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The Global Consequences of Climate Change and Appliance Adoption for Peak Electricity Demand

Maren Ludwig and Stephen Jarvis*

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Abstract

Economic development, rising temperatures, and decarbonisation policy will have profound implications for electricity systems worldwide. Using data on appliance ownership and hourly electricity demand for a large, diverse set of countries, we provide new global evidence on how temperature affects electricity demand. Combining our estimates with climate and development projections, we show that the adoption and use of both air conditioning and electric heating will increase average per capita electricity demand in all regions by mid-century, with peak demand during periods of extreme heat or cold rising nearly twice as much. Global annual electricity grid costs increase by over $0.3 trillion per year in 2050, with the largest burden falling on low- and middle-income countries. Our findings underscore the growing importance of appliance adoption and climate change in electricity system planning.

JEL Codes: Q40, L94, O44

Keywords: Electricity Demand, Temperature, Climate Change, Development

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1 Introduction

Exposure to temperature extremes can have profound implications for human health (Barreca et al., 2016; Burgess et al., 2017; Carleton et al., 2022), educational outcomes (Park et al., 2020; Park, Behrer and Goodman, 2020), economic productivity (Heal and Park, 2016; Dasgupta et al., 2024), and broader well-being (Baylis, 2020). Air conditioning is a key technology for mitigating the harmful effects of extreme heat, while heat pumps and other electric heating appliances are increasingly replacing fossil fuels in protecting people from cold temperatures. Electricity is therefore central to meeting critical cooling and heating needs.

Long-term storage of electricity remains prohibitively costly, so to ensure power supply can reliably meet demand the capacity of the grid must be sized not to average consumption over the year, but to the highest demand hours. These peak periods usually occur when demand for space cooling or heating is greatest (Castillo et al., 2022), meaning electricity systems must be built for the hottest and coldest days of the year. Failing to meet electricity demand during these periods can have severe adverse consequences (Gorman, 2022; Stone et al., 2023; Ghodeswar, Bhandari and Hedman, 2025; Gonzales, Ito and Reguant, 2026). Economic development, warmer temperatures due to climate change, and increasing electrification driven by decarbonisation policy, will likely change adoption and use of air conditioning and electric heating. Yet how these factors combine to reshape electricity demand for cooling and heating, and what that implies for grids worldwide, remains poorly understood

In this paper, we estimate the global impact of changes in electric heating and cooling demand on the electricity grid, and identify the relative importance of income growth, climate change, and electrification of heating systems in driving this change. To do so, we construct a high-frequency dataset of electric load spanning over three hundred distinct geographic areas across seventy countries, covering approximately 50% of the global population and 70% of global GDP. We combine this with gridded daily temperature data and annual region-specific estimates of air conditioning and electric heating adoption. Using these data, we estimate how electricity demand responds to temperature and, crucially, how that response depends on the local prevalence of air conditioning and electric heating. We then pair these response functions with mid-century climate and socioeconomic projections to estimate changes in both average and peak electricity demand, and decompose those changes into the contributions of income growth, climate change, and heating electrification.

Four key findings stand out. First, global per capita electricity demand for heating and cooling is projected to increase substantially (13%) by mid-century. Second, projected increases in peak demand (24%) are roughly double those for average demand, indicating that average consumption impacts understate the grid capacity investments that climate change adaptation and mitigation will require. Third, what drives demand growth is strongly heterogeneous across regions: income-driven air-conditioning uptake dominates in hot, fast-growing economies; warming-driven utilization of existing cooling stock dominates in already-wealthy warm regions; and heating electrification dominates in cold regions, where it offsets and generally reverses the reductions that milder winters alone would bring. Lastly, it is the combination of climate change, rising incomes, and electrification, not any single driver, that explains why electric heating and cooling demand is projected to rise globally. In almost all contexts this yields net increases in both average and peak demand, with some regions seeing modest rises while others will experience large new demands on their electricity systems.

We find that the global cost of meeting this additional demand exceeds \$0.3 trillion USD per year by mid-century under a moderate emissions scenario. Most of this reflects the expense of meeting higher average electricity demand, but at least a tenth stems from investments in spare capacity to meet demand peaks. Just as the demand effects are heterogeneous, cost impacts are also unevenly shared. China and India alone account for nearly half of the global total. Measured relative to local GDP, the burden falls disproportionately on low- and middle-income countries, which therefore face the largest challenge in ensuring their grids can meet rapidly rising cooling and heating needs.

Our paper contributes to a large body of work on the relationship between temperature and electricity demand. Structural approaches have long been used to forecast electricity demand, often through bottom up modeling of underlying drivers like space heating and cooling (Jaglom et al., 2014; White et al., 2021; Castillo et al., 2022; Peacock, Fragaki and Matuszewski, 2023). Energy demand modeling of this sort underpins projections made by major governmental and international organizations (IEA, 2018, 2025; EIA, 2026). This work is increasingly complemented by empirical research using data on observed temperatures and energy consumption (Deschênes and Greenstone, 2011), with a growing focus on high-frequency daily or hourly data (Franco and Sanstad, 2008; Wenz, Levermann and Auffhammer, 2017; Auffhammer, Baylis and Hausman, 2017; Rivers and Shaffer, 2020; Colelli, Wing and De Cian, 2023; Bernard et al., 2024). However, this prior work has largely been confined to high-income settings in North America and Europe. How far these empirical findings carry over to low- and middle-income countries, where the vast majority of future electricity demand growth will occur, has been unclear. We draw on extensive data covering hourly electricity demand in countries spanning a wide range of incomes to shed new light on this question.

The closest papers to ours with a global scope are Rode et al. (2021) and De Cian et al. (2025). The former studies the effect of climate change on average annual country-level energy demand for both electricity and other fuels. The latter examines future residential air conditioning adoption and utilization, drawing on household-level survey data across twenty-five countries. Unlike this prior work, we use a combination of data on hourly electricity demand and household appliance adoption, which enables us to identify changes in peak demand due to the adoption and utilization of both air conditioning and electric heating at a global scale. We find peak effects almost twice as large as the average increase, and it is peak demand, not average consumption, that determines how much capacity must be built and maintained. Furthermore, while we find broadly similar changes in average electricity demand to other studies that examine the partial effect of climate change and focus primarily on air conditioning, we also show that any apparent demand reductions in colder regions due to warmer temperatures are more than offset by demand increases from electrified heating replacing fossil fuels. This margin of adjustment has not previously been studied empirically in an integrated manner, despite being heavily driven by climate policy.

When projecting future changes in electric heating and cooling demand, prior work has generally held the historical electricity–temperature relationship fixed (Wenz, Levermann and Auffhammer, 2017; Auffhammer, Baylis and Hausman, 2017), simulating climate change against today's technology and behavior, or let the relationship evolve with income growth and baseline climate (Rode et al., 2021; Auffhammer, 2022). However, our work emphasizes how income and climate are coarse proxies for the current and future appliance stock that actually mediates the response. Others have accounted for appliance adoption more directly, using data on air conditioning (Rapson, 2014; Davis and Gertler, 2015; Colelli, Wing and De Cian, 2023; De Cian et al., 2025), electric heating (White et al., 2021; Peacock, Fragaki and Matuszewski, 2023), or both (Rivers and Shaffer, 2020). Our work extends this latter approach to explicitly incorporate both the extensive and intensive margins for heating and cooling appliances, and does so to examine mid-century projections at a global scale.

Lastly, our work contributes to the literature on the adoption of durable goods. Several empirical studies have documented how rising incomes lead to a familiar 'S'-shaped adoption curve for long-lived energy-using assets such as cars (Dargay, Gately and Sommer, 2007; Busse, Knittel and Zettelmeyer, 2013), air conditioners (Gertler et al., 2016; Davis et al., 2021), and electric heating (Davis, 2021). We contribute by building directly on the approach developed by Davis et al. (2021), expanding to make global estimates of appliance adoption using newly assembled data on the uptake of air conditioning and electric heating covering the significant majority of the global population.[1] We also incorporate recent insights from (Davis and Gertler, 2025) on the importance of accounting for electricity prices in our adoption model, showing how extensive margin adoption decisions are indeed strongly mediated by ongoing intensive margin operational costs.

Our findings have several important policy implications. The central role of air condition-

[1] Our appliance data includes at least one year of data on countries and regions covering 85% of the global population for air conditioning and 64% of the global population for electric heating.

ing and electric heating to future electricity demand emphasizes the importance of appliance efficiency. Other interventions to improve passive cooling, building insulation, and urban planning may also help flatten the steepness of the electricity-temperature response we find. The costs to the electricity system of reliably meeting increased demand for cooling and heating will depend on the available generation mix at times of peak demand. Greater use of renewable sources could present opportunities, such as the correlation between solar output and cooling demand during heatwaves, as well as challenges, such as the difficulty providing heating during dark winter months if wind output is also low. Ultimately almost all forms of electricity infrastructure face challenges operating during temperature extremes, from thermal fossil and nuclear plants to power lines and substations (Mideksa and Kallbekken, 2010). Adequate long-term capacity planning, improved forecasting, and more efficient short-run price incentives, are all important steps policymakers can take to ensure the grid can meet essential cooling and heating demands when people need them most. As our work highlights, doing so will require carefully accounting for the combined effect of rising incomes, warming temperatures, and policy-driven electrification in the coming decades.

The rest of the paper is structured as follows. Section 2 describes the data used in our analysis. Section 3 covers the appliance adoption model and our predictions for the uptake of air conditioning and electric heating. Section 4 estimates the electricity-temperature response and its dependence on the level of appliance penetration. Section 5 covers our mid-century electricity demand projections and decomposition analysis. Section 6 concludes.

2 Data

To study heating and cooling electricity demand at a global scale, we assemble a novel dataset spanning high-frequency electricity demand, historical climate, residential appliance adoption, and future projections of climate, economic development, and electrification.

Electricity Demand Data. We assemble data on hourly electricity demand for a large sample of countries and territories. The geographic coverage of our sample is illustrated in Figure 1, with over seventy countries and territories spread across North America, Central America and the Caribbean, South America, Europe, Africa, the Middle East, Asia, and Oceania[2]. For a subset of these countries and territories we have sub-national hourly data on over two hundred sub-regions giving us a sample of around three hundred distinct geographic areas.[3] For ease of reference we shall refer to these various national, territorial and sub-national geographic units as "load regions". Our main sample uses sub-national data where available and national or territorial data otherwise.

We obtain the hourly electricity demand data for our sample period from 2015 to 2024 from a mixture of sources, including national electric system operators, government agencies, and international organisations such as the International Energy Agency (IEA). For 98% of

[2]Countries or territories with data include: the United States, Canada, Mexico, Costa Rica, Guatemala, Martinique, Guadeloupe, Argentina, Bolivia, Brazil, Chile, Colombia, Peru, Uruguay, French Guiana, Austria, Bulgaria, Belgium, Bosnia, Switzerland, Cyprus, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, France, Greece, Georgia, Hungary, Croatia, Ireland, Italy, Lithuania, Luxembourg, Latvia, Moldova, Montenegro, North Macedonia, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Sweden, Slovenia, Slovakia, Ukraine, Kosovo, the United Kingdom, Russia, Nigeria, South Africa, Réunion, Iran, Turkey, Israel, Bangladesh, India, Japan, Malaysia, the Philippines, Singapore, South Korea, Taiwan, Australia, and New Zealand.

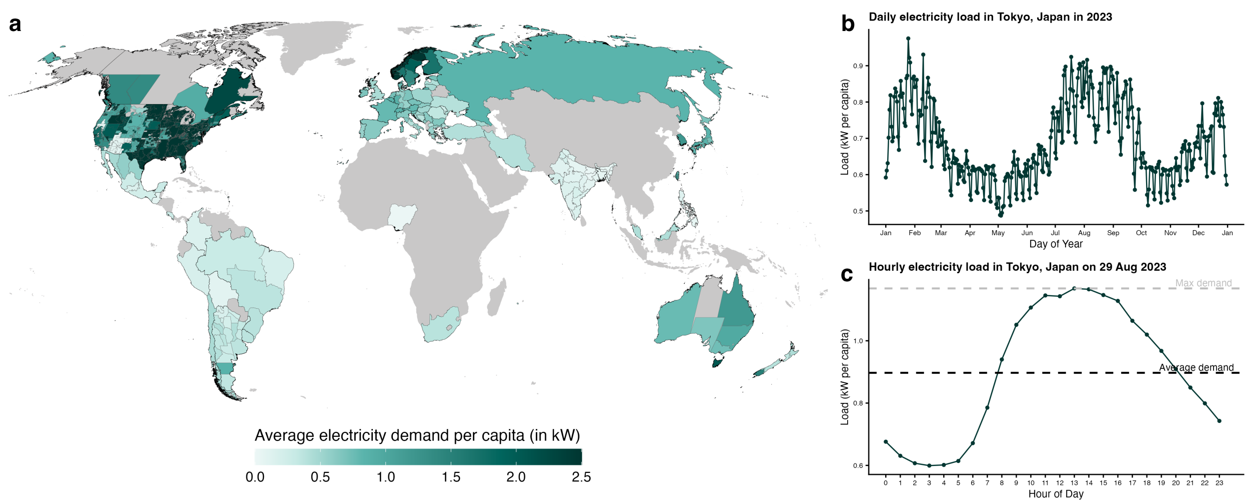
[3]Countries or territories with sub-national data include: the United States, Canada, Mexico, Argentina, Brazil, Germany, Denmark, Italy, France, Spain, Norway, Sweden, the United Kingdom, India, the Philippines, Japan, Taiwan, Australia and New Zealand.

our load regions we have more than five years of data and for 25% we have a full ten years of data (see appendix). The resulting sample of more than twenty million observations spans a diverse range of income levels, climates and geographic locations. In total our sample covers approximately 50% of the global population and 70% of global GDP. We use the hourly electricity demand data to calculate the daily average and daily maximum electricity demand for each day and load region.

Two important things to highlight about these data. First, our data is electricity demand from the grid. As such it is net of any distributed or "behind-the-meter" generation, such as rooftop solar, which will tend to suppress grid demand during daylight hours on sunny days. While the penetration of small-scale solar was relatively limited in most regions over our sample period, it has been increasingly rapidly, especially in recent years. We do not model this explicitly in order to examine gross electricity demand, both due to a lack of available data and because it is ultimately the net that the grid is required to meet. Moreover, even with expanded uptake of distributed solar the vast majority of electricity demand is expected to continue to be supplied by the grid (IEA, 2025).

Second, our data captures the electricity demand actually served and so is net of any outages or supply shortages that led to unserved demand. In most countries electricity reliability is very high and so observed grid demand is basically equivalent to actual consumer demand. Moreover, most outages are driven by things like local distribution infrastructure failures, rather than rationing of supplies during periods of very high demand. However, some low-income countries (e.g. Nigeria, India) do see regular periods where available generation is unable to serve consumer demand. Where these come during periods when cooling or heating needs are high, we will understate the response of electricity demand to temperatures. As these countries become wealthier though, grid reliability should increase. The diverse nature of our load region sample therefore allows us to capture the effects of both increased appliance adoption and improving reliability on the electricity demand being met by the grid as countries develop.

Figure 1: Map of Electricity Demand for Load Region Sample



Notes: This figure illustrates the sample of countries and sub-national regions with hourly electricity demand data used to estimate the electricity-temperature relationship. Panel (a) plots a global map of the sample regions with the colors representing the average electricity demand in kW. Panel (b) and (c) provide illustrations of the daily and hourly resolution of the underlying data in one of the load regions during 2023.

Historical Climate Data. We combine our load region sample with data on ambient temperature collected from the ERA5 reanalysis product provided by the Copernicus Climate Change Service Climate Data Store (Hersbach et al., 2023). Daily data is obtained for the sample period from 2015 to 2024 at a 0.25° resolution (approx 30km). We calculate annual cooling degree days (CDDs) and heating degree days (HDDs), above and below 18°C respectively, and average temperatures.

Table 1 reports summary statistics for our load sample. Our main econometric analysis uses data at the daily level, which reveal substantial heterogeneity in both average and maximum daily demand as well as a wide range of daily average temperatures.

Table 1: Summary Statistics for Electricity Load Region Sample

Variable	N	Mean	SD	Min	Median	Max
Daily Average Electricity Demand per capita (kW)	849781	1.54	1.66	0	0.97	19.22
Daily Maximum Electricity Demand per capita (kW)	849781	1.81	1.89	0.01	1.13	20.43
Daily Average Temperature (°C)	850854	15.31	9.34	-33.81	16.34	39.93

Notes: This table shows summary statistics for the daily data used in our econometric estimation.

Appliance Adoption Data. Our analysis examines heterogeneity in the electricity-temperature relationship by electric heating and cooling appliances adopted. We therefore collect annual air conditioning and electric heating penetration rates for as many countries and sub-national regions as possible over the period 2009–2023. We focus on the penetration rate for residential households and draw on household surveys or censuses that include questions asking about heating and cooling services. For air conditioning we rely on questions that are some version of "do you own an air conditioner / have air conditioning". For electric heating we rely on questions that are some version of "what is your primary heating fuel (electricity)".

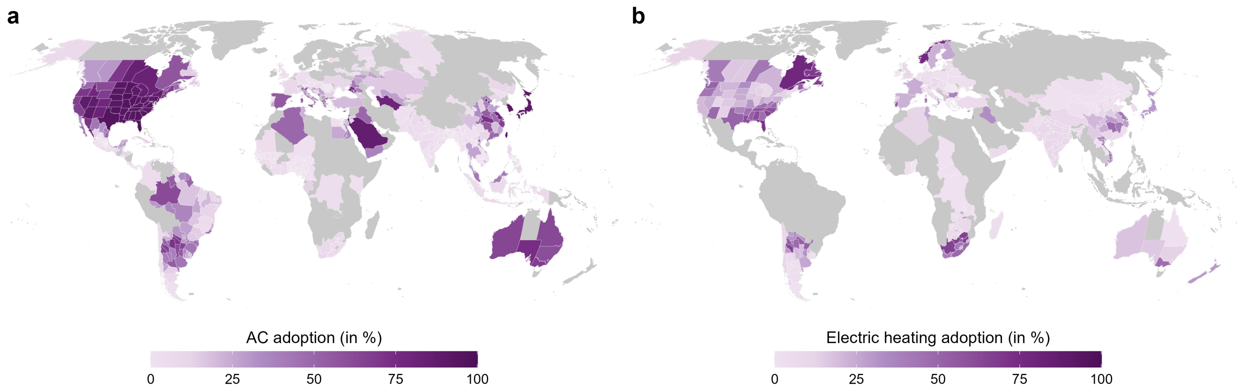
Our load-region data capture total electricity demand across residential, commercial and industrial consumers, not residential consumption alone. We nonetheless rely on residential adoption rates for heating and cooling technologies, because comparable data are unavailable for commercial and industrial users. Residential demand constitutes a substantial share of total demand in nearly all regions and likely accounts for a disproportionate fraction of temperature-responsive load. Residential adoption of air conditioning and electric heating is, moreover, expected to correlate strongly with commercial adoption.

Our appliance data are not able to distinguish between different air conditioning systems of different sizes, or whether they are central, window or portable units. Similarly for electric heating, we lack the data to distinguish between resistive or radiative heating versus the more recent growth of heat pumps. The latter tend to be more efficient and air-to-air units can also provide cooling. As global data improves the scope to study these more detailed aspects of cooling and heating appliances will become more feasible.

Figure 2 maps the national and subnational regions for which we have at least one year of appliance penetration data. We will henceforth refer to these as "appliance regions" to differentiate them from our load regions, although it should be noted that there is substantial overlap between the two. We have wide coverage across income levels and baseline climates. In total our air conditioning sample provides at least one year of data for approximately 85% of the global population and 84% of global GDP. The equivalent coverage for electric heating is 64% of the global population and 62% of global GDP. The coverage for electric heating is less extensive, although this is in part because hotter countries can often not have heating technologies at all, and so surveys in these countries rarely ask about electric heating.

Air conditioning and electric heating adoption rates vary substantially across the sample. Air conditioning adoption is lowest in colder places, such as Germany or Russia, and also in hotter places that have relatively low incomes, such as Nigeria, India or Pakistan. It is primarily in high income, hotter places that air conditioning adoption is more significant, such as Australia, Japan, Saudi Arabia, and much of the US. Electric heating adoption is generally lower across the globe and less correlated with climatic conditions and income

Figure 2: Map of Air Conditioning and Electric Heating Shares for Appliance Region Sample



Notes: This figure plots the countries and sub-national regions for which we have appliance data. Panel (a) plots the average share of households with air conditioning. Panel (b) plots the average share of households with electric heating.

levels, likely due to there being other non-electric forms of heating such as gas. Areas with higher penetration rates of electric heating tend to be those where electricity is cheap and/or alternative heating sources such as gas have not been widely developed, most notably Norway and Quebec in Canada.

Appliance Adoption Drivers. To incorporate information on appliance adoption into our analysis of the relationship between electricity demand and temperature, we predict residential appliance adoption as a function of four key covariates: climate, income, electricity prices, and electricity share of energy use.

First, our measure of average income captures both households' capacity to afford air conditioning or electric heating and the maturity of appliance and electricity-supply markets. We obtain global gridded data on Gross Domestic Product (GDP) per capita and population (Kummu, Kosonen and Masoumzadeh Sayyar, 2024; Schiavina et al., 2023) and extract the population-weighted average for each appliance and load region. We adjust our estimates to align with official national values (World Bank, 2025; IMF, 2025), expressing GDP per capita in real 2021 PPP USD throughout.

Second, we include measures of the local climate to capture potential demand for heating and cooling services, using Cooling Degree Days (CDDs) in the air-conditioning model and Heating Degree Days (HDDs) in the electric-heating model. Both are derived from ERA5 temperature data (Hersbach et al., 2023) and measure the annual cumulative incidence of hot or cold days above and below 18°C.

Third, we include electricity prices to capture appliance running costs. Country-level data on average residential electricity prices in $ per KWh is available for most of our sample (IEA, 2024*a*).[4] We convert the price data to 2021 PPP USD for consistency with our income measure, and compute the inverse of the electricity price to ensure that adoption increases in electricity affordability. We further scale our inverse price measure by the share of households with electricity access (World Bank, 2025).[5]

Finally, to model electric heating adoption, income, prices, and climate alone are insufficient, given the prevalence of non-electric (fossil) heating and the strongly policy-driven nature of future electrification. We therefore add a measure of electrification: the residential electricity share, defined as final electricity use as a share of final total energy use for residential households, is calculated from national energy balance data (IEA, 2024*b*).[6]

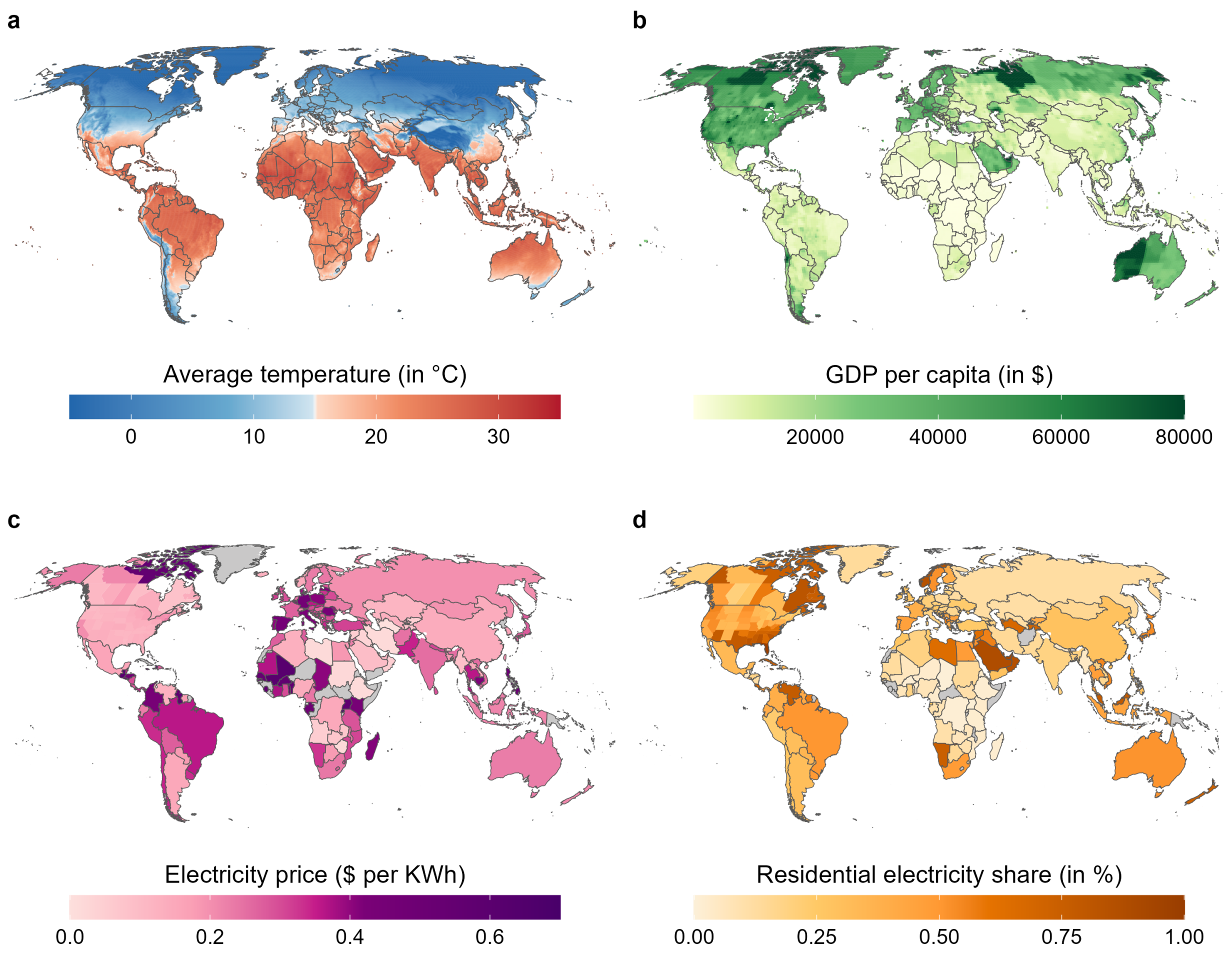
[4] We also include subnational data for US states and Canadian provinces (EIA, 2024; CER, 2024). We use additional sources to include a number of countries not covered by the IEA data (WPR, 2025)

[5] For example, in 2015 Senegal had a residential electricity price of $0.61 per KWh and 60% of households had access to electricity, yielding an average inverse price of approximately $(1/0.61)/0.60 = 1$ KWh per $. By comparison, in 2015 Canada had a residential electricity price of $0.12 per KWh and 100% of households had access to electricity, yielding an average inverse price of more than $(1/0.12)/1 = 8$ KWh per $.

[6] We also include subnational data for US states and Canadian provinces (EIA, 2024; CER, 2024)

Figure 3 illustrates the broad geographic variation in these four main covariates. Table 2 also provides additional summary statistics, highlighting that we have broad support in terms of income, climate, prices, and electrification rates across both our air conditioning and electric heating samples. Our annual residential appliance adoption sample has almost 2,400 region-year observations for air conditioning and 1,200 for electric heating. The median appliance region covers approximately 2 to 3 million people.

Figure 3: Map of Key Covariates for Appliance Adoption Model



Notes: This figure plots the key covariates used in the appliance adoption model. Panel (a) plots the average gridded temperature. Panel (b) plots the average gridded GDP per capita in 2021 USD PPP. Panel (c) plots the residential electricity price in 2021 USD PPP. Panel (d) plots the residential electricity share.

Table 2: Summary Statistics for Appliance Sample

Variable	N	Mean	Std.Dev.	Min	Median	Max
Residential Air Conditioning (%)	2420	29.81	31.34	0	16.82	97.5
Average Temperature (C)	2420	16.48	7.61	-2.02	17.01	30.1
Average Cooling Degree Days	2420	1266	1133	0	778	4416
Average Heating Degree Days	2420	1819	1843	0	1089	7389
Population (millions)	2420	11.48	57.13	0.01	2.24	1402.76
GDP per capita (thousand 2021 PPP USD)	2420	30.29	23.28	1.25	24.56	171.09
Electricity price (2021 PPP USD per KWh)	2388	0.26	0.13	0	0.2	0.72
Access to Electricity (%)	2410	93.91	14.21	14.4	99.8	100
Electricity Share of Residential Energy Use (%)	2389	29.47	18.37	0.72	27.74	100.58
Electricity Share of Total Energy Use (%)	2389	20	6.35	3.11	21.4	54.83

(a) Air Conditioning

Variable	N	Mean	Std.Dev.	Min	Median	Max
Residential Electric Heating (%)	1248	23.44	19.03	0	17.39	92.55
Average Temperature (C)	1248	14.19	5.16	0.07	14.48	28.27
Average Cooling Degree Days	1248	768	641	0	635	3753
Average Heating Degree Days	1248	2158	1387	0	2015	6594
Population (millions)	1248	11.37	51.05	0.02	3.03	1402.62
GDP per capita (thousand 2021 PPP USD)	1248	46.47	24.57	1.13	50.09	171.09
Electricity price (2021 PPP USD per KWh)	1215	0.24	0.13	0.03	0.22	0.59
Access to Electricity (%)	1245	96.47	11.65	8.4	100	100
Electricity Share of Residential Energy Use (%)	1215	36.96	18.72	0.46	31.44	100.58
Electricity Share of Total Energy Use (%)	1215	23.37	5.74	0.96	22.49	54.83

(b) Electric Heating

Notes: This table shows summary statistics for the appliance regions in our sample. The top panel summarizes the air conditioning data and the bottom panel summarizes the electric heating data. The data is annual and so an observation is an appliance region-year.

Climate projections. To quantify future changes in temperatures under climate change we collect high-resolution climate projections under different climate change scenarios from the Global Downscaled Projections for Climate Impact Research dataset (Gergel et al., 2024). This dataset provides global daily climate simulations at a 0.25° times 0.25° resolution over the period from 1950 to 2100. The downscaled climate projections are derived from 25 independent Coupled Model Intercomparison Project Phase 6 (CMIP6) General Circulation Models (GCMs) and are available across four Shared Socioeconomic Pathways (SSPs), namely SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5. Crucially for our analysis, the dataset is bias adjusted to ERA5 and designed to preserve quantile trends, ensuring a better representation of temperature extremes.

Socioeconomic projections. To account for future changes in appliance adoption for air conditioning and electric heating requires future projections for the input covariates to the appliance model. To account for future economic development we collect mid and end of century data on socioeconomic drivers for the different SSPs from the International Institute for Applied Systems Analysis (IIASA) (KC et al., 2024). This includes population, GDP per capita, and sectoral value added shares. Our main analysis uses the SSP2 "middle of the road" scenario. We downscale the country-level data to our sub-national regions assuming present day within-country distributions of people and economic activity persist into the future. For electricity prices, in our main analysis we assume converge over time, although we also explore sensitivities where prices remain constant for each country at their current level. For the residential electricity share we project future changes in this measure based on the final energy use pathways provided alongside the IPCC's Sixth Assessment Report

(AR6) (Byers et al., 2022). We ensure the selected pathways are aligned to the SSP scenarios we study. Further details provided in Section 5.1 and the appendix.

3 Predicting Appliance Adoption

An important potential driver of heterogeneity in the relationship between electricity demand and temperature is the extent of electric heating and cooling appliance adoption. Even for a given long-run income level and climate, regions may still differ in their adoption of electric appliances for heating or cooling. We therefore explicitly account for differential rates of air conditioning and electric heating penetration across our load regions in our response estimation. In doing so we are also able to examine the implications of increased adoption of air conditioning and electrification of heating, both today and into the future.

To incorporate information on appliance adoption into our econometric analysis of the relationship between electricity demand and temperature, we ideally require data on air conditioning and electric heating penetration for each of our load regions over our entire sample period. In practice the data for our appliance regions only covers a subset of our load regions for a subset of sample years. Moreover, in subsequent parts of the analysis we also project our electricity-temperature response out-of-sample to other countries or regions, and into the future to 2050. To tackle these challenges we build on the approach taken by Davis et al. (2021) and fit an econometric model that can predict the appliance penetration rate as a function of a few key widely observable covariates. This approach necessarily restricts adoption to vary by covariates with comprehensive global coverage, precluding other potentially important determinants such as building codes and subsidies.

3.1 Methods

We estimate the share of residential households with air conditioning or electric heating as a function of income, climate, prices and electrification using the following general model:

$$AC_{i,y} = h(GDP_{i,y-1}, P_{i,y-1}, CDD_{i,y-1}) + \upsilon_{i,y}, \tag{1}$$

$$EH_{i,y} = h(GDP_{i,y-1}, P_{i,y-1}, HDD_{i,y-1}, ER_{i,y-1}) + \upsilon_{i,y}, \tag{2}$$

Here AC and EH denote the annual average residential adoption share for air conditioning and electric heating respectively in appliance region i and year y. $h()$ is a flexible function of interacted linear splines for: 1) GDP per capita, GDP; 2) the residential electricity price, P, which we invert and multiply by the share of households with access to electricity; 3) either cooling degree days, CDD, or heating degree days, HDD, and 4) the electrification rate as measured by the share of electricity in total energy use for residential consumers, ER.

Instead of using the contemporaneous value at year y for our covariates, we use a rolling average of the five years up to year $y-1$. This means we model appliance penetration rates today as a function of the average income, prices, climate and electrification rate over the preceding five years. The aim is to capture the gradual nature of appliance adoption decisions and to ensure the analysis is not unduly affected by sudden fluctuations in a single year (e.g. to the weather). Conversely, this design cannot capture short-term responses to individual extreme events (e.g. buying an air conditioner after an unusually hot summer). Lagged averages also help address a potential endogeneity problem: contemporaneous prices, GDP per capita, and the residential electricity share are all plausibly endogenous to electricity consumption. This poses no issue for the adoption model itself, but because its predictions feed into our electricity–temperature regressions, a contemporaneous link to consumption would carry through to the response estimates. Averaging over prior years helps mitigate the endogeneity concern.

We estimate the above equations using machine learning in order to find an econometric model that captures the key relationships of interest while avoiding overfitting and satisfying certain constraints. To do this we use a regularized regression algorithm and make a number of distinct choices on model structure in order to best suit our intended use cases.

First, we include our main covariates using linear splines to allow for non-linear relationships with appliance adoption. To account for interactions between variables (e.g. hotter, high income places will have different adoption patterns than colder, high income places etc.) we include all first order interactions of the linear splines for the income, electricity price and climate covariates included in each model.

Second, including such a large array of interacted linear splines allows for a lot of model flexibility, but also risks overfitting in certain parts of the feature space, especially if there is limited support in the data. To remedy this we fit the model using regularized regression to ensure only the most important combinations of linear splines are retained that best explain observed variation in appliance adoption. We examine both LASSO and ridge regression, with the latter being the preferred model.

Third, we fit our regularized regression model as a binary classifier to ensure our predictions are bounded between 0 and 1, as would be achieved with a binomial logistic regression model. This reflects the fact that the appliance penetration rate cannot be less than 0% or greater than 100%. Alternative machine learning algorithms, or a regression model where the dependent variable is treated as an unbounded linear variable, could produce nonsensical predictions that fall outside this range.[7]

Fourth, even when using a machine learning approach such as LASSO or ridge regression, it is still possible that the key fitted relationships may produce undesirable outcomes. For example, many of the hottest places in our sample also have low incomes (e.g. India or Nigeria). Absent any restrictions on the model we may generate predictions that show a reduction in appliance adoption at the hottest temperatures, even though this is effectively a confounding effect of low incomes in an area of the data where support is sparse. To tackle this we impose constraints during the fitting of our model that ensure all coefficients for our interacted linear spline variables must be positive. This draws on the reasonable intuition that air conditioning adoption should be increasing in income, CDDs, and the inverse of the electricity price, and that electric heating adoption should be increasing in income, HDDs, the inverse of the electricity price, and the residential electricity share.

Finally, we weight all appliance region observations by population to enhance the representativeness of our analysis and account for the fact that some countries have data at a

[7]Strictly speaking our dependent variable in our underlying data is a continuous appliance penetration rate bounded between 0 and 1. To fit this using a logistic model that requires a binary dependent variable we duplicate all region-year observations 100 times and then assign a proportion of them a value of one based on the appliance penetration rate, while setting the remainder to zero. So a single region-year observation in the model with a penetration rate of 45% would become 100 observations, 45 of which take a value of one and 55 of which take the value zero. All covariate values remain the same across these 100 observations, and any sample weights are also duplicated.

more granular subnational level than others.

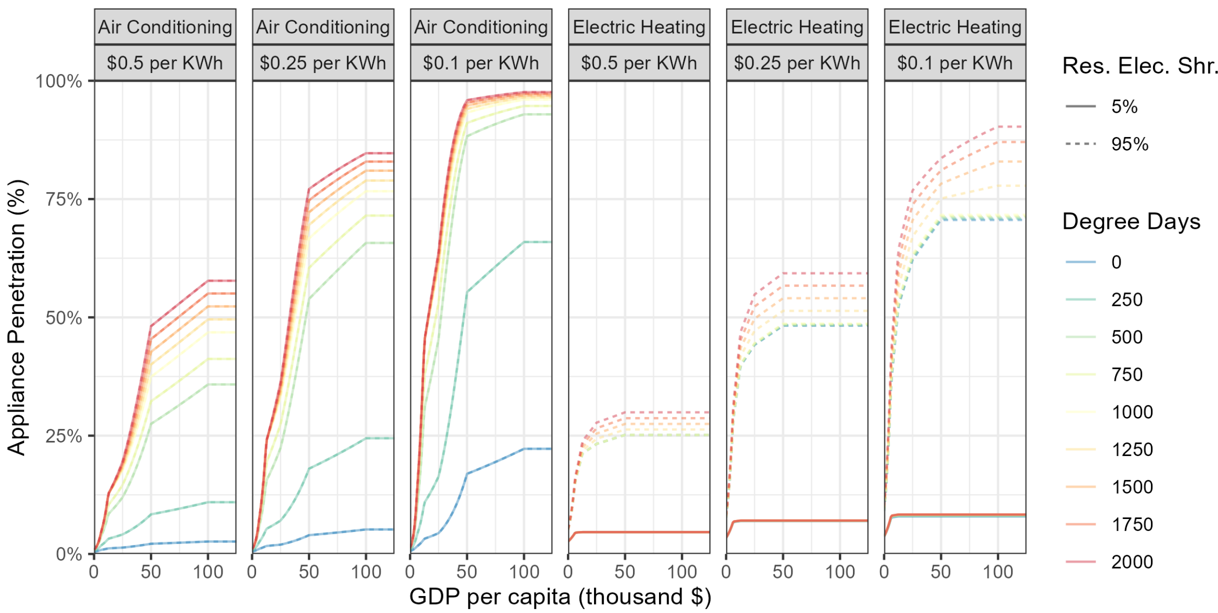
3.2 Results

Our appliance adoption model manages to successfully capture many of the core relationships of interest and achieves a good model fit, with an implied R-squared of 79% for air conditioning and 68% for electric heating. Given the constraints placed on the model in terms of input covariates and structure, including no fixed effects or regional dummies, we take this level of explanatory power to be encouraging.

Figure 4 plots the predictions of our appliance adoption model across a range of simulated incomes, climates, electricity prices, and levels of electrification. For air conditioning in particular we can see the expected S-shaped Engel curve where adoption is increasing in income, with the steepest part of the curve generally arising once an area moves beyond $10,000 in GDP per capita. The steepness and maximum level of the curve is moderated by both the climate and the level of electricity prices. In cool climates and where electricity is expensive air conditioning adoption barely increases, even at high incomes. But as the climate gets hotter and electricity gets cheaper air conditioning increases quickly and to a higher maximum level as incomes rise.

For electric heating, the degree to which the adoption curve responds to income, prices and climate is also moderated by the level of electrification. At low levels of electrification there is limited adoption of electric heating, even at high incomes with cheap electricity and cold climates. But as electrification increases, the familiar S-shaped adoption curve emerges,

Figure 4: Appliance Adoption Prediction Function



Notes: This figure plots the shape of the prediction function from our appliance adoption model. The figure uses the current population-weighted predictions for our sample appliance regions. These are simulated over a range of illustrative values for our main model covariates. In each panel column we plot the predicted appliance penetration share against income, as measured by GDP per capita in 2021 PPP USD. Each curve therefore shows the predicted level of appliance adoption at a given income level. Columns 1-3 show adoption curves for air conditioning and columns 4-6 show adoption curves for electric heating. We then further account for differences based on electricity prices: columns 1 and 4 have a price of $0.50 per KWh, columns 2 and 5 have a price of $0.25 per KWh, and columns 3 and 6 have a price of $0.10 per KWh. All enter the model as the inverse of the electricity price which would be 2KWh per $, 4KWh per $, and 10KWh per $ respectively. The color of each curve refers to the number of degree days in order to captures differences in climate. For air conditioning this is CDDs and for electric heating this is HDDs. Lastly, solid lines refer to predicted adoption where the residential electricity share is 5% and dashed lines refer to predicted adoption where the residential electricity share is 95%. This only affects the electric heating adoption curve.

now with a steeper adoption curve in colder climates and when electricity is cheaper.

When producing our final estimates of appliance shares for different countries or subnational regions, we make some adjustments to the raw model predictions to ensure that baseline values match the observed data in our original appliance region sample. Projections out to 2050 then evolve relative to these adjusted baseline 2025 values. For regions with no underlying observed data we just use the raw model predictions. Full details in the appendix.

Our estimates of the adoption of both air conditioning and electric heating feed into the two analyses that follow. First they enter the electricity–temperature response estimation (Section 4), where predicted appliance penetration shares for our load regions let us capture how the relationship varies with the prevalence of air conditioning and electric heating.[8] Second, they also enter our future demand projections (Section 5), allowing the electricity-temperature response function in each region to evolve over time as appliance uptake changes.

4 Electricity-Temperature Response

This section presents our empirical estimation of the heterogeneous effect of temperature on electricity demand across load regions. The approach allows us to identify differences in temperature sensitivity across regions and link these to differences in air conditioning and electric heating adoption. Section 5 then combines these estimates with projections of climate change and economic development to quantify future shifts in heating and cooling electricity demand.

[8] See Appendix Figure B.7 for a map of these predicted shares across all load regions in our electricity demand sample.

4.1 Methods

Using the appliance adoption shares from Section 3, we estimate the effect of temperature on daily average and daily maximum electricity demand, identified from day-to-day variation in daily average temperatures. To allow this effect to vary by prevalence of air conditioning and electric heating, we interact a nonlinear temperature response function with location-specific appliance adoption rates, estimating the following model:

$$E^{pc}_{j,t} = f(T_{j,t}|AC_{j,y}, EH_{j,y}) + \alpha_j\psi_{dow} + \alpha_j\phi_{moy} + \alpha_j\gamma_{yos} + \epsilon_{j,t}, \tag{3}$$

where $E^{pc}_{j,t}$ denotes daily average and daily maximum per capita electricity demand of load region j on day t, $f(T_{j,t}|\cdot)$ is a restricted cubic spline in average daily temperature with knots at -5°C, 18°C, and 30°C [9], and air conditioning ($AC_{j,y}$) and electric heating ($EH_{j,y}$) are the predicted appliance penetration shares for that region-year.

We let air conditioning (AC) and electric heating (EH) adoption rates shift this response by interacting them with the spline terms, with each appliance acting over the temperature range in which it is used. Air conditioning interacts with the spline on warm days, defined as those with average temperature at or above 18°C, while electric heating interacts with the spline on cold days below 18°C. The choice of 18°C mirrors the setpoint used in the calculation of CDDs and HDDs, and is further validated by the regression results using binned temperatures (see appendix). Our preferred specification includes interactions with a quadratic function of appliance shares to allow for non-linear responses of electricity demand

[9] Knots are chosen based on limited support below -5°C and above 30°C.

to appliance adoption.

We construct all temperature transformations and interaction terms at the grid-cell level and then aggregate to the load region using population weights, so that we recover grid-cell level non-linearities and heterogeneity in the response by appliance adoption.

To isolate the relationship between short-run temperature variation and electricity demand, we include day-of-week (ψ_{dow}), month-of-year (ϕ_{mon}), and year-of-sample (γ_{yos}) fixed effects that we allow to differ across load regions (α_j). These flexibly absorb region-specific seasonal trends, weekly patterns, and annual shocks in demand. We weight all regressions by load region population.

4.2 Results

Here we present results from the estimation of equation 3. Figure 5 shows the resulting electricity-temperature responses, including heterogeneity by appliance adoption. Consistent with prior literature (e.g., Wenz, Levermann and Auffhammer, 2017; Rode et al., 2021) we uncover the familiar U-shaped relationship between electricity demand and temperatures. As temperatures become hotter or colder relative to our moderate central category of 18°C we see increasing electricity demand.

Temperature driven electricity demand increases are shaped substantially by the level of appliance adoption. On average, greater air conditioning and electric heating adoption rates increase demand on hot days and cold days, respectively. In regions where nearly all households have AC, average electricity demand on a 35°C day exceeds that on a 18°C day by more than 1 kW per capita, whereas in regions with near-zero adoption demand is essentially unresponsive to temperature. We see a potentially even larger response in regions where nearly all households have electric heating, with average electricity demand on a 0°C day exceeding that on a 18°C day by almost 1.5 kW per capita.

At warm temperatures, daily maximum demand is notably more responsive than daily average demand as AC becomes more prevalent. Increases in daily maximum demand exceed increases in daily average demand by about 40% at 35°C under high AC adoption rates, indicating substantial within-day fluctuations in cooling loads. Conversely, we see very limited differences between daily maximum and daily average demand changes under cold temperatures.

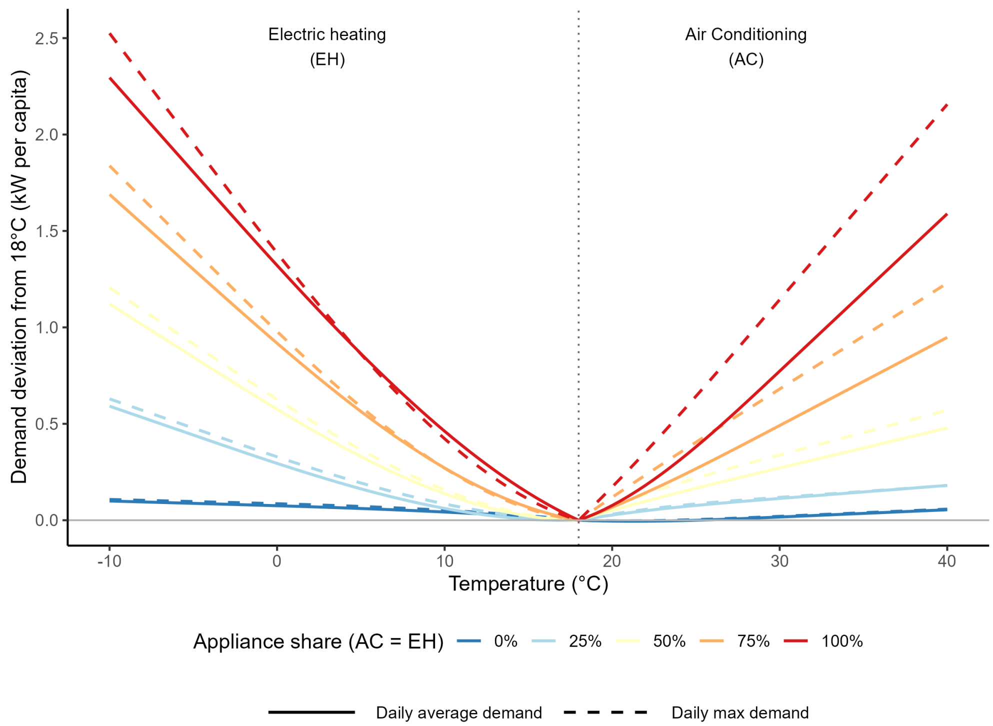
5 Projecting Future Electricity Demand

This section examines the implications of climate change, income growth, and electrification of heating systems for future electricity demand, including the peak demands the grid must serve on the hottest or coldest days. Section 5.1 sets out the framework for extrapolating our analysis to a global sample and estimating future demand changes, with results in Section 5.2.

5.1 Methods

We project mid-century heating and cooling electricity demand by combining our estimated electricity-temperature response with future projections of income, climate, appliance adoption, and aggregate electricity demand growth. Our approach allows us to then decompose

Figure 5: Electricity-Temperature Response by Appliance Adoption



Notes: This figure shows the estimated electricity–temperature relationship and how it depends on the extent of appliance adoption. Regression estimates are from a restricted cubic spline in average daily temperature and show the change in electricity demand for a day at the respective temperatures relative to a day at 18°C. Daily average and daily maximum demand responses are shown in solid and dashed, respectively.

projected demand changes based on their underlying drivers.

Spatial and Temporal Extrapolation.

Hourly electricity demand data are unavailable for much of the world. Although we have, to our knowledge, assembled the most comprehensive hourly load dataset to date, our sample still covers only about half of the global population, leaving the other half outside the regions where we can directly estimate the temperature response. Generating projections of global scope therefore requires extrapolating our estimates both across space, to regions without hourly demand data, and across time.

Our framework allows us to do this: the appliance adoption model in Section 3 predicts AC and electric heating shares from a handful of widely observable covariates, letting us generate adoption rates for any region worldwide and for any recent or future year. Combining these projections with the estimated appliance-interacted response yields a region-specific response function. For future projections, we feed projected income, climate, prices, and rates of electrification into the adoption model and recover response functions that evolve as appliance stocks change. We do this for a global set of "projection regions" which comprise all countries, plus sub-national regions for a selection of the largest countries.[10]

The validity of this extrapolation exercise rests on the assumption that the electricity–temperature response and the appliance model generalize to regions and years outside their estimation samples. While this assumption cannot be verified directly, our original estimation samples for both these models spanned a wide range of incomes, climates, and

[10]This includes states, provinces, or other first level administrative units for: China, the United States, India, Indonesia, Brazil, Argentina, Japan, Mexico, Canada, Australia, Germany, France, the United Kingdom, Pakistan, and Russia.

geographies. It is encouraging that the in-sample versus out-of-sample distributions of our main covariates reveals substantial overlap between the estimation and global samples (see appendix for details).

Electricity Demand Estimation. To assess impacts on both average and peak demand, we decompose daily electricity demand into a temperature-responsive component, which we project using the response function estimated in Section 4, and a non-temperature-responsive baseline, which we model separately. This two-stage structure isolates the part of demand that varies with weather, and which our climate, income, and electrification levers act on, from the structural, non-temperature-responsive level of consumption that evolves independently of daily temperature.

For each projection region k and day t, we first predict the temperature-driven component of per-capita demand using the appliance-interacted response functions from equation 3 for daily average and daily maximum demand, evaluated at projected daily temperatures and projected appliance penetration rates. We refer to this as Stage 1 in the demand estimation:

$$D_{k,t}^{\mathrm{S1}} = \hat{f}\left(\tilde{T}_{k,t} \,\middle|\, AC(\overline{GDP}_{k,t}, \overline{P}_{k,t}, \overline{CDD}_{k,t}),\ EH(\overline{GDP}_{k,t}, \overline{P}_{k,t}, \overline{HDD}_{k,t}, \overline{ER}_{k,t})\right). \quad (4)$$

The response function is anchored at 18°C so that $D_{k,t}^{\mathrm{S1}} = 0$ at the reference temperature: Stage 1 captures deviations from baseline demand driven by heating and cooling demand. Daily temperatures $\tilde{T}_{k,t}$ are obtained from historical and future CMIP6 model runs. Appliance penetration rates are generated by feeding either baseline or projected climate, income, prices, and electrification into the adoption model of Section 3.

Stage 1 alone delivers electricity demand due to deviations around the 18°C reference rather than overall levels of demand. This is sufficient for examining changes in average electricity demand for heating and cooling, but computing changes in annual peak demand requires the full daily load profile. We therefore model the remaining structural component as the region-day residual in Stage 2 of the demand estimation. Here structural demand, $D^{\mathrm{S2}}_{i,t} = E^{\mathrm{obs}}_{i,t} - D^{\mathrm{S1}}_{i,t}$, represents demand at the reference temperature (i.e. electricity demand that is not responsive to temperatures).

To estimate this we regress these residuals on a combination of log GDP per capita and sectoral value-added shares, each interacted with weekend/weekday effects and seasonal effects based on day-of-year.[11] We deliberately exclude region fixed effects to ensure we can predict structural demand for projection regions outside our load region sample. We also exclude any climate-related covariates (e.g. CDDs or HDDs) as the component is non-temperature-responsive by construction.

Because Stage 2 leverages both within-region and cross-sectional variation and therefore recovers structural differences across regions rather than aggregate growth over time, we calibrate the structural non-temperature-responsive level in two steps. First, for each region we scale predicted 2025 Stage 2 demand to ensure our combined total annual predicted demand matches official reported total annual electricity consumption in 2025. Second, we scale the model projected growth in structural annual demand forward to 2050 using country-level SSP projections of electricity consumption growth from 2025 to 2050. Further details available in the appendix.

[11] Seasonal effects include sine and cosine transformations of day-of-year, as well as the number of daylight hours computed using day-of-year and region latitude.

Projection Scenarios and Factor Decomposition. For each projection region we compute a full daily demand profile ($D_{i,t} = D^{\text{S1}}_{i,t} + D^{\text{S2}}_{i,t}$) for both daily average and daily maximum demand. From each region-day demand profile which we derive both annual average demand and annual peak demand respectively, with the latter being the highest maximum daily demand within a year.

To isolate the respective contributions of climate change, income growth, electrification, and structural (non-temperature-responsive) demand growth we produce these projections based on the full $2^4 = 16$ combinations of 2025 and 2050 values for each factor. Demand in a given scenario, $D(c, i, e, s)$, is therefore indexed by climate (c), income (i), electrification (e), and structural (s) flags. Climate enters through both the distribution of projected daily temperatures and through the climate normals (CDDs, HDDs) that feed into the appliance model. Income and electrification enter our temperature-responsive component of demand through the appliance model, shifting AC and electric heating penetration.

To be clear, for all of these projections we are treating our empirically estimated electricity-temperature response functions as fixed. In practice it is highly likely that these response functions will themselves shift over time due to changes in preferences, prices, and technology. We can capture a portion of those shifts by adjusting the steepness of the electricity-temperature response function for a given region based on any predicted change in appliance adoption. However, our analysis will not be able to capture the response function itself changing at a given level of appliance adoption, such as due to improving appliance efficiency, and the results should be interpreted with this in mind.

Because the four factors enter demand non-linearly, e.g. climate and income jointly affect appliance adoption, which in turn shifts the temperature response, the contribution of each factor depends on the order in which it is introduced. We therefore use the Shapley-Owen-Shorrocks decomposition (Shorrocks, 2012; Audoly et al., 2025), which assigns each factor its average marginal contribution across all possible orderings and is a decomposition that is additive, symmetric across factors, and zero for factors with no effect. This allows us to decompose changes in electricity demand into changes in heating and cooling demand induced by climate change (ϕ_{Climate}), income growth (ϕ_{Income}), and electrification (ϕ_{Elec}). The decomposition is also able to separate these factors from the non-temperature-responsive structural demand changes (ϕ_{Struct}) which are not the core focus of our analysis.

We conduct the above analysis under a scenario with moderate growth (SSP2) and emissions (RCP4.5), giving us our required projected changes in incomes, population, daily temperatures, CDDs, HDDs, and the electrification rate. Due to a lack of available projections on future end consumer electricity prices, we assume these converge toward a long-run global average value of \$0.20/kWh by 2050.[12] At the end of this section we explore sensitivity analyses with a lower emissions scenario (RCP2.6) and with electricity prices for each region held fixed at their current levels.

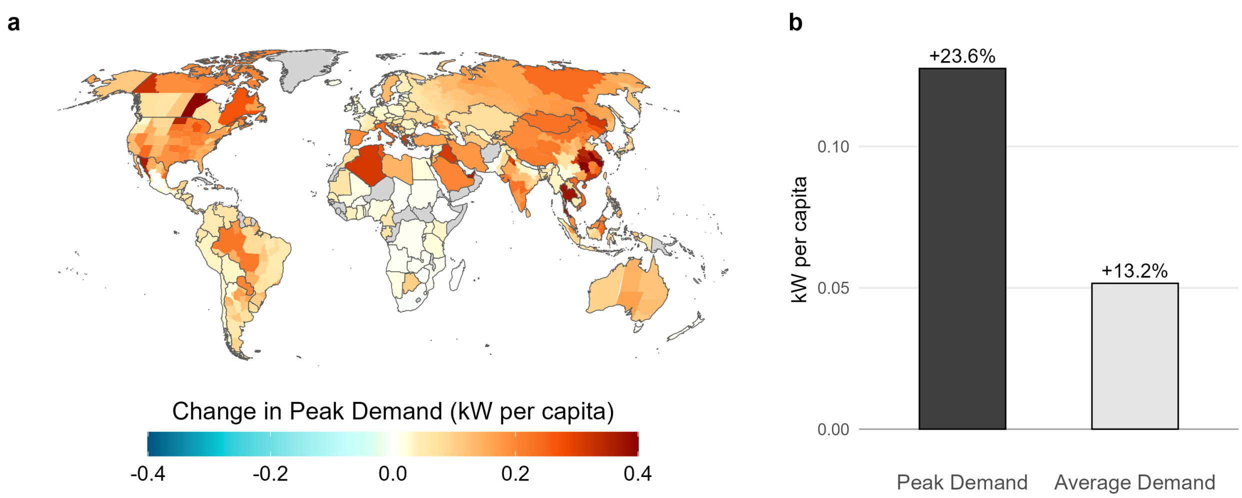
5.2 Results

Combining our electricity–temperature responses with local climate and socioeconomic projections across 660 global regions, we project mid-century changes in average and peak

[12]This is approximately equivalent to the current global population weighted-average price. The IEA also forecasts significant regional converge in electricity system costs, even over the next ten years (IEA, 2025). This is partly attributable to the shift towards a more renewables-heavy generation mix that is less affected by volatile and regionally divergent input fossil fuel prices.

per capita electricity demand for heating and cooling under a moderate growth (SSP2) and emissions (RCP4.5) scenario. Heating and cooling electricity demand is projected to increase globally, but annual average demand and annual peak demand respond at markedly different magnitudes: mid-century annual peak demand increases are projected to be almost twice as large as average demand increases (Figure 6). Peak demand increases are spatially heterogeneous and driven by distinct mechanisms across regions. Decomposing projected peak demand changes into contributions from income growth, climate change, and electrification reveals three dominant patterns (Figure 7).

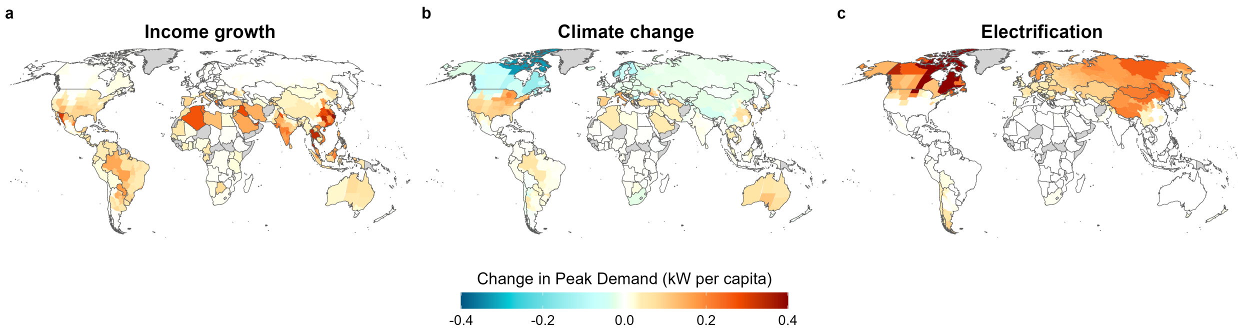
Figure 6: Projected change in average and peak electric heating and cooling demand



Notes: This figure plots the projected mid-century (2050) change in per capita heating and cooling electricity demand under a moderate emissions scenario (RCP4.5). Map (a) shows the spatial distribution of projected peak demand impacts. Barplot (b) shows population weighted average and annual peak demand impacts aggregated globally, with percentages indicating impacts relative to current (2025) demand levels. Displayed are mean impacts across 23 global climate models.

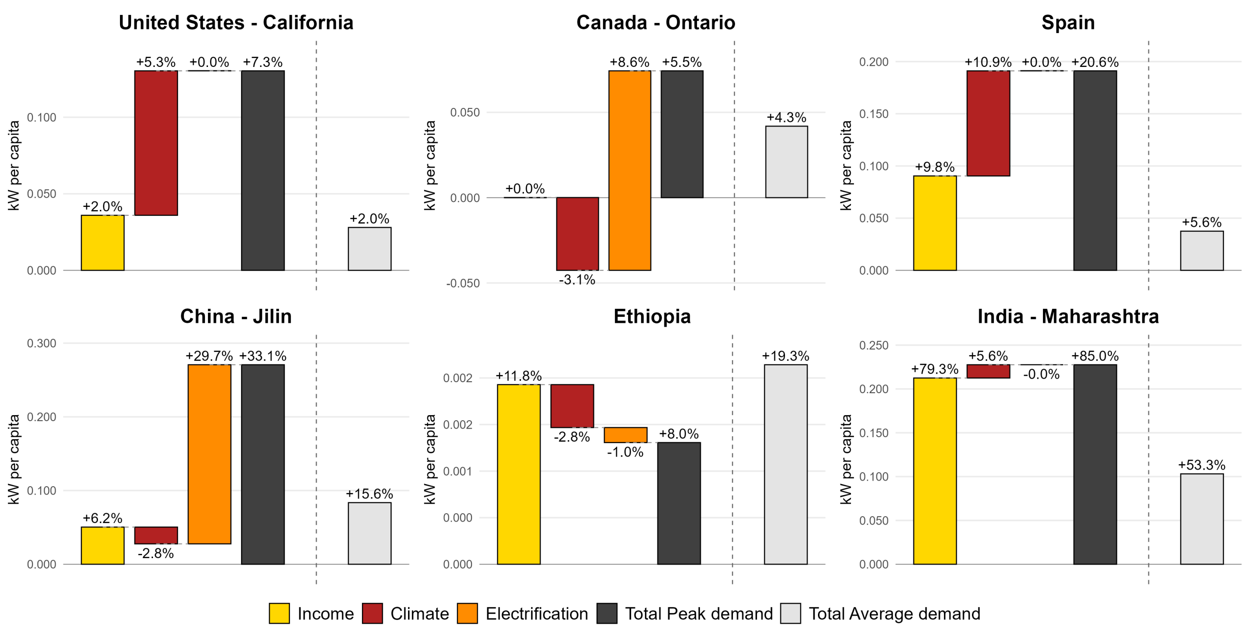
In low- and middle-income economies with hot climates undergoing rapid income growth, notably India, the Middle East, Southeast Asia, and parts of Africa, income growth is the dominant driver. Rising incomes translate directly into air conditioning adoption with significant demand increases even under a fixed climate. Peak demand increases are particularly

Figure 7: Decomposition of change in peak demand due to electric heating and cooling



Notes: This figure plots the projected mid-century (2050) change in per capita heating and cooling electricity demand under a moderate emissions scenario (RCP4.5) decomposed by the three drivers: climate change, income growth, and electrification. Maps show the spatial distribution of projected demand impacts due to income growth (a), climate change (b), and electrification (c). Displayed are mean impacts across 23 global climate models.

Figure 8: Change in demand due to electric heating and cooling in selected regions



Notes: This figure plots the projected mid-century (2050) change in per capita heating and cooling electricity demand under a moderate emissions scenario (RCP4.5) in selected projection regions. Total peak demand impacts (dark grey) are decomposed by the three drivers, income growth (in yellow), climate change (in red), and electrification (in orange), and compared to total average demand impacts (light grey). Percentages indicate impacts relative to current (2025) demand levels. Displayed are mean impacts across 23 global climate models.

large in places approaching middle incomes that are on the steepest part of the AC adoption curve, such as Maharashtra (India) (Figure 8). Increases are still sizable but less pronounced if incomes have not yet hit this threshold at mid-century, such as in Ethiopia (Figure 8).

Climate change is the leading driver in high-income regions with warm climates, where hotter temperatures increase electricity demand for cooling. In these regions air conditioning penetration is often already high and new appliance uptake is primarily driven by adapting to the changing climate, while warming increases utilization of the cooling stock. California (United States) and Spain exemplify this pattern (Figure 8).

In regions with cold climates, such as Canada, Russia, northern China, and Chile, we see two competing drivers. Warming reduces winter heating loads and so climate change in isolation acts to dampen peak demand. However, cold regions with higher incomes are also undergoing rapid heating electrification. Here we see policy-driven shifts from fossil-fuel to electrified heating acts to increase peak demand. Strikingly, in virtually all locations these electrification-driven increases more than offset the climate-driven reductions in heating demand in the same region, reversing the sign of the net impact. Ontario (Canada) and Jilin (China) are illustrative of this, with temperature-responsive demand increases due to electrification projected to be the primary driver of increased total peak demand (Figure 8).

Lastly, because we make projections of the full annual profile of electricity demand for each region, we are also able to examine potential changes to when in the year demand peaks (see appendix). As might be expected, places with hotter climates peak in the summer and places with colder climates peak in the winter. The main changes we see by mid-century are that rising temperatures and increased uptake of air conditioning will see some relatively temperate regions (e.g. Southern France or parts of central China) shift from peaking in the winter to the summer.

Together, these findings show that adequate capacity planning requires properly accounting for how demand for electricity will become more sensitive to temperatures, both on average and during peak periods. It is the combined effects of income growth, climate change, and electrification that will drive changes in temperature-responsive electricity demand, rather than any single driver in isolation. Despite significant heterogeneity in underlying drivers, the overall net effect is an increase in electricity demand for heating and cooling across almost all regions. Many regions will see substantial additional demands placed on their electricity systems, especially at peak times during heatwaves or cold snaps.

To quantify the costs of meeting these increased demands on the electricity grid we value our projected changes in electricity demand using two cost components informed by expected future technology and system costs (full details in the appendix) (IEA, 2025; Cole, Ramasamy and Turan, 2025). Changes in average annual electricity consumption (kWh) are valued using a system-average levelised cost of electricity (LCOE) of 70 \$/MWh, which represents the all-in per-unit cost of supplying electricity across the generation mix. Additional changes in peak demand (kW) over and above the capacity required to serve any change in average demand are then valued using an annualised capital cost of flexible peaking capacity of 75 \$/kW-year, representing the infrastructure cost of meeting demand at the margin during high-load periods.

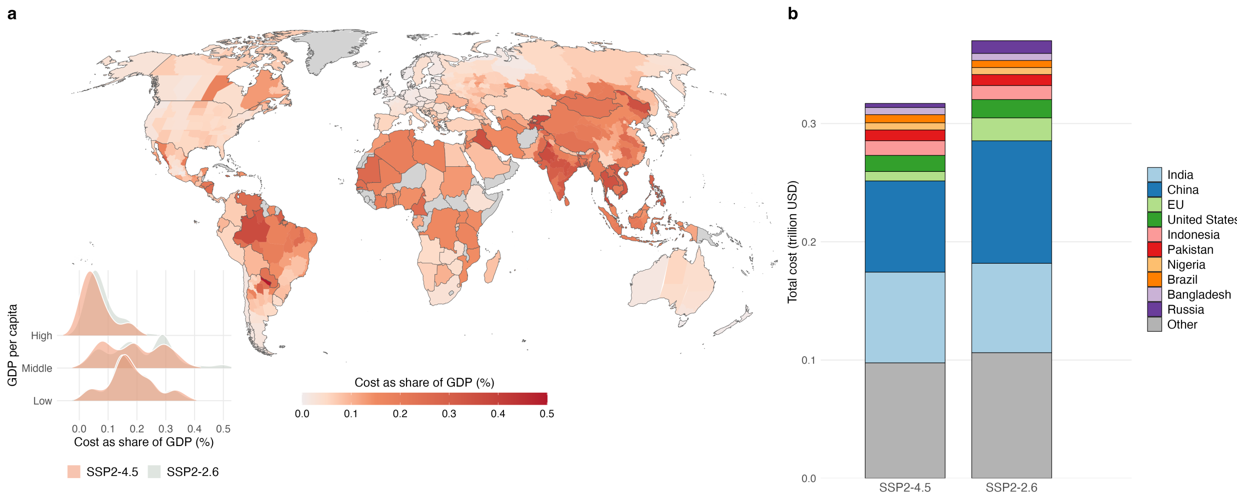
Globally the projected increase in electric heating and cooling demand entails increased costs of over \$0.3 trillion per year at mid-century under the moderate emissions scenario

(SSP2-4.5) (Figure 9b). At least one tenth of this is the cost of additional required investments in peaking capacity alone (see appendix). These costs are highly heterogeneous across regions. India and China show the largest total cost increases, with each projected to incur costs of about $77 billion annually. We further show that the burden of the costs is unequally distributed globally (Figure 9a). While high income regions like the US or parts of Europe are projected to incur significant cost, these costs are generally small relative to mid-century GDP (below 0.1%). In low and middle income regions, relative costs (as a share of local GDP) are 3 to 5 times larger and thus the burden to invest in future grid infrastructure is substantially larger.

Our main analysis projects impacts under a moderate emissions scenario (RCP4.5), which determines not just the degree of warming by 2050 but also the level of abatement, captured in part by the projected change in the electrification rate. We therefore, examine the distribution of costs under a lower emissions scenario (RCP2.6), in which more modest warming is accompanied by more aggressive abatement, reflected in a faster rise in electrification. Under this scenario we project larger total electricity system costs than under RCP4.5, driven by greater heating electrification. These differences are concentrated in middle- and high-income countries, whereas the burden borne by low-income regions is essentially unchanged across scenarios. China, Europe, and Russia in particular face substantial cost increases under the lower emissions scenario, reflecting higher uptake of electric heating.

Lastly, our baseline results assume convergence of electricity prices to a long-run global average of $0.20/kWh by 2050. Holding regional prices fixed at baseline levels instead leaves our broad global findings largely unchanged (see appendix).

Figure 9: Distribution of projected costs at mid-century



Notes: This figure plots costs associated with projected demand changes at mid-century across two scenarios: moderate emissions and abatement scenario (SSP2-4.5) and low emissions and higher abatement scenario (SSP2-2.6). Panel (a) shows the projected local costs as a share of local GDP at mid-century under SSP2-4.5 (map) and under both scenarios (densities). Densities show distributions grouped by long-run income based on average GDP per capita in 2021 PPP USD: Low (<\$15,000), Middle (\$15,000-45,000), and High (\$45,000+). Panel (b) plots the total cost of projected demand changes globally under both scenarios and highlights key regions.

6 Conclusion

Rising incomes, climate change, and the electrification of heating systems will collectively reshape electricity demand for heating and cooling worldwide. Using hourly electricity demand data from a global sample of countries and regions, we provide new empirical evidence on how changes in the adoption and utilization of cooling and heating technologies will jointly impact future electricity demand and capacity needs.

Our analysis reveals the critical role of electric cooling and heating appliance adoption in shaping future electricity consumption patterns. Demand for electricity to meet cooling and heating needs will rise in almost all parts of the world by mid-century. The capacity investment requirements implied by these changes are also substantially larger than average demand impacts alone suggest: annual peak demand increases are projected to be almost double the increase in average demand.

What will drive these projected demand increases is heterogeneous across regions. In warm regions, income growth and warming temperatures jointly amplify cooling demand, while in cold regions, electrification-driven demand increases often reverse climate-driven reductions in heating demand. It is the combination of these three forces, rather than any one alone, that explains why global electric cooling and heating demand is projected to rise, a finding that contrasts with studies which look at climate change in isolation and project electricity demand decreases in cold regions.

Costs associated with these demand increases could exceed \$0.3 trillion annually worldwide by mid-century under a moderate emissions scenario. This burden is projected to fall disproportionately on low- and middle-income regions, where the additional costs could exceed 0.3% of GDP in many cases. India and China alone are projected to account for almost half of the global total, reflecting their rising demand for electric heating and cooling.

Our findings have several important policy implications. The central role of air conditioning and electric heating in driving future electricity demand increases emphasizes the importance of appliance efficiency, especially as these are long-lived assets. Our analysis does not directly account for potential technological improvements, and so improving the energy efficiency of the appliances that people do adopt could meaningfully offset the demand increases we project. For electric heating in particular, heat pumps are generally more efficient than resistive and radiative technologies that have been more widely deployed to date. Other interventions to promote passive cooling, improve building insulation, or plan cities more intelligently may also help flatten the steepness of the electricity-temperature response in our analysis.

The substantial increases in annual peak demand shown across the world also raise urgent questions about how these peaks can be met. Periods of extreme temperature are both when the demand increases we find will be most acute, and when electricity infrastructure is often at greatest risk of failure. Hot temperatures reduce the amount of power that transmission lines can transport, decrease the conversion efficiencies of thermal power plants or solar panels, and drought or high temperatures can limit the output of nuclear and fossil fuel power plants that use river or sea water for cooling. Failures during periods of extreme cold have tended to be more associated with freezing and mechanical failures at gas pipelines or thermal power plants with inadequate winterization measures.

The growing role of intermittent renewable generation, such as wind and solar power, highlights the importance of understanding how output from these sources reliably correlates with the seasonal timing of demand peaks. Fortunately, summer cooling peaks could align well with output from solar PV generation, even within a given day. This could be utility-scale solar that serves the grid demand we model here, or it could be rooftop solar that reduces grid demand directly. On the other hand, increased winter peaks in colder regions, as a result of the electrification of heating systems, may be more at risk from periods of low wind and solar output. The declining cost of battery storage does mean concerns about mismatches between end user demand and intermittent renewables supply are increasingly about persistent multi-day stretches, rather than shorter-run within-day fluctuations. These extended periods may require different infrastructure solutions such as seasonal storage or additional backup capacity. An important direction for future research will be to assess where investments in transmission, storage, or flexible generation should be prioritized, and which energy sources are best able to serve emerging demand peaks.

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Online Supplemental Appendix

The Global Consequences of Climate Change and Appliance Adoption for Peak Electricity Demand

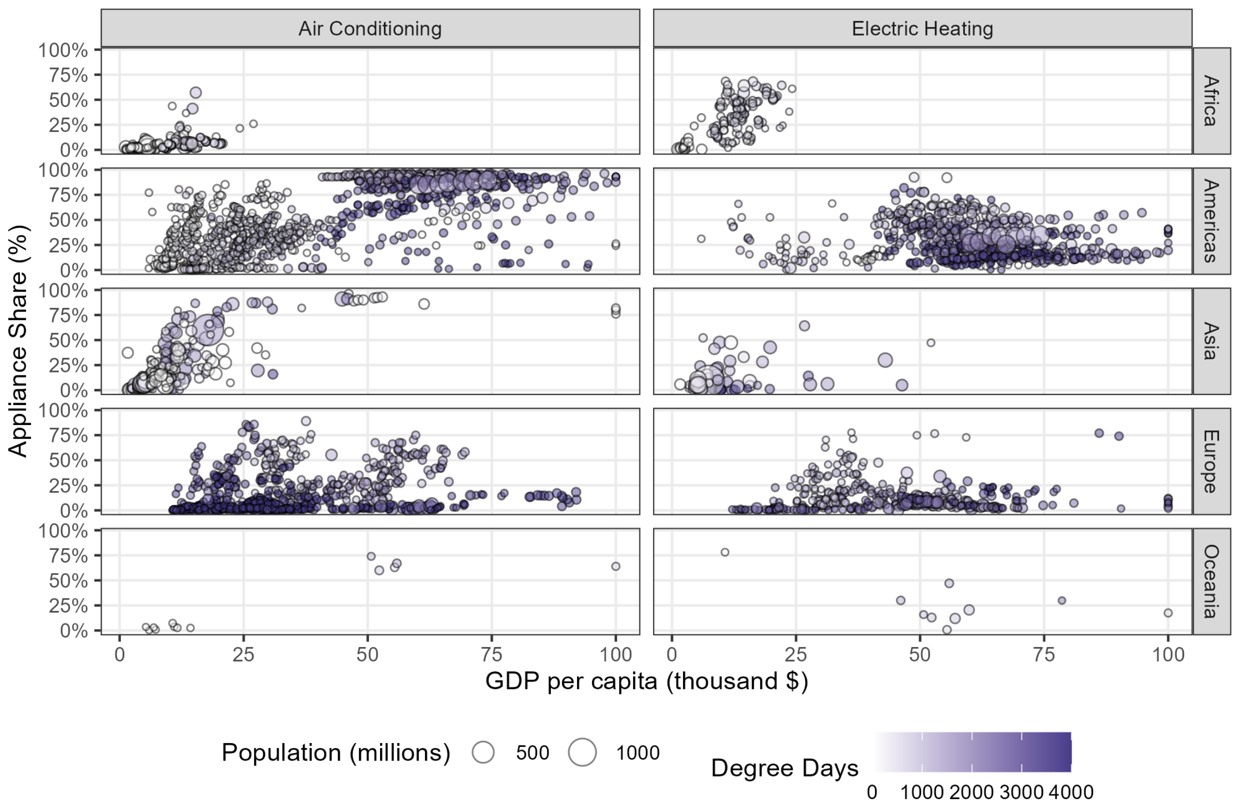
Maren Ludwig and Stephen Jarvis

A Additional Appliance Adoption Results

A.1 Appliance Region Sample Summary Statistics

Figure A.1 provides additional detail on the appliance region sample used in the appliance adoption model estimation.

Figure A.1: Appliance Shares for National and Sub-National Sample Regions by Income and Degree Days



Notes: This figure plots the countries and sub-national regions for which we have appliance data. Appliance penetration shares are plotted separately for air conditioning or electric heating and also by region. Colors denote degree days, with cooling degree days for air conditioning and heating degree days for electric heating.

A.2 Appliance Model Fitting and Diagnostics

We evaluate model fit by aggregating predictions back to the appliance region-year level and computing the share of variance in observed appliance penetration rates explained by the model. Weighting observations by population, the AC adoption model achieves an R-squared of 0.787 and the electric heating model 0.692. The higher performance for the AC model reflects the more complex identification challenge for electric heating adoption given the complicating role of non-electric fossil heating and heterogeneity in policy designed to transition away from this.

Model selection and evaluation is conducted using 5-fold cross-validation, whereby the training data is partitioned into five roughly equal folds and the model is iteratively trained on four folds and evaluated on the held-out fifth. To ensure the integrity of this procedure given the 100x duplication of each region-year observation, fold assignments are made at the region-year level prior to duplication, such that all 100 copies of a given observation are always assigned to the same fold. This prevents data leakage between training and validation sets that would otherwise arise if duplicated copies of the same observation appeared in both.

Prior to fitting, all covariates are standardised to zero mean and unit variance using parameters estimated on the training fold only, with the same transformation applied to the held-out fold at evaluation, ensuring the cross-validation mimics genuine out-of-sample conditions. This normalisation ensures least squares model fitting is not unduly affected by the different units and ranges of the variables (i.e., income per capita spans tens or even hundreds of thousands while degree days spans hundreds or low thousands).

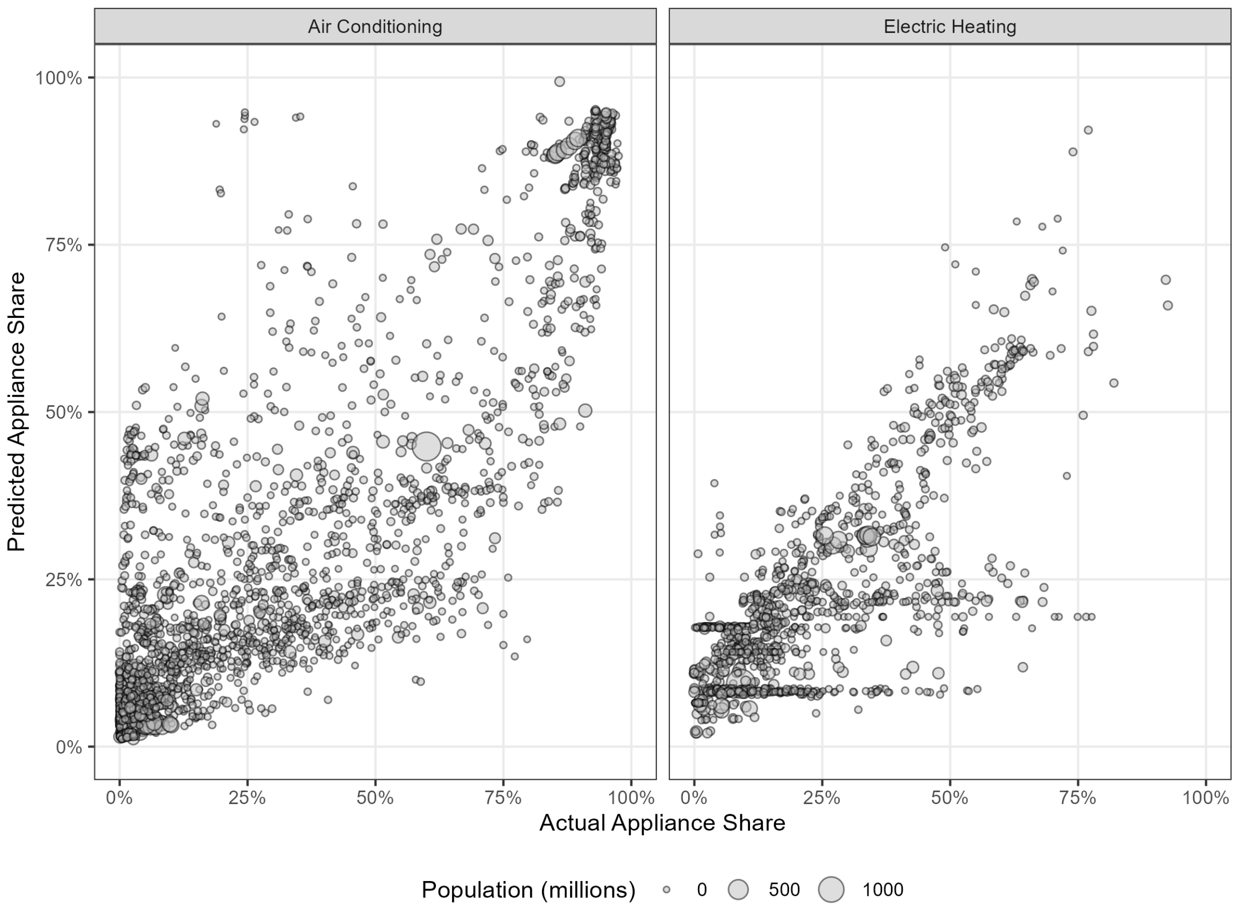
The regularisation parameter lambda is selected as the value minimising held-out cross-validation loss across a pre-specified grid spanning several orders of magnitude. For both the AC and electric heating models the cross-validation loss is stable across a wide range of lambda values at the lower end of the grid, with a clear deterioration only at high regularisation levels. This provides some reassurance that the selected models are not overly sensitive to the precise tuning choice and that the ridge penalty is providing meaningful regularisation without over-shrinking the key relationships of interest.

Figure A.2 plots the raw unadjusted predictions from the appliance adoption model and compares them to the observed appliance shares. In general we can see the plotted predictions do broadly track the 45 degree line, although there are some notable areas of dispersion (e.g. at intermediate levels of air conditioning adoption, or at relatively low levels of electric heating adoption where the model predictions are relatively inflexible).

Of course, we could achieve a stronger model fit by increasing the number of covariates, perhaps to account for temperature shocks or by incorporating information on the building stock. Relaxing some of the model fitting constraints by including more detailed splines or allowing for negative coefficients may also permit more complex non-linear interactions to emerge. However, changes of this nature would risk undermining the economic logic underpinning the model structure and impinge on our intended application of the fitted adoption curves to forward-looking projections.

Figure A.3 plots the final predictions from the appliance adoption model for our projection regions in 2025 and 2050 under our central SSP2 scenario. Here we see significant increases in AC penetration, particularly driven by rapidly growing countries in Asia and Africa with

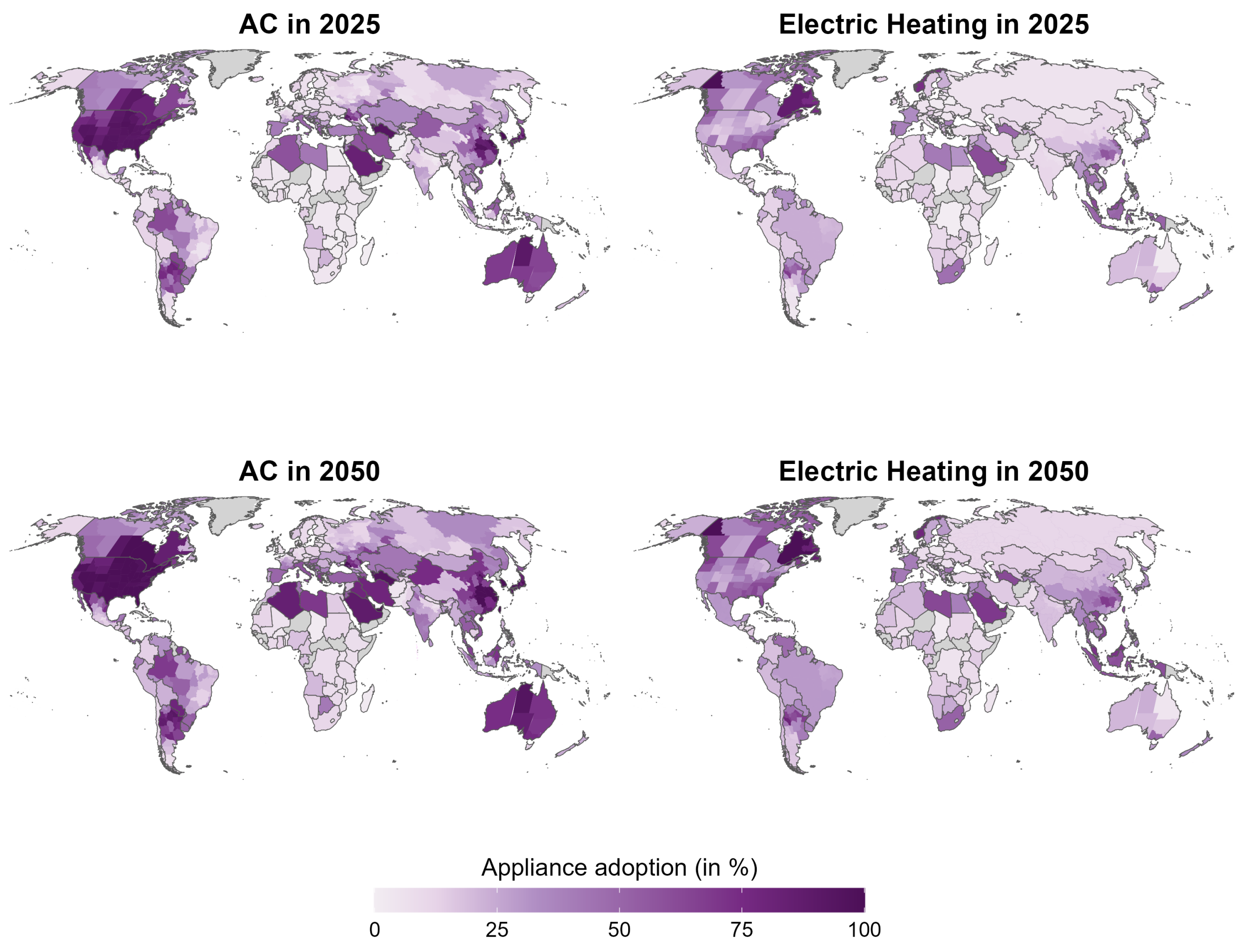
Figure A.2: Appliance Share Model Raw Prediction Performance



Notes: This figure plots the actual and predicted appliance share for the observed appliance region data used to train our prediction model. Point sizes are proportional to the appliance region population. Note these are the raw model predictions.

hot climates and low or middle-incomes. Electric heating adoption is more widespread given the link with wider decarbonisation and electrification policy, although is most notable in countries with colder climates and middle or high-incomes.

Figure A.3: Map of Projected Appliance Shares for National and Sub-National Regions from 2025 to 2050



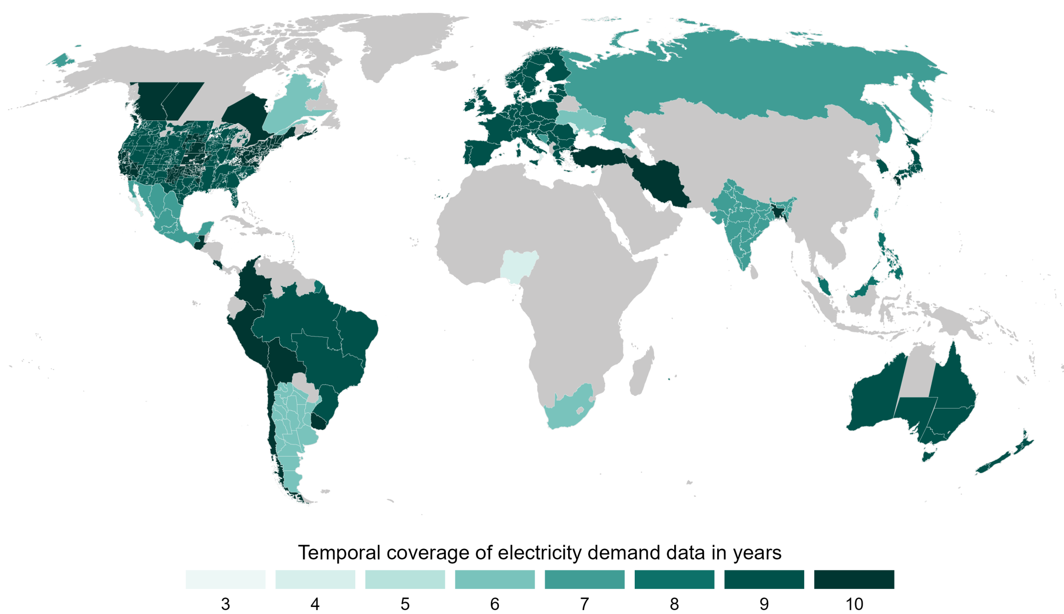
Notes: This figure plots appliance adoption shares for the global sample of countries and sub-national regions that we are able to make predictions for. The left two plots show the predicted average share of households with air conditioning. Panel right two plots show the predicted average share of households with electric heating. The top plots show values for 2025 and the bottom plots show values for 2050.

B Additional Electricity-Temperature Response Results

B.1 Load Region Sample Summary Statistics

Figure B.4 displays the number of years with hourly load data for each of our load regions, showing that for most load regions the data covers more than 8 years.

Figure B.4: Map of Load Sample Years

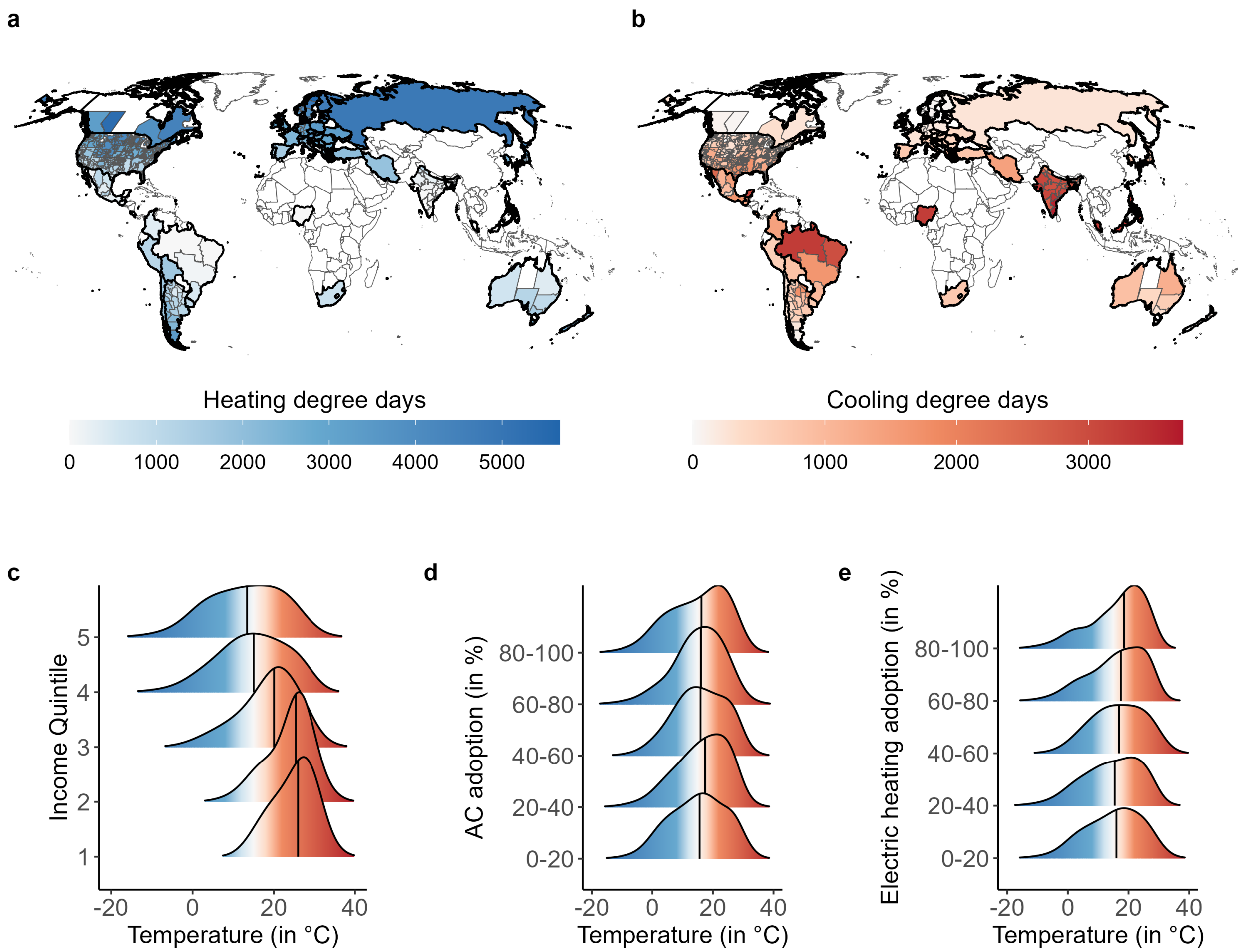


Notes: This figure plots the countries and sub-national regions included in our sample used to estimate the electricity-temperature relationship. Colors indicate the number of years for which the hourly load data is available in each load region.

Figure B.5 provides additional detail on the support of the data for our load regions. Here we can see the sample spans a wide range of both HDDs and CDDs. Moreover, while the distribution of daily temperatures in the sample is necessarily skewed across income quintiles, across appliance penetration rates the spread is much more even.

Figure B.6 provides an illustration of how the daily electricity demand profile varies over

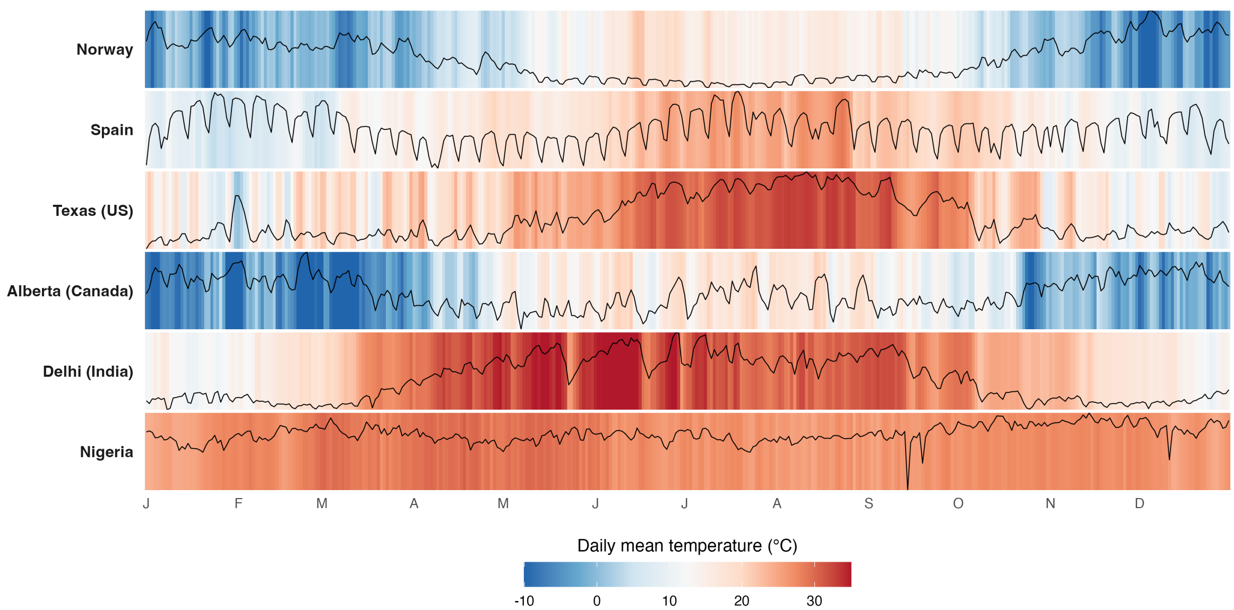
Figure B.5: Daily Temperature Support across Sample



Notes: Maps **a** and **b** show the number of heating and cooling dregree days, respectively, across the sample period. Plots **c**, **d** and **e** show the distributions of daily temperatures across income deciles, air conditioning adoption rates and electric heating adoption rates.

the year for a selection of different regions in our load sample. For some regions we can see these are winter peaking, such as Norway and Alberta (Canada). Others are clearly summer peaking, such as Texas (US) and Delhi (India). Lastly, some do not have a clear summer or winter peak, either because they have a relatively mixed climate like Spain, or because they are sufficiently low-income that they lack substantial heating or cooling demand like Nigeria.

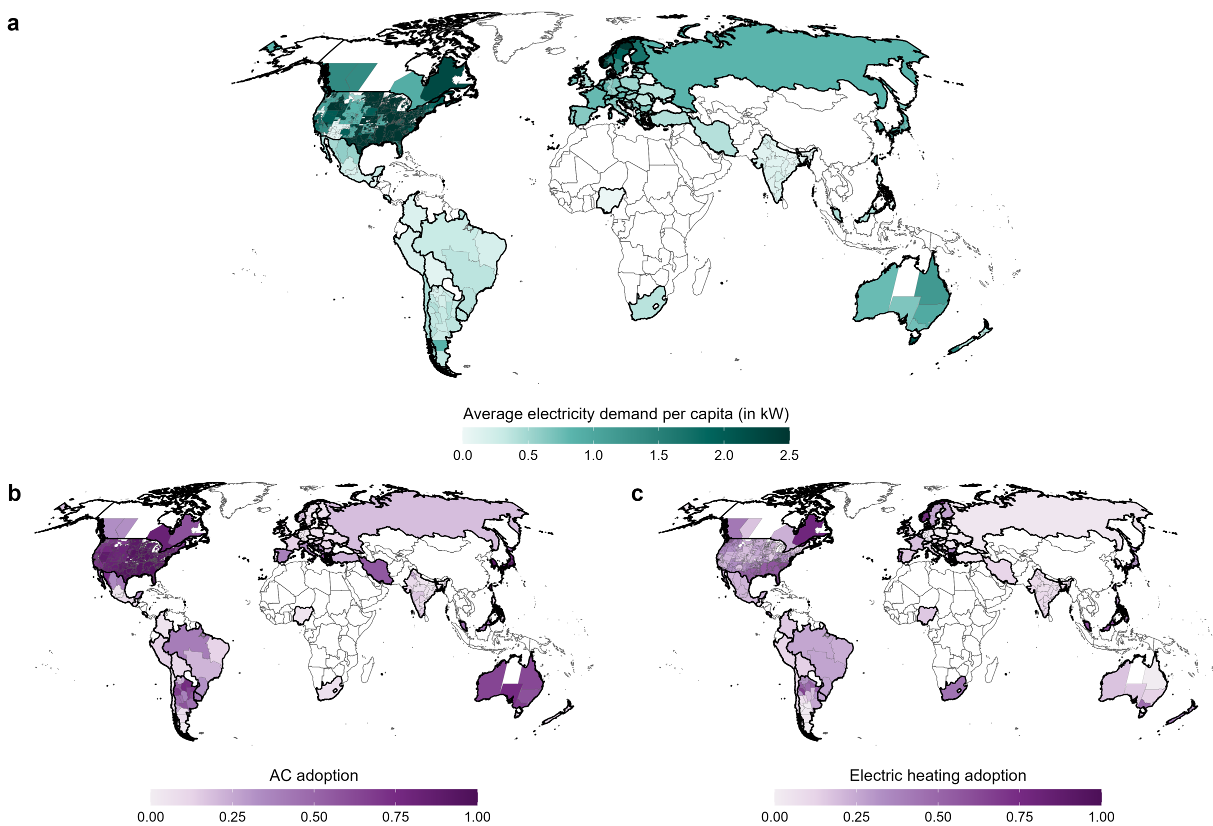
Figure B.6: Daily Electricity Demand and Temperature Profile for Select Regions



Notes: Maps **a** and **b** show the number of heating and cooling dregree days, respectively, across the sample period. Plots **c**, **d** and **e** show the distributions of daily temperatures across income deciles, air conditioning adoption rates and electric heating adoption rates.

Figure B.7 plots the appliance shares for both air conditioning and electric heating for our load regions. In most instances these values are based on direct data, although for a subset of regions these values are based on the predictions from our appliance adoption model.

Figure B.7: Map of Predicted Appliance Shares for National and Sub-National Regions



Notes: This figure plots the countries and sub-national regions for which we have hourly electricity load data. Panel (a) plots the average per capita electricity demand (in kW). Panel (b) plots the predicted average share of households with air conditioning. Panel (c) plots the predicted average share of households with electric heating.

B.2 Binned Response Estimation

Our main analysis estimates a smooth continuous electricity-temperature response and identifies heterogeneity based on the level of heating and cooling appliance penetration. Here we include results from alternative econometric specifications for additional context.

Figure B.8 shows the results using discrete bins of temperature and allowing for heterogeneity by income levels and baseline climatic conditions. Here we conduct our analysis by grouping all regions in the sample based on 20-year average GDP per capita and 20-year average temperatures.[1] We then estimate the response for each group separately.

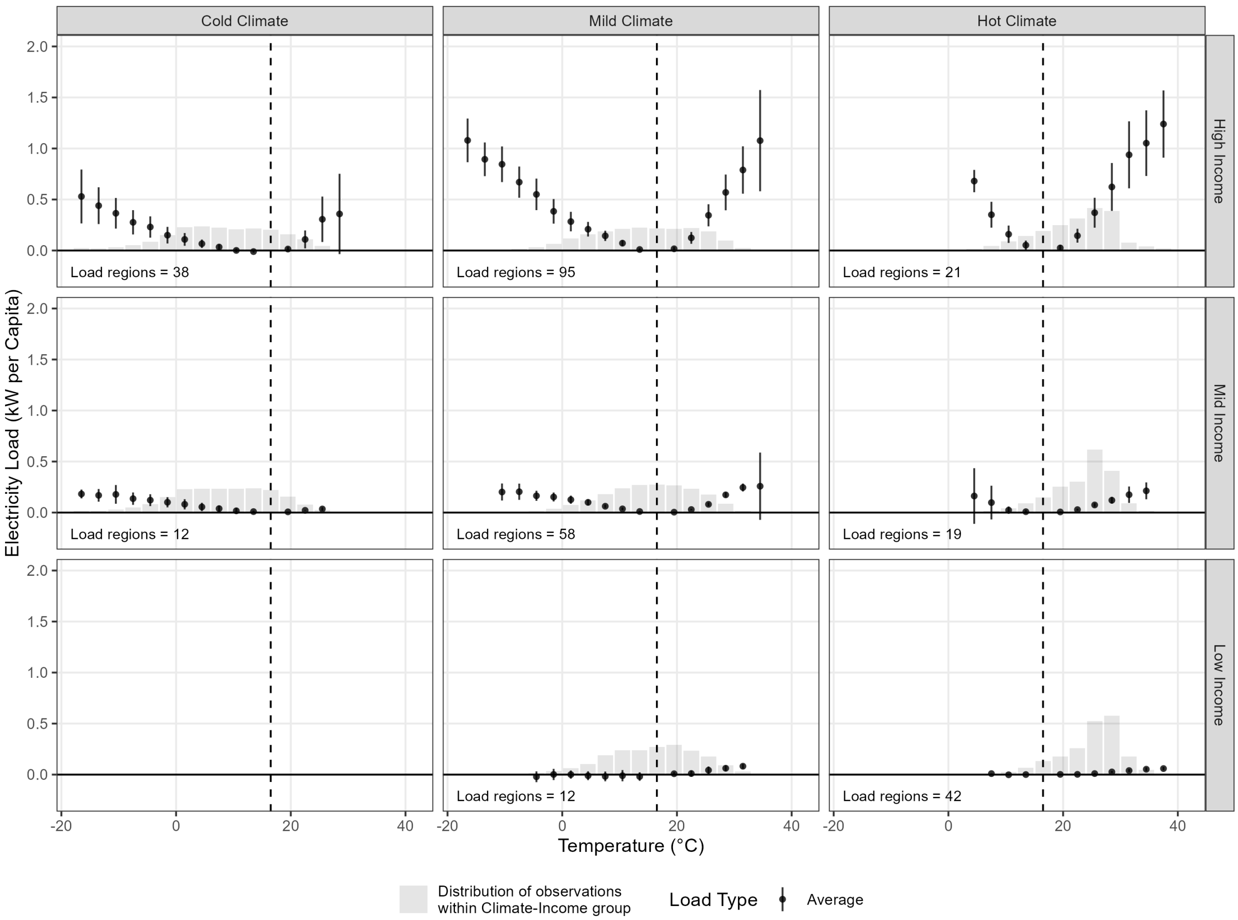
First, we can see the familiar U-shaped relationship between electricity demand and temperatures. As temperatures become hotter or colder relative to our moderate central category of 15-18C we see increasing electricity demand. This justifies our choice of functional form in the main specification.

Second, the responsiveness of electricity demand to hot or cold temperatures depends heavily on long-run income. Higher incomes are clearly associated with a much steeper electricity demand response. This is an intuitive result reflecting the greater demand for heating and cooling energy services in higher income settings.

Third, long-run climate also has a modest but noticeable impact on the estimated relationship. This is clearest in higher income regions where we see a steeper response of electricity demand to colder temperatures in areas with hotter average climates. This may

[1] For income we specify three groups based on average GDP per capita in 2021 PPP USD: <\$15,000, \$15,000-45,000, and \$45,000+. For climate we specify three groups based on average temperatures: <10C, 10-20C, and 20C+

Figure B.8: Electricity Demand Temperature Response by Climate and Income



Notes: This figure shows the estimated electricity–temperature relationship and how it depends on long-run income and climate. Electricity is in per capita terms (in kW per capita) and based on daily average load. Temperature is divided into bins, with the 15-18C bin as the omitted category. Each panel illustrates the average electricity–temperature relationship for a level of income and long-run climate. Panel rows refer to long-run income groupings based on average GDP per capita in 2021 PPP USD: Low (<\$15,000), Medium (\$15,000-45,000), and High (\$45,000+). Panel columns refer to long-run climate groupings based on average temperatures: Low (<10C), Medium (10-20C), and High (20C+). Coefficients are only plotted where there are a minimum number of sample observations falling into the relevant climate-income grouping and temperature bin.

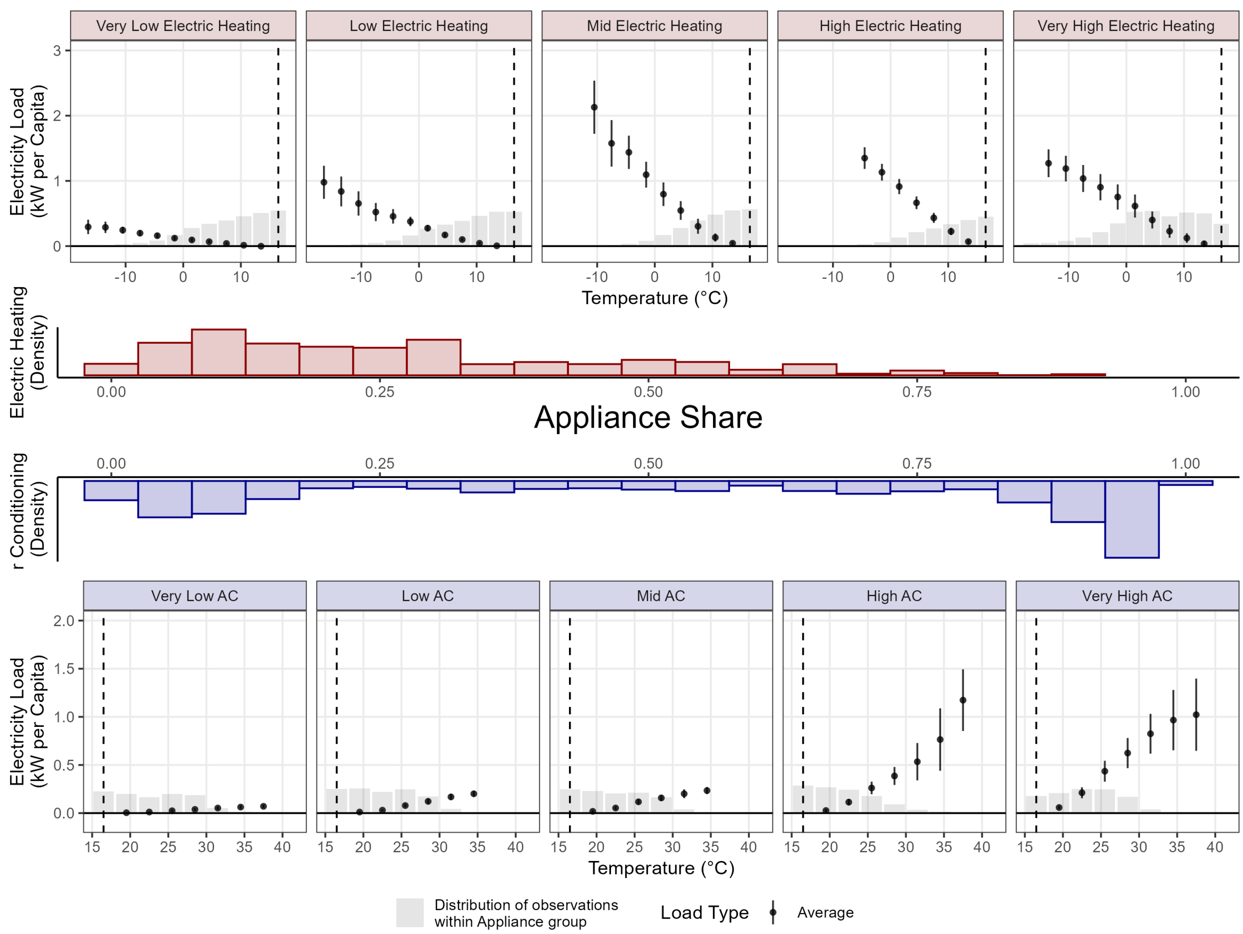
reflect poorer adaptation to cold temperatures in these areas (e.g. less insulated buildings or physiological and behavioral factors). A related driver may also be the greater prevalence of gas and other non-electric energy use for heating in areas with colder climates.

For hotter temperatures the moderating effect of long-run climate is less clear and potentially even reversed, with a steeper response of electricity demand to hotter temperatures also tending to arise in areas with hotter average climates. This almost certainly reflects the greater adoption of air conditioning in these regions. The air conditioning adoption effect likely dominates other adaptive factors that may mitigate sensitivity to hot temperatures in places with hot climates (e.g. physiological and behavioral factors). Further, we find a steeper response of daily maximum demand compared to daily average demand to hotter temperatures in high-income areas.

A key insight raised by the binned results is the potentially significant role of appliance adoption in explaining the observed short-run responsiveness of electricity demand to temperature. All else equal we expect that areas with higher penetration of air conditioning or electric heating will see larger increases in electricity demand during periods of particularly hot or cold temperatures.

Figure B.9 shows the results of our analysis examining heterogeneity in the electricity-temperature response based on appliance adoption. We estimate the same model as shown in Figure B.8, except this time we group observations into appliance groups based on the share of residential households in a given country or region that have air conditioning or electric heating respectively.

Figure B.9: Electricity Demand Temperature Response by Appliance Adoption



Notes: This figure shows the estimated electricity–temperature relationship and how it depends on appliance penetration. Electricity is in per capita terms (in kW per capita) and based on daily average load. Temperature is divided into bins, with the 15-18C bin as the omitted category. Each panel illustrates the average electricity–temperature relationship for a level of either air conditioning or electric heating penetration. Coefficients are only plotted where there are a minimum number of sample observations falling into the relevant appliance penetration grouping and temperature bin.

Here we can see that the response of electricity demand to temperatures is clearly mediated by the degree of air conditioning and electric heating penetration. This is what motivates our main specification that focuses on appliance penetration, rather than incomes or climate, as the core margin of heterogeneity along which the electricity-temperature response function is allowed to vary.

C Additional Future Projections Results

C.1 Spatial and Temporal Extrapolation

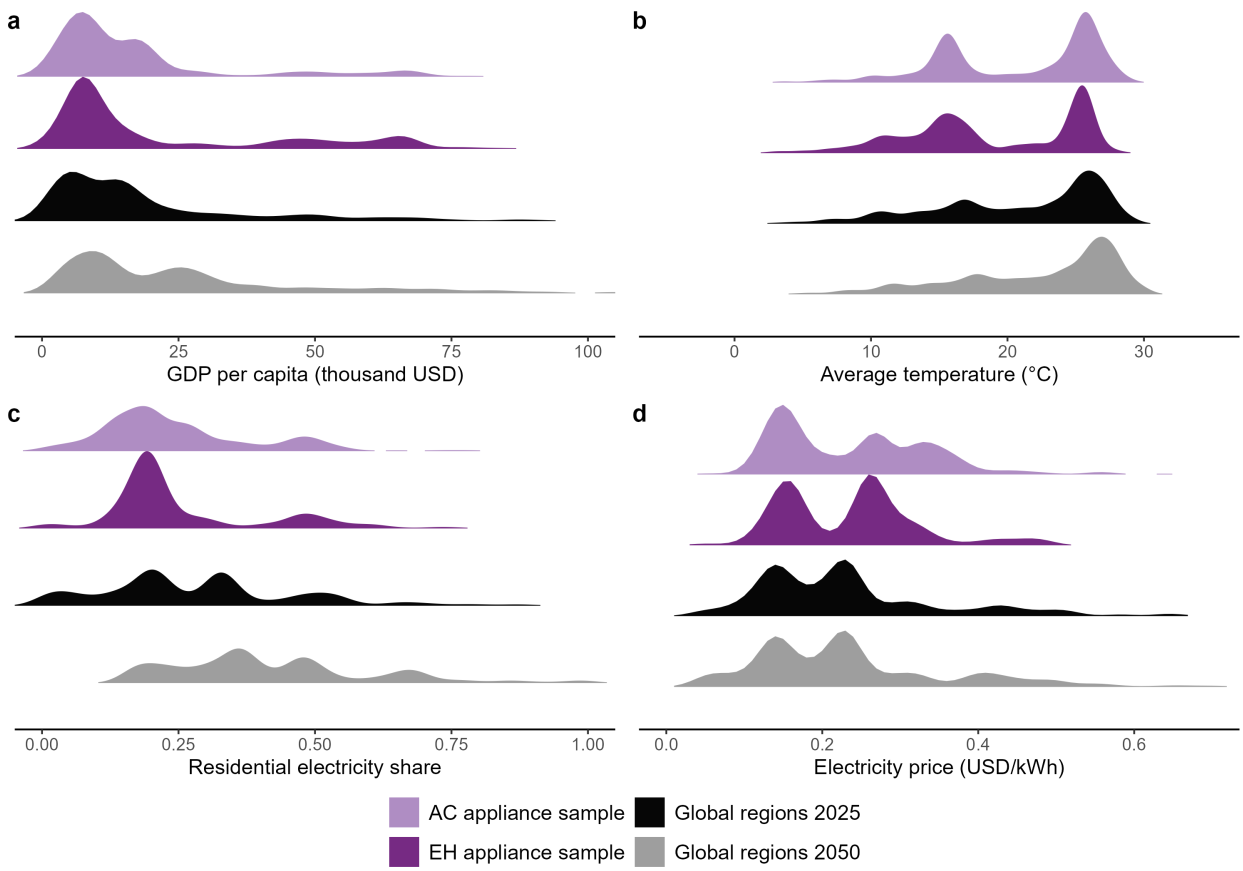
Figure C.10 shows the distribution of the four covariates (income, climate, electrification and electricity prices) that feed into the appliance model. Here we can see that our appliance region samples do provide robust covariate overlap with our target projection regions, indicating that our appliance adoption model is well suited to being used for a global sample. Moreover, Figure A.3 also illustrated the projected appliance shares for our global projection region sample for reference.

C.2 Scenario Projections and Decomposition

To isolate the contributions of climate change, income growth, electrification, and structural demand growth we produce our projections of region-day electricity demand for the full $2^4 = 16$ combinations of 2025 and 2050 values for each factor. Table C.1 lists these 16 scenarios, with $D(c, i, e, s)$ denoting demand in the scenario indexed by climate (c), income (i), electrification (e), and structural (s) flags.

We use the Shapley-Owen-Shorrocks decomposition (Shorrocks, 2012; Audoly et al., 2025) to isolate the effects of income, climate, electrification and structural factors across our scenarios. This method assigns each factor its average marginal contribution across all possible orderings and is a decomposition that is additive, symmetric across factors, and zero for factors with no effect. This allows us to decompose changes in electricity demand

Figure C.10: Coverage of covariates for estimation and full sample



Notes: This plot shows the distribution of the four covariates (income, climate, electrification and electricity prices) that feed into the appliance model. Distributions are shown for regions within the air conditioning (AC) and electrified heating (EH) estimation sample as well as for the global projection regions in 2025 and 2050.

Table C.1: Scenario grid

Scenario	Climate	Income	Electrification	Structural
$D(0,0,0,0)$	2025	2025	2025	2025
$D(1,0,0,0)$	2050	2025	2025	2025
$D(0,1,0,0)$	2025	2050	2025	2025
$D(0,0,1,0)$	2025	2025	2050	2025
$D(0,0,0,1)$	2025	2025	2025	2050
$D(1,1,0,0)$	2050	2050	2025	2025
$D(1,0,1,0)$	2050	2025	2050	2025
$D(1,0,0,1)$	2050	2025	2025	2050
$D(0,1,1,0)$	2025	2050	2050	2025
$D(0,1,0,1)$	2025	2050	2025	2050
$D(0,0,1,1)$	2025	2025	2050	2050
$D(1,1,1,0)$	2050	2050	2050	2025
$D(1,1,0,1)$	2050	2050	2025	2050
$D(1,0,1,1)$	2050	2025	2050	2050
$D(0,1,1,1)$	2025	2050	2050	2050
$D(1,1,1,1)$	2050	2050	2050	2050

Notes: This table shows the 16 scenarios considered in the analysis. $D(c,i,e,s)$ denotes demand in the scenario indexed by climate (c), income (i), electrification (e), and structural (s) flags. The columns indicate the projection year that is used for each respective variable and scenario.

into changes in heating and cooling demand induced by climate change(ϕ_{Climate}), income growth(ϕ_{Income}), and electrification (ϕ_{Elec}). The decomposition is also able to separate these factors from the non-temperature-responsive structural demand changes(ϕ_{Struct}).

For example, the future climate change impact on heating and cooling demand in projection region k is computed as follows:

$$\begin{aligned}\phi_{\text{Climate},k} = {} & \tfrac{1}{4}[D_k(1,0,0,0) - D_k(0,0,0,0)] + \tfrac{1}{12}[D_k(1,1,0,0) - D_k(0,1,0,0)] + \\ & \tfrac{1}{12}[D_k(1,0,1,0) - D_k(0,0,1,0)] + \tfrac{1}{12}[D_k(1,0,0,1) - D_k(0,0,0,1)] + \\ & \tfrac{1}{12}[D_k(1,1,1,0) - D_k(0,1,1,0)] + \tfrac{1}{12}[D_k(1,1,0,1) - D_k(0,1,0,1)] + \\ & \tfrac{1}{12}[D_k(1,0,1,1) - D_k(0,0,1,1)] + \tfrac{1}{4}[D_k(1,1,1,1) - D_k(0,1,1,1)]\end{aligned}$$

By construction, the four contributions sum to the total change in electric heating and cooling demand for every projection region: $\phi_{\text{Climate},k} + \phi_{\text{Income},k} + \phi_{\text{Elec},k} + \phi_{\text{Struct},k} = D_k(1,1,1,1) - D_k(0,0,0,0)$.

C.3 Cost Estimation

C.3.1 Average Levelised Cost (\$/kWh)

Our system LCOE assumptions are drawn from the IEA Global Energy and Climate Model (GECM) documentation accompanying the World Energy Outlook 2025 (IEA, 2025), which reports generation-mix-weighted average electricity generation costs. These include capital recovery, fuel, CO_2, and operation and maintenance costs, but exclude grid transmission costs. While grid transmission and distribution costs can represent 20–40% of total delivered electricity costs, we exclude these here as we are primarily valuing changes in generation-side resource requirements rather than retail supply costs. Including network costs would necessarily increase the overall cost impacts we estimate.

Outputs are available from the IEA for four major regions or countries (European Union, US, India and China) across three scenarios (CPS, STEPS, NZE) and three time periods (2024, 2035, 2050). We use STEPS "stated policies" as our central 2050 scenario on the grounds that it represents the closest analogue to SSP2-4.5. NZE "net zero" provides a sensitivity scenario broadly consistent with the more aggressive climate mitigation in SSP2-2.6.

Table C.2 shows the regional system LCOE values from the IEA. While there is some notable variation in costs, there is significant convergence by 2050.[2] It is challenging to make complex country or region specific assumptions about electricity prices across our global projection region sample using this data. As such we assume a single global average cost of approximately 80 $/MWh for 2025 and 70 $/MWh for 2050.

Table C.2: IEA system-average LCOE by region and scenario (USD 2025/MWh)

Region	**2024**	**2050 STEPS**	**2050 NZE**
United States	65	70	70
European Union	125	85	80
China	75	80	75
India	75	50	40

We note that the IIASA SR1.5 and AR6 IAM databases (Riahi et al., 2017; Byers et al., 2022) includes some limited measures of future electricity prices or costs for SSP-adjacent scenarios, and that these values have been used in other research projecting future energy costs (Rode et al., 2021). However, these price paths appear to suffer from large inter-model differences in technology cost assumptions and market structure, producing widely divergent cost numbers for the limited number of models that generate these outputs. At minimum,

[2] India is the one notable outlier here, apparently due to some relatively aggressive assumptions on solar costs in that region.

one common feature appears to be a general trend for prices to remain largely flat out to 2050, and so that is the logic that motivates both our assumed electricity price pathways - i.e. convergence to a global average and a sensitivity that holds prices fixed at their baseline 2025 levels.

C.3.2 Peak Capacity Cost ($/kW-year)

We value changes in peak demand using the annualised capital cost of the set of technologies that would plausibly serve as the marginal peaking resource. We consider three candidate technologies: open-cycle gas turbines (OCGT), combined-cycle gas turbines (CCGT), and utility-scale battery storage (4-hour Lithium-ion). OCGTs and batteries are the most relevant for short-duration daily or hourly peaks. CCGTs are more relevant for peak periods with elevated demand for multiple days.

For gas technologies we use regional capital cost figures from the IEA GECM 2025 Power Generation Assumptions (IEA, 2025). OCGT and CCGT capital costs are stable across all three scenarios (CPS, STEPS, NZE) although they do vary by region. For batteries we use a combination of IEA assumptions as well as supporting information from the US National Renewable Energy Laboratory (Cole, Ramasamy and Turan, 2025). The IEA does not provide information on battery costs of equivalent detail to the information for power plants. However, the GECM documentation and IEA WEO do identify assumed battery capital costs of 150 $/KWh in 2024 (which we take as corresponding to 800 $/KW), falling to 80-90 $/KWh by 2050. Fixed annual O&M costs are added from the same sources.

We convert overnight capital costs to annual charges using the capital recovery factor:

$$\text{CRF} = \frac{r(1+r)^n}{(1+r)^n - 1} \tag{C.1}$$

where r is the weighted average cost of capital (WACC) and n is the asset lifetime in years. We use $r = 8\%$. We use lifetimes of 25 years for gas technologies and 15 years for batteries, consistent with IEA and NREL assumptions. This yields CRF values of 0.094 (25 years, 8%) and 0.117 (15 years, 8%).

Table C.3 reports the resulting annualised costs. Note that OCGT and CCGT figures do not change over time where as battery costs do. Given the uncertainties in these numbers we adopt a single global average value of 75 $/KW-yr for peak capacity costs in both 2025 and 2050.

Table C.3: Annualised peak capacity costs (USD 2025/kW-year)

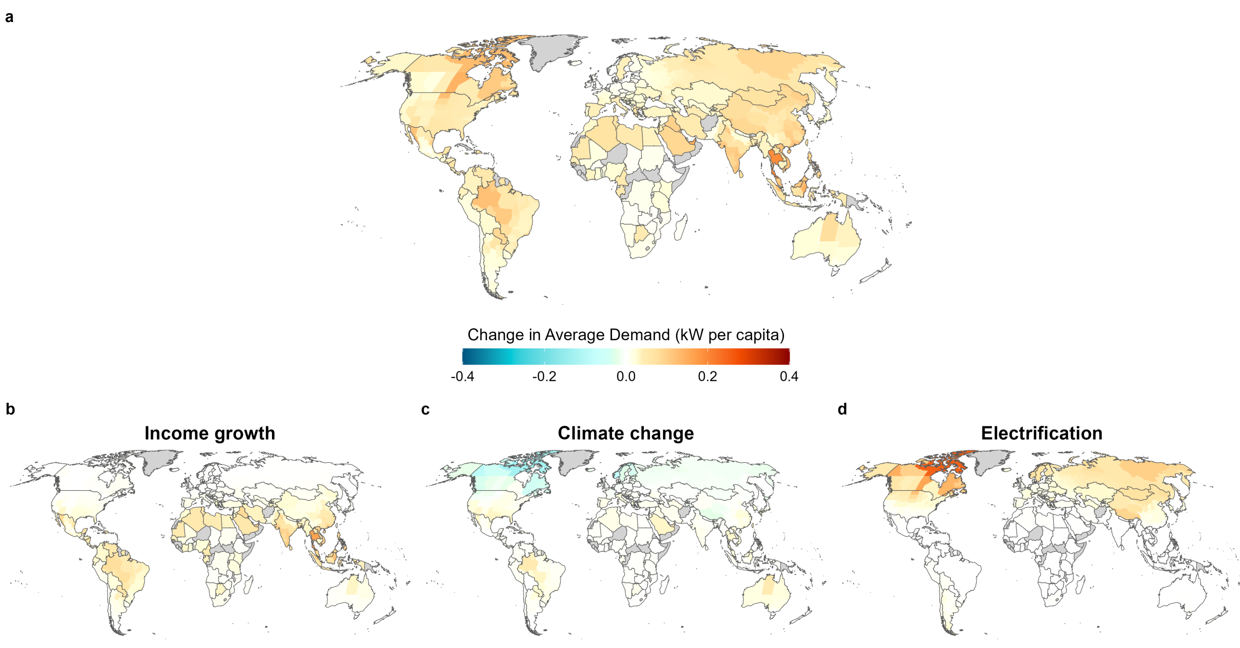
Technology	**Year**	**Capex** ($/kW)	**Lifetime** (years)	**CRF**	**Ann. capital** ($/kW-yr)	**Fixed O&M** ($/kW-yr)	**Total** ($/kW-yr)
Gas OCGT		350-500	25	0.094	33-47	20-25	**~53-72**
Gas CCGT		560-1100	25	0.094	52-103	20-30	**~72-133**
Battery 4h	2025	600-1200	15	0.117	70-140	20	**~90-160**
Battery 4h	2050	300-600	15	0.117	35-70	20	**~55-90**

Lastly, when calculating costs we only apply the peak capacity costs to the portion of projected peak demand that exceeds any projected change in average demand. The logic here is that an increase in overall average annual demand (e.g. due to increased heating or cooling loads throughout the year) will in the first instance be met by increases in the capacity that serves the average generation mix and constitutes the basis for the system-average LCOE. Any peak demand capacity requirements over and above this level can then be deemed to require additional investments in the kind of infrequently used standby capacity captured by our peak capacity cost assumption.

C.4 Additional Figures

Figure C.11 shows maps of our main findings but for average per capita electricity demand rather than the annual demand peak. Both play an important role in our analysis and affect overall electricity system costs differently. As highlighted earlier, the peak demand effects are larger in both absolute and relative terms for most countries and regions.

Figure C.11: Decomposition of change in average demand due to electric heating and cooling



Notes: This figure plots the projected mid-century (2050) change in per capita heating and cooling electricity demand under a moderate emissions scenario (RCP4.5) decomposed by the three drivers: climate change, income growth, and electrification. Maps show the spatial distribution of projected total heating and cooling demand changes in panel **a** and impacts decomposed by income growth (**b**), climate change (**c**), and electrification (**d**). Displayed are mean impacts across 23 global climate models.

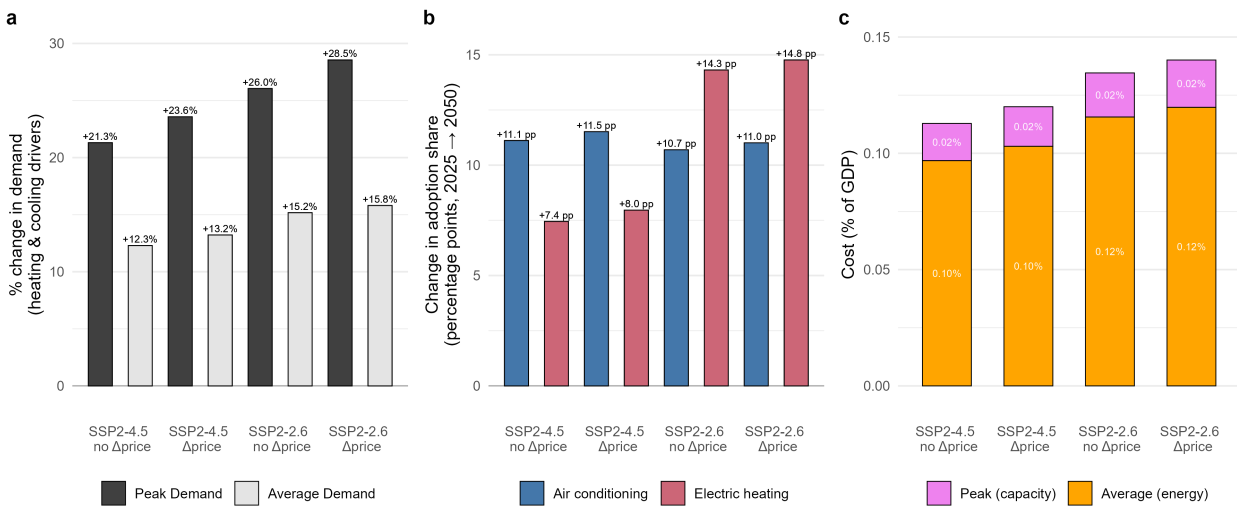
Figure C.12 shows how are overall global results change as we vary both the emissions scenario (RCP4.5 vs RCP2.6) and our assumption for the path of future electricity prices.

The choice of emissions scenario does have a marked effect on the results. As discussed in the main text, increased electrification under the more aggressive decarbonisation required for RCP2.6 entails more rapid electrification of heating. This outweighs any slight reduction in air conditioning uptake due to lower temperatures.

With regard to the role of electricity prices, our main results assume convergence to a long-run global average of \$0.20/kWh by 2050. If we instead hold regional prices fixed at baseline levels, prices remain relatively high in certain regions (e.g. Europe, large parts of Africa and South America) and relatively low in other regions (e.g. North America, China, the Middle East). Doing so does not lead to meaningful changes in appliance adoption at the global scale, meaning any differences in overall electricity demand and costs are modest. We attribute this to reduced adoption in regions with high prices at baseline being largely balanced out by increased adoption in regions with low prices at baseline.

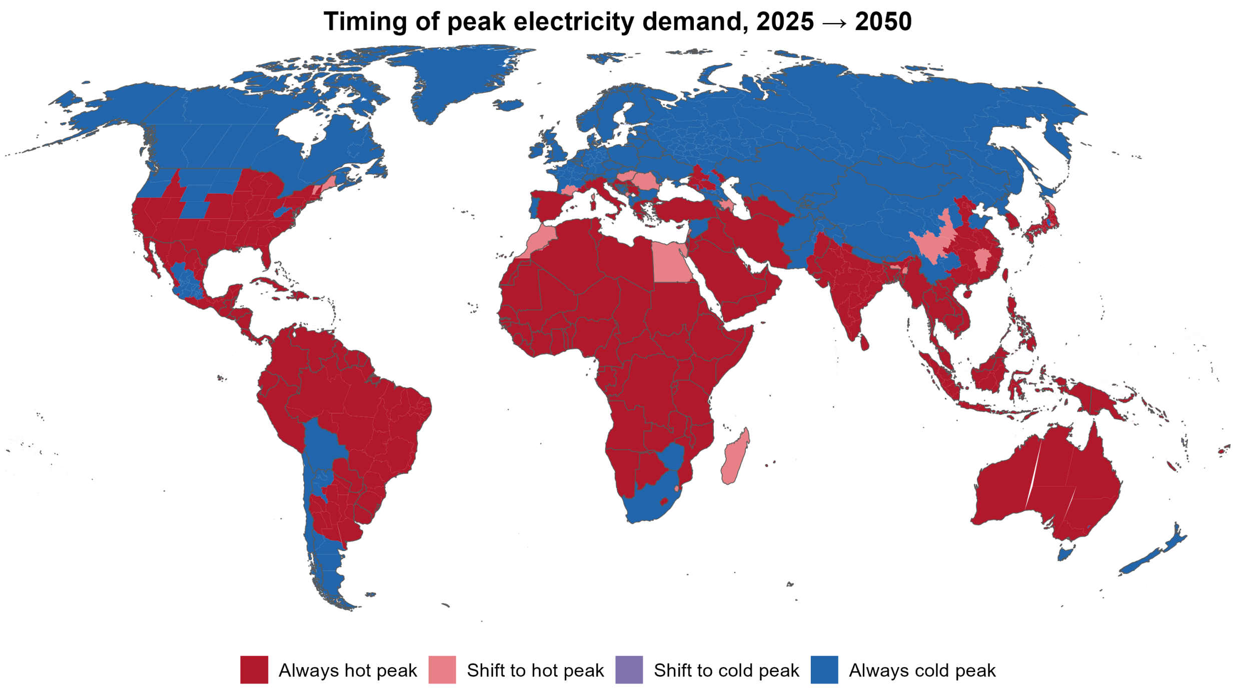
Figure C.13 shows whether demand peaks due to cooling when temperatures are hot, or due to heating when temperatures are cold. We calculate this by identifying the day of the year when demand peaks in 2025 and 2050 for each region. Where this occurs on a cold day (temperature $< 18°$C) we define this as a cold peak driven by heating demand. Where this occurs on a hot day (temperature $> 18°$C) we define this as a hot peak driven by heating demand. We then classify regions as being consistently cold temperature peaking, consistently hot temperature peaking, or having shifted between 2025 and 2050.

Figure C.12: Global change in electricity demand and appliance adoption across abatement and electricity price scenarios



Notes: This figure plots key global average outcomes for our mid-century projections across four overarching scenario assumptions. We show the sensitivity of our results to two abatement scenarios (SSP2-4.5 and SSP2-2.6) and two electricity price scenarios (no change in prices from 2025 and prices change to converge by 2050). Panel (a) shows the % change in average and peak electricity demand. Panel (b) shows the percentage point change in air conditioning and electric heating. Panel (c) shows the change in electricity costs as a % of GDP.

Figure C.13: Change in peak demand timing due to electric heating and cooling



Notes: This figure plots the change in the timing of the electricity demand peak between 2025 and 2050. Peak is based on the highest demand day from our electricity demand projections. A cold peak due to heating demand arises on a peak day with temperature less than 18°C and a hot peak due to cooling demand arises on a peak day with temperature greater than 18°C.