO	NO	NO	NO
R^2	0.730	0.731	0.730	0.731	0.672	0.675	0.596	0.598	0.729	0.731
Mean Outcome (kWh)	2495.943	2495.943	2495.943	2495.943	2277.863	2277.863	2123.612	2123.612	2495.943	2495.943
Countries	25	25	25	25	25	25	25	25	25	25
Observations	682 727	682 727	682 727	682 727	682 727	682 727	616 531	616 531	682 727	682 727

Notes: Dependent variable: logarithm of electricity consumption (kWh). ”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. Regressions (1)–(20) are conducted using survey weights. Standard errors are clustered at the first sub-national (ADM1) level in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.4
Instrumenting electricity prices.

	DMF	2SLS	2SLS
	(1)	(2)	(3)
AC	0.339***	0.336***	0.338***
	(0.040)	(0.040)	(0.040)
Log(P)	−0.530***	−0.638***	−0.557***
	(0.069)	(0.108)	(0.084)
Controls	YES	YES	YES
Correction Term	YES	YES	YES
Instruments		Country	ADM-1
Kleibergen-Paap Wald F test		86 693.923	322.667
R^2	0.627	0.626	0.627
Mean Outcome	2439.238	2439.238	2439.238
Countries	25	25	25
Observations	692 718	692 718	692 718

Notes: Dependent variable: logarithm of electricity consumption (kWh). “Controls” include weather and socio-economic and demographic variables. Regressions are conducted using survey weights. Standard errors are clustered at the ADM1 level; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.5
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	−0.043	0.102	0.248***	−0.045	0.128*
	(0.091)	(0.082)	(0.079)	(0.121)	(0.071)
AC × CDD	0.075***	0.042***	0.004	0.050***	0.028***
	(0.015)	(0.013)	(0.012)	(0.017)	(0.010)
AC × 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
ADM-1 FE	YES	YES	YES	YES	YES
R^2	0.664	0.627	0.696	0.656	0.674
Mean Outcome	1711.097	2076.010	2533.789	2925.536	3755.844
Countries	22	25	24	25	25
Observations	123 449	131 311	131 715	132 250	134 060

Notes: Dependent variable: logarithm of electricity consumption (kWh). "Controls" include natural logarithm of electricity price, and weather and socio-economic and demographic variables. Regressions are conducted using survey weights. Standard errors are clustered at the ADM1 level; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.6
Air conditioning and refrigerators electricity use.

	DMF (1)	DMF (2)	DMF (3)	DMF (4)	DMF (5)	DMF (6)
AC	0.369***	0.339***	0.044	0.339***	0.337***	0.049
	(0.033)	(0.027)	(0.069)	(0.027)	(0.026)	(0.068)
AC × CDD			0.032***			0.030***
			(0.010)			(0.010)
AC × CDD^2			−0.001**			−0.000*
			(0.000)			(0.000)
Refrigerator		0.370***	0.370***	0.385***	0.320***	0.366***
		(0.030)	(0.029)	(0.060)	(0.082)	(0.079)
Refrigerator × CDD				−0.001	0.009	0.006
				(0.002)	(0.009)	(0.009)
Refrigerator × CDD^2					−0.000	−0.000
					(0.000)	(0.000)
Correction Term (AC)	YES	YES	YES	YES	YES	YES
Correction Term (Refrigerator)	NO	YES	YES	YES	YES	YES
ADM-1 FE	YES	YES	YES	YES	YES	YES
R^2	0.726	0.737	0.738	0.737	0.737	0.739
Mean Outcome	2378.582	2378.582	2378.582	2378.582	2378.582	2378.582
Countries	24	24	24	24	24	24
Observations	669 551	669 551	669 551	669 551	669 551	669 551

Notes: Dependent variable: logarithm of electricity consumption (kWh). "Controls" include natural logarithm of electricity price, weather and socio-economic and demographic variables. Regressions are conducted using survey weights. Standard errors are clustered at the ADM1 level; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jeem.2025.103122.

Data availability

Replication code is available at the following Github repository: https://github.com/FPavanello/acglobal.

Table A.7
Air conditioning and television electricity use.

	DMF (1)	DMF (2)	DMF (3)	DMF (4)	DMF (5)	DMF (6)
AC	0.365***	0.358***	0.053	0.359***	0.359***	0.055
	(0.035)	(0.034)	(0.085)	(0.034)	(0.034)	(0.085)
AC × CDD			0.033**			0.033***
			(0.013)			(0.013)
AC × CDD^2			−0.001*			−0.001*
			(0.000)			(0.000)
TV		0.243***	0.238***	0.146**	0.170*	0.191*
		(0.030)	(0.030)	(0.056)	(0.100)	(0.100)
TV × CDD				0.005*	0.001	−0.001
				(0.003)	(0.012)	(0.012)
TV × CDD^2					0.000	0.000
					(0.000)	(0.000)
Correction Term (AC)	YES	YES	YES	YES	YES	YES
Correction Term (TV)	NO	YES	YES	YES	YES	YES
ADM-1 FE	YES	YES	YES	YES	YES	YES
R^2	0.676	0.679	0.680	0.679	0.679	0.680
Mean Outcome	1767.430	1767.430	1767.430	1767.430	1767.430	1767.430
Countries	23	23	23	23	23	23
Observations	586 153	586 153	586 153	586 153	586 153	586 153

Notes: Dependent variable: logarithm of electricity consumption (kWh). "Controls" include natural logarithm of electricity price, weather and socio-economic and demographic variables. Regressions are conducted using survey weights. Standard errors are clustered at the ADM1 level; $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table A.8
Air conditioning and PC electricity use.

	DMF (1)	DMF (2)	DMF (3)	DMF (4)	DMF (5)	DMF (6)
AC	0.412***	0.352***	0.011	0.350***	0.351***	0.004
	(0.036)	(0.030)	(0.102)	(0.030)	(0.029)	(0.099)
AC × CDD			0.038***			0.038***
			(0.014)			(0.014)
AC × CDD^2			−0.001			−0.001
			(0.000)			(0.000)
PC		0.257***	0.254***	0.221***	0.230***	0.277***
		(0.018)	(0.017)	(0.034)	(0.054)	(0.046)
PC × CDD				0.003	0.002	−0.003
				(0.002)	(0.008)	(0.007)
PC × CDD^2					0.000	0.000
					(0.000)	(0.000)
Correction Term (AC)	YES	YES	YES	YES	YES	YES
Correction Term (PC)	NO	YES	YES	YES	YES	YES
ADM-1 FE	YES	YES	YES	YES	YES	YES
R^2	0.697	0.706	0.708	0.706	0.706	0.708
Mean Outcome	1936.902	1936.902	1936.902	1936.902	1936.902	1936.902
Countries	19	19	19	19	19	19
Observations	384 391	384 391	384 391	384 391	384 391	384 391

Notes: Dependent variable: logarithm of electricity consumption (kWh). "Controls" include natural logarithm of electricity price, weather and socio-economic and demographic variables. Regressions are conducted using survey weights. Standard errors are clustered at the ADM1 level; $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table A.9
Air conditioning and washing machine electricity use.

	DMF (1)	DMF (2)	DMF (3)	DMF (4)	DMF (5)	DMF (6)
AC	0.356***	0.311***	0.034	0.311***	0.309***	0.044
	(0.033)	(0.029)	(0.062)	(0.029)	(0.029)	(0.062)
AC × CDD			0.035***			0.033***
			(0.010)			(0.010)
AC × CDD^2			−0.001**			−0.001**
			(0.000)			(0.000)
Washing Machine		0.273***	0.266***	0.241***	0.198***	0.231***
		(0.024)	(0.024)	(0.040)	(0.044)	(0.042)
Washing Machine × CDD				0.002	0.010*	0.006
				(0.002)	(0.006)	(0.005)
Washing Machine × CDD^2					−0.000	−0.000
					(0.000)	(0.000)
Correction Term (AC)	YES	YES	YES	YES	YES	YES
Correction Term (Washing M.)	NO	YES	YES	YES	YES	YES
ADM-1 FE	YES	YES	YES	YES	YES	YES
R^2	0.694	0.702	0.703	0.702	0.702	0.703
Mean Outcome	2651.020	2651.020	2651.020	2651.020	2651.020	2651.020
Countries	21	21	21	21	21	21
Observations	443 388	443 388	443 388	443 388	443 388	443 388

Notes: Dependent variable: logarithm of electricity consumption (kWh). "Controls" include natural logarithm of electricity price, weather and socio-economic and demographic variables. Regressions are conducted using survey weights. Standard errors are clustered at the ADM1 level; *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Table A.10
Evolution of air-conditioning adoption and utilization drivers used for household-level projections, by country/region.

Country	Scenario	CDD	HDD	Expenditure	Age	Edu	Housing index	Urban
		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

Notes: Values are population weighted.

Table A.11
The role of solar power generation — PV potential output.

	DMF (1)	DMF (2)	DMF (3)
AC	0.361***	0.552***	0.361***
	(0.031)	(0.186)	(0.031)
PVOUT	−0.207**	−0.195*	−0.140
	(0.099)	(0.101)	(0.179)
AC × PVOUT		−0.051	
		(0.047)	
Log(P)	−0.386***	−0.385***	−0.549*
	(0.039)	(0.039)	(0.315)
Log(P) × PVOUT			0.041
			(0.081)
Controls	YES	YES	YES
Correction Term	YES	YES	YES
ADM-1 FE	YES	YES	YES
R^2	0.730	0.730	0.730
Mean Outcome	2495.943	2495.943	2495.943
Countries	25	25	25
Observations	682 727	682 727	682 727

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

Table A.12
The role of solar power generation — PV capacity.

	DMF (1)	DMF (2)	DMF (3)
AC	0.361***	0.401***	0.361***
	(0.031)	(0.043)	(0.031)
asinh(PV Capacity)	−0.008	−0.007	−0.042*
	(0.008)	(0.008)	(0.024)
AC × asinh(PV Capacity)		−0.008	
		(0.008)	
Log(P)	−0.393***	−0.395***	−0.369***
	(0.040)	(0.040)	(0.038)
Log(P) × asinh(PV Capacity)			−0.018*
			(0.010)
Controls	YES	YES	YES
Correction Term	YES	YES	YES
ADM-1 FE	YES	YES	YES
R^2	0.730	0.730	0.730
Mean Outcome	2495.943	2495.943	2495.943
Countries	25	25	25
Observations	682 727	682 727	682 727

Notes: Dependent variable: logarithm of electricity consumption (kWh). "Controls" include natural logarithm of electricity price, weather and socio-economic and demographic variables. Regressions are conducted using survey weights. Standard errors are clustered at the ADM1 level; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.13
The role of solar power generation — PV Generation.

	DMF (1)	DMF (2)	DMF (3)
AC	0.361***	0.412***	0.361***
	(0.031)	(0.046)	(0.031)
asinh(PV Generation)	−0.005	−0.004	−0.030
	(0.006)	(0.006)	(0.018)
AC × asinh(PV Generation)		−0.009	
		(0.007)	
Log(P)	−0.393***	−0.395***	−0.370***
	(0.040)	(0.040)	(0.037)
Log(P) × asinh(PV Generation)			−0.013*
			(0.007)
Controls	YES	YES	YES
Correction Term	YES	YES	YES
ADM-1 FE	YES	YES	YES
R^2	0.730	0.730	0.730
Mean Outcome	2495.943	2495.943	2495.943
Countries	25	25	25
Observations	682 727	682 727	682 727

Notes: Dependent variable: logarithm of electricity consumption (kWh). "Controls" include natural logarithm of electricity price, weather and socio-economic and demographic variables. Regressions are conducted using survey weights. Standard errors are clustered at the ADM1 level; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.14
Air conditioning ownership and PV generation.

	Logit (1)	Logit (2)
asinh(PV Generation)	0.031	
	(0.025)	
𝟙(PV Gen. > Median)		0.388***
		(0.119)
Controls	YES	YES
ADM-1 FE	YES	YES
Mean Outcome	0.263	0.263
Countries	25	25
Observations	682 727	682 727

Notes: Dependent variable is air conditioning (0,1). "Controls" include natural logarithm of electricity price, weather and socio-economic and demographic variables. Regressions are conducted using survey weights. Standard errors are clustered at the ADM1 level; $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.15
CO_2 emissions from air-conditioning electricity use.

Country	2020	SSP2-4.5 (2050)	SSP5-8.5 (2050)
	Mean	Mean	Mean
Pooled	339.40	669.70	955.80
Africa	1.30	2.40	2.60
Argentina	1.90	4.50	5.20
Brazil	9.10	23.40	35.60
China	136.60	252.80	289.20
Indonesia	4.80	13.30	26.20
India	31.80	133.30	205.40
Italy	3.30	7.30	10.70
Mexico	3.10	5.90	6.70
OECD-EU	7.40	18.10	25.40
OECD-NonEU	17.90	32.80	55.10
Pakistan	6.50	13.70	15.40
United States	178.70	234.00	310.70

Notes: Values are in $MtCO_2$.

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